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Application of a Separation Approach on the CT Target/Actual Comparison of Injection Mould Plastic Parts for Dimensional Quality Control

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Finally, my family and friends for their support during my stay in Germany.

Resumo

Este trabalho foi realizado no Laboratório de Máquinas-Ferramenta (Werkzeugmaschinenlabor - WZL) da universidade RWTH-Aachen, em Aachen, Alemanha. O projeto tem o objetivo de analisar a influência de fatores controláveis de um processo de produção de peças de plástico por meio de máquinas injetoras. Deseja-se encontrar um ponto ótimo para esses fatores de maneira que o erro dimensional entre as peças produzidas e o modelo CAD seja o mínimo possível. Para atingir esse objetivo, é proposto um experimento no qual se variam seis fatores controláveis em torno de seus valores usuais de produção, obtendo assim para cada um deles os níveis baixo, central e alto. A combinação das variações destes seis fatores nos leva à produção de 53 amostras que passaram por um processo de reconstrução tridimensional utilizando-se tomografia computadorizada. Após a reconstrução as peças foram comparadas com seu modelo em CAD e os seus desvios foram analisados utilizando-se uma metodologia de separação por ordens (zero, primeira, segunda, terceira e superiores) com o uso de um software previamente desenvolvido em Matlab no WZL para uso neste projeto. Foi então gerado um modelo matemático capaz de representar os valores dos desvios em cada ordem em função dos parâmetros de entrada. Com o uso deste modelo é possível prever o tipo de desvio e a sua intensidade em função dos parâmetros escolhidos no momento da produção da peça. A influência individual de cada parâmetro sobre a saída também foi analisada, e os fatores mais críticos do processo (que exercem maior influência sobre os desvios) foram definidos. Por fim, foi simulado um novo ponto de produção que, de acordo com o modelo produzido, minimiza os desvios e poderá ser utilizado como ponto central para próximos estudos ou para produção comercial com maior precisão dimensional.

Abstract

This work was performed at the Laboratory for Machine Tools (Werkzeugmaschinenlabor - WZL) of the RWTH-Aachen University, Aachen, Germany. The project aims to analyze the influence of controlled factors in plastic parts production process by injection molding machines. It is desirable to find an optimal point for these factors so that the dimensional error between the parts produced and the CAD model is minimized. To achieve this goal, we propose an experiment in which six controllable factors vary around their usual production values, defining for each three levels: low, middle and high. The combination of variations of these six factors leads to the production of 53 samples. The samples were measured using three-dimensional computed tomography. After reconstruction the parts were compared with its CAD model. Their deviations were analyzed using a method of separation by deviation orders (zero, first, second, third and above) with a at WZL previously developed software to be used in this project. Then, a mathematical model capable of representing the values of the deviations in each order as a function of the input parameters was created. Using this model it is possible to predict the type of deviation and its intensity depending on the chosen parameters at the time of production of the piece. The individual influence of each parameter on the output was also analyzed, and the most critical factors of the process (which most influence on deviations) were defined. Finally, a new production point was defined. According to the produced model, the deviations were minimized. The new parameter set may be used as a central point for further studies and for commercial production with higher dimensional accuracy.

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List of Abbreviations

- DOE - Design Of Experiment
- WZL - Werkzeugmaschinenlabor
- RWTH - Rheinisch-Westfaelische Technische Hochschule
- CT - Computed Tomography
- CAD - Computer-Aided Design
- ANOVA - Analysis of Variance
- CMM - Coordinate Measuring Machine

1 Introduction

The dimensional quality control is an extremely important factor to ensure that produced parts follow its specifications and meet satisfactorily the levels of dimensional tolerances for these stipulated.

Plastic injection tools require constantly analysis of its produced pieces in order to ensure that the deviations of the parts conform to tolerance stipulated levels. If the deviations are above these levels, a correction of injection factors is needed to return the system to its ideal operation point. The same optimization loop can be used to produce parts with increasingly smaller deviations and will be used in this project with this purpose.

Figure 1.1: Tactile CMM measurement system [1].

Currently for the sample inspection of injection molded plastic parts mainly optical and tactile measurement (figure 1.1) processes are used, whereas the geometry of the tools' cavity, used to form the part, is deduced from the measurement of the geometry of the part itself. Inaccessible features are revealed by cutting the parts, wherein the geometry of the part may change, e.g. by release of internal stress or feathering. The tool correction based on this conventional inspection process is iterative and can be very time consuming. The delay of the start of production due to the non-approved tool causes high costs [2].

Due to this scenario, an optimization loop (figure 1.2) is proposed making use of CT measure system and math analytical software. As in this method the CT measuring is non-destructive and independent of the shape of the samples, the optimization can be performed faster, more accurate and with less iteration loops compared to other measurement systems such as optical and tactile.

The proposed optimization loop can be divided into three parts: Measure, Compare and Act, as is presented below:

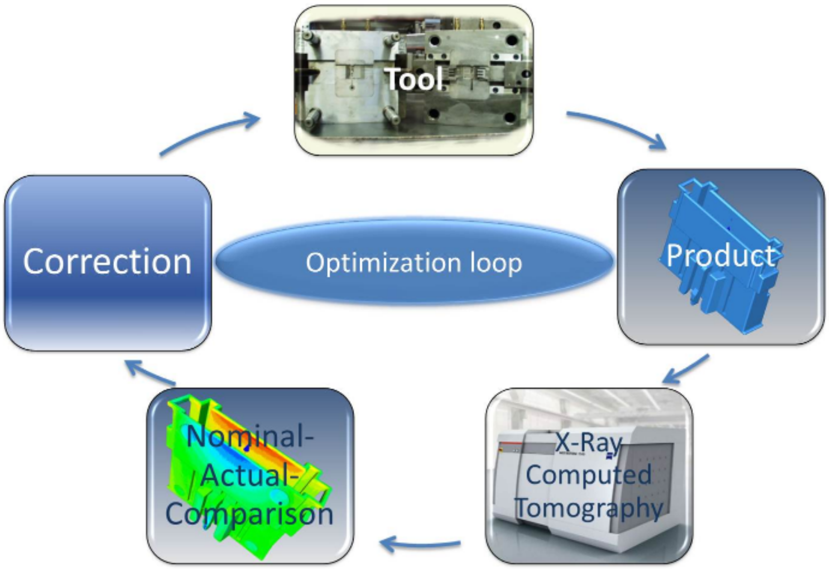


Figure 1.2: Optimization loop for the tool correction.

- Measure: An experiment is proposed to vary some plastic injection factors around an operation point and samples are produced with a combination of different values of these factors. Then, all samples are measured with CT and tridimensionally reconstructed;

- Compare: Mathematically compare the measured part 3D reconstruction with its reference (CAD model) in order to analyze deviations;

- Act: With the comparison data, model the process and simulate the factors that minimize deviations, and update the machine tool with these values. A new experiment can be done around this operation point, restarting another iteration of the optimization loop.

1.1: Project objectives

The project objective is to reduce the amount of iteration loops for the tool correction by giving, more rapid, accurate and meaningful parameters for the tool correction. In order to achieve this goal, a DOE is proposed to analyze the samples deviation to CAD model when subjected to different values of input parameters. Therefore, it is possible to create a model that represents the behavior of the system and simulate a point where the deviations are minimal.

A separation approach of the deviations in different orders was used to quantify the influence of the input factors in each deviation order (zero, first, second, third and residuals). The order zero will also be represented by offset. For this separation analysis, the software SmartInspect (previously developed in Matlab) was used.

By making use of this separation methodology it is possible to determine which factors will be relevant in each deviation order. It is also possible to find factors that despite being considered in the experiment are not significant for any order of deviation and can be considered a noise in the analyses and removed from the next iteration loop, making the whole process easier.

2 Plastic parts highlights

Product designers have a big variety of different materials when selecting the material of construction for a particular product. Plastic is one of those materials and compete with other materials such as steel, wood, ceramics or glass. In most cases each one of the materials offer inherent benefits and of course some limitations. Some plastics characteristics that can be crucial for the designer's choice is presented [3]:

- Versatility;
- Relatively easy to mold into complex shapes;
- Low specific gravity;
- Sometimes transparent;
- Coloring throughout;
- Relatively low energy requirements for processing;
- Chemical resistance;
- Good electrical insulation.

But it also presents some disadvantages:

- Expensive equipment investment;
- Potentially high running costs;
- Need to design moldable parts.

2.1: Molding process

Injection molding is used to create many things such as wire spools, packaging, bottle caps, automotive dashboards, pocket combs, some musical instruments, one-piece chairs and small tables, storage containers, mechanical parts (including gears), and most other plastic products available today. Injection molding is the most common method of part manufacturing. It is ideal for producing high volumes of the same object.

The injection molding process is a high speed, automated process that can be used to produce plastic parts with very complex geometries. The process can produce either very small or very large parts using virtually any plastic material. It is important, however, for part designers to recognize that the design of the product will ultimately determine the 'ease of molding' or 'manufacturability' of the part, as well as tooling requirements and costs.

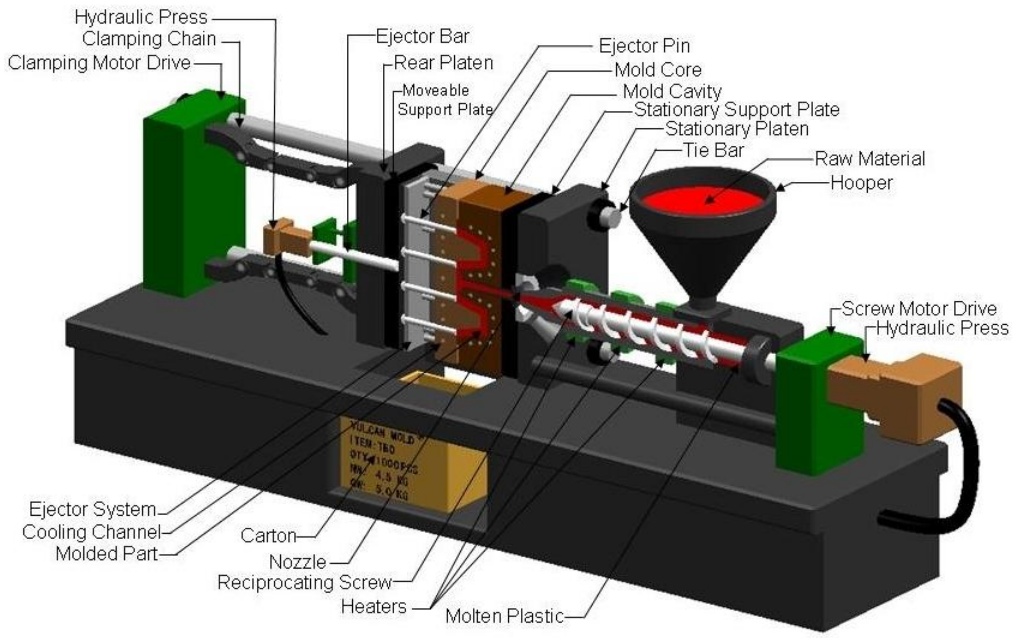


Figure 2.1: Schematic representation of a plastic injection tool [4].

The injection molding process is a complex process that involves a series of sequential process steps. The different phases of the injection molding process are presented below [3]:

2.1.1: Molding filling

After the mold closes, the melt flows from the injection unit of the molding machine into the relatively cool mold trough the feed channel and then into the cavity.

2.1.2: Packing

The melt is pressurized and compressed to ensure complete filling and detailed surface replication

2.1.3: Holding

The melt is held in the mold under pressure to compensate for shrinkage as the part cools. Holding pressure is usually applied until the gate solidifies. Once gate solidifies occurs, melt can no longer flow into (or out of) the cavity.

2.1.4: Cooling

The melt continues to cool and shrink with no shrink compensation.

2.1.5: Part ejection

The mold opens and the cooled part is then stripped from the core of cavity, in most cases using a mechanical ejector system.

3 Computed tomography

X-Ray computed tomography (CT) is a rather new technology in manufacturing metrology as the first devices designed specifically for metrological purposes came to the market after the year 2000.

After being used for medical purposes, the use of this technology in non-destructive manufacturing metrology made sense. The incorporation of manufacturers known from CMM metrology assured the traceability of CT systems and made the use of it as a measurement device possible.

The volumetric model which results from each measurement offers not only high point density known from optical metrology but even represents the whole volume of a measurement object holistically. As a result it is possible to analyze interior and hidden features of an object in addition to evaluations on the surface without destroying the workpiece [5].

3.1: CT operation

The CT is a non-destructive technique to obtain cross-sectional images from a work piece. A schematic figure of the CT operation is shown in figure 3.1. In a typical procedure, a work piece is placed on a rotary table and parameters, such as tube voltage, exposure time and number of projections, are set. A source inside the CT machine emits x-rays that penetrate the part and are attenuated according to the part geometry, density, material and x-ray energy. A detector placed behind the rotary table is used to record the intensity of the attenuated x-rays. The detector provides a bi-dimensional grayscale image representing the amount of attenuation of the current projection. After several attenuation images from different rotation angles are obtained it is possible to create, through a mathematical reconstruction, a 3D voxel model (equivalent 3D of the pixel) in which the voxel gray value represents the absorvity of the material. This 3D voxel model can be used to generate a 3D data set (point cloud) of the current scanned part.

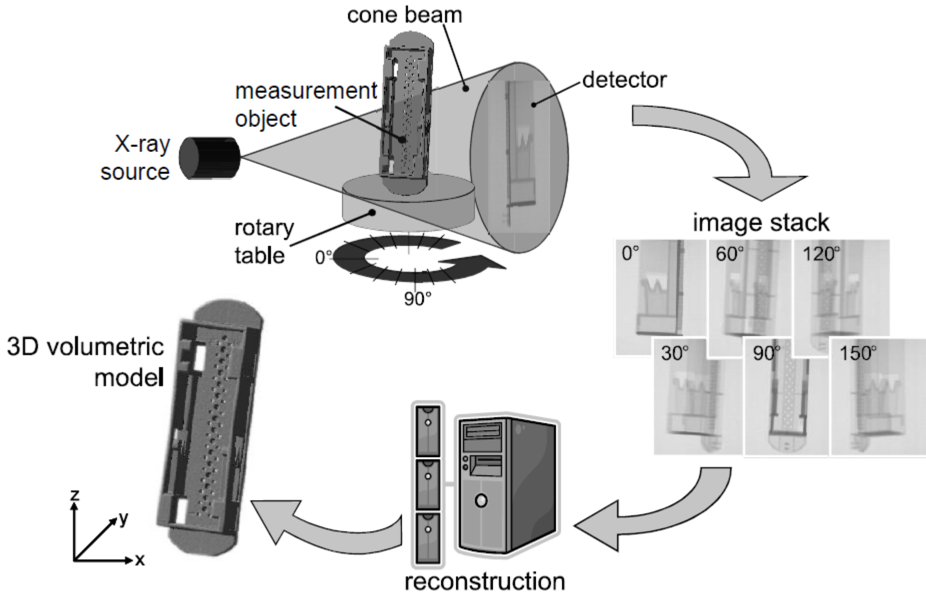
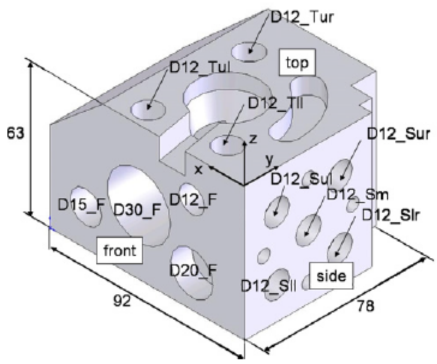


Figure 3.1: Schematic description of CT operation and reconstruction process.

