

Multi-Parameter Optimization of Process Modes in Injection Molding of Plastic Product [†]

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Abstract

The work presented demonstrate a methodology for multi-parameter optimization of process parameters in plastic injection molding, with a focus on established techniques such as DOE (Design of Experiment) Taguchi, root cause diagram, and rapid prediction methods. The aim of the study is to improve the efficiency and accuracy of the production process by reducing the iterations for searching the optimal parameters to satisfy specific requirements and constraints. Through the implementation of these methods, it strives to achieve more stable and predictable process conditions, which ultimately leads to a reduction in crucial defects and improvement in the quality of the manufactured products. Exploring the possibilities of multi-parameter optimization offers an innovative approach to solving complex problems in engineering practice by providing a systematic method to analyze and manage various factors affecting the final result. This approach not only improves production processes, but also contributes to a wider understanding and optimization of the operation of the system as a whole.

Keywords: molding; parameter optimization; plastic; Taguchi; cae

1. Introduction

In the production of plastic products, the injection molding process plays a critical role in achieving the desired characteristics and quality of the product. The multi-parameter optimization of the process modes in the injection molding of plastic products is a key stage for improving efficiency and reducing waste in the production process [1,2].

Taguchi's method of quality control is to look at the product design stage and the process design stage to improve product performance and reliability by creating products that are not affected by the environment and variations in components. These methods allow engineers to extract valuable information from complex data and optimize process settings [3–5].

Taguchi's method defined a quality loss function to measure quality. The quality loss function is a continuous function defined by the deviation of design parameters from ideal or target values. Figure 1 shows quadratic loss function where target is the ideal value with zero loss, LSL (Lower Specification Limit) and USL (Upper Specification Limit) are the lower and upper specification limits defining the acceptable range, and \$Loss represents the cost that increases quadratically as the actual value deviates from the target. In this traditional (goalpost) loss model (Figure 2), LSL and USL define strict acceptance limits



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where the loss is zero inside the range and jumps abruptly to a fixed \$Loss once the value falls outside these limits, regardless of how far it deviates. Taguchi's view of the nature of the quality loss function represents a fundamental paradigm shift in how manufacturers judge whether a product is good or not. The traditional approach used by US manufacturers was to use a "step function" that ensured this performance was within the upper and lower specification limits [6–8].

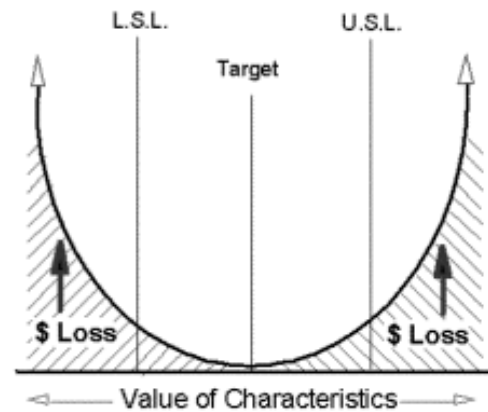


Figure 1. Quadratic loss function.

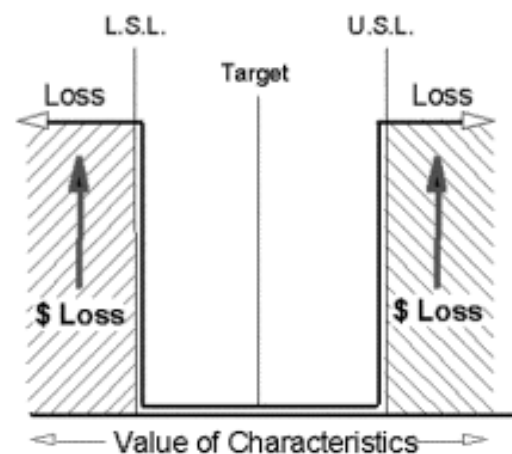


Figure 2. Step function.

The Taguchi loss function can be expressed by a quadratic equation:

$$L = k (y - m)^2$$

where y is the value of the critical performance parameter, L is the loss associated with the particular parameter y , m is the nominal specification value of the parameter, and k is a constant that depends on the cost at the specification limits (can be determined by dividing the cost of scrap in dollars, the square of the lower or higher tolerance).

In the design of the parameters, there are two types of factors that affect the functional characteristics of the product: control and noise factors. Control factors are those factors that can be easily controlled, such as material selection, cycle time, or injection mold temperature in a molding process [9].

To establish the appropriate factor levels for each control factor, usually two or three levels are selected for each factor. Choosing the right number of levels and quantities constitutes the majority of the effort in planning robust design experiments.

