Inspection Model and Correlation Functions to Assist in the Correction of Qualitative Defects of Injected Parts

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To perform quality inspection in the injection process is a complex task due to high number of defects that could occur in an injected part and the high number of process parameters that could produce them. Injection defects, in particular qualitative ones, are not a clear reference to determine correct process parameter value setting to produce good quality parts. Research results show that the occurrence of each injection defect could be caused by specific parameters with values above or below an optimal one. Although this information is a guide for the defect correction, the effective correction of qualitative defects with parameter modifications is very complex. This is due to the problems that arise when transforming a qualitative defect into a quantitative inspection. This article shows an inspection model to assist the qualitative detect intensity classification using defect behavior tendency curves. These curves have been deduced from generic analytical relationships established between injection defects and injection process parameters. Conducted tests allow validating the approach and its initial effectiveness.

INTRODUCTION

Injection molding is characterized by the complex interaction among a high number of variables: material variables, mold variables, geometrical parts design variables, and process variables. To identify analytical relationships between injection variables and possible part defects is a research topic that shows the complexity of the task. Industrial practice shows that to produce an injection molded part with the specified quality is a challenge [1]. Research tends to focus mainly in the study of how injection parameters influence quantitative part features. However, the quality of an injected part is defined both by quantitative features (e.g., dimensions) and by qualitative features (e.g., flash formation, sink marks, and wave marks). The assessment of how process parameters affect qualitative part features, the inspection of the part, and the adoption of corrective actions based on the results of the inspection is particularly complex.

The aesthetic defects are the ones inspected in first place by visual inspection that is usually done by the machine operator when standing in front of the machine. The operator decides at that time if the part is acceptable or not. This judgment is based on the qualitative evaluation of the part performed by the operator. To perform this task, the operator needs a reference about how to inspect and evaluate the part quality. The operator could modify the machine injection setting aiming to get a visually acceptable part in the next machine run. To do so, the operator needs a reference about how to change the machine setting depending on the results of the qualitative inspection. However, some part defects have their main causes in the mold design or in the material. In such cases, modifying the machine setting diminishes the defect but it does not eliminate it completely. Some part defects are dimensional or can be measured directly. In such cases, research aims developing systems with online quality measurement to achieve closed-loop quality control without human intervention [1].

Indirect measurement methods have been proposed to inspect qualitative defects on plastic injected parts. Part weight control is one of them [2]. However, such method has some limitations, for instance there is no 1:1 mapping between part weight and part quality features. The use of an indirect key part characteristic may also lead to the loss of the causality between the process variable and the part quality characteristic [3]. This control method has also limitations when there are opposite defects affecting weight simultaneously, e.g., flash and voids.

Saint-Martin et al. [4] proposed a method based on the measurement of the part density to overcome the limitations of the part weigh method. With this method it is possible to detect and measure internal defects such as voids, holes, and cracks without interpretation mistakes.

From the industrial practice perspective, the disadvantage of this indirect measurement method is the increase in the production time, due to the complicated measurements needed.

Other indirect method used is the separation profile control of the mold plaques as used by Wang and Zhou [5]. To apply this method, displacement transducers placed in the partition line to control and to measure flash defects were used. In addition, an indirect method based on the tensional module control was proposed by Kenig et al. [6] to avoid injection defects and to establish a relation between tensional module, part quality, and injection parameters.

Research is also conducted in identifying relationships between injected part defects and process variables. An example is the study carried out by Xu and Koelling [7], where flow marks are mainly caused by inappropriate injection speed, high dynamic viscosity, and high elasticity modulus. Other studies investigate about flow mark physical causes, such as cohesion/adhesion failure of polymer layers, irregular fill flow front, and the existence of an excessive runner tension [8]. The harmonization of the recommendations provided in different research works is difficult, and frequently, the actions that should be taken during the injection process setting to produce good quality parts is unclear.

Injection molding process simulation allows predicting the occurrence of some injection defects such as: sink marks, incomplete filling and dimensional consistency [9, 10], warpage [11], and bubbles and weld lines [12]. In addition, this kind of application provides initial values for process parameters setting.

The setting of the process parameters demands combining heuristic and mathematical models. Design of experiment (DoE) techniques: factorial design, orthogonal arrays, and response surface analysis (RSA) are used to assess the influence of injection variables on the part quality and to predict correlations between process parameters and part features. Lu and Khim [13] apply factorial design to analyze the influence of mold temperature, injection speed, and holding pressure on the surface contours of optical lenses. Orthogonal arrays using Taguchi's method are used on studies focused on the analysis of some specific injection defect such as warpage [14–16], sink index [16], or weld line [17]. Min [18] uses RSA to define a regression equation and to calculate optimal conditions for holding pressure and injection velocity monitoring part shrinkage.

Results and conclusions derived from the experiments defined using DoE and RSA are a fundamental source of information used to develop expert systems. Artificial Intelligence techniques are applied to the field of plastic injection process aiming to select values for the process parameters and to optimize the process conditions to obtain a part with the specified quality [1]. In particular, fuzzy logic (FL) allows managing a big number of qualitative part features without a training phase. Several specific applications have been developed using this technique [e.g.,19, 20]. From literature, it was observed that the input membership functions used in the FL applications were not fitted to the processing window [21, 22].

One of the main issues when dealing with qualitative defects is the complexity on establishing a precise diagnosis of the defect intensity. Another issue is to eliminate the operator's bias and make the inspection independent of the operator's conduct. To overcome these issues, the proposal is to define two procedures, one for part inspection and a second one for machine setting. Such procedures should allow performing an intervention over the machine parameters to correct the identified defects and produce good quality parts [21].

The inspection model is based on the definition of a defect level classification, and on the use of an inspection reference document showing the defect level and its associated rationale. The machine setting procedure is based on the creation of defect/process parameter correlation curves. Such curves can be used as input membership functions in a FL application to assist in the machine setting [21, 22].

