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OPTIMIZATION OF INJECTION MOLDING PROCESS FOR SINK MARKS REDUCTION BY INTEGRATING RESPONSE SURFACE DESIGN METHODOLOGY & TAGUCHI APPROACH

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ABSTRACT

The purpose of this paper is to present an integrated approach for improving the quality characteristics of the injection molded part (Honda Upper Part) being manufactured at manufacturing industry (Pakistan), where the rejection rate for Honda upper part was on ramp due to sink marks defects. The proposed integrated approach embraces the concept of Design of Experiments (Taguchi Approach) and Response surface design methodology for injection molding process optimization. The Taguchi Method (TM) was used to short list the variables that have significant effects on the sink marks in injection molded parts. Furthermore, the optimization approach of Response Surface Methodology (RSM) was utilized for the experimental research to acquire a prediction model that can be used to optimize injection molding process in terms of fine sink marks reduction. The result shows that the sink marks reduction predicted by the integration of the Taguchi Method and RSM indeed decreased from 0.0088 (Taguchi's result) down to 0.0080 mm. The empirical results reveal that the integration of the Taguchi Method and RSM could effectively improve the quality. Basically with these experiments, we tried to open the vision of manufacturers and designers regarding the application of integrated RSM/Taguchi approach using linear cum interaction regression model with selected parametric/levels setting for the dimensional accuracy of the injection molded part, and thus contributing towards improvement in process's reliability. The integrated approach with regression model for optimization does not only provide theoretical worth to the literature and manufacturers/designers but can also be applied to different manufacturing industries for quality parts production.

Keywords: *Injection Molding Process Optimization, Sink Marks, Design of Experiments, Taguchi Approach, Response Surface Methodology*

1) INTRODUCTION

Injection molding has been a challenging process for many manufacturers and researchers to produce products meeting all quality requirements at economized cost. In competitive environment, the trial and-error approach to determine the process parameters for injection molding is no longer effective. As the plastics products reveal extremely complicated material properties, the molding process becomes very challenging to attain desired part properties and thus causes difficulty in maintaining quality products during production (Sanjay N. Lahoti, 2013). The present technology drift is towards the high performance engineering plastics in order to merge a healthy number of features into small volumes and to increase the internal space. (S.H. Tang, et al 2007) (B. Ozcelik and Sonat (2009).

During production, quality characteristics may deviate due to drifting of processing conditions caused by machine's physical or characteristic change and operator's in efficiency. Generally quality defects are mainly caused due to improper selection of the processing conditions during production. This is one of the main root causes leading to above quality deviations during production (Mr. Aditya M. Darekar, et al 2015). So, the selection of the optimal processing conditions during production is recognized as one of the most important step in injection molding for improving the quality of molded products. Since the quality of injection molded plastic parts are mostly influenced by process condition, hence to determine the optimum process parameters becomes the key to improving the part quality and achieving robust process. Optimization of injection molding process results in improved performance, reliability etc. and reduces field failure of a product. Thus, research in the injection molding processes is concerned on increasing production efficiency and quality by fully utilizing the resources. Selection of optimum process control parameters plays a key role in the improvement of process efficiency and product's quality. Hence, to achieve the desired responses, the independent control parameters which affect the responses are to be set at optimal values. Such problems can be solved by first developing optimization models correlating the responses and the process parameters. A suitable optimization technique is then applied to search for fine tuning of parameter values to obtain the desired responses.

In industrial processes, like injection molding, the Taguchi Method is the most commonly used optimized experimental design method as compared to traditional experimental designs that requires the healthy number of experimental runs and consumes too many valuable resources. Comparatively, the Taguchi Method makes it possible to identify an optimal value from the preset factor levels with fewer experiments and in a shorter period of time. Nonetheless, the value of the optimal level acquired with the Taguchi Method might not be the global optimum (Yung-TsanJou, et al 2013). As a result, fine parameter optimization is necessary, by integrating the experimental design methods of the Taguchi Method and other methodologies to identify the fine optimal process parameters setting.

2) LITERATURE REVIEW

The amount of literature reviews is quite healthy regarding theoretic methodologies for process parametric setting in order to optimize the product responses, generally based on computer simulation. Many studies demonstrated that DOE, CAE and statistical tools, such as RSM, can be successfully integrated for fine optimization. Many researchers, have applied combined approach of Taguchi and Response Surface Methodology (RSM) to plan experiments and improve the quality of products in the past years for different industrial applications having different optimization approaches to process response with own parametric settings and levels.

M.N. Dhavlikar et al (2003) induced a successful application of combined Taguchi and dual response methodology for identification of optimum process parameter values for minimization of out of roundness error of work pieces in center less grinding operation. Jae Seob Kwak et al (2005) developed second order response model to predict geometric error in the surface grinding process that was mainly affected by the thermal effects and the stiffness of the grinding system. He applied Taguchi and Response surface methodologies for controlling the geometric error. C. Chen, et al (2009) proposed the use of CAE software to identify some crucial settings for the IM process of a thin-shell plastic part. A predictive model of warpage, based on RSM was developed modeled on 3-levels orthogonal array for sampling the design space. W.L. Chen, et al (2010) investigated the warpage and shrinkage of a molded part with RSM modeled on a Taguchi 3-level orthogonal array; with simulated results. A.O. Andrisano et al (2011) developed method consisting of screening of factors based on a fractional DOE followed by a systematic experimental plan based on the

Response Surface Methodology (RSM), in which regression model was finally developed to describe the responses as functions of key factors to obtain optimal responses by tuning the process factors in their variability range. Yung-TsanJou, et al (2013) used Taguchi Method (TM) to screen the variables that have significant effects on the contraction rate of the outer coating of the optical fiber and finally the Response Surface Methodology (RSM) was utilized to acquire a prediction model that can be used to fine optimize the optical fiber outer coating injection molding process. S. E. S. Bariran and K. S. M. Sahari (2013) have concluded that Taguchi method combined with other heuristic methods such as Artificial Neural Network and Genetic Algorithm proved to be a better tool for optimization especially for material selection and mold design.

2.1) Analysis of Literature Review

The primary objective of the above presented research was to study the possibility of modeling and predicting the desired quality characteristics of injection molded parts and optimizing the process conditions so as to improve the part quality by using the combined tools of DoE, RSM and other methods. CAE based simulations were used to replace real experiments for the sake of cost and time saving. In above researches, various process defects were investigated and different experimental design, the analysis of variance (ANOVA) was used to optimize the process response. In all approaches, the influence of different control parameters on process response was examined. In the same back drop, the present work aims to select and originally integrate two engineering procedures and techniques to develop an easy-to-use Design of Experiments (DOE) methodology which integrates DOE and RSM to identify the set of IM process parameters (factors) to be tuned for optimizing the product key requirements (sink marks minimization) aiming to easy to use design of experiments, applicability, speed and optimum results attainment.

The paper is involved in optimization of IM process through multiple potentially correlated control variables, by searching the entire search space for potential and feasible combination of process control parameter values for minimum value of sink marks. The design integrated method predicts good response in terms of dimensional part's accuracy requirements (minimum sink marks), and can improve the Honda upper part mold ability. The method is feasible and has potential to be easily adopted in industrial product/process development to define the optimal process parameters. The Figure-1 gives an over view of above approach. The first step towards optimization focuses on factors screening based on Taguchi experimental design, to evaluate main effects and interactions. The main purpose of a DOE is to determine level of selected factors that leads to optimum performance. The selected factors are data inputs for the next step. The second optimization step is based on RSM plan to sample the space design. The data were analyzed, and the fitting model was applied to study the interactions among factors. Based on above an optimal set of values was determined for each factor by tuning the parameters in their variability range. The output is a linear cum regression model that describes the system responses as functions of the selected factors. The developed regression model describe the process responses as functions of key factors and an objective optimization is proposed by tuning the process factors in their variability range.