3.2: Determination of the uncertainty in measurement

Currently, there is no standard that set the uncertainty of a CT measurement, but is known that it varies with the input parameter values (such as Tube voltage, Tube current, pre-filter thickness, exposure time, Detector sensitivity) used for each measurement. It is very difficult to calculate analytically the uncertainty in measurement of CT systems due to the existence of various factors and their interactions that would have to be considered. However, experimental investigations considering probing deviations have been performed for custom-designed standards, e.g. step cylinders, ball bars or titanium calotte cubes and a cylinder head [6]. According to an experiment with calibrated work pieces proposed by [6], the variation of the parameters made the standard deviation derived from five repetitions varies between approximately 1 and 7.5 μm. This experiment has shown how the CT measurement uncertainty range can vary with the set of the parameters for each sample to be measured, and give us an idea about the uncertainty of the computed tomography system.



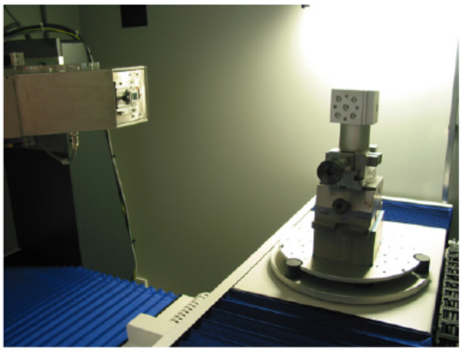


Figure 3.2: Calibrated work piece being used to determine CT uncertainties.

3.3: CT limitations

The use of CT for measuring plastic parts is very convenient, since such materials generally do not have high density, so the x-rays emitted by the CT source does not suffer much attenuation, allowing a good reconstruction of the part.

However, it does not occur with the use of denser materials such as metals. With this kind of material analysis, the high density of the material can compromise the quality of the reconstruction of parts. Besides this, the choice of appropriate parameters of CT also directly affects the quality of the reconstruction.

4 Separation methodology

The CT provides a point cloud with very high point density, which can be used to calculate a 3D surface model as described in chapter 3. This 3D surface model and the CAD-model can be used to create a nominal-actual comparison, e.g. in form of a color-coded deviation representation (figure 4.1).

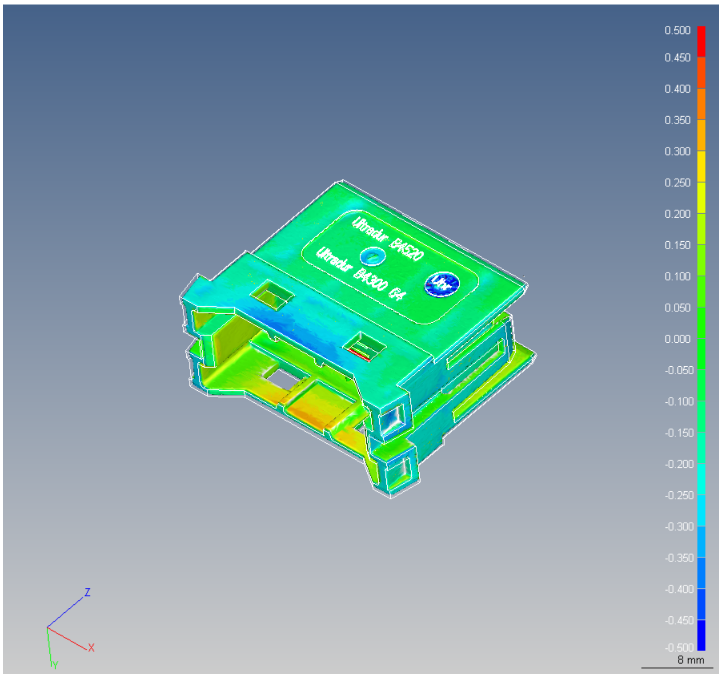


Figure 4.1: Color-coded deviation representation of one of analyzed samples.

In this nominal-actual comparison different orders of geometric deviations (offset, slope, curvature, waviness) are overlaid (figure 4.2). These geometric deviations will be separated to figure out their causes (tool geometry and injection molding process) more easily and to be able to adapt specifically the tool correction (e.g. process of eroding) [2].

A separation approach for flank topographies using CMM measurements as measuring instrument was proposed in [7]. This approach was adapted and used for

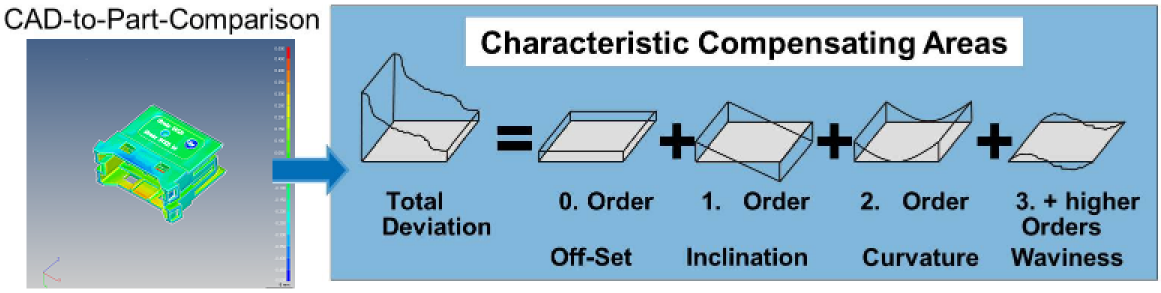


Figure 4.2: Total deviation and separation methodology.

the current work. All mathematical derivations presented in this chapter are credited to the approach authors.

The punctual deviations between a nominal and actual surface can be considered as an overlaid of several order form deviations. In this project we will consider, basically, the three first global forms deviations and the residuals forms:

- The 0th order form with the meaning of an offset;
- The 1st order form with the meaning of inclination;
- The 2nd order form with the meaning of curvature;
- The residual forms composed by the 3rd order form, with the meaning of waviness, plus the higher orders.

The global forms and residuals are represented in figure 4.3.

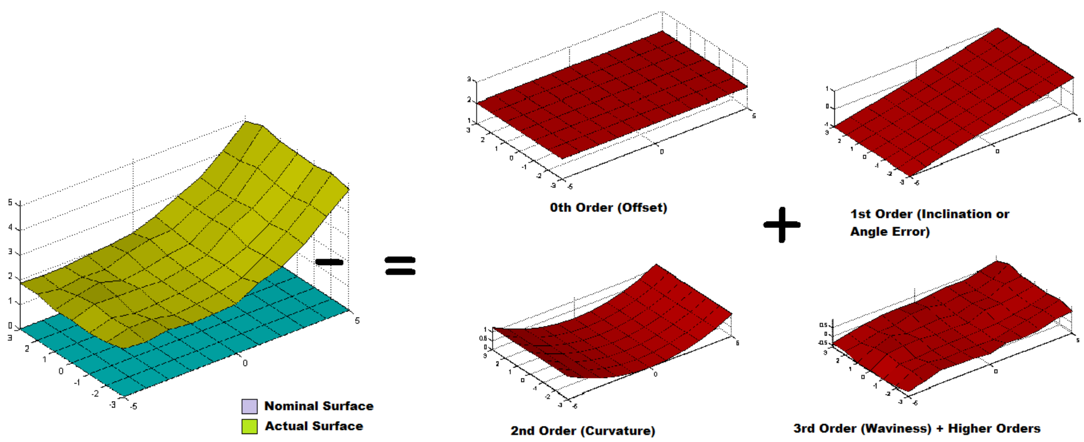


Figure 4.3: Global forms and residuals from deviations separation.

The separation and calculation of parameters of each order can be done by best-fit approximation and least square method by minimizing the sum of the squares of the residual deviations and the best-fit function s for each order. The objective function is given by:

$$f(x) = \sum_{i=1}^{n} (\delta - s_i)^2 \tag{4.1}$$

4.1: The 0th order form deviations

The 0th order form deviations have the meaning of an offset or in some cases can be described as a pitch error. The best-fit function for this order is given by:

$$s_0(x, y) = z_0 \tag{4.2}$$

The deviations used are the current deviations between nominal and actual surfaces.

$$\delta_0 = \delta \tag{4.3}$$

4.2: The 1st order form deviations

The first order form deviations are considered as a plane which has the meaning of inclination of the global topography. The equation of a plane is given by:

$$Ax + By + Cz + D = 0 \tag{4.4}$$

In this case the domain is considered as the set of pairs (x,y). Thus the best-fit function s for this order can be written as:

$$s_1(x, y) = z = ax + by + c \tag{4.5}$$

The deviations values used for the first order are the difference between the nominal deviations and the zero order form.

$$\delta_1 = \delta - s_0(x, y) \tag{4.6}$$

4.3: The 2nd order form deviations

The second order form deviations can be interpreted as the curvature and anisotropy of the global topography. The general form of a second order surface can be written as:

$$a_{11}x_1^2 + a_{22}x_2^2 + a_{33}x_3^2 + 2a_{12}x_1x_2 + 2a_{23}x_2x_3 + 2a_{31}x_3x_1 + 2b_1x_1 + 2b_2x_2 + 2b_3x_3 + c$$

$$or$$

$$\sum_{i,j=1}^{3} a_{ij}x_ix_j + 2\sum_{i=1}^{3} b_ix_i + c = 0 \quad (a_{ij} = a_{ji}) \tag{4.7}$$

The second order surface can also be expressed in the matrix notation by:

$$s(x) = \tilde{x}^T\tilde{A}\tilde{x} = (\tilde{A}\tilde{x}, \tilde{x}) = 0 \tag{4.8}$$

Where the matrix $\tilde{A}$ and $\tilde{x}$ are given by:

$$\tilde{A} = \begin{pmatrix} A & b \\ b^T & c \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & b_1 \\ a_{21} & a_{22} & a_{23} & b_2 \\ a_{31} & a_{32} & a_{33} & b_3 \\ b_1 & b_2 & b_3 & c \end{pmatrix}, \quad \tilde{x} = \begin{pmatrix} x \\ 1 \end{pmatrix} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ 1 \end{pmatrix} \tag{4.9}$$

The second order surfaces are the points that satisfy the equation S(x)=0 when rank(A)=0. Moreover, since the second order surface expressed as matrix notation is a quadratic form and A is a real symmetric matrix, it is possible to classify the surfaces in five forms as shown in figure 4.4.

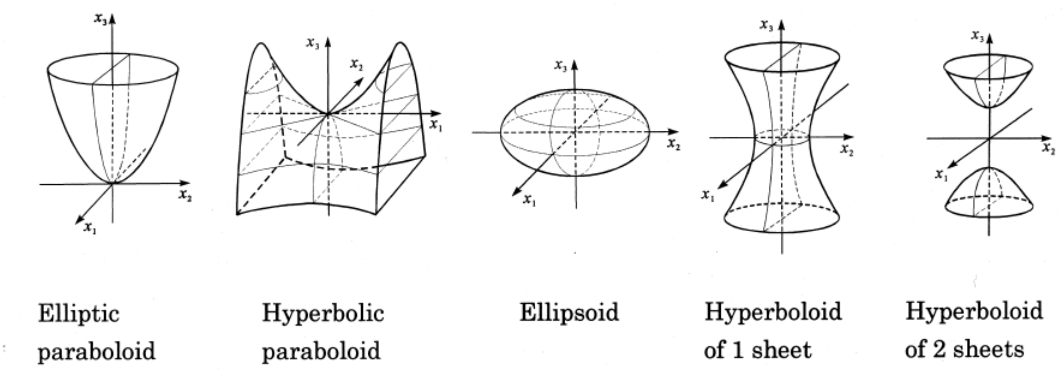


Figure 4.4: Second order surfaces forms.

These forms are, basically, described by the following equations:

Name	**Equation**
Ellipsoid	$X^2 + Y^2 + Z^2 = 1$
Hyperboloid of 1 sheet	$X^2 + Y^2 - Z^2 = 1$
Hyperboloid of 2 sheets	$-X^2 - Y^2 + Z^2 = 1$
Elliptic paraboloid	$X^2 + Y^2 = Z$
Hyperbolic paraboloid	$X^2 - Y^2 = Z$

Table 4.1: Equations for each second order surface form.

This means that an arbitrary surface can be obtained from the proper forms by applying a suitable rotation R, parallel translation Q and scaling transformation S matrices. Where the matrices R, Q and S are given by:

$$S = \begin{pmatrix} S_x & 0 & 0 & 0 \\ 0 & S_y & 0 & 0 \\ 0 & 0 & S_z & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad Q = \begin{pmatrix} 1 & 0 & 0 & Q_x \\ 0 & 1 & 0 & Q_y \\ 0 & 0 & 1 & Q_z \\ 0 & 0 & 0 & 1 \end{pmatrix} \quad R = \begin{pmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{pmatrix} \tag{4.10}$$

Although there are five fundamental forms we can reduce them into two types: a paraboloid and an ellipsoid/hyperboloid function.

The paraboloid equation is given by:

$$z = x^2 \pm y^2 \tag{4.11}$$

After applying the rotation, parallel translation and scaling transformation the equation can be written by:

$$s_2(x,y) = z = \frac{S_z}{S_x^2}[\cos\theta_z x + \sin\theta_z y - Q_x]^2 \pm \frac{S_z}{S_y^2}[-\sin\theta_z x + \cos\theta_z y - Q_y]^2 + Q_z \tag{4.12}$$

In this project the paraboloid function has been chosen as best-fit function for the second order. The paraboloid is enough to evaluate the curvature and the anisotropy of the second order. In addition, it has more stability and is more time saving, as long as it needs to calculate 6 parameters (instead of 7 as in the case ellipsoid/hyperboloid function). [7]

In contrast with the first and zero order, the second order form cannot be solved analytically. For a good approximation the quasi-Newton method can be used with initial values chosen so that:

$$Q_x = Xlenght/2, \qquad Q_y = Ylenght/2, \qquad Q_z = 0.0$$

The deviations used for the best fit, in this case, are the difference between the nominal deviations and the sum of the zero order and first order form.

$$\delta_2 = \delta - s_0(x, y) - s_1(x, y) \tag{4.13}$$

4.4: SmartInspeCT software

The SmartInspeCT is a software created by WZL in Matlab environment based on the separation methodology described in this chapter. The software inputs are a nominal file (CAD model) and an actual file (point cloud). After the CAD model is loaded, the user must select one surface of the part to be analyzed (figure 4.6) by clicking on it with the mouse cursor.