DEFECT LEVEL CLASSIFICATION

When dealing with qualitative defects, it is necessary to define a way to allow a quantitative result from the part inspection. Such approach allows reducing operator's bias and time dependency. The way a qualitative defect inspection can be transformed into a quantitative value depends on the defect type. The term used for such quantitative value is: defect intensity level. Table 1 shows the criteria considered to define the defect intensity level for each type of qualitative defect [21].

In this study, a mapping of the qualitative defect intensity into quantitative levels of intensity is proposed. The defect magnitude was established through a scale that indicates the defect intensity level. Defect level classification was established from 0 to 10, where 0 means no defect and 10 is the highest defect intensity level. The defects considered for such mapping were: sink marks, burning marks, flashes, and incomplete filling.

Visual inspection of the part demands having an evaluation criteria explicitly defined. For this purpose and to reduce the operator's bias, it was defined as a reference document with the following content: defect level, picture of the part illustrating the defect level, and the explanation of the defect level. Such reference document was created for each defect type [21]. The structure and content of the documents could be generalized to any other part. Table 2 shows the example of such document for flash defect.

PARTS TO BE TESTED

Small parts, those with an enclosing block of volume lower than 1000 mm^3, are the target of this study. Two

TABLE 1. Classification criteria for selection of defect levels.

No.	Defects	Criteria for selection of defect level
1	Short shots	Percentage of affected surface
2	Sink marks	Percentage of affected surface + percentage of dept defect
3	Flash formation	Percentage of excess material
4	Fragility (cracks)	Percentage of affected surface + facility of defect visualization + facility of manual break of the part
5	Weld lines	Percentage of affected surface + weld line thickness
6	Row lines	Percentage of affected surface + wave width
7	Voids	Percentage of affected surface + depth defect
8	Unmelted particles	Percentage of affected surface + facility of defect visualization
9	Pin marks	Ejectors incident depth in the part
10	Burn marks/dark specks	Percentage of affected surface + defect darkness intensity
11	Bubbles	Percentage of affected surface + facility of defect visualization
12	Delamination	Percentage of affected surface + facility of layer recognition
13	Discoloration	Percentage of affected surface + comparison of tone patterns
14	Marble appearance	Percentage of affected surface + facility of defect visualization
15	Differences in gloss	Percentage of affected surface + facility of defect visualization
16	Deformation on demolding	Percentage of affected surface + facility of defect visualization
17	Gate blush	Depth mark/thickness mark
18	Immersed part in the cavity	Adhesion time (easy to remove it manually)
19	Jetting	Percentage of affected surface + facility of defect visualization
20	Cold slug	Percentage of affected surface + Facility of defect visualization

part types were selected to identify and illustrate the defect behavior when process parameters change. The two parts contain geometrical features that can be generalized to others parts.

First part type is "Thin Parts with 2D behavior." These are parts with thin walls and the polymeric flow does not have important direction changes. The geometrical shape could be circular, squared, rectangular, or any flat polygonal shape. For the injection tests, a rectangular flat small part with 1 mm wall thickness was selected (see Fig. 1).

Second type parts are "Parts with 3D behavior." These are parts with flow direction changes, with perpendicular angles or other angles on a face or between faces, and with thickness wall changes. The geometrical shape has a high level of variety. For the injection test, a part with three thin faces of 1.5 mm wall thickness, where flow has direction changes and wall thickness changes (maximum wall thickness: 2 mm) was selected (see Fig. 2).

EXPERIMENTAL METHOD

For the injection tests, two materials were selected: Polypropylene ISPLEN PC47AVC and Polyethylene REPSOL PE017PP. Injection tests were conducted for each testing part using both materials: P1-PP, P1-PE, P2-PP, and P2-PE. Along the testing process, it was concluded that the trends observed with both materials were similar [21], the data showed in this study relates to PP.

To reduce human bias, three different operators were selected, and each of them conducted a whole set of the experimental injection tests. The tests were carried out in a Babyplast 6/10P injection machine.

The experimental development was constituted by several phases that allowed calculating the defect tendency behavior curves (see Fig. 3). Such curves are relevant for their use as membership functions in Fuzzy Logic systems. The use of membership functions based on the processing window and in how each process parameter affects each defect is an innovative approach [22].

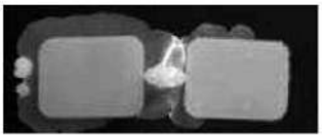
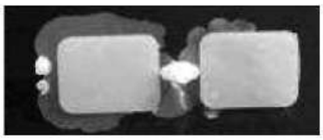
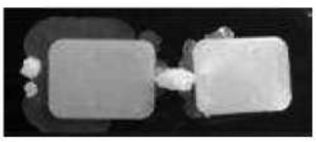
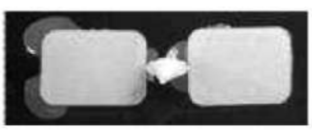
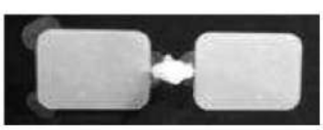
The conducted phases were: Injection molding simulation—processing window and initial process setting, Injection tests—optimal conditions, Injection molding simulation—changing process variables, Injection tests—changing process variables, Injection tests—validation and creation of the correlation curves [21]. The following sections present each of these phases.

Injection Molding Simulation: Molding Window and Initial Process Setting

The injection molding process simulation was carried out using a commercial software application (Moldflow MPI). Simulations were conducted for each combination of part and material to identify the processing window and to obtain the recommended initial conditions to carry out the injection tests in the injection machine. The simulation provides initially specific values for three main process parameters: mold temperature, melt temperature, and fill time. According to the simulation software, such values will provide injected parts with the best quality. The provided values should be within the range defined by the material manufacturer. Once the values of these three main parameters are selected, four different graphs can be created: molding window, minimum temperature of the melt front, pressure, and shear strength.