Figure 3 shows orthogonal arrays (L4, L8, L9) where each row is an experimental run and each column is a factor, arranged so that factor levels are balanced and statistically

independent, enabling efficient analysis with a minimal number of experiments. The product array is used to systematically test different combinations of the control factor settings on all combinations of noise factors, after which the average response and standard deviation can be approximated for each run.

$$\text{Generalized answer : } \bar{y} = \frac{1}{n} \sum_{i=1}^n y_i$$

$$\text{Standard deviation : } S = \sqrt{\sum_{i=1}^n \frac{(y_i - \bar{y})^2}{n - 1}}$$

where n is the number of trials.

Factors			
Run	A	B	C
1	1	1	1
2	1	2	2
3	2	1	2
4	2	2	1

(a) $L_4 (2^3)$ array

Factors							
Run	A	B	C	D	E	F	G
1	1	1	1	1	1	1	1
2	1	1	1	2	2	2	2
3	1	2	2	1	1	2	2
4	1	2	2	2	2	1	1
5	2	1	2	1	2	1	2
6	2	1	2	2	1	2	1
7	2	2	1	1	2	2	1
8	2	2	1	2	1	1	2

(b) $L_8 (2^7)$ array

Factors				
Run	A	B	C	D
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

(c) $L_9 (3^4)$ array

Figure 3. Example tables of orthogonal arrays.

S/N, or also known as SNR with its analog from digital communications, refers to signal-to-noise ratio, a ratio of the strength of a desired signal relative to the background noise (unwanted signal).

Standard ratios are: nominal value best (NB), smaller is better (LB), bigger is better (HB). As an example, injection molding causes shrinkage of the material on cooling, making lower shrinkage values expected. Thus, the analysis applies the characteristics of the S/N ratio, the lower the better, and can be calculated by the formula:

$$\frac{S}{N} = -10 \log_{10} \left(\frac{1}{n} \sum \frac{1}{y_i^2} \right)$$

where y_i is the value of the quality features for the trial, and n is the number of repetitions.

2. Materials and Methods

The goal of the development is to build an approach for quickly finding the most optimal operating parameters during injection molding through multi-parameter optimization. In order to do this, it is necessary to define the objectives, the evaluation criteria of the developed options, the requirements and the restrictive conditions.

The product is part of a pre-assembled plastic respirator shell (Figure 4). The choice was influenced by the fact that the detail has a real application in industry and benefits people in need of respirators. The objective of the subsequent analyzes is to produce a “respirator cover” part with minimal displacement of the contact surface of the assembly with its adjacent components and fasteners, so as to obtain a functional part with no visual evidence of defects.

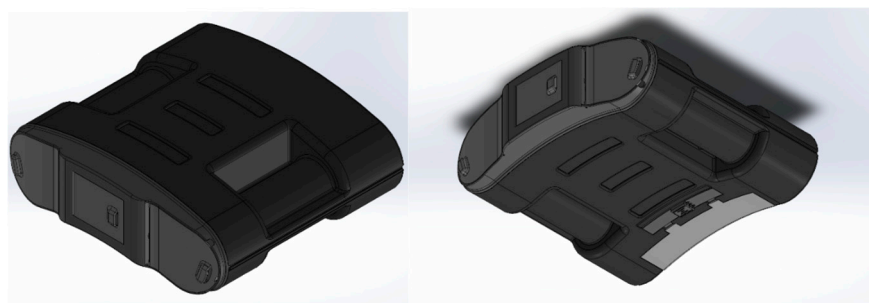


Figure 4. Examined design of test product.

3. Results

The following material for the examined test product is set as: PA6GF30.

In Table 1 are the set working parameters of the injection molding analysis.

Table 1. Process condition.

Parameter	Value
Filling, s	2
Packing, s	5
Cooling, s	10
Melt temperature, °C	260
Mold temperature, °C	70
VP Switch-Over, %	98

Meshed structures are built, based on the abovementioned geometry model. Figure 5 shows the examined model in a virtual environment Moldex3D 2022, which presents the density of the mesh with a total number of 822,802 solid elements.