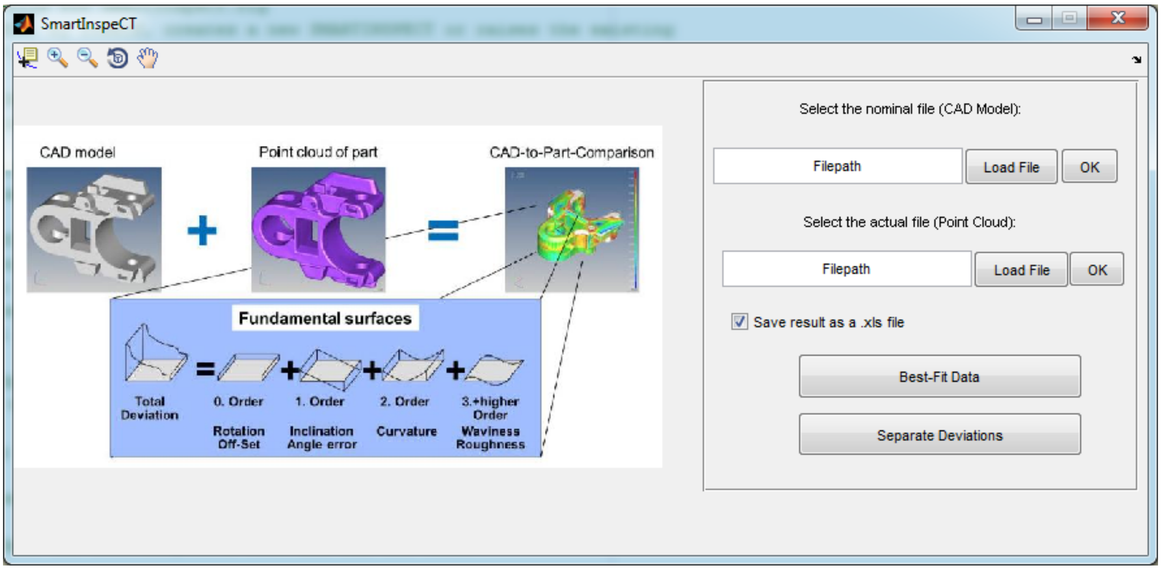


Figure 4.5: SmartInspeCT software interface.

The CAD model filetype used for this application is a standard STL (stereolitography) ASCII file which is supported in many CAD softwares. The STL file contains unstructured information (vertices and normals of triangles) from the model in the form of triangles.

On the other hand, the point cloud contains the actual points in the xyz co-ordinates obtained from the measurement of the real part. This information can be introduced to the software using three different formats: STL ASCII file (.stl), text file (.txt) and spreadsheet file (.xlsx).

In this project, the SmartInspeCT 'Best-fit' feature was not used. Instead of that, the best-fit was performed in Calypso software and will be described in chapter 5.

Once both models are loaded in the software and one surface is selected (figure 4.6), it is possible to start running the separation by pressing the 'Separate deviations' button. After the software calculates the deviations of the surface, a response window appears with the deviation results in each order (figure 4.7).

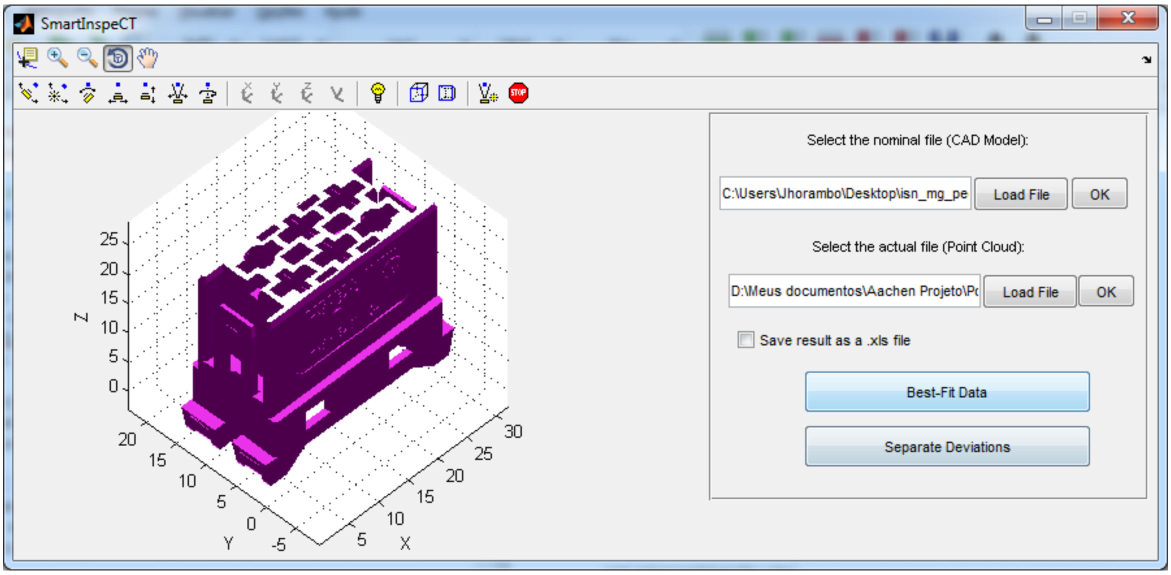


Figure 4.6: SmartInspeCT software with the upper surface selected.

The response window shows two results for the offset, four results to the first order, seven results for the second order and two results for third order and superiors, as is shown in table 4.2. Although all this deviations have been calculated, once the main objective of the project is to minimize all deviations, and also in order to simplify the analysis, just the RMS results for offset, first, second, third and superior orders were considered. So, from now on, when a value of any order deviation is cited, it means its RMS value.

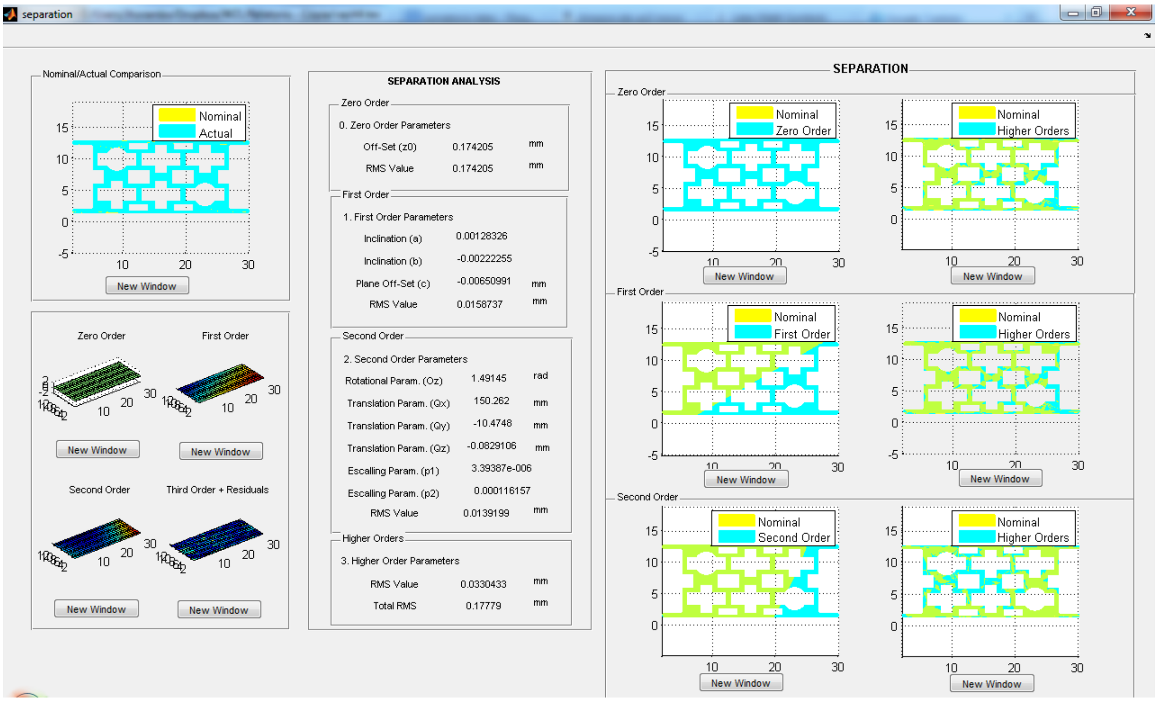


Figure 4.7: SmartInspeCT software results for the upper surface selected.

Order	Deviation
0. Order	Off-Set (mm)
	RMS Value (mm)
1. Order	Inclination(a)
	Inclination(b)
	Plane Off-Set (c) (mm)
	RMS Value (mm)
2. Order	Rotational Param. (Oz) (rad)
	Translation Param. (Qx) (mm)
	Translation Param. (Qy) (mm)
	Translation Param. (Qz) (mm)
	Escaling Param. (p1)
	Escaling Param. (p2)
	RMS Value (mm)
3.+ Order	RMS Value (mm)
	Total RMS (mm)

Table 4.2: SmartInspeCT software output parameters.

The methodology used to perform all comparisons using SmartInspeCT software will be presented in chapter 5.

4.4.1: SmartInspeCT modifications

As previously described, the SmartInspeCT software was already developed in WZL to be used in this project, but some modifications had to be done because of the geometry of the samples analyzed and in order to make the comparison most automated possible.

4.4.1.1: Region Growing Algorithm

The region growing algorithm segments surfaces with continuity in their normal. How the part analyzed in this work has rounded corners, some different surfaces of the sample was understood by the original software to be only one surface, what made it not work for those surfaces. In order to fix this issue, the comparative parameter that fragments the surfaces has been changed to be more accurate to rounded corners surfaces.

4.4.1.2: XLS file auto save

Throughout the project, 13 surfaces of each 53 samples has been compared through the SmartInspect software. How the software returns 15 results for each comparison, more than 10.000 data values were taken from the software to be later analyzed.

In order to make this process automated and easier, a xls file auto save feature was implemented. With this modification, after each comparison, the 15 results of the SmartInspeCT software were automated written to a xls file. The software interface (figure 4.5) was modified to include a check button in which the user decides to save or not the results in a xls file.

5 DOE - Design Of Experiment

DOE involves making a set of experiments representative with regards to a given question. The way to do this is problem dependent, and the shape and complexity of a statistical experimental design may vary considerably. A common approach in DOE is to define an interesting standard reference experiment and then perform new, representative experiments around it (figure 5.1). These new experiments are laid out in a symmetrical fashion around the standard reference experiment. Hence, the standard reference experiment is usually called the center point [8].

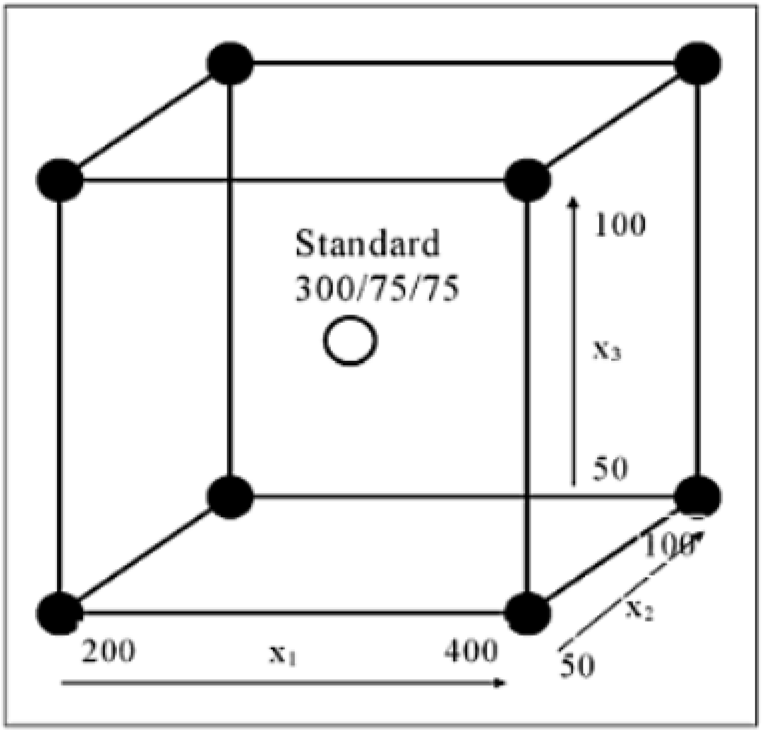


Figure 5.1: DOE with center point and other points obtained trough factors variation.

5.1: Factors analyze

In DOE, there are two fundamental types of variables, factors (inputs) and responses (outputs) - as is shown in figure 5.2. The responses inform us about properties and general conditions of the studied system or process. The responses are, in this case, the samples shape deviations between the measurement and the nominal CAD model. On the other hand, factors are the controllable inputs, and will be our tools to manipulate the system.

Figure 5.2: System process describes the relationship between Factors and Responses.

In this project, six controllable injection molding most important factors were selected and are presented below:

- Pressure [bar]
- Pressure time [s]
- Cooling time [s]
- Injection rate [cc/s]
- Cylinder temperature [°C]
- Temperature [°C]

Since these factors exert an influence on the system, it is usually possible to force the system towards a region where the responses becomes better. With the use of the DOE methodology, a modeling of the system can be build and the factors chosen in order to make the responses as good as possible.

5.2: Selection of appropriate model

It is of utmost importance to recognize that a model is an approximation, which simplifies the study of the reality. A model will be never 100% perfect, but can still be very useful. It constitutes an excellent tool for understanding important mechanisms of the reality, and for manipulating parts of the reality according to a desired outcome [8].

When making a DOE, there are some different models that can be used, and each of them can be better or worse depending on the characteristics of the process and the desired goals to be achieved.

For the current project, describing how the response varies as a function of the different input factors and determine these factors values that give optimal responses (minimum deviation) is the main goal. According to [9], Factorial design could be used for this kind of experiment, but when input factors can be varied across a continuous range of values, other treatment designs may be more efficient. Response surface methods are designs and models for working with continuous factors when finding optima or describing the response is the goal. Even so, factorial analyzes have also been done in order to compare the results.

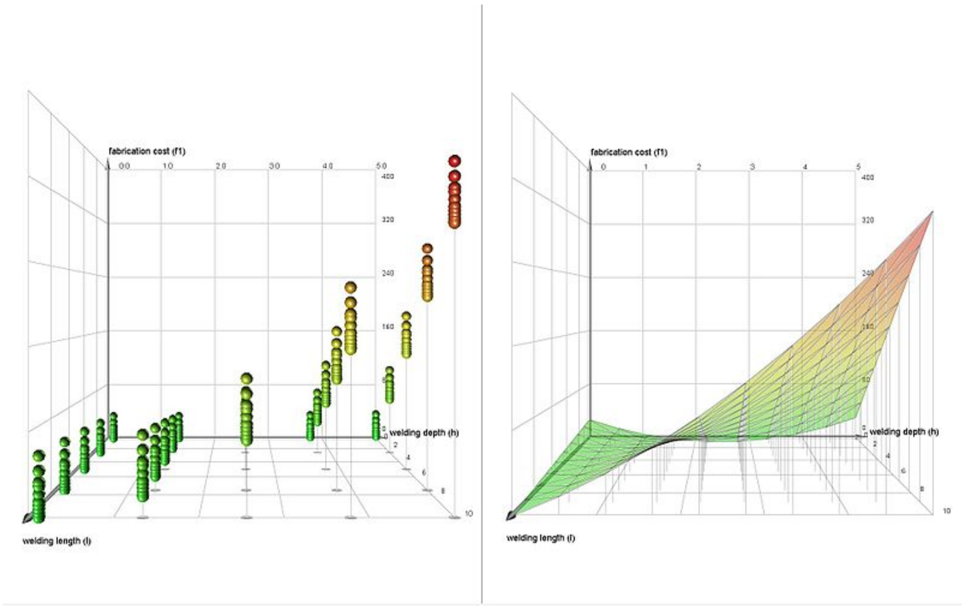


Figure 5.3: Design of experiments with full factorial design (left), response surface with second-degree polynomial (right).