In the molding window, it can be checked that the selected parameter values provide a feasible process and that they lay within the preferred conditions area. In the configuration of the simulation, the following conditions were adopted: the shear strength should not be higher than the maximum shear strength defined for the material, a maximum melt front temperature drop of 10°C, a maximum melt front temperature increase of 10°C, and the maximum injection pressure should not be higher than the 80% of the maximum injection pressure given by the machine. Once the main parameters are set, a fill analysis

TABLE 2. Flash defect classification levels.

Flash level	Picture	% Excess material
10		Flashes are more than 50% of affected part surface. Flashes are around 90–100% of surface part
9		Flashes are 45–50% of the part surface material. Flashes are around 80–89% of surface part
8		Flashes are 40–44% of the part surface material. Flashes are around 70–79% of surface part
7		Flashes are 35–39% of the part surface material. Flashes are around 60–69% of surface part
6		Flashes are 30–34% of the part surface material. Flashes are around 50–59% of surface part
5		Flashes are 25–29% of the part surface material. Flashes are around 40–49% of surface part
4		Flashes are 20–24% of the part surface material. Flashes are around 30–39% of surface part
3		Flashes are 15–19% of the part surface material. Flashes are around 20–29% of surface part
2		Flashes are 10–14% of the part surface material. Flashes are around 10–19% of surface part
1		Flashes are 1–9% of the part surface material. Flashes are around 1–9% of surface part

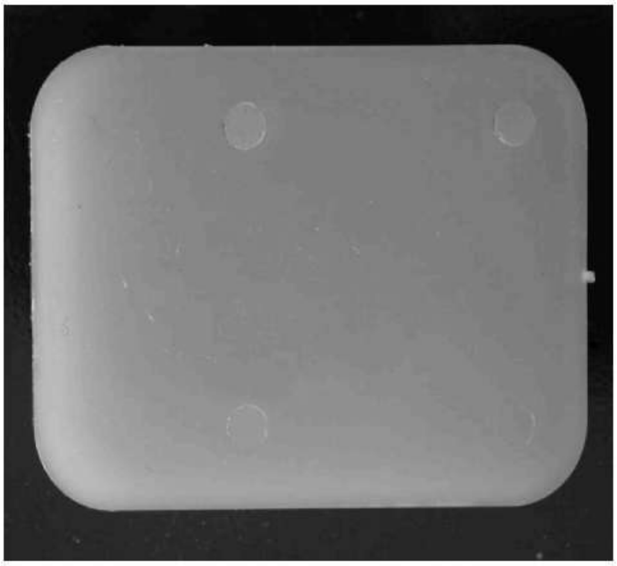


FIG. 1. Thin part with 2D behavior.

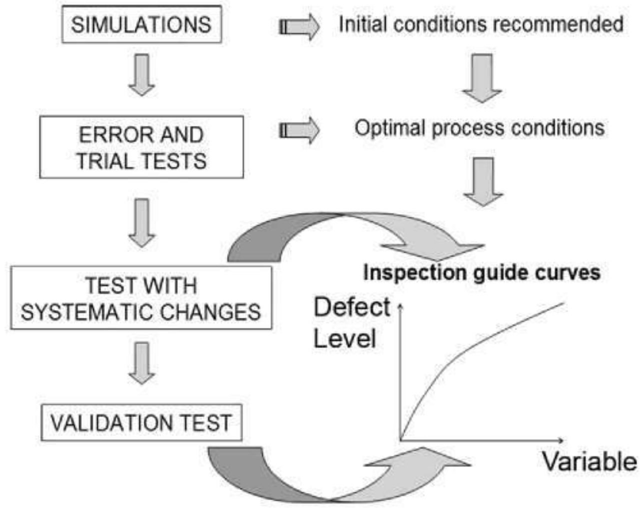


FIG. 3. Experimental development phases.

can be carried out. With the fill analysis, it is possible to predict possible defects such as: weld lines and voids. Variations in the flow front temperature during the filling process could also lead to irregular contractions and deformations. The objective with this analysis was to avoid uncompleted filling, welding lines and voids, to obtain front flow temperature as uniform as possible, and to avoid solidified material at the end of the filling. Figure 4 shows the result of the fill analysis for the second tested part.

After the fill type simulation, a flow type simulation comprising filling and compacting phases is carried out. This second simulation allows checking for sink marks and nonuniform contractions. The objective is to minimize the sink index and to obtain a uniform volumetric contraction in the part. Once a complete simulation was finished, the value of a set of process parameters to manufacture good quality parts were known: mold temperature, melt temperature, fill time, compacting pressure, cooling time, injection rate, injection pressure, and material volume.

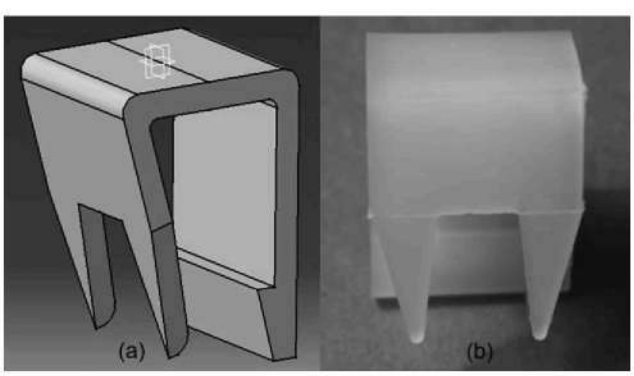


FIG. 2. Part with 3D behavior.

Because of the characteristic of the injection machine (Babyplast 6/10P) and the mold used, the process parameters that could be set in the machine were: melt temperature (it was approximated by the nozzle temperature), fill time, cooling time, injection pressure (constant over time), injection volume (expressed in the form of injection unit screw displacement in mm, derived from the injection rate, fill time, and injection unit screw diameter). The values of such parameters were used in the initial setting of the injection machine to start the injection tests.

In addition to this process, simulations were also carried out to analyze the influence that variations in the processing variables had on part quality and to validate the defect cause and the action for correction compiled from literature [21].