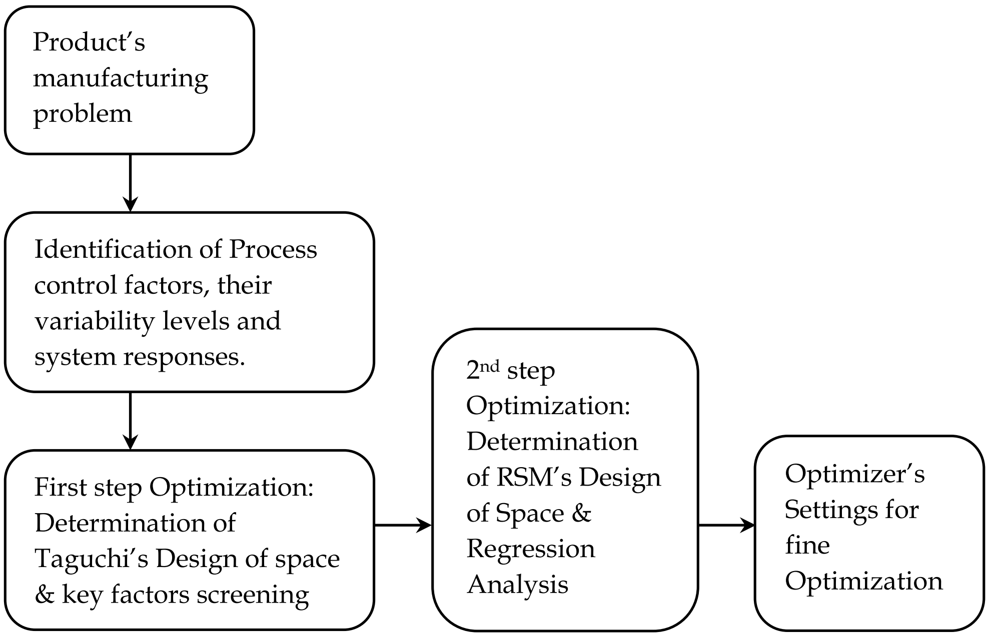


Figure 1: Flow Diagram for Optimization of IM Process Response

2.2) Taguchi Method

After setting the optimization goal and identifications of control variables as the first initiating point of analysis, the screening of process parameters is to be performed. The factors screening is based on experimental design, to evaluate main effects and interactions. The screening phase involves three steps; determination of design space; execution of simulation experiments; and finally marking of screened factors. The number of screened factors and their levels' settings determine the design space, and it also represents the number of simulation runs. (A.O. Andrisano, et al 2011).

A very useful DoE approach namely Taguchi's Quality function that maximizes the investigated process parameter space through minimal number of experiments. Taguchi's approach to quality control applies to the entire process of developing and manufacturing a product from initial concept to manufacturing/production in computer integrated manufacturing environment. Taguchi's method is a systematic application of design and analysis of experiments for the purpose of robust designing and improved quality. Taguchi achieves this objective by making the process insensitive to variations in output even though noise is present in the process as described by P-diagram (Figure-2). The process is then said to have become ROBUST (Y.P Tidke et al 2014).

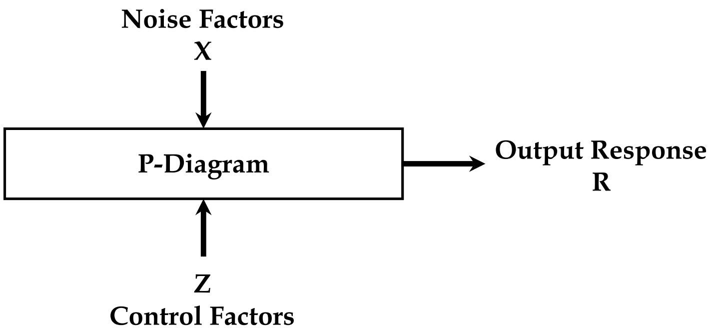


Figure 2: Process Diagram

The approach to optimization in Taguchi, for feasible and potential combinations of process parameters with parametric settings has the attractions for manufacturers and designers to implement in real time industrial applications. Taguchi parametric design approach has been utilized in past years for identifying the significant processing parameters and optimizing parametric setting. S.H. Tang et al. (2006) have analyzed thin plate for warpage, while doing ANOVA using Taguchi's L9 orthogonal array. The authors screened out melt temperature, packing time and packing pressure as significant factors while filling time is insignificant towards warpage defect. Feng, Chung et al. (2006) examined multiple quality optimization of the injection molding process for Polyether Ether Ketone while looking into the dimensional deviation and strength of screws produced by the injection molding. He applied the Taguchi method and combined grey relational analysis to determine the optimal processing parameters for multiple quality characteristics. B. Sha, S. Dimov, et al (2007) conducted design of experiments and data analysis in Micro Injection Molding (MIM). They focused on the analysis with three factors barrel temperature, mold temperature and injection velocity to find their effects on achievable aspect ratios in three different plastics. Babur Ozcelik (2011) investigated influence of the injection parameters and weld line on the mechanical properties of Polypropylene (PP) during plastic injection molding by using Taguchi experimental method. Z. Shayfull et al. (2011) and S.M Nasir et al. (2011) adopted Taguchi method to establish the optimum parameters of injection molding process for warpage of ultra-thin shell part. Wei Guo, et al (2012) analyzed a warpage in the automobile interior housing trim using FEA simulation and Design of Experiments (DOE) using a fractional factorial design of experiments (FFD). They proposed that FFD is suitable to arrive at the most influential processing parameters and their effects. Anand KR Dwiwedi et al (2015) presented injection molding process parameter optimization for polypropylene material using the Taguchi methodology with the help of orthogonal array by conducting only few experiments. They used Processing temperature, Injection pressure, Cooling time and Injection speed as a process parameter and optimized the process parameters by considering Tensile strength as a resulting factor.

From above review, it is evident that researchers have successfully used Design of Experiments approach for optimizing injection molding parameters related to processing, and mold design using many Simulation packages for performing virtual trials. It can be seen that optimization of plastic injection molding process using Simulation Analysis coupled with various optimization techniques is more economic and effective way in improving product quality and reducing manufacturing cost. There always lies a future scope of conducting a more comprehensive parametric study of the injection molding process parameters using Finite Element Simulations and their interactions for optimizing the process using different design of experiments approaches for getting an exact desired solution (Mr. Aditya M. Darekar et al 2015).

In this case study, the Taguchi experimental design was initially used to investigate the relationship between injection processing parameters and sink marks defects in injection molded parts by searching feasible parametric design. Taguchi's Quality Function's prediction based on signal-to-noise ratio was applied to obtain an overall space for potential combination of process control parameter values. The parametric design method of Taguchi adopted includes the major steps as shown in Figure-3. It includes determining of the viable and tractable process control factors and levels that influence the performance of output response, which is critical and initial step towards optimization of process. The above step is followed by the selection of experimental lay out design for the Injection Molding through Orthogonal Arrays. For experimental analysis, the Taguchi's method uses S/N ratio to measure quality characteristics deviation from the desired value. Finally based on data analysis, the additional experimental run will be conducted for validation of main effects graph.