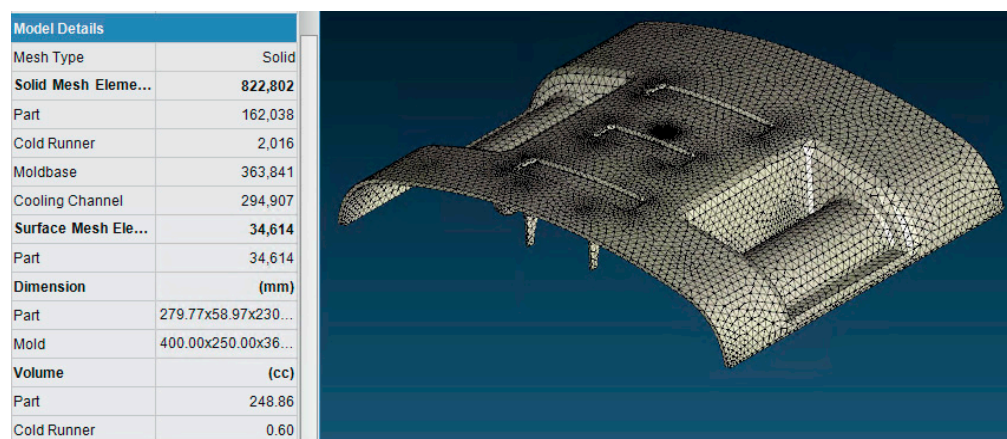


Figure 5. FEM (Finite Element Method) model.

After the stage of determining the parameters of the process, the control zones (Figure 6) should be selected, through which the behavior of the respective zones after cooling will be observed. An important role is played by the displacement values in the region of the isolated zones, as they are critical to the assembly and functionality of the part.

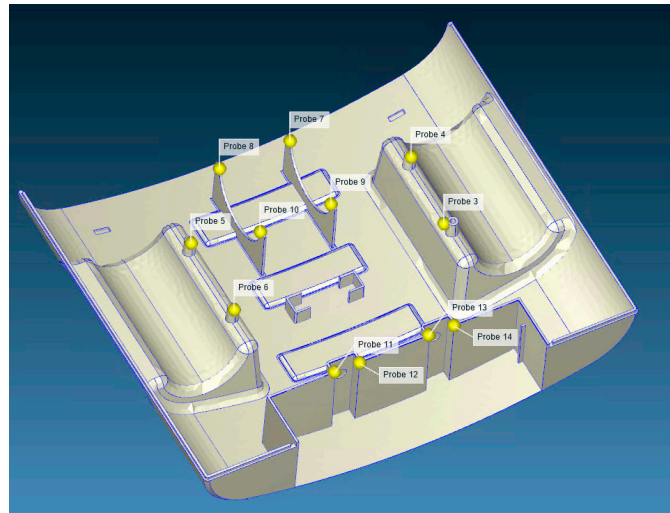


Figure 6. Control zones.

Filling simulation provides a visual presentation of the cavity-filling process of the forming tool where it is crucial to be fully filled.

The data from the simulation analyses show the zones of high temperature accumulation after cooling, which according to Figure 7 would affect the formation of a warping defect.

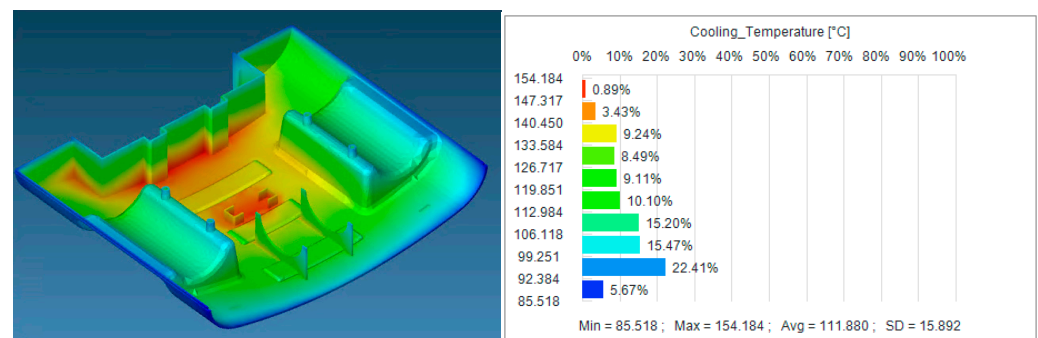


Figure 7. Temperature after cooling.

3.1. Multi-Parameter Process Optimization

The results obtained from the injection fill analyses give a clear picture of the behavior of the material in the mold after cooling, as well as giving an indication of the possible occurrence of defects. Due to this, a methodology has been developed (Figure 8) for rapid prediction and optimization of process parameters of injection molding of complex plastic products. The possibilities for multi-parameter optimization have been investigated in order to accelerate the convergence of the search for a solution that best satisfies the requirements under set constraints.