Injection Tests: Best Conditions

Using the initial process parameter values provided in the previous phase, a set of injection tests were carried out to identify the optimal processing conditions. Even though the computer simulation showed that the parts would be free of defects, the execution of the injection tests showed that was not exactly the case. This situation

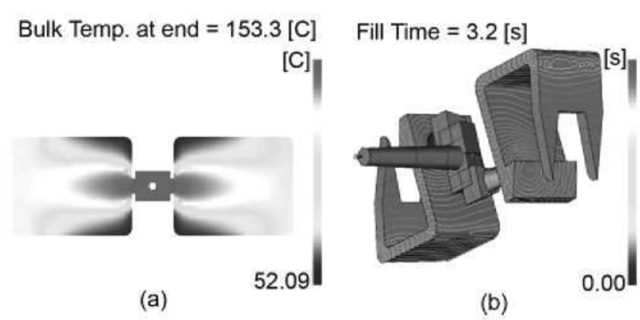


FIG. 4. Example of simulations of the two tested parts.

TABLE 3. Initial process parameter values from simulation software and final values from injection tests.

Parameters	Part 1		Part 2	
	Simulation	Test best value	Simulation	Test best value
Melt temperature (°C)	215	210	240	230
Mold temperature (°C)	40	30	40	30
Fill time (s)	1	3	1	3
Cool time (s)	3.34	3.5	5	6
Injection pressure (Bar)	30	40	99	85
Injection volume (mm^3)	35	35	30	35

led to conduct a set of injection tests to identify processing conditions under which the part was free of any defect. Table 3 shows both the initial values provided by the process simulation software and the final values adopted as a result from the conducted injection tests. Results show that the simulation phase assists in the initial setting of the injection machine. However, trial and error tests have to be conducted to identify the final best processing conditions to produce good quality parts.

Injection Molding Simulation: Changing Process Variables

Once the best process parameters setting was identified, a set of simulations were conducted to check how the simulation software could help in predicting defect occurrence. The simulation tests were conducted changing one process parameter at a time. The change in the process parameters was from the best value to the upper and to the lower limit of the processing window. Table 4 shows the levels of each process parameter tested [21]. The overshadow values correspond to the best parameter value obtained in the previous phase and showed in Table 3. From the simulation results obtained, it was concluded that injection tests had to be carried out to define mathematically the impact of each process parameter on the part quality.

Injection Molding Tests: Changing Process Variables

Similar to the simulation tests, injection experimental tests were carried out increasing and decreasing systematically the best value of the parameters identified in the second phase. Initial tests were run changing only one parameter at a time. The reason for this constraint resides in the fact that when considering the manual setting of an injection machine in a workshop, operators change just one process parameter at a time. For that reason, the possible interactions between process parameters were not considered. To identify possible interactions, the Taguchi method could be used. The objective of these tests was to define how the change of one single parameter at a time would affect the quality of the part. From the tests, data were collected to define individual correlations functions to define the impact of each process parameter on the studied part defects. In addition, they allowed verifying theoretical and simulation results regarding defect causes and possible corrections.

For each parameter change, 10 tests were conducted. About 20 levels were used for each parameter, taking upper and lower values from the best parameter value within the processing window. The number of parts injected was of 2400 parts for each part type. The size of the sample should allow identifying the trend of each studied defect. Table 4 shows the best parameter values (shadowed cells) and the tested levels for each parameter.

For every test, the part produced was inspected. From the inspection, the occurrence of each defect was identified. Then, following the inspection procedure, and using the inspection reference document a defect intensity level was assigned [21].

Validation of the Tests

The tests carried out needed their validation regarding two main noise factors: time (ambient conditions) and operator's bias. For such purpose, in the validation phase, two types of tests were defined and conducted. The first validation test aimed to verify the repeatability of the results at different times, for that purpose, a set of injection test were carried out at three different months and year seasons: November, February, and May. Tests were

TABLE 4. Process parameter levels tested.

Injection volume (mm^3)	Injection pressure (Bar)	Mold temperature (°C)	Melt temperature (°C)	Cool time (s)	Fill time (s)
5	5	20	110	0	0.5
7.5	10	25	120	1	1
10	15	30	130	2	1.5
12.5	20	40	140	3	2
15	25	50	150	4	2.5
17.5	30	60	160	5	3
20	35	70	170	6	3.5
22.5	40	80	180	7	4
25	45	90	190	8	4.5
27.5	50	100	200	9	5
30	55	110	210	10	6
32.5	60	120	220	12	8
35	65	130	230	14	10
37.5	70	140	240	16	12
40	75	150	250	18	14
42.5	80	160	260	20	16
45	85	170	270	22	18
47.5	90	180	280	24	20
50	95	190	290	26	22
52.5	100		300	28	24
55	105		310	30	26
57.5	110		320		28
60	115		330		30
	120				
	125				
	130				

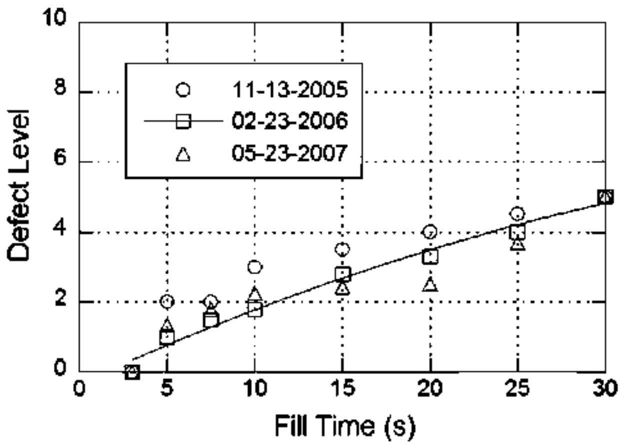


FIG. 5. Burning marks behavior repeatability verification over time.

done for the two tested parts and considering fill time as process parameter to change. Fill time was fixed in each test, and the operator had to classify the defect intensity level of the injected parts. Figure 5 shows the fill time and the average value of the defect intensity level for the burning marks for the tests carried out at three different dates. The trend showed by each set of data is similar, and it was concluded that time effect could be disregarded. The trend curve could be interpolated considering all the data without applying any time correction.