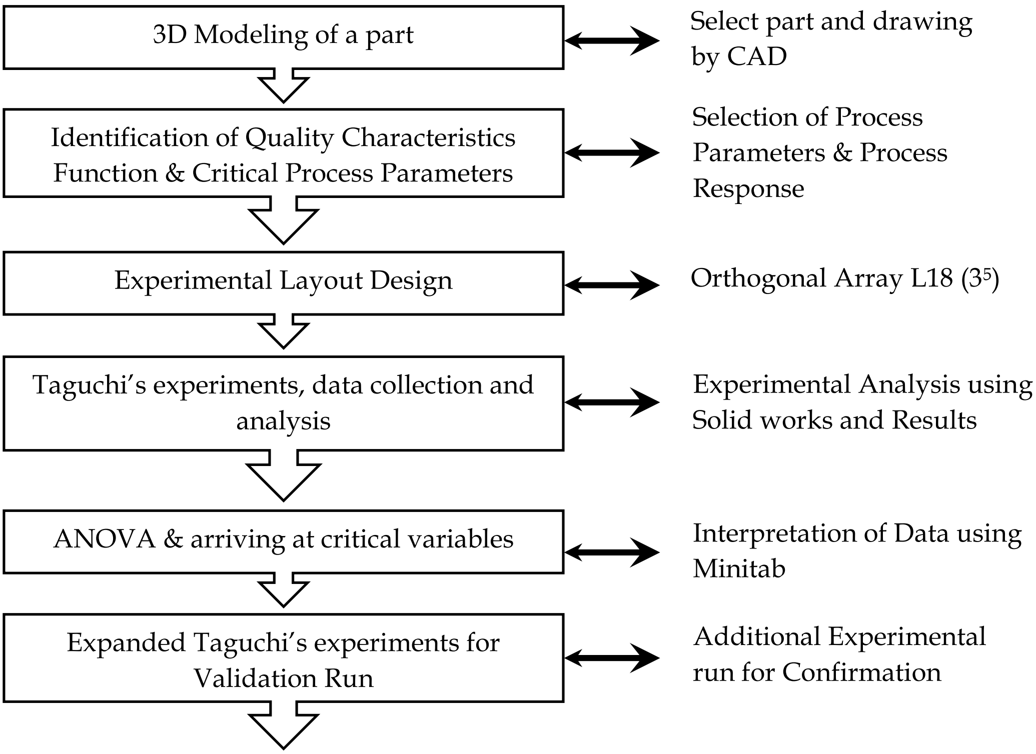


Figure 3: Major Steps of Taguchi Approach

2.3) Response Surface Methodology

Response Surface Methodology (RSM) based experimental designing was established to develop a Regression Model for identifying the fine optimal parametric settings. Response Surface Methodology (RSM) is based on experimental design to sample the system responses by varying the parameters in their variability ranges. The system responses are described by regression models as function of the input variables to obtain Response Surfaces (RSs) (A.O. Andrisano, et al 2011). Many studies have been conducted to optimize performances in the field of Injection Molding by the application of RSM based experimental design method. K.T. Chiang (2007) applied RSM based on centered Central Composite Design matrix to identify the effects of process parameters on shrinkage and warpage. W.L. Chen et al (2010) investigated the warpage and shrinkage of a molded part with RSM modeled on a Taguchi 3-level orthogonal array using process simulation tool. Long Wua et al (2012) presented a response surface methodology as the approach for parametric design and process parameter optimization of bra cup molding. T Amit Kumar, et al (2015) presented study to optimize the process parameters during forming of PVC (L-bow) fitting by injection molding machine using response surface methodology (RSM).Four input process parameters ; filling time, refill time (RFT), tonnage time (TT) and Ejector retraction time (ERT)) were chosen as variables to determine the process performance in terms of cycle time (CT). C. Chen et al (2009) presented a preliminary study, and proposed a predictive model of warpage, based on RSM and Mold flow analyses. A 3-levels orthogonal array was used for sampling the design space. Simulation results were then validated with physical experiments.

In this report, after the step of factors′ screening, the final regression model(linear cum interaction model) for determination of system responses by RSM was then implemented considering only the significant factors found by the Taguchi, i.e. Melt temperature, Molding temperature, Fill time and Pressure holding Time. A CCI design was used for approximating model between the response y as sink depth and 04 independent variables x1, x2, x3 and x4 as mentioned above .With the sink depth as response ‘y’, the response surface can be expressed generally as Equation (1).

$$y = f(x1, x2, x3, x4) + e \tag{1}$$

The relationship describes a curved surface y = f (x1, x2, x3, x4) that is known as a Response Surface function. The standard RSM first employs an experimental methodology to generate design axial points in the design space, then applies either the first-order model or the second-order model to approximate the objective function as feasible. If the response can be defined by a linear function of independent variables, then the approximating function is a first-order model. If there is a curve in the response surface, then a higher degree polynomial function should be used. A first-order model with 2 independent variables and approximating function with 2 variables having non linearity in response w r t input variables can be expressed as Equation 2 & 3.

$$y = \beta_o + \beta_1 x1 + \beta_2 x2 + e \qquad (2)$$

$$y = \beta_o + \beta_1 x1 + \beta_{11} (x1)^2 + \beta_{22} (x2)^2 + \beta_{12} (x1x2) + e \qquad (3)$$

Where 'Y': response variable, β_o: Constant coefficient (offset),β_1 , β_2 : linear terms, β_{11} ,β_{22} : quadratic terms ,β_{12} , : interaction term and X_1andX_2: independent variables. The second-order model is widely used in response surface methodology for reasons of flexibility and near to the true response surface. The Optimization in RSM involves creation of Response surface through objective function's approximation and it includes followings major steps as enumerated in Figure-4

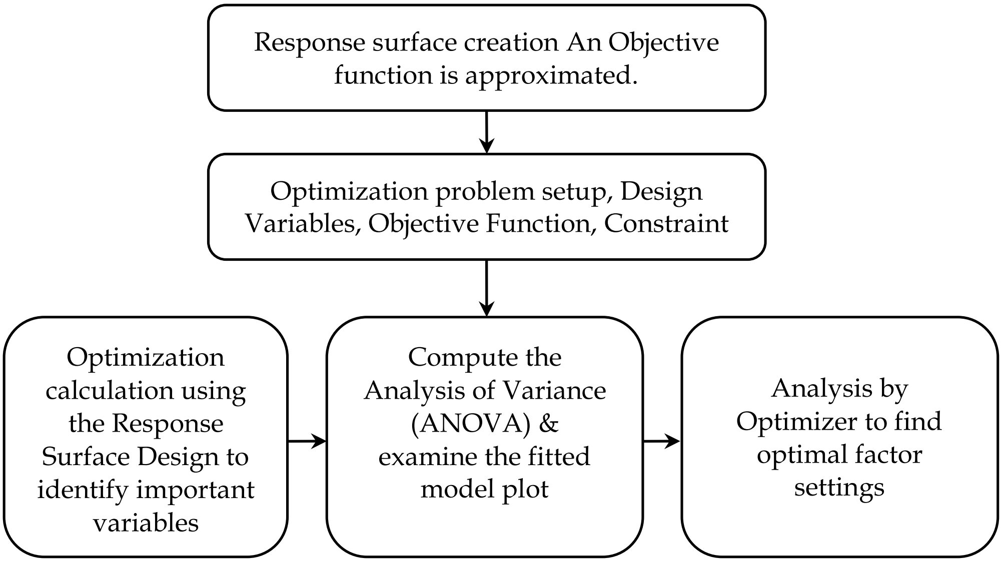


Figure 4: Flow Diagram for Response Surface Design Methodology

3) CASE STUDY

3.1) CAD of Product

In this case study, Honda Upper Part (product by Alsons Auto Pvt. Ltd.) was taken for experiments. The Sink marks was marked as one of the significant defect mostly occurred in molded Honda upper part causing many manufacturing line rejection. The developed method was applied to the Injection molding process simulation of the Honda Upper Part housing. Simulation trials taken in such a way that to check how Sinks Marks defect changes as we change the parametric settings. The Honda upper part was designed using the CAD software. It was designed to its dimension according to the part drawing dimension data provided by the company. The part and its CAD design are shown in Figure-5. The optimization goal in the above study is the first point to be illuminated before initiating the analysis. The goal of the study is to determine the set of parameters which leads to the best part mold ability with lowest Sink Marks. The formulation of the goal leads to the identification of critical factors and the characterization of process performance variable. The feasible space for the molding parameters was defined in light of the data available in the literature, technical data sheets, and manufacturing expert's opinion.