Taguchi's design of experiments is a systematic, highly effective method that allows the study of the relationship between multiple input parameters (known as factors) and output parameters (quality response). Figure 9 shows all the control factors; the current experiment is composed of five factors with four different values each and with 16 different combinations between them, so the orthogonal array is L16 (4^5).

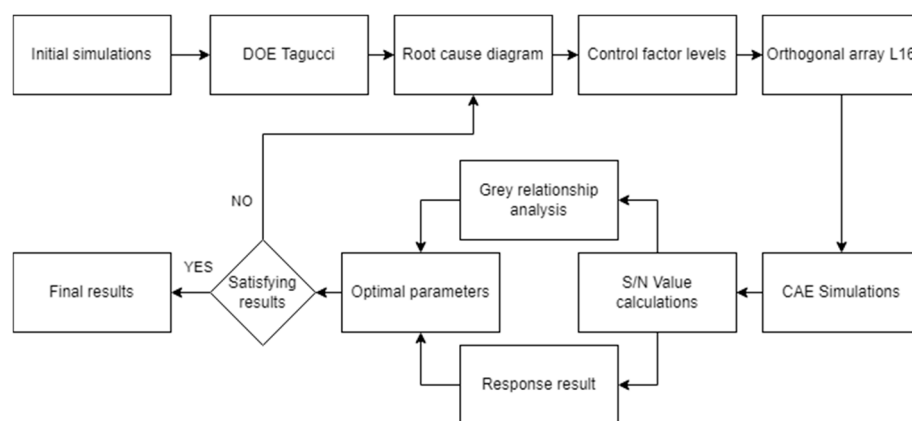


Figure 8. Block scheme.

#	Control Factor	Level 1	Level 2	Level 3	Level 4	Level 5
1	Filling Time [sec]	1.5	2	2.5	3	
2	Packing Time [sec]	4.5	5	5.5	6	
3	Cooling Time [sec]	8	10	12	14	
4	Mold Temperature [°C]	60	65	70	80	
5	Melt Temperature [°C]	265	275	285	290	

#	Quality Factor	Target	Goal	Weighting	%	Delete
1	Cooling_Temperature [°C]	Global	Smaller	1	50.0%	
2	Warpage_Total Displacement [mm]	Global	Smaller	1	50.0%	

Figure 9. DOE control factors.

When creating a root cause diagram, it is necessary to know the control factors, their values, and the purpose. The chart will contain five control factors in order to reduce deformations and cooling temperature.

The control factor table (Table 2) is correlated with the root cause diagram shown in Figure 10, giving the information used to create the tests.

Table 2. Control factor table.

Control Factors	Levels			
	1	2	3	4
Filling (s)	1.5	2	2.5	3
Packing (s)	4.5	5	5.5	6
Cooling (s)	8	10	12	14
Mold temperature (°C)	60	65	70	80
Melt temperature (°C)	265	275	285	290

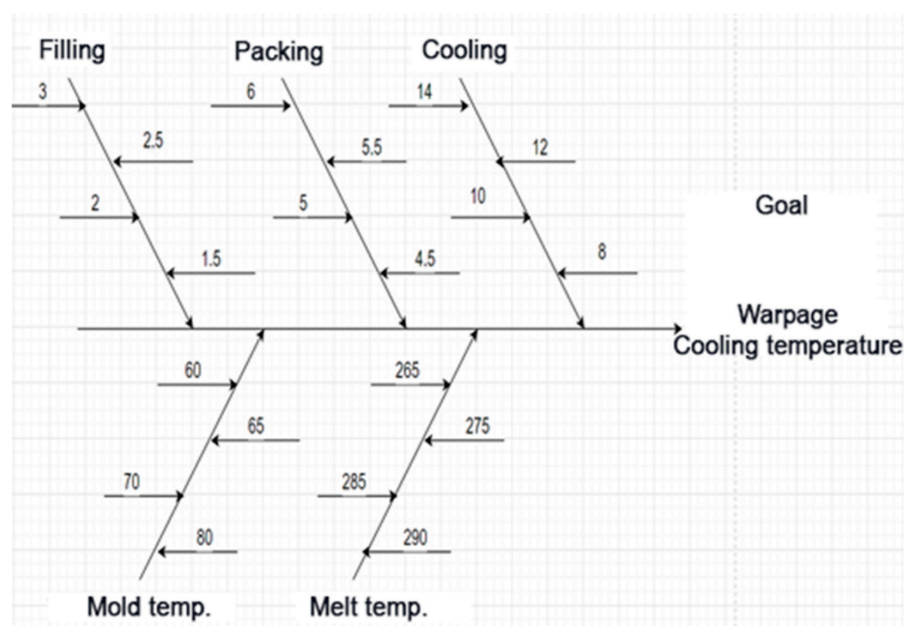


Figure 10. Root Cause Diagram.