A second validation test aimed to verify the operator's bias. Operator may affect the operation of the machine, but mainly the evaluation of the part quality. Similar information and instructions were provided to three different operators. Before the tests execution, the machine operator was instructed about the inspection procedure, including each defect type and the defect intensity level identification. Figure 6 shows the injection volume and the average value of the defect intensity level for the sink marks for the tests carried out by three different operators. Results showed a similar defect evaluation from the operator, but it pointed out that the defect intensity level scale from 0 to 10 should be reviewed. Making a distinction between levels 2-3-4, 4-5-6, and 7-8-9 was not so straight forward for an operator even when an inspection reference document was available. It was suggested to reduce the levels of the scale to five levels, ranging from 0 for no defect, to 4 for part with its surface almost fully affected.

Defect Behavior Curves: Correlation Functions

Defect behavior curves were deduced from the experimental results. All the data were analyzed by regression analysis. This technique allows modeling causal relationships. The resultant polymeric regression curves were validated through the use of the proportion of variability in data set or coefficient of determination R squared (R^2), which should be up to 0.8 to be accepted as good tendency estimation.

A set of charts was created. Each chart represented the results of pairs defect/process parameter. Figure 7 shows an example of two charts created. In this case, charts represent the variation from the lower level of the processing window to the optimal value. Figure 7a shows the relationship between injection volume and defect level of sink marks. Figure 7b shows the relationship between injection volume and defect level of incomplete part. Tests were carried out by modifying the injection volume value according to the levels defined in Table 4. The produced part was inspected and the defect intensity level assigned following the inspection procedure [21].

To establish a comparison between the influences of each process parameter in the occurrence of each defect, it was necessary to define a parameter unit homogenization scale. With this scale, it was possible to identify which parameter had a higher tendency to produce each defect. This allowed recognizing a parameter intervention order. Such order was independent from the operator experience and allowed creating a machine setting guidance for the operator.

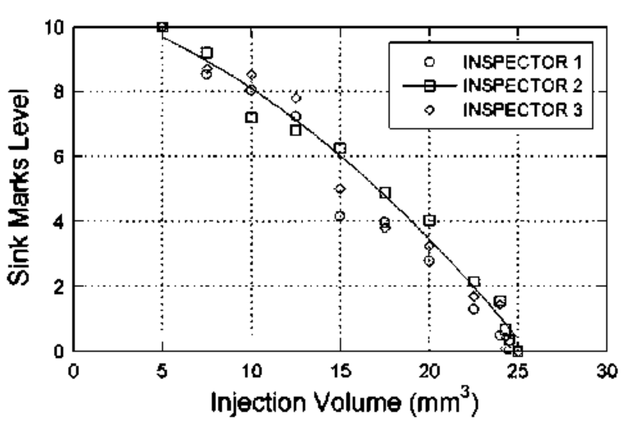


FIG. 6. Sink marks behavior repeatability for different machine operators.

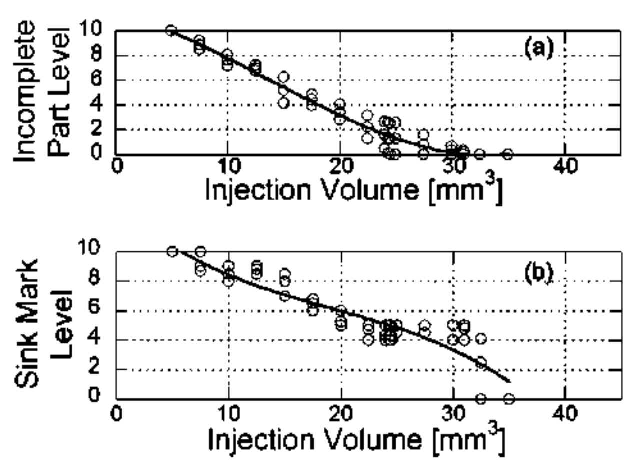


FIG. 7. Example of created charts showing defect level versus process parameter.

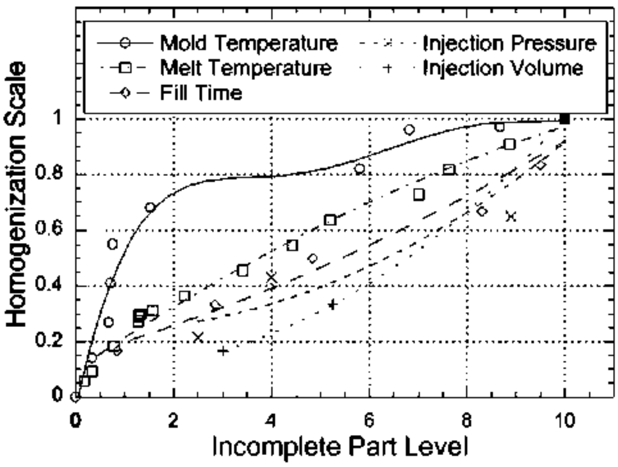


FIG. 8. Homogenization charts created for incomplete part.

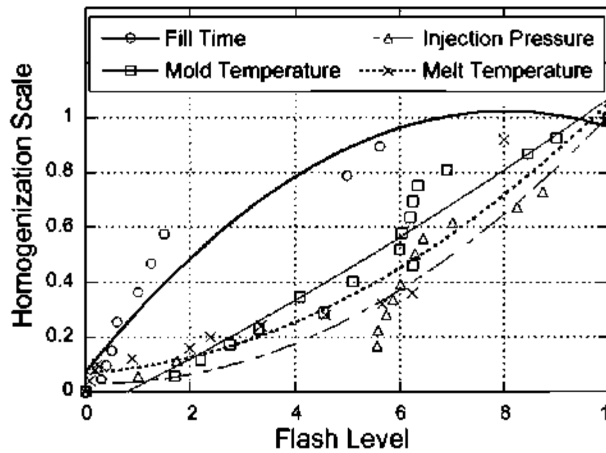


FIG. 10. Homogenization charts created for flashes.