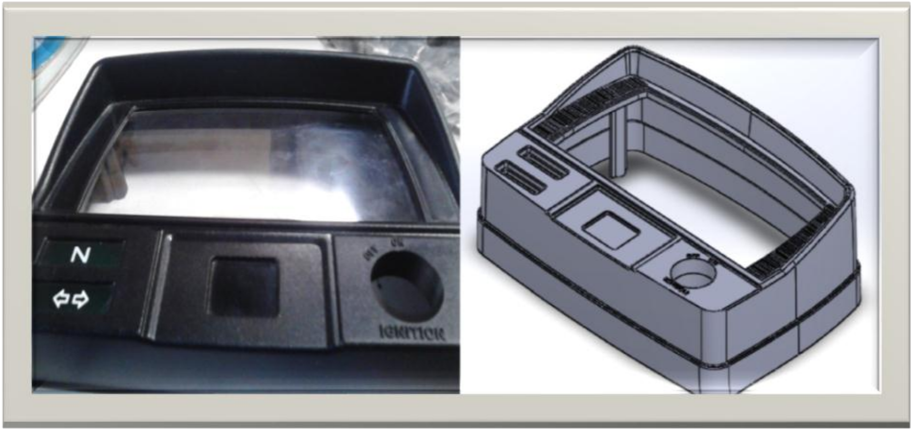


Figure 5: Product Taken and its three-dimensional elements representation

3.2) Screening of factors & Selection of Orthogonal Array

The number of factors and their levels determine the design space and their variability ranges, and it also represents the number of simulation runs. Looking at sink marks as the process response selected, list of related key factors includes filling time, injection holding pressure time, mold temperature, melt temperature, packing pressure and time, cooling time and fill time. According to the literature reviews and manufacturing expert's opinion, several factors affect the shape and dimensional accuracy of molded parts. The present work investigated the following control factors for process response; Melt temperature, Mold temperature, Filling time, Cooling Time and Holding pressure time. Once determined which predominant factors affect the process, their variability range must be derived with investigations. The working material used in injection molding process was Acrylonitrile Butadiene Styrene (ABS). Screened out parameters accompanied with different levels are shown in Table-1

Table 1: Control Parameters & their Levels

Factors	**Level 1**	**Level 02**	**Level 03**
Fill time: A	12.4 sec	12.2 sec	12 sec
Melt temperature: B	230 C	240 C	250 C
Mold Temperature: C	50 C	65 C	85 C
Cooling Time: D	10 sec	13 sec	15 sec
Pressure Holding Time: E	3.4 sec	4 sec	4.5 sec

Three levels of each factor were taken for L_{18} (3^5) array, where the selection of the array is meant because of its suitability for 05 factors as given in Table below. The criterion used for choosing the three parameter levels is based on covering extended ranges of experimental variables and to maximize the volume of experimental parameters space. Array selector Matrix and experimental layout using L_{18} (3^5) Orthogonal Array are shown in Table -2 & 3.

Table 2: Array Selector Matrix

Number of Levels	Number of Parameters (P)														
	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
2	L4	L4	L8	L8	L8	L8	L12	L12	L12	L12	L16	L16	L16	L16	L32
3	L9	L9	L9	L18	L18	L18	L18	L27	L27	L27	L27	L27	L36	L36	L36
4	L'16	L'16	L'16	L'16	L'32	L'32	L'32	L'32	L'32						
5	L25	L25	L25	L25	L25	L50	L50	L50	L50	L50	L50				

Number of Levels	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
2	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32	L32
3	L36	L36	L36	L36	L36	L36	L36								
4															
5															

Table 3: Experimental Layout using (L_{18}) Orthogonal Array

Expt. No.	Fill Time: A	Melt Temp: B	Mold Temp: C	Cooling Time: D	Pressure Holding Time: E
1	1	1	1	1	1
2	1	2	2	2	2
3	1	3	3	3	3
4	2	1	1	2	2
5	2	2	2	3	3
6	2	3	3	1	1
7	3	1	2	1	3
8	3	2	3	2	1
9	3	3	1	3	2
10	1	1	3	3	2
11	1	2	1	1	3
12	1	3	2	2	1
13	2	1	2	3	1
14	2	2	3	1	2
15	2	3	1	2	3
16	3	1	3	2	3
17	3	2	1	3	1
18	3	3	2	1	2

3.3) Simulation Model & Analysis

For conducting the experiments scheduled by Taguchi experimental design, simulations of experimental process for injection molding were set up. All the factors assumed their selected levels according to the DOE matrix as given in Table-3. A Finite Elements model of the Honda upper part was created and CAE simulation software, Solid Works was used to simulate the injection molding process. The simulation result of an experimental run is shown in Figure-6. Similar 18 simulation runs were conducted. Collected data points were analyzed using the "smaller-the-better approach". The aim of above experimental run is primarily to determine the highest possible S/N ratio for the result. A high value of S/N implies that the signal is much higher than the random effects of the minimum variance. The data analysis was mainly applied to screen out the experimental variables with significant effects on sink marks reduction, so the interactions among variables are not assumed in this experimental design. The step of Taguchi method delivered a list of significant factors as data input for 2nd step of optimization through RSM.

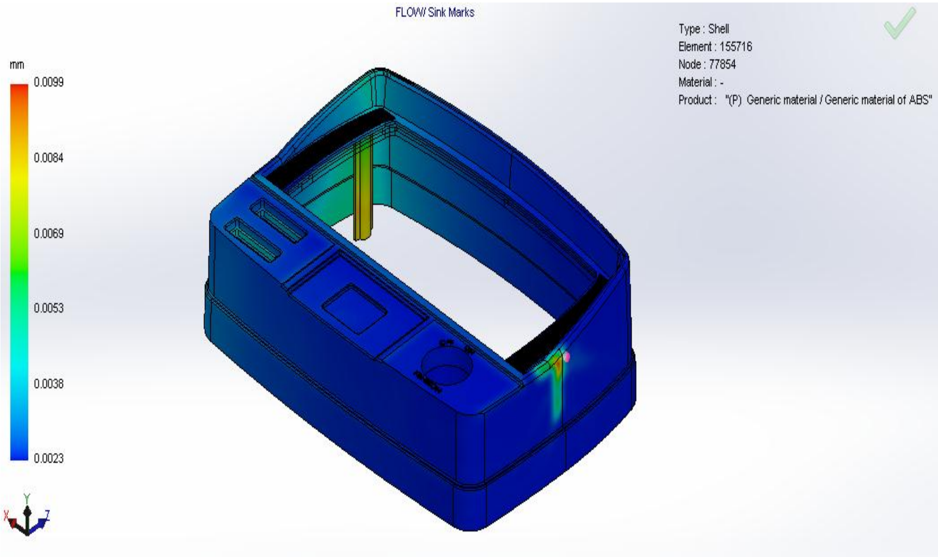


Figure 6: Honda Upper Part- Simulation Result for Injection Molding Process

3.4) Analysis Result - Signal to Noise Ratio (S/N)

Experimental data analysis was performed to determine the optimum process design, influence of individual factors and performance at the optimum condition. Influence of each experimental factor (A, B, C, D, E) on the sink marks reduction was determined with a so-called S/N ratio based response table. Table-5 shows the orthogonal array and the associated experimental results for the sink marks. In this method, signal to noise ratio (S/N ratio) was used to measure the sensitivity of the quality characteristic being investigated in a controlled manner. In Taguchi method, the term 'signal' represents the desirable mean effect for the output characteristic and the term 'noise' represents the undesirable standard deviation effect from mean, which influence the outcome due to controllable factors. The S/N ratio is also used in Analysis of Variance (ANONA), which reflects the relative influence of factors to the variation of result. In this study, the objective function relates to sink marks reduction, so the Smaller-the-better quality function was chosen. The S/N ratio for Smaller-the-Better approach can be defined as Equation (4)

$$^{S}/_{N}\,STB = -10\log_{10}(MSD) \qquad (4)$$

Where S/N_{STB} stands for Smaller-the-better Signal-to-Noise ratio and MSD is the mean square deviation around the target (smallest sink marks in this case).The goal of this experiment is always to determine the highest possible S/N ratio for the result. A high value of S/N implies that the signal is much higher than the random effects of the minimum variance. To obtain optimal molding performance in this case, the-lower-the-better quality characteristic for sink marks must be taken. The mean-square deviation (MSD) for the-lower-the-better quality characteristic can be expressed as Equation (5). Table-4 shows the Orthogonal Array (L18) and the associated experimental results for the Sink Marks

$$MSD = \frac{1}{N}\sum_{i=0}^{N} Y_i^2 \qquad (5)$$

MSD = Mean Square Deviation,
Y_i= Response Value for each run
N=No. of tests run.