Figure 11 shows all the tests done, which is 17 in total, with an additional one done by the software in which it chooses a combination that achieves criteria values to be the most favorable combination of control factor levels. Run 18* is run which is the optimized run with best control factors combinations. Both criteria are given equal weight when calculating the best combination.

DOE Wizard								
Setting Summary								
DOE Table								
Control Factor	Filling Time [sec]	Packing Time [sec]	Cooling Time [sec]	Mold Temperature [°C]	Melt Temperature [°C]	Quality Factor	Cooling_Temperature [°C]	Warpage_Total Displacement [mm]
Level	4	4	4	4	4	Target	Global	Global
Min	1.5	4.5	8	60	265	Goal	Smaller	Smaller
Max	3	6	14	80	290	Weighting	1	1
1. Run 2	1.5	4.5	8	60	265	1. Run 2	172.002	1.42658
2. Run 3	1.5	5	10	65	275	2. Run 3	156.167	1.48647
3. Run 4	1.5	5.5	12	70	285	3. Run 4	157.458	1.50241
4. Run 5	1.5	6	14	80	290	4. Run 5	159.241	1.64309
5. Run 6	2	4.5	10	70	290	5. Run 6	163.199	1.5656
6. Run 7	2	5	8	80	285	6. Run 7	181.569	1.4955
7. Run 8	2	5.5	14	60	275	7. Run 8	153.271	1.77066
8. Run 9	2	6	12	65	265	8. Run 9	149.44	1.68761
9. Run 10	2.5	4.5	12	80	275	9. Run 10	153.458	1.67001
10. Run 11	2.5	5	14	70	265	10. Run 11	149.3	1.87388
11. Run 12	2.5	5.5	8	65	290	11. Run 12	183.368	1.58382
12. Run 13	2.5	6	10	60	285	12. Run 13	158.387	1.70659
13. Run 14	3	4.5	14	65	285	13. Run 14	157.186	1.6984
14. Run 15	3	5	12	60	290	14. Run 15	159.286	1.77447
15. Run 16	3	5.5	10	80	265	15. Run 16	149.635	1.757
16. Run 17	3	6	8	70	275	16. Run 17	173.582	1.72246
Run 18*	1.5	4.5	10	65	265	Run 18*	152.235	1.50311
Prediction								
Setting	1.5	4.5	10	65	265	Predicted Value	152.235	1.50311

Figure 11. DOE result table.

Figures 12 and 13 shown above provide a visual representation of the data from Figure 11. The lower values are what the optimization is aiming for. Test 17 is the optimized one created by the software.

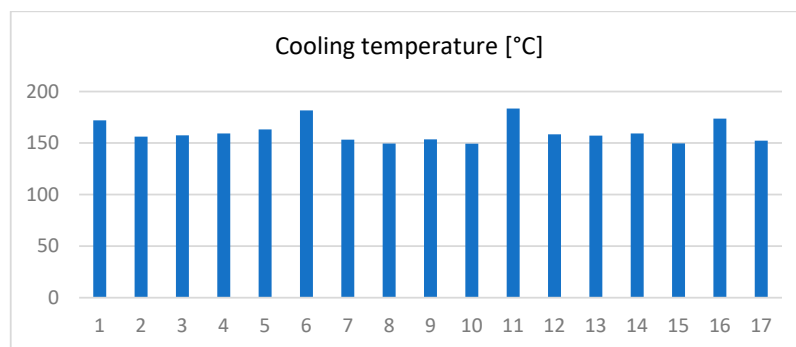


Figure 12. Cooling temperature results.

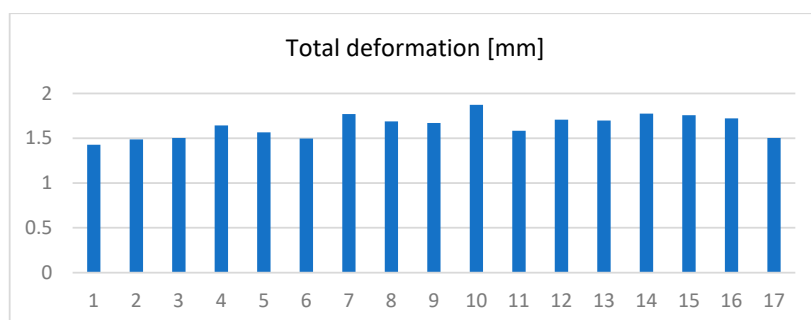


Figure 13. Total deformation results.