5.3: Samples generation

In DOE methodology, new experiments are done around the standard reference (figure 5.1), in order to evaluate and model the behavior of the system in the vicinity of the center point.

The standard reference used is a known operation point by WZL, and the factors were varied around it with the statistical software Minitab 14 to create a worksheet with the input factors of the samples.

The values of the minimum, center and maximum for each input factor were entered in the Minitab software, and can be found in table 5.1.

Factors	Min	Center	max
Pressure [bar]	400	500	600
Pressure time [s]	1	1.5	2
Cooling time [s]	7	10	13
Injection rate [cc/s]	10	20	30
Cylinder temp [°C]	250	260	270
Temperature [°C]	60	75	90

Table 5.1: Minimum, center and maximal factors values to current DOE

In the Minitab 14 software, a new Response surface DOE was created, with a central composite, in a Half Design, and gave the output of 53 samples.

The worksheet (figure 5.4) is a display of the values on the above table, and each one of the 53 samples has different combinations of these factors values. The complete worksheet is shown in Appendix B

5.4: Samples build

After the input factors have been defined, the samples production has started. The factors Pressure, Cooling time, Injection rate and Cylinder temperature can be directly set and were not an issue, but the Temperature represented a problem while producing the samples. Due to the inaccuracy of the plastic injection equipment to measure and control the temperature, and the long time that takes to change the temperature set-point (temperature change has great inertia due to the need for cooling or heating large quantities of plastic and the entire injection system of the machine), some samples were produced with a different values of temperature that was specified

MINITAB - projeto 3 todos dados.MPJ - [Worksheet 3 ***]

↓	C1	C2	C3	C4	C5	C6	C7
	Versuch	Nachdruck [bar]	Nachdruckzeit [s]	Kühlzeit [s]	Einspritzgeschwindigkeit[ccm/s]	Zylindertemperatur [°C]	Temperatur [°C]
1	1	400	1.5	10	20	260	75
2	2	500	1.5	10	20	260	75
3	3	500	1.5	10	20	260	75
4	4	500	1.0	10	20	260	75
5	5	500	1.5	10	20	260	75
6	6	500	1.5	10	30	260	75
7	7	500	1.5	10	20	260	75
8	8	500	1.5	7	20	260	75
9	9	500	1.5	10	20	260	75
10	10	600	1.5	10	20	260	75
11	11	500	1.5	10	20	260	75
12	12	500	2.0	10	20	260	75
13	13	500	1.5	10	20	260	75
14	14	500	1.5	13	20	260	75
15	15	500	1.5	10	20	260	75
16	16	500	1.5	10	10	260	75
17	17	500	1.5	10	20	260	75
18	18	500	1.5	10	20	260	90
19	19	500	1.5	10	20	260	60
20	20	400	1.0	13	30	250	60
21	21	400	1.0	7	10	250	60
22	22	600	1.0	13	10	250	60
23	23	600	2.0	7	10	250	60
24	24	600	1.0	7	30	250	60
25	25	400	2.0	13	10	250	60
26	26	400	2.0	7	30	250	60
27	27	600	2.0	13	30	250	60
28	28	500	1.5	10	20	250	75
29	29	400	2.0	13	30	250	90

Figure 5.4: Worksheet with combination of levels for each factor

in the worksheet. This fact can have introduced a systematic error in the model, but made the production costs lower.

All samples were produced with three replications, but only one of those was in fact analyzed in WZL, the other two replications were sent to a third company to be measured, in order to hereafter compare the results.

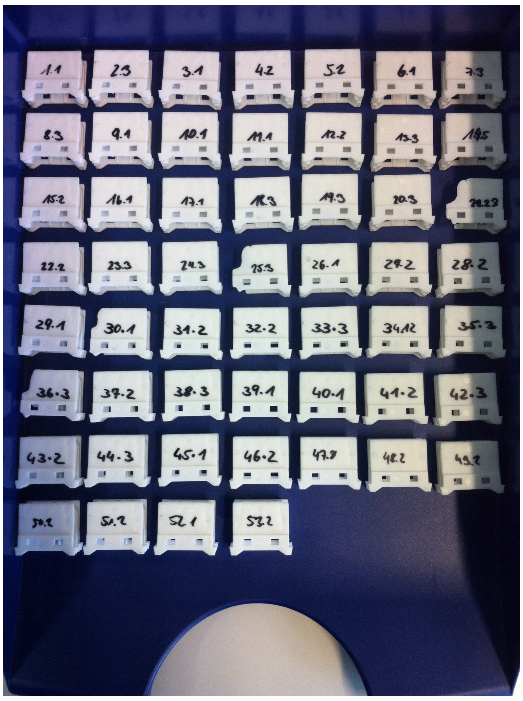


Figure 5.5: All 53 produced samples used in this experiment.

5.4.1: Samples defects

Four of the fifty-three samples presented visual defects (as figure 5.6) and were not considered in the analysis once it was not possible to execute the best-fit in order to compare those samples with the CAD model. The loose of those four samples also contributes to an inaccuracy of the modeling.

Figure 5.6: Four defect samples (bottom) and non-defect sample (top).

5.5: CT measurement

The first task when measuring a sample with the CT is to find a way to hold the part in the CT rotational desk. In this case, the sample cannot have perpendicular edges with the CT X-ray emission source, and any object used to hold the sample could overlap the sample and prejudice the measure result. To solve this problem, a low density sponge was used to hold the sample. How the density of the sponge is much less than the plastic, it did not detracted the reconstruction quality.

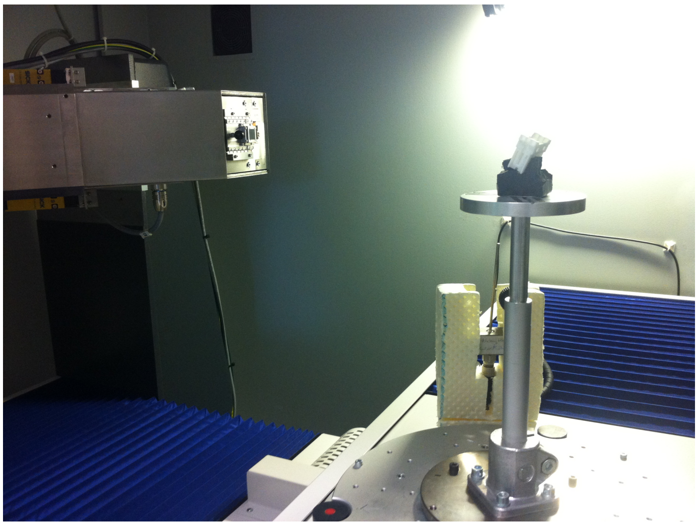


Figure 5.7: One of the samples being placed in the CT to be measured.

The next task is to define the CT parameters, such an exposition time, number of pictures, sensor gain, pre-filter, etc. It was defined with the assistance of Fabricio Borges, a master's CT student, and [10], as follows:

- Voltage: 100 kV;
- Current: 550 μA;
- Integration time 1000 ms;
- Gain: 16x;
- Number of images: 500;
- Pre-filter: 0 (no pre-filter).

This CT reconstruction has been analyzed at the software VG Studio Max (figure 5.9) and was considered adequate to the measurement of all of the samples with those parameters.

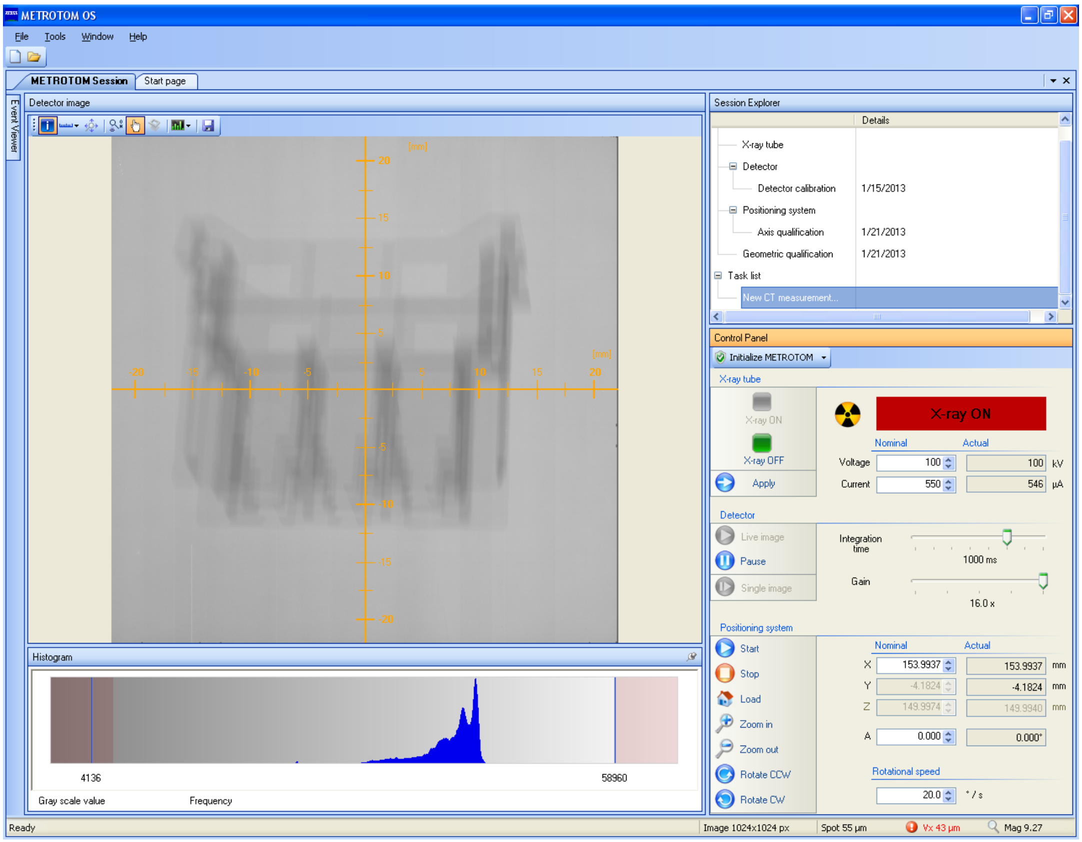


Figure 5.8: Interface of Metrotom OS while measuring one sample.

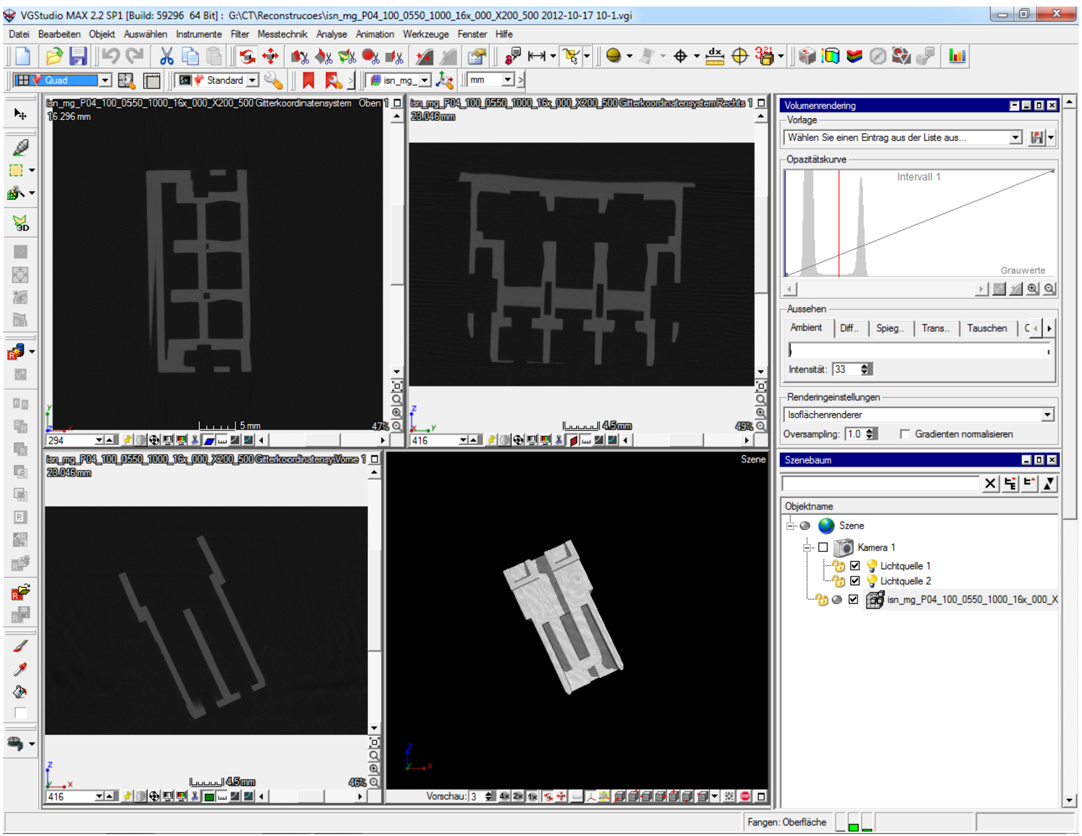


Figure 5.9: 3D representation of sample voxel model.

5.6: Best-fit, point clouds and comparison

The Best-fit is the alignment between the CT 3D reconstruction and the CAD model that was done for each sample in the Calypso software. It is an algorithm that starts with two data sets (CAD and 3D reconstruction) and an initial estimate of the aligning rigid-body transform. It then iteratively refines the transform by alternately choosing corresponding points in the meshes and finding the best translation and rotation that minimizes an error metric based on the distance between them [11].

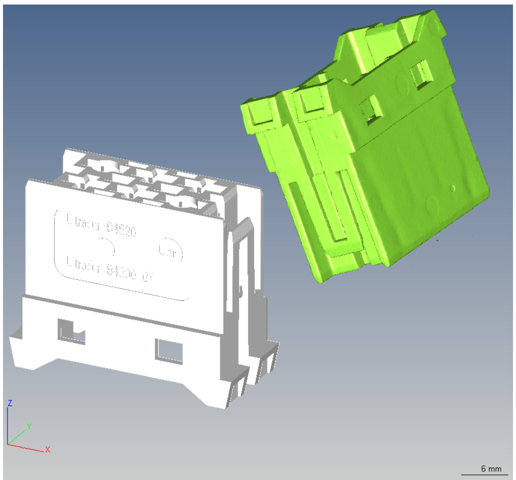


Figure 5.10: CAD model (white) and voxel model (green) before best-fit.

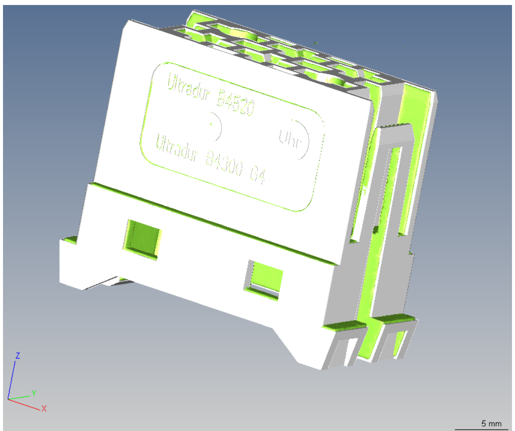


Figure 5.11: CAD model (white) and voxel model (green) after best-fit.