Table 4: Summary of Results for Sink Marks

Expt. No.	Fill Time: A	Melt Temp: B	Mold Temp: C	Cooling Time: D	Pressure Holding Time: E	Sink Depth	Mean	MSD	S/N Ratio
1	12.4	230	50	10	3.4	0.0099	0.0099	0.00009801	40.0873
2	12.4	240	65	13	4	0.0099	0.0099	0.00009801	40.0873
3	12.4	250	85	15	4.5	0.0097	0.0097	0.00009409	40.2646
4	12.2	230	50	13	4	0.0104	0.0104	0.00010816	39.6593
5	12.2	240	65	15	4.5	0.0105	0.0105	0.00011025	39.5762
6	12.2	250	85	10	3.4	0.0099	0.0099	0.00009801	40.0873
7	12	230	65	10	4.5	0.0104	0.0104	0.00010816	39.6593
8	12	240	85	13	3.4	0.0096	0.0096	0.00009216	40.3546
9	12	250	50	15	4	0.0106	0.0106	0.00011236	39.4939
10	12.4	230	85	15	4	0.0103	0.0103	0.00010609	39.7433
11	12.4	240	50	10	4.5	0.0117	0.0117	0.00013689	38.6363
12	12.4	250	65	13	3.4	0.0104	0.0104	0.00010816	39.6593
13	12.2	230	65	15	3.4	0.01	0.01	0.0001	40
14	12.2	240	85	10	4	0.0092	0.0092	0.00008464	40.7242
15	12.2	250	50	13	4.5	0.0119	0.0119	0.00014161	38.4891
16	12	230	85	13	4.5	0.0096	0.0096	0.00009216	40.3546
17	12	240	50	15	3.4	0.0104	0.0104	0.00010816	39.6593
18	12	250	65	10	4	0.0100	0.01	0.0001	40

3.5) Analysis of Experimental Factors

The main effect plots for the S/N ratio are shown in Figure-7. The optimal levels for each experimental factor could be easily determined from these graphs in accordance with Taguchi's "the smaller the better" performance characteristic. The response graphs showed the variation of the S/N ratio when the setting of the experiment factors was changed from one level to another. The optimal levels for each experimental factor could be easily determined from these graphs in accordance with Taguchi's "the smaller the better" performance approach. The response graphs showed the variation of the S/N ratio when the setting of the experiment factors was changed from one level to another. Figure-7 suggests that the optimal settings for obtaining the minimum contraction rate involve the following combination of the experimental factors: A1, B1, C3, D1, and E1, levels. Table-5 shows the summary of best combinations of parameter for validation run. The prime objective of Taguchi approach attained by finding the optimum level for each of the variables and to arrive at a best combination of these factors that could result in minimum sink marks as predicted.

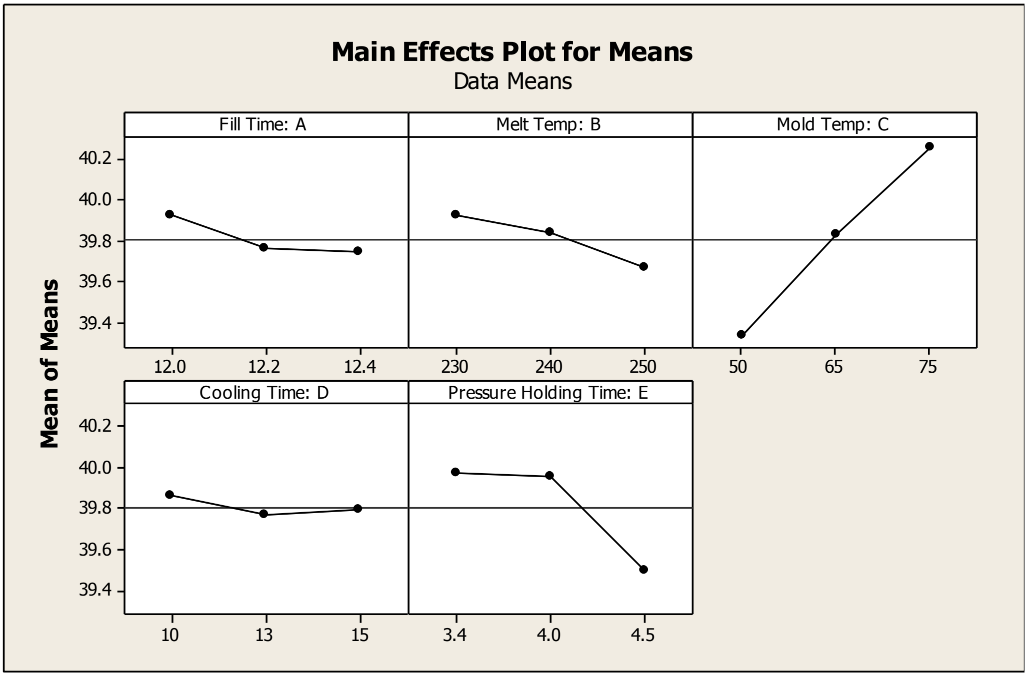


Figure 7: Main Effects Plot

Table 5: Validation Run

Fill Time	Melt Temp	Mold Temp	Cooling Time	Pressure Holding Time	Sink Depth	Remarks
12	230	85	10	4.0	0.0088	Min Sink Marks
12.4	250	50	13	4.5	0.0134	Max Sink Marks

3.6) Predictions & Discussions

Confirmation test was required in the present study because the optimum combination of parameters and their levels (A1, B1, C3, D1, E2, levels) obtained from ANOVA did not correspond to any experimental run of the orthogonal array obtained for the Taguchi experimental design selected. The validation run at optimal combination of parameters was conducted and the estimated value of the total sink marks at optimum condition was also computed. The results given in Table-5 shows that the optimum combinations (A1, B1, C3, D1, E2, levels)yields a smallest value of sink marks, and thus it confirms that the optimum combination taken from main plot is validated.

The analysis result of sink marks from Table-4 is appended below into a form of response table of S/N ratio as in Table 3. From this table, the most optimum parameter for minimizing the sink marks defects can easily be observed. The experimental factor with the strongest influence was determined depending on the value of delta, as shown in Table-6. Referring to H.H. Lee, (2009), and S.F. Yang (2006), the experimental factors with a value of delta larger were selected as the rank wise key factors in this study. It can be concluded from Table-6, that the significance of factors prevails in the following order of importance: (1) Mold Temperature; (2) Pressure Holding Time (3) Melt temperature (4) Fill Time. The analysis of S/N ratio revealed, that the most significant factor towards optimization of process, is Mold Temperature; the percentage contribution of that parameter to Sink Depth will be determined using F-ratio.

Table 6: S/N ratio Response for Sink Depth using Smaller-the-Better

S. No.	Fill Time	Melt Temp	Mold Temp	Cooling Time	Pressure Holding Time
1	39.74635	39.9173	39.33753333	39.86573333	39.97463333
2	39.75601667	39.83965	39.83035	39.76736667	39.95133333
3	39.92028333	39.6657	40.25476667	39.78955	39.49668333
Δ(Effect)	0.173933333	0.2516	0.917233333	0.098366667	0.47795
Rank	4	3	1	5	2

Figure-8 shows the graphical representation of factors having the most significant and in significant impacts on the sink marks using tornado charts. With a small number of experiments it was established that the mold temperature has the biggest effect on the dimensions and dimensional variation of the molded parts. The melt temperature and the holding pressure time also slightly influence the dimensional variations in molded part.