In the diagrams shown in Figure 14 of filling and packing, similar characteristics are shown: as their values increase after level 2, the temperature decreases. The situation in the diagram of cooling time is similar; as the values increase, a sharp drop in temperature is observed with a subsequent smooth one. In the diagram of mold temperature, there is no clear dependence.

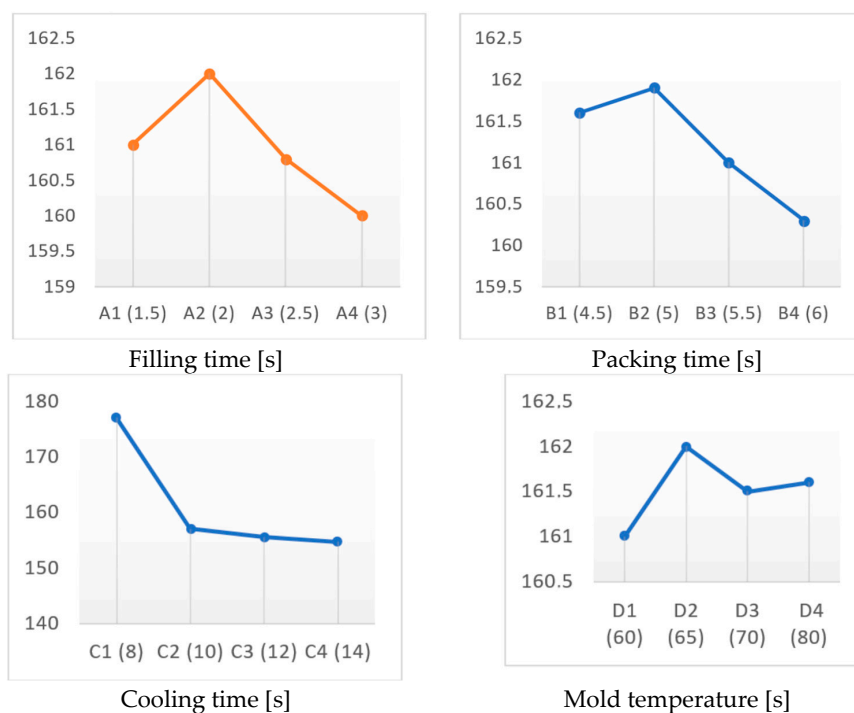


Figure 14. Quality response: cooling temperature [°C].

According to the overall deformation criterion, there is a clear trend in the diagrams shown in Figure 15 of filling, packing and cooling time; as the values of the control factors increase, the overall deformation also grows. In the diagram of mold temperature, there are fluctuations as the increase in the control factor in 33% of the cases leads to a greater deformation, and in the remaining cases it is the opposite.