After the voxel model was aligned with the CAD, the point cloud can be created, and will be used as an input of the SmartInspeCT Matlab software to calculate the deviations of the part and the CAD models.

The comparison is one of the most important parts of the project, and will inform us how much each sample differed from the CAD model in each order (zero, first, second, third and residuals) as proposed in chapter 4.

For the analysis, 13 surfaces (figure 5.12) of the samples were chosen to have its deviation compared with the CAD model trough the SmartInspeCT software. Each sample had the same surfaces analyzed, and the average of the absolute deviations was considered as input to model the system. This average method was chosen because the desired model have to be independent of the surfaces of the sample, being capable to represent the entire part in just one model.

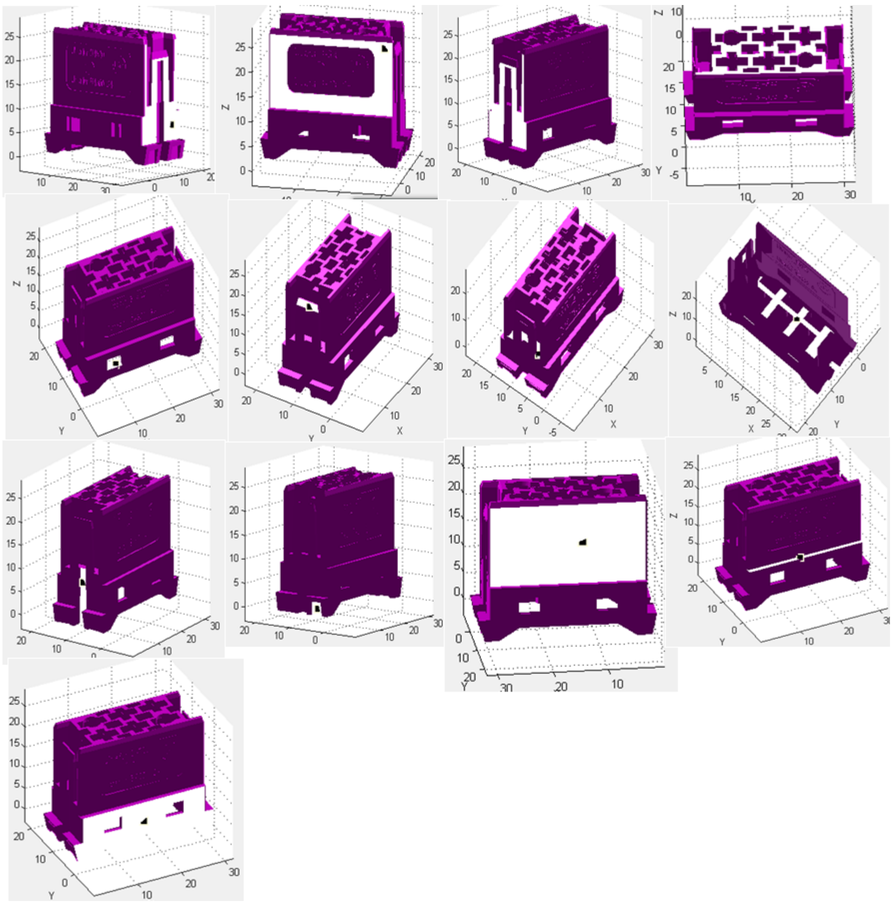


Figure 5.12: Sample surfaces that have been analyzed in the project.

5.7: System modeling

For the system modeling, both response surface and factorial methodology were analyzed and compared. As it was previously proposed by [9], the response surface methodology presented better results than the factorial model.

5.7.1: Factorial modeling

In factorial modeling, the factors are considered with only two levels (often labeled + and -). For this reason, the factorial models are linear, i.e., unlike response surface models, no quadratic or higher order influence of one factor is considered in the model. This difference can be notice when comparing both models response, in appendix E.

Because of the Minitab 14 software limitations, and little influence of higher orders for the factorial modeling, only the factors themselves, and their interactions one by one (up to second degree) was used to create the system model. The factorial model function and the parameters for each deviation order is presented:

Factors	**Abbreviation**
Pressure [bar]	P
Pressure time [s]	Pt
Cooling time [s]	Ct
Injection rate [cc/s]	Ir
Cylinder temp [°C]	Ct
Temperature [°C]	T

Table 5.2: Abbreviations of factors

$$\delta = a + b*P + c*Pt + d*Ct + e*Ir + f*Ct + g*T + h*P*Pt + i*P*Ct + j*P*Ir + k*P*Ct + l*P*T + m*Pt*Ct + n*Pt*Ir + o*Pt*Ct + p*Pt*T + q*Ct*Ir + r*Ct*Ct + s*Ct*T + t*Ir*Ct + u*Ir*T + v*Ct*T \tag{5.1}$$

Deviation	a	b	c	d	e	f
Offset	0.254833	0.000733	-0.05949	0.013558	0.000544	-0.00096
First	0.439707	0.000296	-0.07808	-0.00047	-0.00499	-0.0016
Second	0.312854	0.000592	-0.08655	0.003695	-0.00481	-0.00122
Third	0.892813	0.00053	-0.18414	0.009369	-0.00809	-0.00342
Deviation	g	h	i	j	k	l
Offset	-0.00565	-3.71E-05	3.35E-07	-2.32E-06	-2.31E-06	-4.56E-07
First	-0.00399	-6.99E-06	2.53E-06	-6.19E-07	-6.51E-07	-1.44E-06
Second	-0.00436	-1.50E-05	1.58E-07	-1.09E-06	-1.38E-06	-2.30E-06
Third	-0.00831	-3.19E-05	3.70E-06	-1.43E-06	-1.29E-06	-1.83E-06
Deviation	m	n	o	p	q	r
Offset	-8.9E-05	0.00012	0.000254	5.84E-06	5.13E-05	-3.60E-05
First	0.000417	0.000314	0.000153	0.000386	-4.42E-05	1.53E-05
Second	0.000756	0.000386	0.000145	0.000468	-3.37E-05	-4.36E-07
Third	-0.00015	0.000744	0.000627	0.000218	-8.41E-05	-1.21E-05
Deviation	s	t	u	v		
Offset	-7.34E-05	-1.22E-07	1.51E-06	2.74E-05		
First	-6.81E-05	1.37E-05	2.07E-05	1.62E-05		
Second	-6.31E-05	1.28E-05	2.36E-05	1.88E-05		
Third	-8.25E-05	2.26E-05	3.29E-05	3.42E-05		

Table 5.3: Values of constants for each deviation order with factorial model.

After the model was calculated, the input factors used to produce the samples were given as entrance of this model, and the resulted was compared with the measured values, in order to validate the model.

In general, the model represented well the reality, with average errors of about 2.9 to 9.6%. In figure 5.13 it is possible to see the comparison of the measured values deviation, and the values calculated with the model for the offset (0th degree). The absolute errors for all samples deviations is found in appendix C.

By the comparison in figure 5.13, we conclude that, even with all the uncertainties in the manufacturing and measuring processes, the generated model was able to

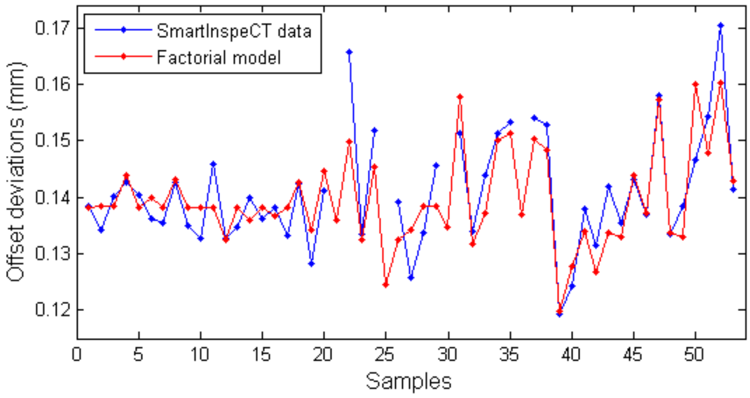


Figure 5.13: Deviation of CT samples measurement and factorial model response values.

represent the real plastic injection system.

5.7.2: Response surface modeling

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. By careful design of experiments, the objective is to optimize a response (output variable) which is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

Generally, the structure of the relationship between the response and the independent variables is unknown. The first step in RSM is to find a suitable approximation to the true relationship. The most common forms are low-order polynomials (first or second-order)[12].

For this analyzes, a Response surface modeling was proposed. In the response surface methodology, a full-quadratic model was used, that is, besides only the factors themselves, and their interactions one by one (as used in factorial modeling), in this model the quadratic influence of each factor has also been modeled. For the representation of the model, the same abbreviation of table 5.2 was used. Response surface model function and the parameters for each deviation order is presented:

$$\delta = a+b*P+c*Pt+d*Ct+e*Ir+f*Ct+g*T+h*P^2+i*Pt^2+j*Ct^2+k*Ir^2+l*Ct^2+m*T^2+n*P*Pt+o*P*Ct+p*P*Ir+q*P*Ct+r*P*T+s*Pt*Ct+t*Pt*Ir+u*Pt*Ct+v*Pt*T+w*Ct*Ir+x*Ct*Ct+y*Ct*T+z*Ir*Ct+aa*Ir*T+ab*Ct*T \tag{5.2}$$

Deviation	a	b	c	d	e	f
Offset	0.557024	0.000374	-0.09494	0.010432	-0.00397	-0.00342
First	0.962526	6.14E-05	-0.07881	0.010253	-0.00632	-0.00872
Second	1.77584	0.000575	-0.13479	0.026125	-0.00766	-0.01521
Third	-2.06E-01	0.000134	-0.19906	0.009018	-0.00876	0.004741
Deviation	g	h	i	j	k	l
Offset	-1.07E-04	-1.23E-08	7.86E-03	4.20E-04	1.48E-05	2.13E-06
First	7.15E-03	8.43E-08	3.90E-03	1.90E-04	-1.14E-06	1.13E-05
Second	0.003955	-1.42E-07	0.019398	-5.71E-04	3.23E-05	2.50E-05
Third	-0.00408	2.68E-07	0.004695	0.000265	-1.57E-05	-1.70E-05
Deviation	m	n	o	p	q	r
Offset	-3.61E-05	-3.14E-05	3.85E-07	-1.06E-06	-1.06E-06	-4.47E-07
First	-7.06E-05	-5.27E-06	2.24E-06	-6.86E-08	-1.21E-07	-1.47E-06
Second	-5.19E-05	-1.45E-05	-2.76E-08	-5.09E-07	-8.20E-07	-2.33E-06
Third	-2.73E-05	-2.98E-05	3.65E-06	-9.90E-07	-8.55E-07	-1.83E-06
Deviation	s	t	u	v	w	x
Offset	-2.62E-04	0.000167	0.000315	-8.21E-05	5.50E-05	-3.11E-05
First	-2.09E-04	3.29E-04	2.01E-04	1.43E-04	-3.56E-05	3.09E-05
Second	0.000299	0.00039	0.000172	0.0003	-2.68E-05	1.14E-05
Third	-3.49E-04	0.000761	0.000657	0.000135	-8.09E-05	-6.71E-06
Deviation	y	z	aa	ab		
Offset	-1.57E-04	1.14E-05	2.44E-06	3.08E-05		
First	-2.98E-04	1.66E-05	2.32E-05	2.49E-05		
Second	-2.38E-04	1.67E-05	2.54E-05	2.49E-05		
Third	-1.62E-04	2.61E-05	3.38E-05	3.74E-05		

Table 5.4: Values of constants for each deviation order with response surface full quadratic model.

In this case it was possible to confirm the statement of [9], that when treatment factors can be varied across a continuous range of values, Response surface methods treatment designs may be more efficient. In this situation, the Response surface method model, when compared to the CT measured values, returned most error values between 2.4 to 11.5%, and was considered better than the factorial model.

In the figure is possible to see how the model followed the model for the offset (0th degree). The absolute errors for all samples deviations is found in appendix D.

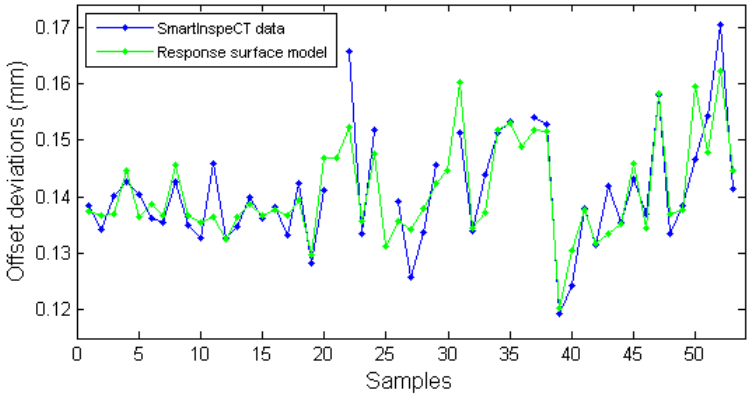


Figure 5.14: Deviation of CT samples measurement and response surface model calculated values.

5.7.3: Response surface versus factorial models

The models were different, but both gave a good representation of reality. The response surface model was better in orders 0th and 1st, while the factor model was better in the orders 2nd and 3rd plus residuals. The complete error data for both models is presented in appendix C and D.

By analyzing of error, the response surface model was chosen to be the main model representation of the project, due to its accuracy in lower orders (0th and 1st), and the better treatment with continuous range of inputs.

The below figure illustrate the offset deviation for the factorial and response surface models, compared with SmartInspeCT software values. In this first order analyzes, it is possible to realize that the two models were very similar, but the response surface model was slightly better.

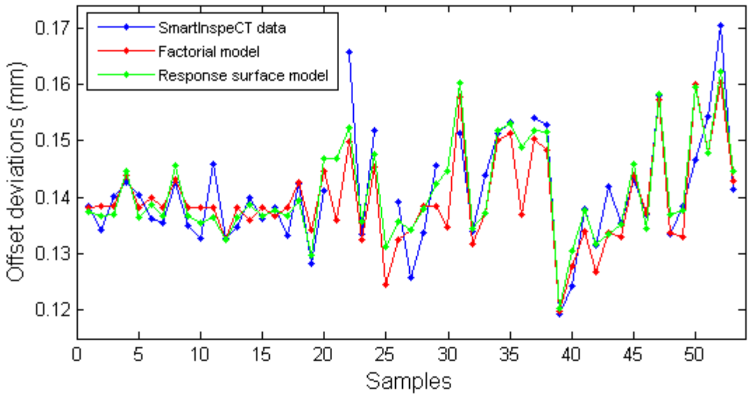


Figure 5.15: Deviation of CT samples measurement and both models calculated values.

6 Results

With the system's models, it is now possible to simulate inputs and outputs in order to define which factor represents most influence of each degree of deviation. Based on the models, we used the Matlab and Minitab software to evaluate if each one of the factors are significant or not for each kind of deviation.