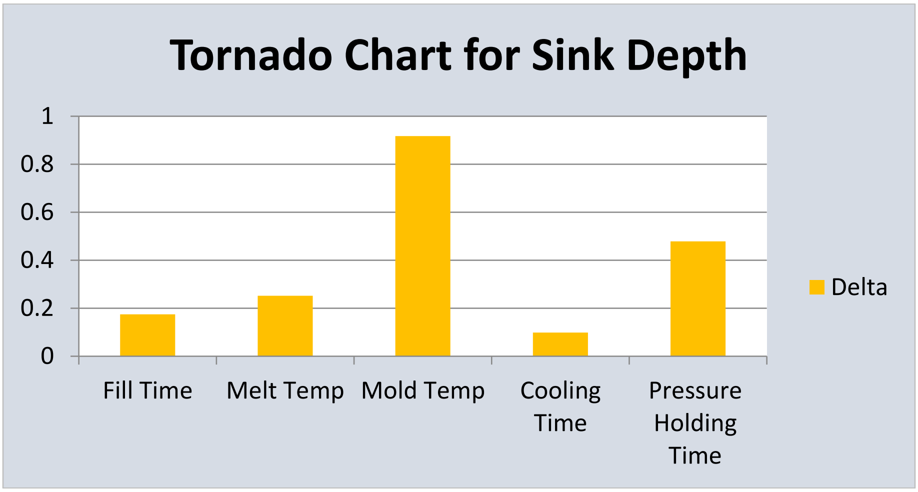


Figure 8: Tornado Chart for Sink Depth

3.7) ANOVA

ANOVA was used to investigate which design parameter significantly affected percentage wise the quality characteristic. ANOVA was performed by separating the total variability of the S/N ratio into contributions from each of the design parameter and the errors. After determining the order of significance for factors as shown in Table-7, the percentage of affecting parameters on the sink marks are to be determined using ANOVA. The main objective of this analysis is to determine the influence's percentage of each parameter on the variance of the results. This is defined by the sum of squares. The total sum of the squared deviations SSt is bifurcated into two sources: the sum of the squared deviations SSp due to each process parameter and due to error, and can be obtained by Equation (6) (7) & (8)

$$\mathrm{SSt} = \sum_{i=0}^{N}(\mathrm{yi} - \bar{\mathrm{y}})^2 \qquad (6)$$

SSt = Total Sum of squares,
SSp = Sum of Squares for Factor p
SSe = Sum of Squares for error 'e'
yi = Sink Marks value of eachith result,
$\bar{\mathrm{y}}$ = Mean of sink Marks results
N = Total No of experiments

$$SSp = \frac{A1^2}{NA1} + \frac{A2^2}{NA2} + \dots\dots + \frac{An^2}{NAn} - \frac{T^2}{N} \qquad (7)$$

A1 = the sum of results (yi) where parameter A1is present,
N A1 =number of experiments where parameter A1 is present in the experiments.

$$\mathrm{SSe} = \mathrm{SSt} - \mathrm{SSp1} - \mathrm{SSp2} - \mathrm{SSp3} - \qquad (8)$$

After determining the ratio of the mean of squares deviations to the mean of the squared error (Fp = Vp/Ve), the F-value for each parameter can be determined.

$$\mathrm{V\,p} = \frac{\mathrm{SSp}}{\mathrm{Dp}}$$

D p = degrees of freedom for factor p.
V p = mean of squares deviations for factor 'p'.
V e = mean of squares deviations for error' e'.

The percentage contribution "ρ" for each factor can be calculated as:

$$\rho\, p = \frac{SSp}{SSt}$$

ρ p = Influence of factor "p".

The total variability of the S/N ratio was measured by the sum of the squared deviations from the total mean S/N ratio and applied F-test values to proceed with the decision-making process. The F- value was calculated for each design parameter. Statistically, larger F value indicates that the variation of the process parameter makes a big change on the quality performance. The examination of the calculated F- test values and percent contribution for all experiment factors also shows a very high influence of factor C (Mold Temperature) and factor E(Pressure Holding time) on the sink marks as shown in Table-7.According to this analysis, the most effective parameters with respect to sink marks reduction are Molding temperature and Holding pressure time.

Table 7: Results of ANOVA for Factors' Contribution

Parameters	**DOF**	**Sum of Square**	**Mean Square**	**F-Ratio**	**Contribution %**
Fill time: A	2	0.1146	0.0573		
Melt temperature: B	2	0.1991	0.0996	0.0375	3.76
Mold Temperature: C	2	2.5286	1.2643	0.476	47.6
Cooling Time: D	2	0.0319	0.016		
Pressure Holding Time: E	2	0.8714	0.4357	0.164	16.4
Error	17	5.3106			
Total	27	9.0562			

4) OPTIMIZATION OF SCREENED VARIABLES BY RESPONSE SURFACE DESIGN

RSM, a multivariate statistical tool, initiates from experimental data obtained from Taguchi design of experiments (DOE). Response Surface Methodology (RSM) is based on experimental design to make the system response in discrete by varying the parameters in their variability ranges. The system responses are described by regression models as function of the input variables to obtain 3D graphical representations, i.e. Surface Plots. In this method, a response surface was mapped to facilitate in-depth formulation of the Response Surface Design to identify the regions that would produce the fine optimal response with respect to minimization of sink depth in injection molded part. This optimization step includes determination of the design space and creation of fitting regression model for fine optimized process.

The Mold temperature, the Holding Pressure time and Melt temperature were regarded as experimental variables for the Central Composite Inscribed (CCI) that was created using the Minitab 17 software package. The experimental allocation, factor levels, and experimental results are shown in Table-8.The general relationship between the Injection Molding process screened parameters, Molding Temperature (Mo), Pressure Holding time (Ho), Melting temperature(Me), Filling Time(Ft) and the response variable Y as Sink Depth can be given as Equation: 9

$$Y = f\ (A, B, C, D) \tag{9}$$

Where 'f' is the response curve function, and A, B , C& D are independent input variables as Mold Temperature, Melt Temperature, Fill Time, Pressure Holding Time and 'Y' is response variable as Sink Depth

Table 8: Experimental Design Matrix and Response Values

Expt. No.	Melt Temp (C°) Me	Mold Temp: Mo (C°)	Fill Time (Sec) Ft	Pressure Holding Time (Sec) Ho	Sink Depth (mm)
1	230	50	12.4	3.4	0.0099
2	240	65	12.4	4	0.0098
3	250	85	12.4	4.5	0.0097
4	230	50	12.2	4	0.0104
5	240	65	12.2	4.5	0.0105
6	250	85	12.2	3.4	0.0099
7	230	65	12	4.5	0.0104
8	240	85	12	3.4	0.0096
9	250	50	12	4	0.0106
10	230	85	12.4	4	0.0103
11	240	50	12.4	4.5	0.0117
12	250	65	12.4	3.4	0.0104
13	230	65	12.2	3.4	0.01
14	240	85	12.2	4	0.0092
15	250	50	12.2	4.5	0.0119
16	230	85	12	4.5	0.0096
17	240	50	12	3.4	0.0104
18	250	65	12	4	0.0100
19	230	85	12	4.0	0.0088
20	250	50	12.4	3.4	0.0134
21	230	50	12.4	3.4	0.0099
22	240	65	12.4	4	0.0098
23	250	85	12.4	4.5	0.0097
24	230	50	12.2	4	0.0104
25	240	65	12.2	4.5	0.0105
26	250	85	12.2	3.4	0.0099
27	230	65	12	4.5	0.0104
28	240	85	12	3.4	0.0096
29	250	50	12	4	0.0106
30	230	85	12.4	4	0.0103

4.1) Experimental Description

On the basis of Taguchi's screening for significant factors having direct influence on response variable(sink depth),following factors were selected for response surface design i.e. Mold Temperature, Melt temperature, Filling Time and Holding Pressure Time. The experimental design configuration with response values is shown in the Table-9. The Mathematical model based on second order linear cum interaction model was developed for sink depth using the experimental outcomes which is shown in Table-9. Table-10 represents the coefficients of regression analysis for sink depth along with their F and P- values of the parameters, and interactions. The F and P-values of regression analysis of Sink Depth in Table-10 indicates that linear effect of Mold Temperature(Mo), Holding Pressure Time (Ho), Filling time (FT) have significant effect while Melting Temperature (Me) shows insignificant effect on Sink Depth . In case of Square all the parameters have insignificant effect, while 01 interactions term (Mo*Ho) have significant effects on response variable. The steps that will be chased for the implementing Response surface Methodology are presented in Figure-9.