The homogenization scale was established ranging from 0 to 1, where 0 correspond to the parameter value that produce a good part and 1 to the parameter value that produce a part with the maximum defect level (10). This scale represents the existing distance (absolute value) between the best parameter value and the worst parameter value.

Resultant polynomial regression curves created for three defects that most frequently occur in an injected part are showed in this article. These defects are: incomplete part (see Fig. 8), sink marks (see Fig. 9), and flashes (see Fig. 10). Figures 8–10 comprises three graphs that show how each defect behavior is different depending on the parameter that produces the defect. The change in the parameter intervention should be interpreted according to the homogenization scale (Table 5).

The behavior of each defect was defined with respect to each process parameter considering each of them independently. The following step was to identify the global relation that exists between the injection process parameters and the part quality. Part quality was considered as a normalized value of nonconformity level, where 0 represents a part with no defect and 1 represents a part with the highest defect level. The nonconformity level represents the average degree of influence on the part quality. It is calculated as the average of all the defect levels of all the defects identified in the part for a given set of values of the process parameters: fill time, injection pressure, melt temperature, injection volume, mold temperature, and cooling time.

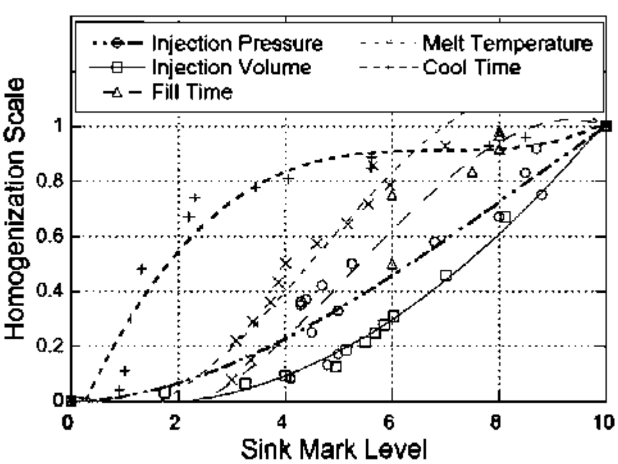


FIG. 9. Homogenization charts created for sink marks.

Figures 11–13 are three graphs showing the influence on the nonconformity level of the parameters: fill time, injection pressure, and injection volume. Data related to the tested part 1 are represented as a triangle and data related to the tested part 2 are represented as a square. Figure 11 shows a specific zone around the fill time of 3 s where both parts are mainly defect free. The trend in both cases is quite similar. The impact of fill times below the best value is higher than the impact of having fill time above such best value.

Figure 12 shows two specific zones where parts are mainly defect free. For the part 1 the area is around an injection pressure of 40 bar and for the part 2 the area is around an injection pressure of 85 bar. The data shows a clear shift along the pressure axis for the part 2, but the kind of trend showed is very similar in both cases. The impact of injection pressures below the best value is smoother than the impact of using values above. Figure 13 shows a similar behavior for both parts, being the best value for the injection volume 35 mm^3.

Fuzzy logic systems traditionally use some type of general membership function, e.g., triangular, gamma, Gaussian, trapezoidal, etc., such curves have no connection to the process itself. The objective was to use the calculated curves: nonconformity level/process parameter; as membership functions, and to evaluate their impact on the results obtained from a fuzzy logic system to assist in the setting of an injection machine to produce good quality parts [21, 22]. The differences observed in the results for part 1 and part 2 were disregarded since the trend and shape of the curves is similar in both cases. The adjustment to different best values could be implemented by shifting the curves along the X axis.

TABLE 5. Homogenization scale.

		Parameter					
Defect	Scale	Injection volume (mm^3)	Injection pressure (Bar)	Melt temperature (°C)	Mold temperature (°C)	Fill time (s)	Cool time (s)
Incomplete part	1	5	5	134	20	0.1	–
	0	35	40	180	30	1	–
Sink marks	1	5	20	300	–	0.1	0.1
	0	35	90	240	–	6	5
Flashes	1	60	130	300	190	30	–
	0	35	90	210	30	1	–

Process Parameters Modification Order

Once the effect of each process parameter on the part quality was determined, it was necessary to define how to proceed when a defect is identified. The order of modification of the process parameters to eliminate the defect had to be defined. For each defect, the action order on the parameters was deduced by analyzing which parameter has to change less than others having a bigger impact on getting a correct part. The same procedure was used to establish a way to change the parameters, and the intervention order to correct all the injection defects. The way and intervention order deduced are shown in Table 6. This table leads to the definition of rules of action on each parameter to correct each defect.

There are two types of rules. The first type corresponds with the action rules represented in the form: "If defect exists then (increase/reduce) parameter." The second type of rules refers to priority. Priority was defined in two levels: defect level and variable level. The first priority applies when more than one defect is identified. In this case, a prioritization order for correction has to be applied and it showed in the defect listing of Table 6. The prioritization order was based on four important characteristics. The first important characteristic was the simplicity of the correction: the simplest the highest priority. The second important characteristic was the visual detection level of the defect: the highest visibility sets the highest level and the highest priority. The third important characteristic was the frequency of occurrence: the highest frequency the highest priority. And the fourth characteristic had in account was the quality damaging level.

The second level of priority applies within each defect and it defines the order of correction for each process variable.

Inspection Model Proposed

The proposed inspection model is constituted by three elements: the defect level classification, the calculated defect correlation functions, and the action priority order. The steps to follow can be summarized in the following ones.