With the Matlab software, and using the response surface model, the influence of each factor separately in the center point has been analyzed. Factors were varied independently one by one around the central point from its minimum to maximum, and the amplitude of their influence on deviation was analyzed with the assistance of charts that are shown in this chapter.

How the factors have different ranges of variation, an encoding was adopted in which the value -1 represents the minimum value, 0 represents the central value and 1 the maximum value of each factor. This encoding is necessary so that the variation of all factors can be displayed at the same chart.

In order to confirm which factors are significant, an analysis of variance (ANOVA) was performed in Minitab with a significance level of 0.05, i.e., all factors that have probability lower than this value ($p<0.05$) are significant. These results are written in red in the ANOVA result tables.

ANOVA is a particular form of statistical hypothesis testing heavily used in the analysis of experimental data. A statistical hypothesis test is a method of making decisions using data. A test result (calculated from the null hypothesis and the sample) is called statistically significant if it is deemed unlikely to have occurred by chance. A statistically significant result (when a probability (p-value) is less than a threshold (significance level)) justifies the rejection of the null hypothesis.

6.1: Offset deviations

With the aid of the graph of factors variation one by one and table of results of the ANOVA, it can be concluded that Temperature, Pressure time and Cooling time are significant to the offset deviation. On the other hand, Pressure and Cylinder temperature are not significant in the Offset deviation results.

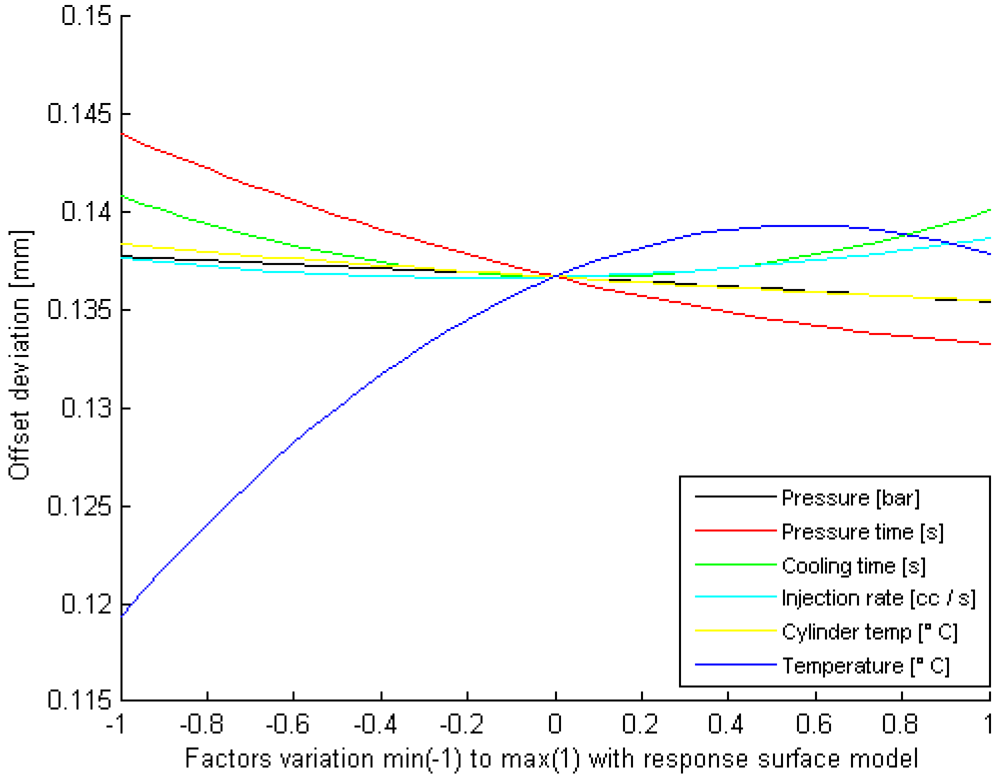


Figure 6.1: Offset deviations according to factors variation.

ANOVA for Offset deviations					
	Degrees of freedom	Sum of squares	Mean squares	F	P
Pressure [bar]	2	0.000435	0.0002175	2.31	0.111
Pressure time [s]	2	0.0014981	0.000749	10.54	0
Cooling time [s]	2	0.0009932	0.0004966	6.05	0.005
Injection rate [ccm/s]	2	0.0004476	0.0002238	2.38	0.104
Cylinder temperature [°C]	2	0.0003918	0.0001959	2.06	0.139
Temperature [°C]	41	0.0046743	0.000114	8.65	0.003

Table 6.1: ANOVA results for offset deviations analysis.

6.2: First order deviations

For the first order deviations, the Temperature had more influence than the other parameters and is the only significant factor.

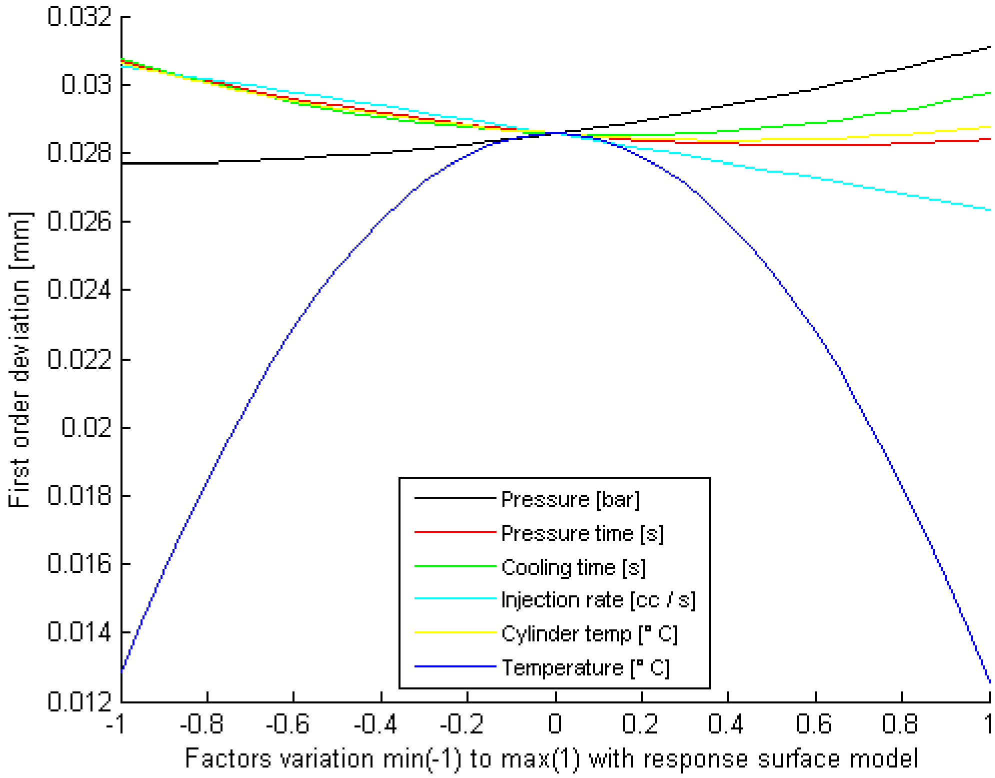


Figure 6.2: First order deviations according to factors variation.

ANOVA for First order deviations					
	Degrees of freedom	Sum of squares	Mean squares	F	P
Pressure [bar]	2	0.0001456	0.0000728	1.84	0.17
Pressure time [s]	2	0.0000358	0.0000179	0.43	0.655
Cooling time [s]	2	0.0000598	0.0000299	0.72	0.491
Injection rate [ccm/s]	2	0.0000853	0.0000426	1.04	0.361
Cylinder temperature [°C]	2	0.0000181	0.000009	0.21	0.808
Temperature [°C]	41	0.0018867	0.000046	4.1	0.029

Table 6.2: ANOVA results for first order deviations analysis.

6.3: Second order deviations

For the second order deviations, Temperature and Pressure time are the significant factors.

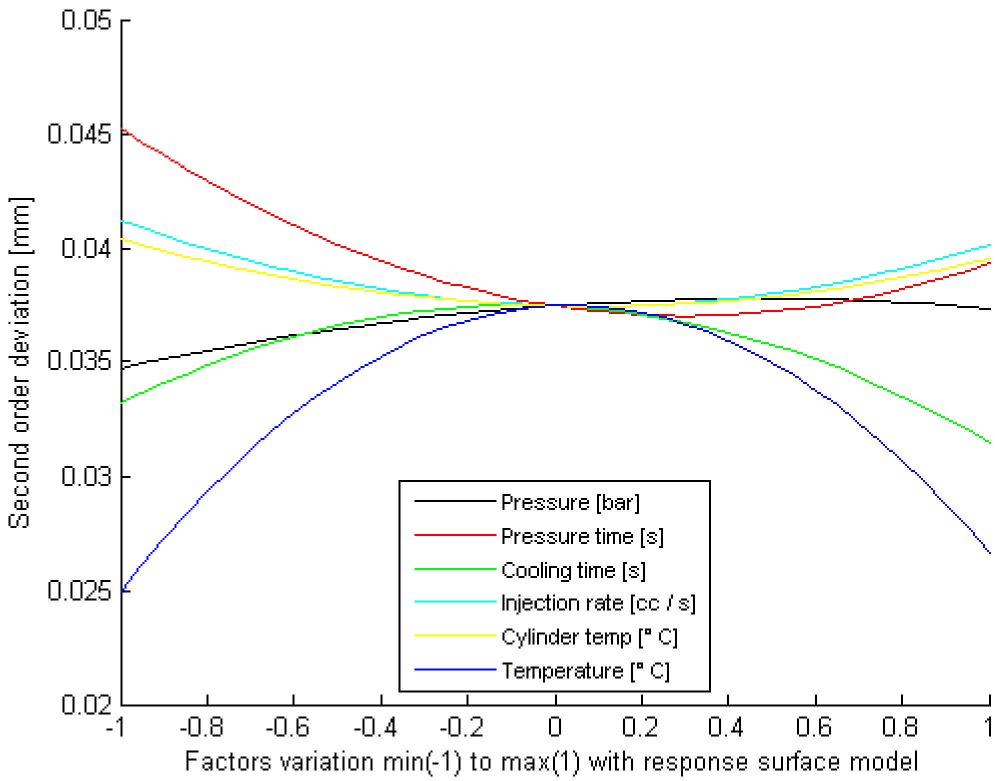


Figure 6.3: Offset deviations according to factors variation.

ANOVA for Second order deviations					
	Degrees of freedom	Sum of squares	Mean squares	F	P
Pressure [bar]	2	0.0000617	0.0000308	0.59	0.558
Pressure time [s]	2	0.0003048	0.0001524	3.25	0.048
Cooling time [s]	2	0.0001038	0.0000519	1.01	0.372
Injection rate [ccm/s]	2	0.00006	0.00003	0.57	0.567
Cylinder temperature [°C]	2	0.0000582	0.0000291	0.56	0.577
Temperature [°C]	41	0.0024369	0.0000594	15.15	0.001

Table 6.3: ANOVA results for second order deviations analysis.

6.4: Third order deviations

For the third order deviations, only Temperature is a significant factor.

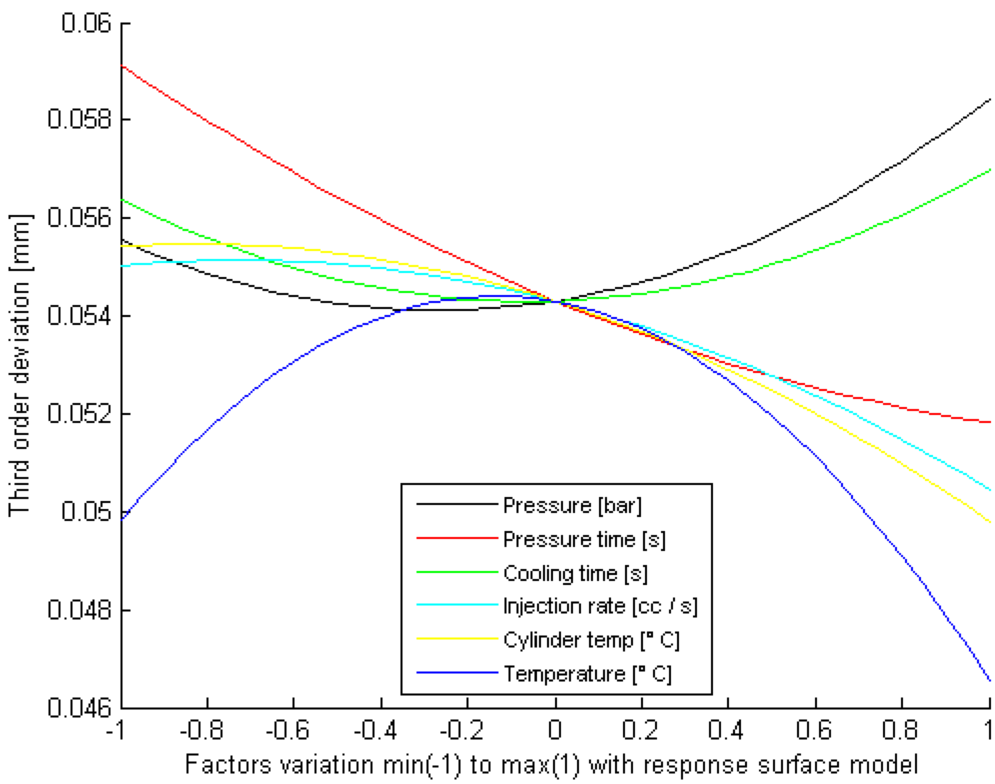


Figure 6.4: Offset deviations according to factors variation.

ANOVA for Third order deviations					
	Degrees of freedom	Sum of squares	Mean squares	F	P
Pressure [bar]	2	0.000147	0.000073	0.52	0.598
Pressure time [s]	2	0.000337	0.000169	1.23	0.302
Cooling time [s]	2	0.00006	0.00003	0.21	0.812
Injection rate [ccm/s]	2	0.000086	0.000043	0.3	0.741
Cylinder temperature [°C]	2	0.000135	0.000068	0.48	0.623
Temperature [°C]	41	0.0065623	0.0001601	13.38	0.001

Table 6.4: ANOVA results for Third order deviations analysis.

By the presented results, is possible to see that the factors are significant to deviation orders as follows:

- Temperature - Offset, First, Second and Third orders;
- Pressure time - Offset and Second order;
- Cooling time - Offset;
- Pressure - Not significant to any deviation order;
- Injection rate - Not significant to any deviation order;
- Cylinder temperature - Not significant to any deviation order.

According to the presented ANOVA results, the factors Pressure, Injection rate and Cylinder temperature were not significant to any deviations order, i.e., these factors can be understood as a ”noise” in the analysis because of its small influence in the final deviation results. With this conclusion, these parameters may no longer be considered in next iteration loops, making the whole process much easier.

In all ANOVA results tables is possible to see that the Temperature factor has a higher degree of freedom that the other factors. This fact is due that while producing the samples, it was not possible to keep the temperature in only three levels, as previously described in section 5.4.

To compare the influence of having more than three levels for the temperature, the ANOVA has been done considering only the original three levels of temperature, and then the temperature lost its significance in first, second and third orders. Although, the coefficient that measures the fit of the model with the variables has decreased from about 90% to about 10%. So, the first ANOVA proposed was used to obtain the results of this project. The ANOVA results with three temperature levels can be seen in appendix A.