Table 9: Experimental Configuration and Response values for the Sink Marks

Origin	DoF	Adj SS	Adj MS	F-Value	P-Value
Regression Model	6	0.000024	0.000004	20.54	0.000
Linear	4	0.000019	0.000005	24.22	0.000
Melt Temp(Me)	1	0.000000	0.000000	0.29	0.597
Mold temperature(Mo)	1	0.000007	0.000007	36.42	0.000
Fill time(Ft)	1	0.000001	0.000001	6.31	0.019
Holding Pressure time(Ho)	1	0.000005	0.000005	24.27	0.000
2-Way Interaction	2	0.000003	0.000001	7.32	0.003
Me*Ft	1	0.000001	0.000001	4.64	0.042
Mo*Ho	1	0.000003	0.000003	14.64	0.001
Error	23	0.000004	0.000000		
Lack-of-Fit	12	0.000003	0.000000	1.21	0.379
Pure error	11	0.000002	0.000000		
Total	29	0.000020			
S 0.0004410 R-sq84.27% R-sq(adj) 80.17%					

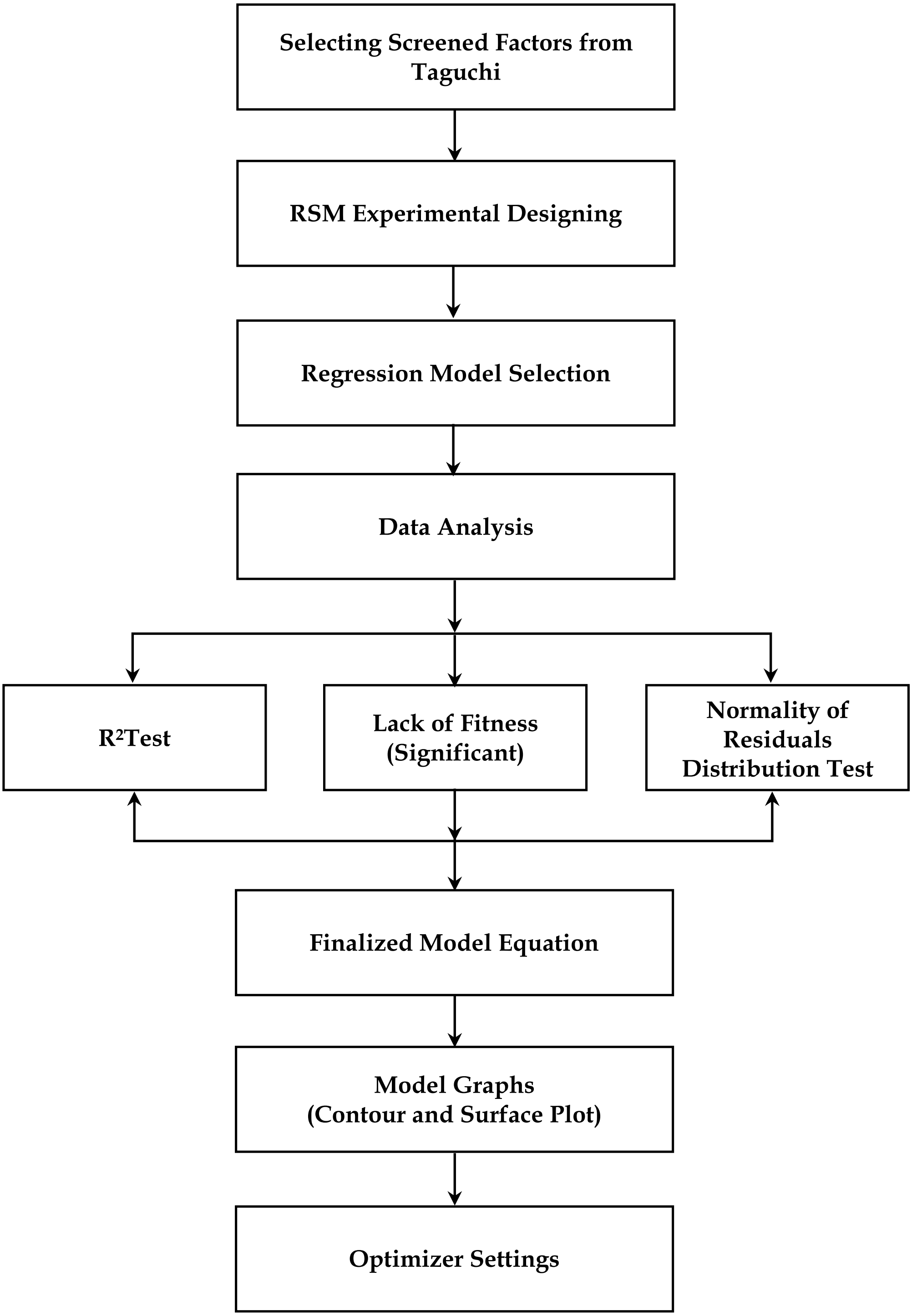


Figure 9: Flow Diagram of Experimental Design in RSM

4.2) Fitting of RSM Model

For the Response Surface Analysis, the fitness of the established Regression Model needs to be tested and confirmed. The significance analysis of the Lack-of-Fit is normally applied to understanding the fitting between repressors' and responses. Table-11 shows the Second-Order fitting results, where the P value of Lack-of-Fit appears to be 0.386 < F value, indicating that the Linear + Interaction Model did not exhibit any significant Lack-of-Fit; R-Sq = 84% revealed that the (Linear + Interaction) model is marked as acceptable statistical model. In order to find the important factors and build a model to optimize the injection molding process, initially the full quadratic model including all terms was employed. The stepwise regression methodology was applied using significant linear and interaction parameters to reach fitting model equation. Based on the proposed linear cum interaction model, the following regression equation was developed to predict the response variable in terms of independent variables and their interactions. Based on numerical results in Table-9, the responses are expressed as functions of input factors and polynomial models for the available data set. With 'Y' as the sink depth (response variable) the relation between the repressors' and the response is shown as Equation (10).

$$Y = -0.464 + 0.00184\,Me + 0.000221\,Mo + 0.0374\,Ft + 0.00532\,Ho - 0.000151\,Me{*}Ft - 0.000071\,Mo{*}Ho \qquad (10)$$

Me:	Melt Temperature	Mo:	Mold Temperature
Ho:	Pressure Holding Time	Ft:	Fill Time
Y:	Sink Depth		

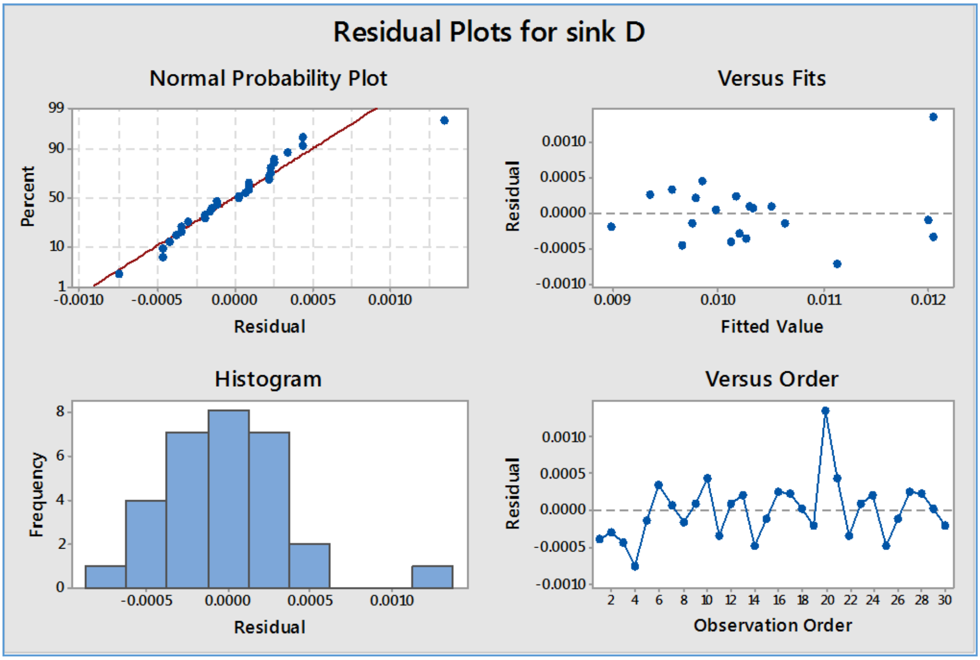


Figure 10: Residuals Plots for sink depth

4.3) The Test for Significance of Regression model

There are certain tests about the model parameters that help in determining the effectiveness and fitness of the model. The above fitted model plot as enumerated in Figure-10 and ANOVA statistics have been examined through normal distribution plot, $R^2$and lack-of-fit test, and it revealed model fitness. If the residuals normal distribution plot approximately along a straight line, then the normality assumption is satisfied. In this study, the residuals can be judged as normally distributed and the residual plots do not expose any major violations of the core assumptions. From the above residuals plots output for sink depth and results in Table-9, we make the following conclusions.

a) The R^2 is very good for fitting Sink Depth.
b) The lack-of-fit test is not significant.
c) Residuals normal distribution plot depicts normality assumptions satisfied.