First, the simulation of the part injection process should be done to identify the processing window and to find process parameter values close to the real optimal ones. Such parameter values obtained from the process simulation should be set in the injection machine. With such configuration, the machine should be used to inject parts until the process is stable, and the produced parts have the same appearance from one injection cycle to other. Once the injection machine is stable, the operator has to inspect the injected parts and evaluate the part quality using the inspection procedure to identify defects and to assign a defect intensity level (e.g., Table 2).

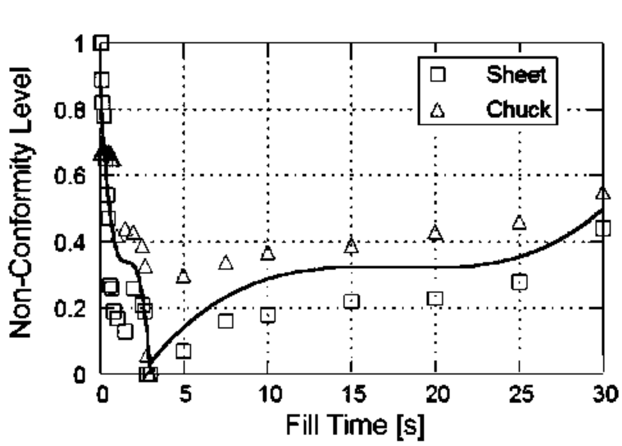


FIG. 11. Correlation curves, influence of fill time on the nonconformity of the injected part.

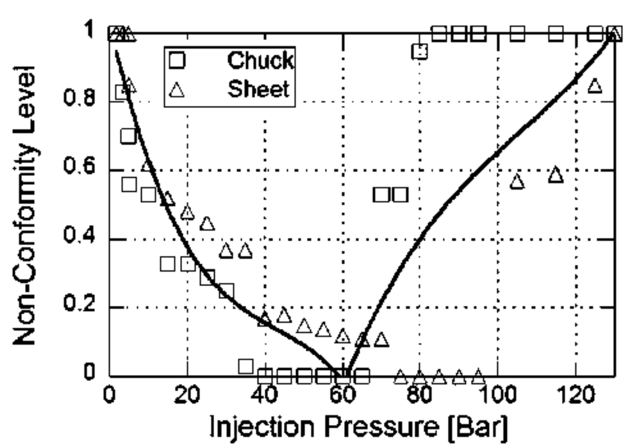


FIG. 12. Correlation curves, influence of injection pressure volume on the nonconformity of the injected part.

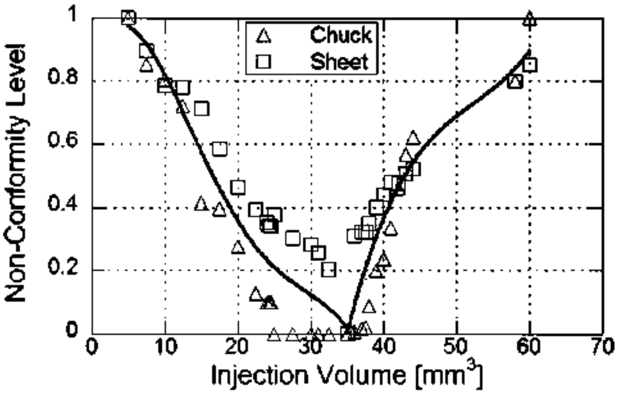


FIG. 13. Correlation curves, influence of injection volume on the non-conformity of the injected part.

Then, with the results from the part inspection, the operator should check the action procedure and verify the parameter intervention recommended for the defects identified in the part (e.g., Table 6). Following the recommendations for the new process parameter setting, the machine will have a new configuration. The operator should run new cycles, until the injection machine is stable, with the new value of the modified parameter. Once the process is stable, the operator should inspect the new part appearance, and compare the new defect level with the level obtained in the previous test.

Using the specific defect chart, the operator should locate the defect levels obtained (on the first and second cycle) and their correspondences with the homogenization scale values (e.g., Fig. 14). Then, the operator should identify the distance between the initial correspondence value of first identified defect level and the correspondent value of the second identified defect level (after first parameter change). The operator should compare this calculated distance with the distance needed to find cero value (defect free) of the homogenization scale and using the corresponding defect/process parameter curve deduce a new approximated parameter value.

With the new parameter value, the operator should run again new cycles and inspect the part. Continue with changes over the same parameter while the defect level is decreasing. When a new value does not produce an improvement in the defect level, then following the order provided in Table 6, take the next parameter recommended to act on. This procedure should be done until a good part is produced and best parameter values are identified.

Verification of the Initial Effectiveness of the Proposed Inspection Model

To verify the inspection model effectiveness, two kinds of tests were carried out. Tests of type O were carried out by a machine operator without using the inspection model. In this type of test, the evaluation of the part defects and the modifications in the process parameter setting was conducted based on the experience of the operator. Tests of type M were carried out by a different machine operator using the proposed inspection model. The objective of the tests was to identify an initial magnitude of the possible benefit that the inspection model could bring to a machine operator.

TABLE 6. Parameter intervention deduced.