6.5: Response optimizer

With the Response surface model and using the Response optimizer function on Minitab 14 software, the combination of factors that return the smallest possible deviation can be found.

In this Minitab feature, it is possible to minimize the value of each deviation, in order to find the input factors that should be used to reach this goal. It is still possible to define weight and importance for each considered deviation order (figure 6.5), but since this is an academic research and all deviations is desirable to be minimized, weight and importance was set 1 for all orders. However, in an industrial application, these parameters could be changed according to priorities of each project.

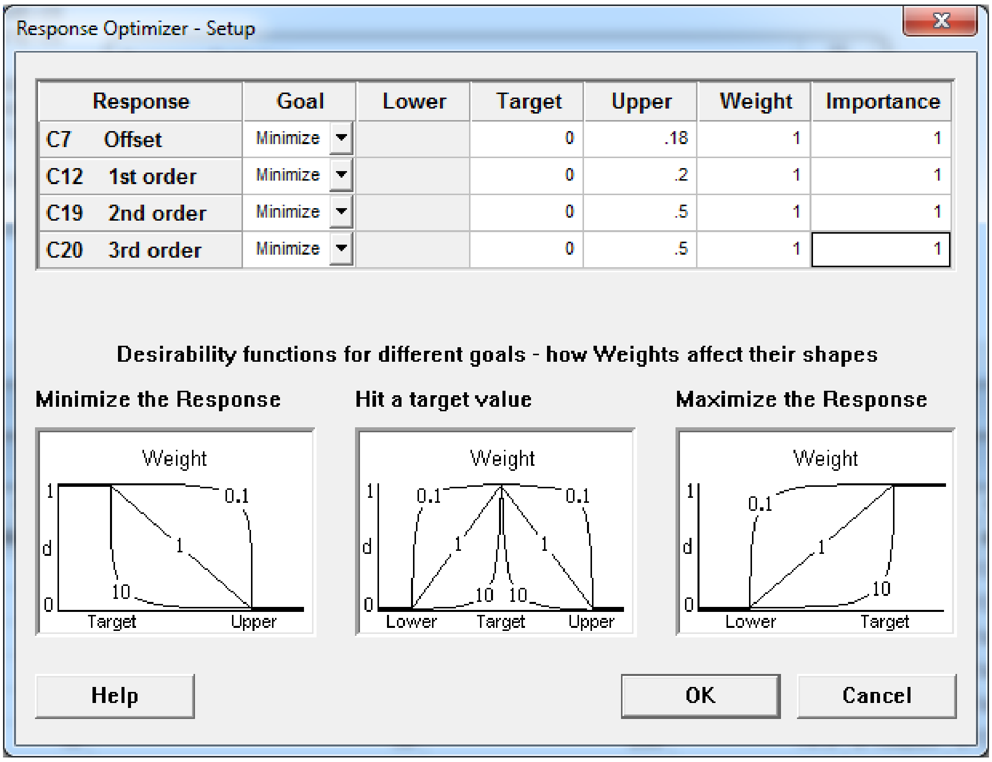


Figure 6.5: Response optimizer interface in Minitab.

The output of the response optimizer is a new set of factors (new center point), and an estimate of the deviation for each order with use of those parameters as is displayed in figure 6.6.

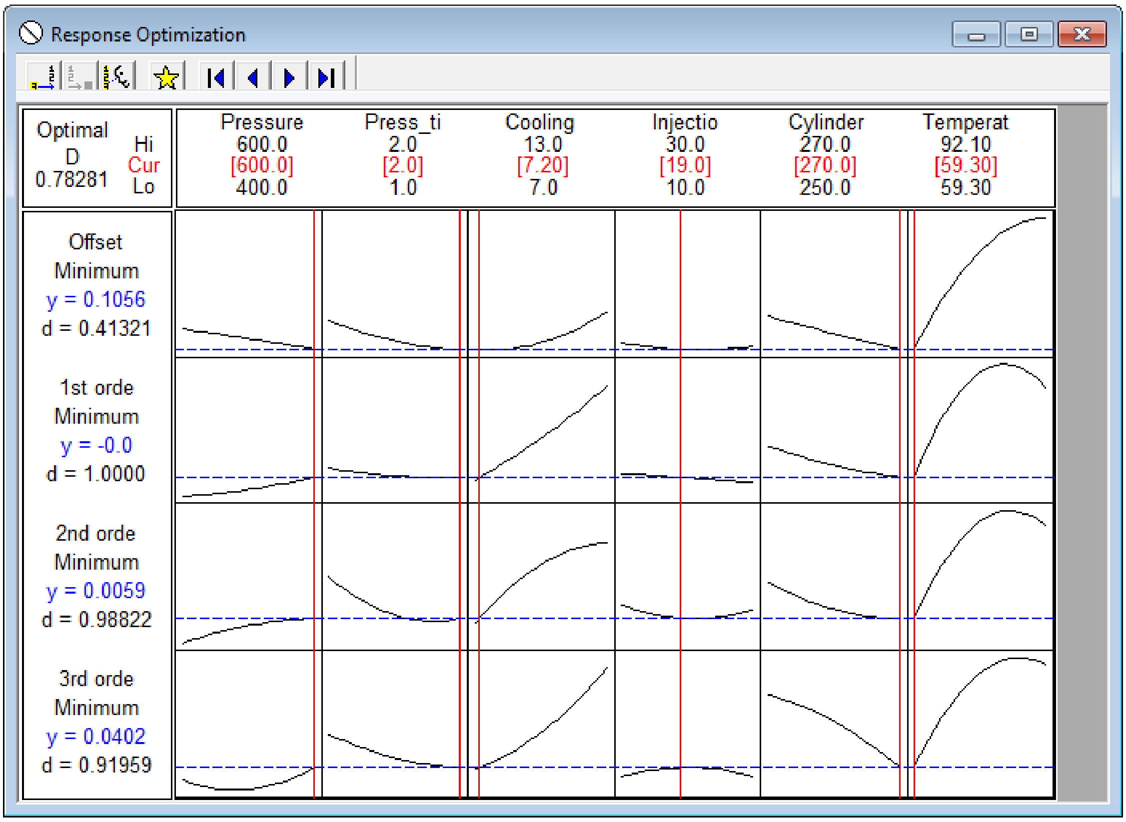


Figure 6.6: Response optimizer result in Minitab.

Response optimizer results		
	Center point used in analysis	New calculated center point
Pressure [bar]	500	600
Pressure time [s]	1.5	2
Cooling time [s]	10	7.2
Injection rate [ccm/s]	20	19
Cylinder temperature [°C]	260	270
Temperature [°C]	75	59.3

Table 6.5: New center point calculated with response optimizer.

With the results of the Response optimizer, the deviations measured in the center point used in this analysis and the simulated results for the new calculated center point have been compared with each other. Through this comparison it is possible to visualize the improvement of the new calculated center point compared to the original center point used in the proposition of this experiment. The values of the deviations are displayed in table 6.6.

Deviation [mm]	Offset	First order	Second order	Third order	Sum
Center point used in analysis	0.1372	0.0296	0.0342	0.0595	0.2605
New calculated center point	0.1056	0.0000	0.0059	0.0402	0.1517
Absolute improvement	0.0316	0.0296	0.0283	0.0193	0.1088
Relative improvement (%)	23.03	100	82.75	32.44	41.77

Table 6.6: Comparison between measured and calculated deviations.

With the interpretation of the given results, it is possible to conclude that just this first optimization loop run has made all deviations lower, improving the total accuracy of the tool.

6.5.1: Offset deviations

The offset is one of the most important deviations to be considered when analyzing the dimensional properties of one sample. Offset deviations can be responsible to several kinds of trouble with the produced part, e.g. a connector that does not fit properly into one product for having a smaller size than the stipulated. In this sense, the reduction of 23% in the offset deviations can be considered a good achievement, but there is still room for improvement. Even after the optimization loop, the offset deviation represents almost 70% of the sum of all deviations.

6.5.2: First order deviations

For the calculated factors input, the first order deviations has reached zero. This is an important achievement in the project, once no kind of improper inclination can be expected in the surfaces of the pieces produced with the set of given parameters according to the model.

6.5.3: Second order deviations

Second order deviations has also presented a major breakthrough, being the error calculated for the new center point almost six times smaller than the measured error for the center point used in analysis. For the new calculated center point the second order deviations represents 3.89% of the sum of deviations.

6.5.4: Third order and residual deviations

Third and superior orders deviation can be understood as waviness and undesirable roughness in the samples, and can be a crucial factor when the smoothness of the parts is important to assure some characteristics of it, for example when producing the bottom of a computer mouse, it is desired that the part has a smaller roughness to reduce frictional forces and ease the handling of the product by the user. This kind of deviations has presented a significant improvement of 32% and for the new calculated center point represents 26.5% of the sum of deviations. Despite the result, it serves only informative character, because the resolution of CT and the uncertainty involved in the process does not allow accurate conclusions about the third and higher order deviations.

6.5.5: Sum of deviations

The sum of all deviations orders has decreased from 0.2605 mm to 0.1517 mm (relative improvement of 41.77%) with the application of this optimization loop.

Although it is a significant improvement, the best tolerances that can normally be met in injection molding, with classical equipment are inside of a total composite error between 0.05 and 0.15 mm [13]. The total deviation values of 0.2605 mm measured and 0.1517 calculated for the new center point are both above this range, what suggest that more progress can be done with new iterations of this methodology to approximate the total deviation to zero or at least to the lower reference of 0.05 mm.

7 Conclusion

With this work it was possible to define a methodology for correcting plastic injection machines more quickly and efficiently compared with traditional methods of measurement such as tactile or optical. The use of tomography, although still a new technology in industrial metrology, proved to be a valuable tool during the project.

With the completion of this work several objectives were achieved, as listed below:

7.1: Modeling

We conducted a mathematical model able to relate the input values of the controllable factors to ”predict” the deviations of the part produced in different orders.

7.2: Elimination of ”noise”

With the analysis of variance (ANOVA), it was concluded that the factors Pressure, Injection rate and Cylinder temperature are not significant in any order of considered deviations. Therefore, these variables may no longer enter the analysis of the next iteration loop of the process, making it much simpler. Because of it, the next loop iteration will require only 20 samples, compared to 53 needed in this experiment with the six factors analyzed.

7.3: Defining optimal point

Using the Response Optimizer in Minitab 14, a new set-point was defined at which the deviations considered in this document are minimized. According to the deviations calculated for the new point, offset is 23% lower than the average obtained for the original center point. Deviations of first order reached zero, while the second has decreased 82.75% and third 32.44%. The sum of all deviations presented 41.77% improvement, going from 0.2605 mm to 0.1517 mm.

This new defined set point will also work as a central point for carrying out an experiment in order to increasingly reduce the errors of injection molding machines with successive loops of the process as described herein. In general the work has met the initial goals, which were kept in creating a system model and defining a new set of factors that minimizes the deviations and to be the new center point to the next iteration of the system. The surprise was the discovery of non-significance in three of the six factors considered in the analysis. But still, this is a good result since with fewer factors the next analysis iteration loop will become much simpler.

8 Future prospects

Future prospects for the project are to conduct further experiments to increasingly reduce the error of the parts produced trough making new optimization loops like the one presented in this document. The sum of all orders deviation in the new calculated center point is still 0.1517 mm, and with the error proposition in [13], is possible to conclude that this deviation can be reduced with more interactions of this optimization loop, in order to find another set of factors that makes the deviations even lower.

With the three significant variables isolated in this first study only 20 samples would be produced in the next experiment. In this way, it will probably be possible to assure the production with just the three levels of temperature in order to minimize possible errors in the system. It is also desirable that further experiments are performed and compared with this to validate the model proposed herein.

Finally, the implementation of an updatable database with values of each new measured part to be added. The new measures would be considered in the model, thus making it more independent of the part geometry.

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Appendix A : ANOVA with three levels of temperature

Factor	Degrees of freedom	Sum of squares	Mean squares	F	P
ANOVA for Offset deviations					
Pressure [bar]	2	0.000435	0.0002175	2.31	0.111
Pressure time [s]	2	0.0014981	0.000749	10.54	0
Cooling time [s]	2	0.0009932	0.0004966	6.05	0.005
Injection rate [ccm/s]	2	0.0004476	0.0002238	2.38	0.104
Cylinder temperature [°C]	2	0.0003918	0.0001959	2.06	0.139
Temperature [°C]	2	0.0010928	0.0005464	6.84	0.003
ANOVA for First order deviations					
Pressure [bar]	2	0.0001456	0.0000728	1.84	0.17
Pressure time [s]	2	0.0000358	0.0000179	0.43	0.655
Cooling time [s]	2	0.0000598	0.0000299	0.72	0.491
Injection rate [ccm/s]	2	0.0000853	0.0000426	1.04	0.361
Cylinder temperature [°C]	2	0.0000181	0.000009	0.21	0.808
Temperature [°C]	2	0.0000799	0.0000399	0.97	0.385
ANOVA for Second order deviations					
Pressure [bar]	2	0.0000617	0.0000308	0.59	0.558
Pressure time [s]	2	0.0003048	0.0001524	3.25	0.048
Cooling time [s]	2	0.0001038	0.0000519	1.01	0.372
Injection rate [ccm/s]	2	0.00006	0.00003	0.57	0.567
Cylinder temperature [°C]	2	0.0000582	0.0000291	0.56	0.577
Temperature [°C]	2	0.0000245	0.0000123	0.23	0.795
ANOVA for Third order deviations					
Pressure [bar]	2	0.000147	0.000073	0.52	0.598
Pressure time [s]	2	0.000337	0.000169	1.23	0.302
Cooling time [s]	2	0.00006	0.00003	0.21	0.812
Injection rate [ccm/s]	2	0.000086	0.000043	0.3	0.741
Cylinder temperature [°C]	2	0.000135	0.000068	0.48	0.623
Temperature [°C]	2	0.000082	0.000041	0.29	0.751

Table A.1: ANOVA with only three levels of temperature.