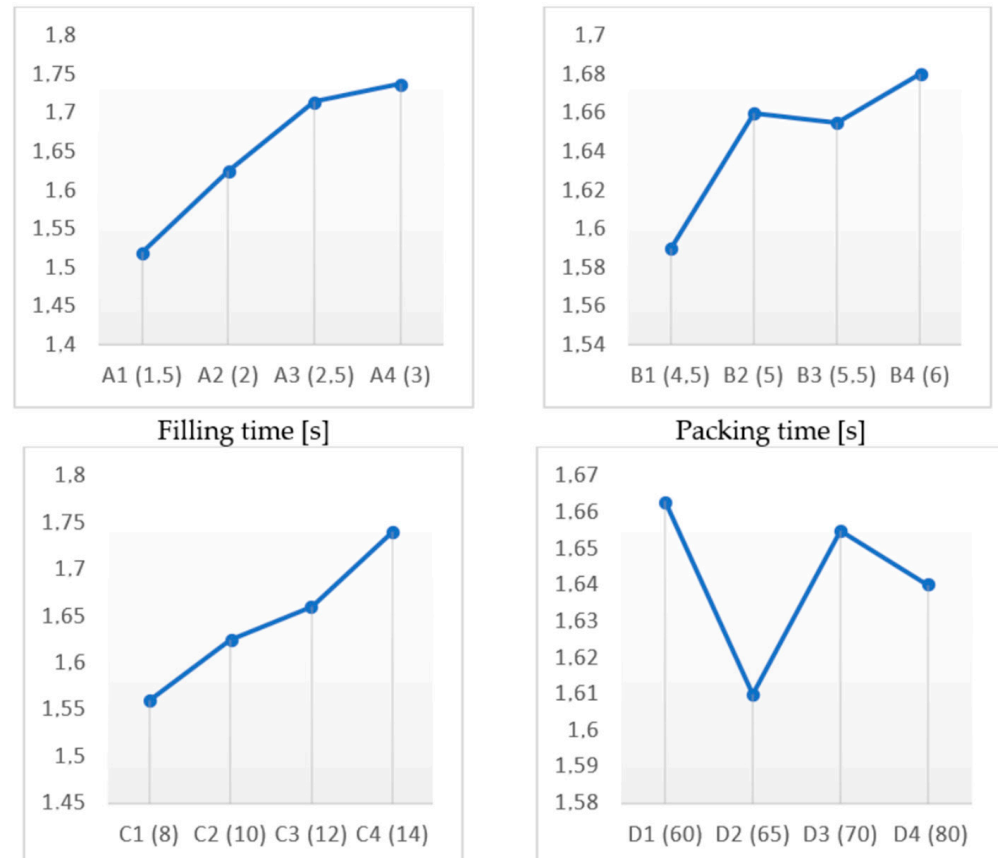
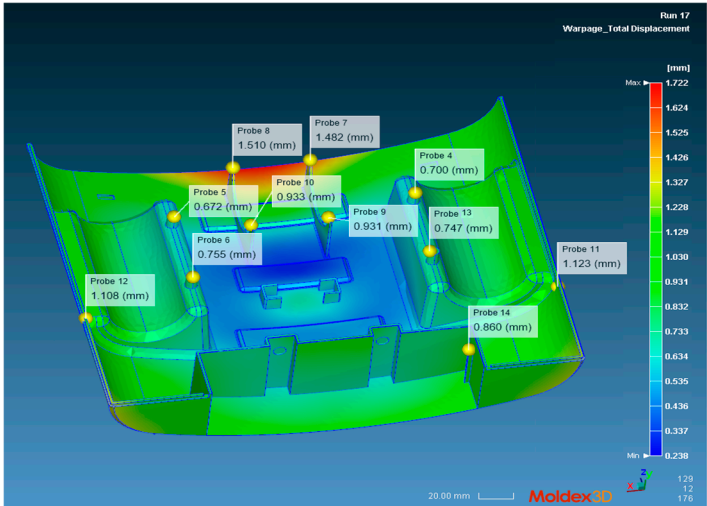


Figure 15. Quality response: total deformation [mm].

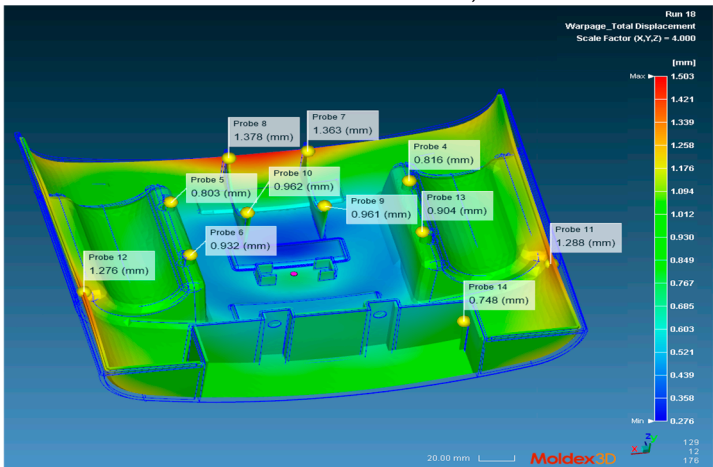
3.2. Comparative Analysis of Displacement in Control Zones

The diagrams shown above give an idea of how the control factors affect the overall deformation and the cooling temperature, but no clear conclusion can be reached regarding the most appropriate values of the parameters. Namely for this, the images of the potential deformations are also considered in the tests (16 tests and an optimized test).

Figure 16 shows the deformations of each individual sample taken from the two tests. As can be seen the optimized test has large deformation in most samples. For the purpose of the injection-molded part, it is necessary to achieve such an accuracy that allows unhindered assembly of the part to the other parts. From this point of view, Samples 4, 5, 6 and 13 are of the greatest importance and should be placed with the highest priority. From the collected data shown in Figure 17, it is clear that Test 16 is the most suitable for injection molding of the studied part.