		Time				Temperature				Pressure		Volume	
		Fill		Cool		Melt		Mold		Injection		Injection	
Priori	Defect	⇩	⇧	⇩	⇧	⇩	⇧	⇩	⇧	⇩	⇧	⇩	⇧
1	Incomplete parts		3				4		5		2		1
2	Sink marks		3		5	4					2		1
3	Flashes	5				3		4		2		1	
4	Fragility						1		3	2			
5	Weld lines		4				2		3		1		
6	Flow marks	3			6		2		1		4		5
7	Voids	1			2	5		6			3		4
8	Unmelted particles						1		2		3		
9	Pin penetration		5		1	3		2		4		6	
10	Burn marks		4			1		2		3		5	
11	Bubbles	4				1			2		3		5
12	Delamination		3				1		2		5	4	
13	Discoloration			3		1		2					
14	Marble appearance	1			4		2		3				
15	Glossy spots	2				3			4	1			
16	Deformation on demolding		5		1	3		2		4		6	
17	Gate smear		1		4	2			3				
18	Sticking on cavity mold		5		1	3		2		4		6	
19	Jetting		1				4		3	2		5	
20	Cold slug						1						

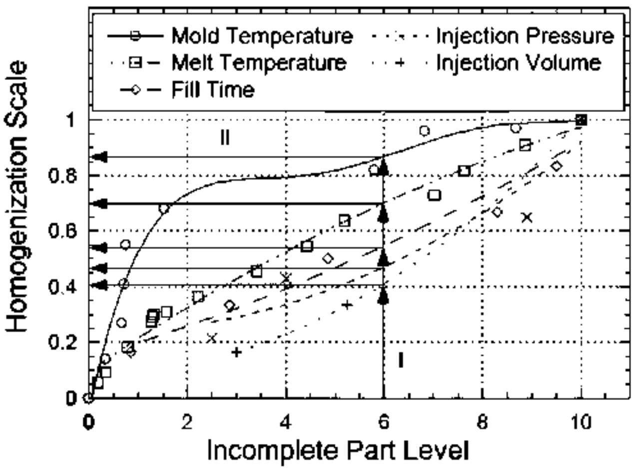


FIG. 14. Chart with procedure to identify the correspondent homogenization scale value.

Considering the characteristics of the machine (Babyplast 6/10P) the process parameters to be modified were limited to: injection volume, fill time, injection pressure, and melt temperature. Process parameters were modified one at a time whereas the others remained unchanged. No coupling or interaction was considered between process parameters.

The part selected for the tests was the part 2 (see Fig. 2), due to its higher complexity, and the material used was PP ISPLEN PC47AVC. The execution of the tests, both in type O and in type M, started with the setting of one process parameter that produced parts with defects. Four different tests were conducted for each of the four process parameters considered: injection volume, injection pressure, fill time, and melt temperature. In each test, the machine operator had to modify the setting of the corresponding process parameter in the injection machine to achieve good quality parts. The quantity of cycles required to produce a good quality part was captured. The tests were carried out taking into account the defect considered as more important. The number of cycles needed by the machine of operator in each type of test was compared. To avoid any learning curve effect, two separate machine operators conducted the tests, for the same reason, they did not repeat the tests.

Table 7 shows the results obtained in the tests where injection volume was the process parameter to adjust, the three other process parameters were set with the best value (Table 3). In the test I-2M, the machine operator used the proposed inspection model, and in the test I-2O, the machine operator did not used the proposed inspection model. Similar results were obtained for the setting of the other three process parameters: injection pressure, fill time, and melt temperature [21].

In average, the results obtained show a reduction in the machine setting of about 20% for all the tests executed. More than 10,000 tests were executed in total along the research, from all of them about 100 tests were conducted in the verification phase. Considering the conditions of the verification tests: one single material, one single part with 3D features, and two machine operators; the relevance of the result was to confirm if this approach of developing a formalized inspection model for qualitative defects to be used by a machine operator would provide promising results.

CONCLUSIONS

An inspection model for qualitative defects was presented. The approach adopted allows grading the qualitative defect by a defect intensity level number. By associating to the defect intensity level, a figure showing the

TABLE 7. Test results with and without the inspection model.

						Defect level		
Test	No. of cycles	Injection volume	Injection pressure	Fill time	Melt temperature	SM	FI	SS
I–2M	1	5	90	3	230			10
	2	15	90	3	230			6
	3	25	90	3	230			2
	4	30	90	3	230	3		1
	5	33	90	3	230	2		
	6	34	90	3	230	1		
	7	35	90	3	230		Correct Part	
I–2O	1	5	90	3	230			10
	2	44	90	3	230		6	
	3	15	90	3	230	8		6
	4	42	90	3	230		5	
	5	20	90	3	230	7		5
	6	40	90	3	230		5	
	7	28	90	3	230	5		2
	8	38	90	3	230		1	
	9	35	90	3	230		Correct Part	

SM, sink marks; Fl, flashes; SS, short shots.

defect intensity and a written explanation of the defect, a machine operator is able to carry out a more accurate and impartial inspection of the part qualitative defects. A defect qualitative inspection is an effective guide to find process parameter values that will produce good quality parts. From the results obtained it was concluded that the proposed defect intensity level with 11 grades should be reduced to just five, ranging from 0 (no defect) to 4 (maximum defect level).

The inspection model is also based on the correlation between the defect and each process parameter modification. This information allows a better approximation to understand the real causes of a defect, and its correction in the machine setting. The change of the process parameters in the machine setting can be improved and made faster by following the charts deduced by regression analysis showing the trend of each defect against each process parameter. Such correlation curves are also relevant for its use as membership functions in Fuzzy Logic systems.

This model requires a short period of time for training of the machine operator. The input received from the machine operators and the tests show that the operator is able to make a proper defect level classification and make use of the proposed defect behavior charts.

The reduction in the machine setting time to produce good quality parts will be always dependent on the expertise of the machine operator. The objective of the approach proposed in this study aimed to show if such dependency could be reduced by using a formalized inspection model for qualitative defects. The 20% reduction in the number of machine setting cycles provides a promising indication. It is expected that when the complexity of the part is higher, the material to inject is more technical and the expertise of the machine operator is lower, then this approach could have a more relevant impact. Following the promising results presented in this study, it is aimed to conduct further research in this direction.

The main trend should be to improve process simulation in a way that results obtained from simulation programs provide process parameter values that set in an injection machine will produce good quality parts with less human intervention. However, before this situation is achieved, the approach proposed in this study could be considered a promising path to explore further for small companies with limited expertise and access to simulation software applications and heavily dependent on the expertise of their machine operators.

The approach of improving process simulation has also been explored. The defect intensity level, the action priority rules, and the correlation functions presented in this article were used in the development of a Fuzzy Logic expert system [21, 22].

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