Appendix B : DOE worksheet

Sample number	Pressure [bar]	Pressure time [s]	Cooling time [s]	Injection rate [ccm/s]	Cylinder temp. [°C]	Temp. [°C]	Real temp. [°C]
1	400	1.5	10	20	260	75	74.5
2	500	1.5	10	20	260	75	75.1
3	500	1.5	10	20	260	75	75.2
4	500	1	10	20	260	75	75.9
5	500	1.5	10	20	260	75	74.7
6	500	1.5	10	30	260	75	74.9
7	500	1.5	10	20	260	75	74.9
8	500	1.5	7	20	260	75	80.3
9	500	1.5	10	20	260	75	74.8
10	600	1.5	10	20	260	75	74.9
11	500	1.5	10	20	260	75	74.7
12	500	2	10	20	260	75	73.8
13	500	1.5	10	20	260	75	74.7
14	500	1.5	13	20	260	75	70.3
15	500	1.5	10	20	260	75	74.8
16	500	1.5	10	10	260	75	75
17	500	1.5	10	20	260	75	74.9
18	500	1.5	10	20	260	90	82.9
19	500	1.5	10	20	260	60	67.3
20	400	1	13	30	250	60	61.4
21	400	1	7	10	250	60	69.8
22	600	1	13	10	250	60	62.3
23	600	2	7	10	250	60	71
24	600	1	7	30	250	60	73.9
25	400	2	13	10	250	60	59.3
26	400	2	7	30	250	60	70.9
27	600	2	13	30	250	60	61.5
28	500	1.5	10	20	250	75	73.6
29	400	2	13	30	250	90	77.9
30	400	2	7	10	250	90	86
31	600	1	7	10	250	90	89.4
32	600	2	13	10	250	90	79.3
33	600	2	7	30	250	90	88.6

Sample number	Pressure [bar]	Pressure time [s]	Cooling time [s]	Injection rate [ccm/s]	Cylinder temp. [°C]	Temp. [°C]	Real temp. [°C]
34	600	1	13	30	250	90	81.3
35	400	1	7	30	250	90	91.1
36	400	1	13	10	250	90	80.6
37	400	1	13	30	270	90	82.6
38	400	1	7	30	270	60	77.4
39	600	2	13	10	270	60	62.5
40	400	1	13	10	270	60	62.7
41	400	2	7	10	270	60	71.8
42	600	2	7	30	270	60	71.8
43	400	2	13	30	270	60	61.9
44	600	1	13	30	270	60	62.9
45	600	1	7	10	270	60	73.2
46	500	1.5	10	20	270	75	74
47	600	1	7	30	270	90	92.1
48	400	2	13	10	270	90	80.5
49	600	2	13	30	270	90	80.9
50	400	2	7	30	270	90	90.1
51	600	2	7	10	270	90	89.6
52	400	1	7	10	270	90	91.9
53	600	1	13	10	270	90	81.5

Table B.1: DOE worksheet with parameters for samples production

Appendix C : Factorial model absolute error compared to measured values

	Offset	1st Order	2nd Order	3rd Order
1	0.002121584	0.084330129	0.047351	0.040211588
2	0.030583694	0.175093164	0.262942	0.036676361
3	0.012429524	0.07280779	0.015466	0.687499648
4	0.008186574	0.148182024	0.059267	0.092357949
5	0.016201093	0.075279747	0.059536	0.134795043
6	0.026229483	0.170033977	0.061228	0.077239177
7	0.020024404	0.056579278	0.041368	0.027376421
8	0.004187401	0.079749259	0.2337	0.119757517
9	0.023434438	0.006125526	0.049124	0.013043999
10	0.040918585	0.147251229	0.115353	0.050797144
11	0.055941851	0.124979082	0.019369	0.067476801
12	0.000241234	0.091151399	0.284564	0.034668009
13	0.024191035	0.044699221	0.053839	0.047086888
14	0.028079793	0.013792933	0.048712	0.12136833
15	0.01458656	0.049695018	0.185872	0.059393886
16	0.011317584	0.020466607	0.040504	0.084289663
17	0.037467277	0.067114437	0.030772	0.015141994
18	0.002302336	0.080512916	0.031514	0.069800723
19	0.043770467	0.255913212	0.261819	0.043090795
20	0.024554354	0.145662811	0.030503	0.145705337
21				
22	0.106866903	0.203576688	0.128349	0.212362528
23	0.007613827	0.101878064	0.218839	0.06439859
24	0.044172506	0.009529685	0.140737	0.019496258
25				
26	0.050716634	0.057854069	0.022386	0.072748731
27	0.063339592	0.201208745	0.140123	0.061696269
28	0.034250069	0.136139972	0.047047	0.1435279
29	0.051600337	0.082499666	0.034058	0.112543029
30				
31	0.040459076	0.162187225	0.05765	0.107123155
32	0.016641819	0.125756874	0.062654	0.065209663
33	0.048687783	0.182522061	0.129213	0.139957574
34	0.007967265	0.032977842	0.255976	0.001556969
35	0.014567269	0.072811962	0.035546	0.07473526

	Offset	1st Order	2nd Order	3rd Order
36				
37	0.025006151	0.078240157	0.206091	0.093509758
38	0.03012155	0.112368657	0.050165	0.123662992
39	0.004100962	0.000656558	0.018933	0.071348385
40	0.028627684	0.211724498	0.130313	0.089807705
41	0.029787464	0.018686431	0.264148	0.042522537
42	0.036376992	0.019601261	0.007441	0.022510278
43	0.062482845	0.142207745	0.049126	0.159747024
44	0.018484956	0.019037434	0.012095	0.025775899
45	0.005599755	0.069559001	0.022762	0.04877245
46	0.001208563	0.065856813	0.00066	0.019690524
47	0.005292705	0.051906682	0.015267	0.00381593
48	0.001303634	0.038831885	0.209226	0.07697944
49	0.04131461	0.002118322	0.008	0.04721319
50	0.08374583	0.290504789	0.147423	0.252629798
51	0.043437798	0.091181172	0.020809	0.217986938
52	0.0628939	0.135300707	0.100521	0.06845168
53	0.011703868	0.096781549	0.049591	0.031207751
Smaller	0.000241234	0.000656558	0.00066	0.001556969
Bigger	0.106866903	0.290504789	0.284564	0.687499648
Average	0.02867636	0.09638625	0.092203	0.090587051

Table C.1: Factorial model absolute error compared to measured values

* the samples 21, 25, 30 and 36 were defective and for this reason they were not measured due to impossibility to make the best-fit.

Appendix D : Response surface model absolute error compared to measured values

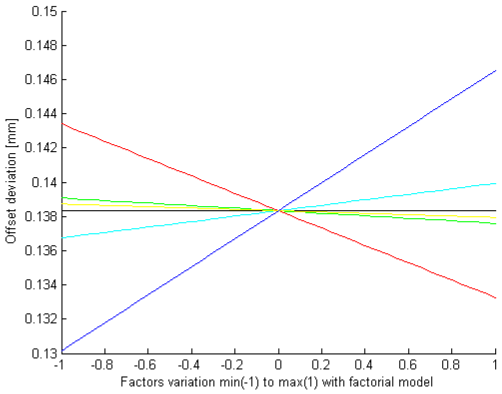
	Offset	1st Order	2nd Order	3rd Order
1	0.009031047	0.093556096	0.083217774	0.035676887
2	0.016760313	0.135496769	0.309714606	0.011554653
3	0.026815413	0.123700056	0.078246925	0.771823626
4	0.010647852	0.140484669	0.211517206	0.070491577
5	0.03095082	0.028331758	0.117811606	0.091048088
6	0.014690493	0.104549917	0.074798063	0.008810025
7	0.005936108	0.108649259	0.101535744	0.079047184
8	0.019151534	0.024955199	0.196698634	0.116891092
9	0.00933024	0.043567984	0.016316996	0.064124677
10	0.017783137	0.120255377	0.127029811	0.044638055
11	0.071268399	0.080554325	0.043795782	0.020326064
12	0.002831064	0.110929081	0.049511519	0.068117759
13	0.010027583	0.097738534	0.112467147	0.001094814
14	0.011685964	0.061455875	0.017481654	0.1246159
15	0.000354575	0.102179542	0.111900549	0.011965741
16	0.00627654	0.052155321	0.111694218	0.019467452
17	0.023629743	0.119703608	0.091604097	0.06619744
18	0.023869954	0.085377235	0.026096694	0.00029467
19	0.009524575	0.043155861	0.223944736	0.043785329
20	0.037516568	0.087061157	0.111461791	0.117418127
21				
22	0.089820317	0.217356438	0.066532379	0.228919582
23	0.015854681	0.089587204	0.284484323	0.047074321
24	0.030005175	0.031110048	0.065192301	0.000873729
25				
26	0.027728631	0.110579957	0.064493234	0.100194489
27	0.061124567	0.169353878	0.207480685	0.02571144
28	0.028487135	0.132127829	0.077543557	0.082186651
29	0.024831812	0.056016543	0.09726347	0.131324145
30				
31	0.054652541	0.153356184	0.13817571	0.090497124
32	0.002436241	0.055495691	0.001632017	0.035349439
33	0.051825818	0.237808796	0.05132247	0.186481798
34	0.000518185	0.031814414	0.312991334	0.031185881
35	0.004862857	0.006321324	0.09289761	0.109976718

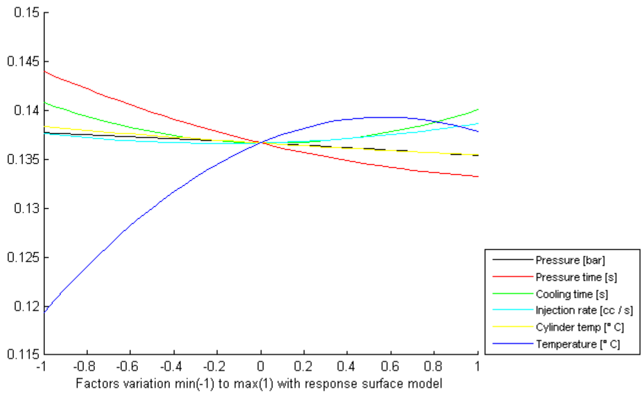
	Offset	1st Order	2nd Order	3rd Order
36				
37	0.017998526	0.160208893	0.111085543	0.14554387
38	0.010146523	0.085949018	0.145910439	0.145713342
39	0.005681953	0.014996087	0.080869303	0.035415389
40	0.047416334	0.189371138	0.210285488	0.060636336
41	0.00283248	0.00562988	0.104881477	0.072309143
42	0.00120395	0.006565507	0.10448717	0.042240286
43	0.06682269	0.2571659	0.049546318	0.231621929
44	0.004955112	0.029595719	0.088813661	0.06908789
45	0.016455246	0.006459921	0.071912689	0.013114087
46	0.02053167	0.102859731	0.114253911	0.08060698
47	0.000928764	0.007930514	0.087199952	0.042572286
48	0.022682762	0.000163366	0.291389643	0.115376277
49	0.009215794	0.029475879	0.093914115	0.069829897
50	0.079397852	0.256229671	0.189753259	0.22618451
51	0.044584776	0.120991019	0.084014901	0.276765728
52	0.05209028	0.194542601	0.016443885	0.109045441
53	0.021630218	0.080528462	0.139047736	0.001575342
Smaller	0.000354575	0.000163366	0.001632017	0.00029467
Bigger	0.089820317	0.2571659	0.312991334	0.771823626
Average	0.023975608	0.093947944	0.115523758	0.093363331

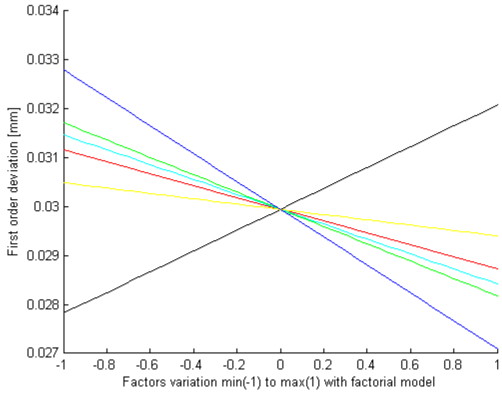
Table D.1: Response surface model absolute error compared to measured values

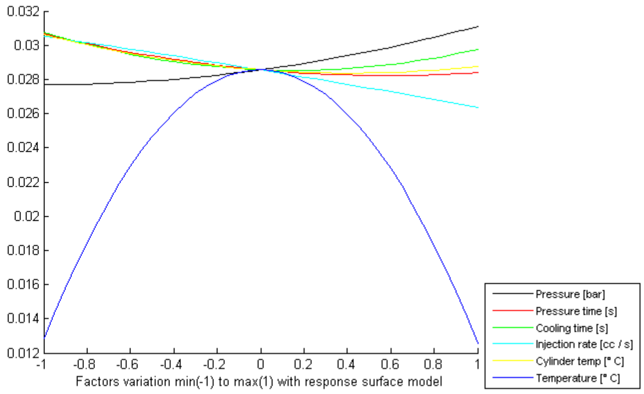
* the samples 21, 25, 30 and 36 were defective and for this reason they were not measured due to impossibility to make the best-fit.

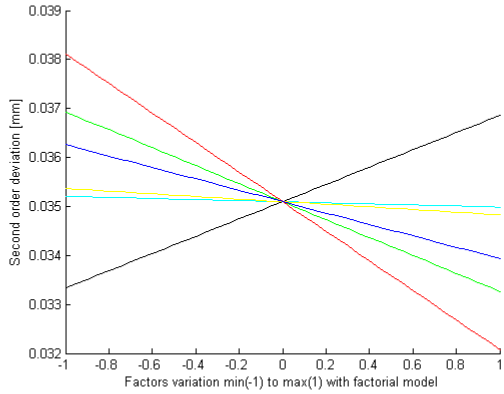
Appendix E : Response surface and factorial models comparison

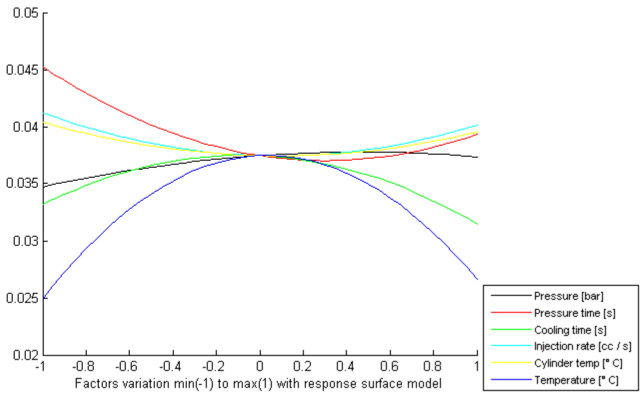


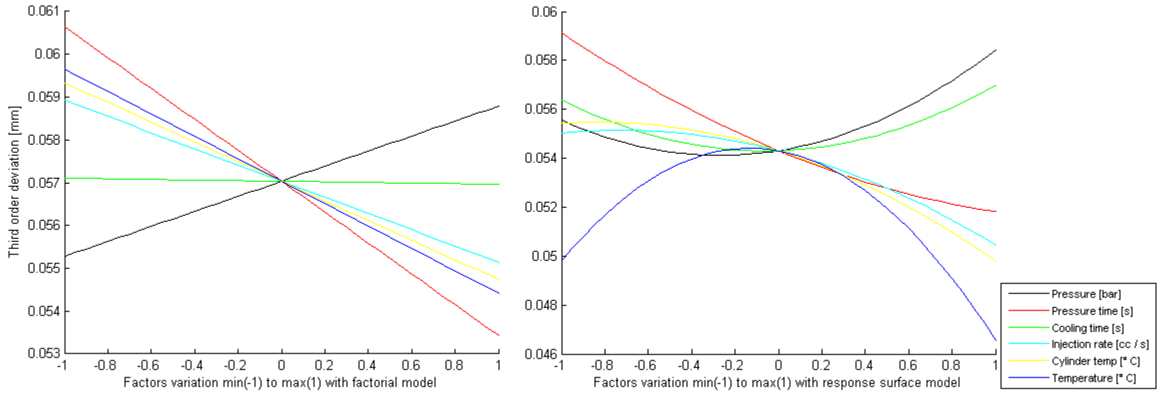












Third order deviation [mm]
Factors variation min(-1) to max(1) with factorial model
Factors variation min(-1) to max(1) with response surface model
Pressure [bar]
Pressure time [s]
Cooling time [s]
Injection rate [cc / s]
Cylinder temp [° C]
Temperature [° C]