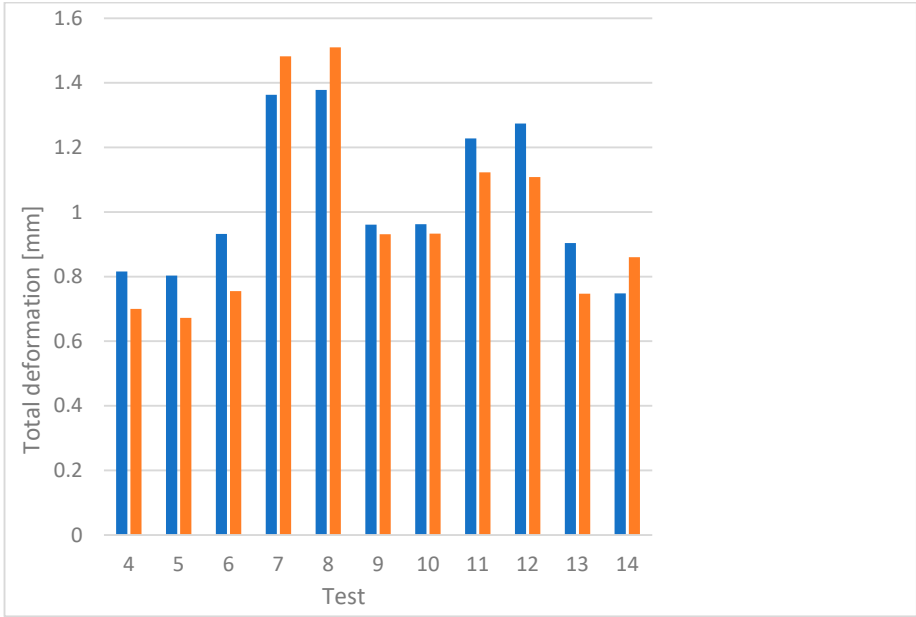


Total deformation for Test 16, scaled *5



Total deformation for optimized test, scaled *5

Figure 16. Total deformation in control zones.



Blue—total deformation for optimized test Orange—total deformation for 16th test

Figure 17. Chart of total deformation in control zones.

4. Discussion

The obtained results from the multi-parameter optimization of the injection molding process demonstrate a clear relationship between the selected control factors and the resulting quality characteristics, namely cooling temperature and total deformation. The application of Taguchi's method and DOE approach proved to be an effective tool for systematically analyzing the influence of multiple process parameters and reducing the number of required experimental iterations.

The graphical and tabular results indicate consistent trends for several key parameters. In particular, increasing filling, packing, and cooling times lead to a reduction in cooling temperature, which is beneficial for minimizing thermal gradients. However, this improvement comes at the cost of increased total deformation, highlighting the inherent trade-off between thermal behavior and dimensional accuracy.

The mold temperature does not exhibit a clearly defined trend, suggesting that its influence is more complex and potentially dependent on interactions with other parameters. This reinforces the importance of using multi-parameter optimization techniques rather than single-factor analysis.

A significant contribution of this study is the comparative evaluation of deformation in critical control zones. While the optimized solution generated by the software (Test 17) provides balanced results according to the selected criteria, the detailed analysis of displacement in key functional areas reveals that Test 16 offers superior performance in the most critical regions of the part. This emphasizes the necessity of incorporating localized analysis when the functionality of the product depends on specific geometrical features.

Furthermore, the integration of simulation tools with statistical methods enables rapid prediction of process outcomes and supports informed decision-making during process setup. The developed methodology demonstrates strong potential for practical implementation in industrial environments, where reducing trial-and-error iterations is essential for improving efficiency and reducing costs.

Overall, the study confirms that multi-parameter optimization, combined with targeted evaluation of critical zones, provide a robust framework for improving the quality and reliability of injection-molded products.

5. Conclusions

As a result of studying the behavior of the injection molding process for the selected part, it was found that, in general, the diagrams and tables of quality response are complete and provide a large set of information that can serve to quickly reduce most of the appropriate filling process parameters. In particular cases such as the one in the article, when the best results are sought in given critical areas of the detail, additional research is resorted to taking control points in the zones to establish the influence of the parameters.

- Through implementation of the proposed methodology, it has been established that there are real possibilities to control the deformations through the correct selection of the process parameters.
- A methodology for rapid prediction and optimization of process parameters of injection molding of complex plastic products has been developed. The possibilities for multi-parameter optimization have been investigated in order to accelerate the convergence of the search for a solution that best satisfies the requirements under set constraints.
- It is clear that Test 16 is the one that offers the best results in the critical joining areas, namely Samples 4, 5, 6 and 13. This leads to the test being ready for use in the final production.

- The proposed methodology and simulation analysis can be applied in a real environment to solve and optimize injection filling processes.

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