The contour and surface plots of the response surface as given in Figure-11 & 12 were used to investigate the effect of changing factor levels on the Sink depth. Figure 11 shows the sink depth in the form of a contour plot, with the region representing distinct levels for minimum sink depths. Figure-12 (01 figure for each experimental factor) shows the Surface Plots for sink depth Vs the Mold Temperature, Melt Temperature, Fill time and Holding pressure Time.

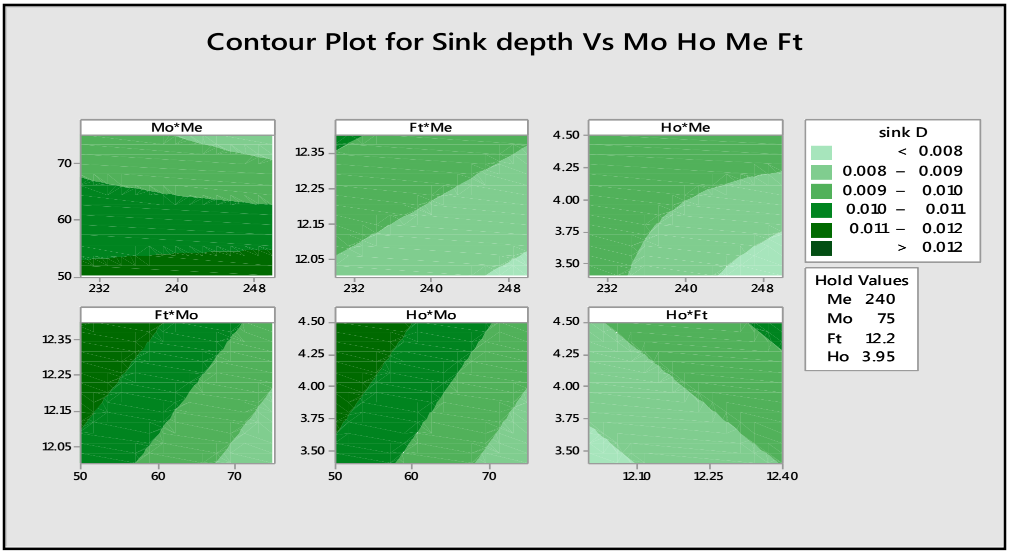
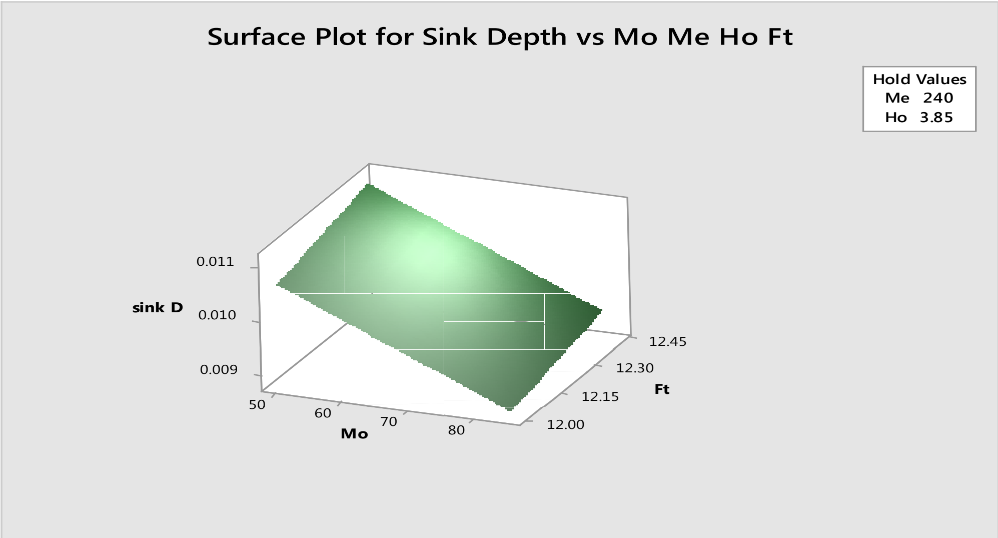
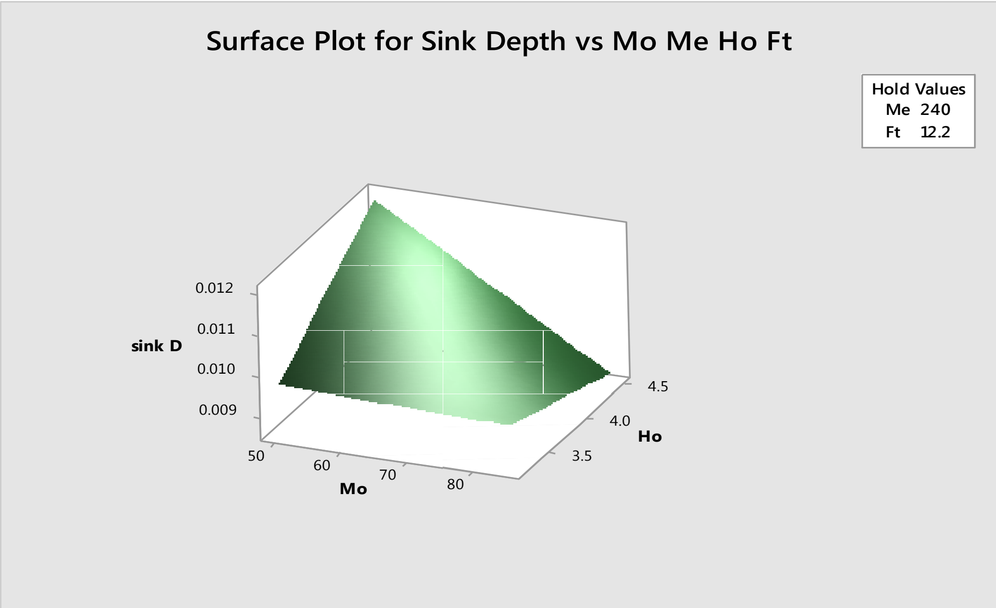
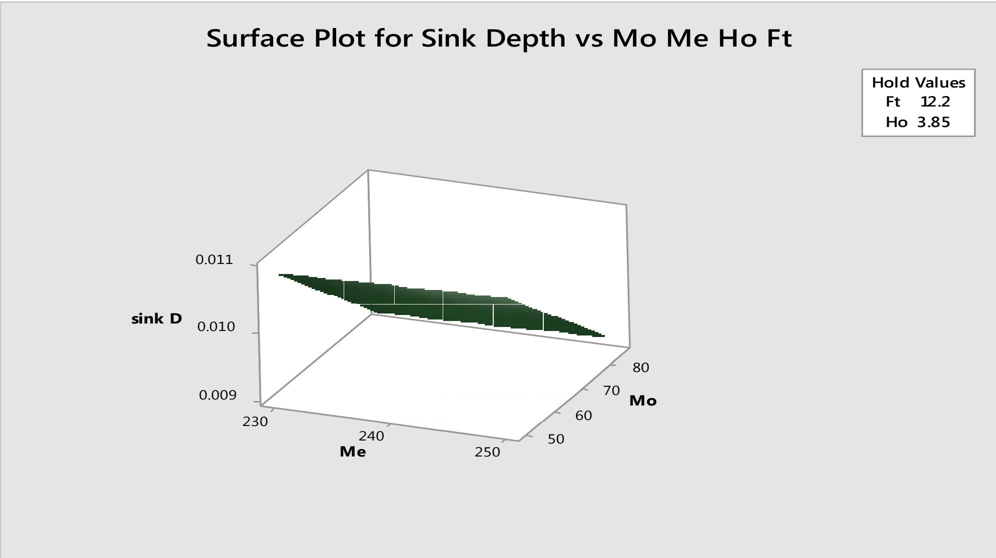
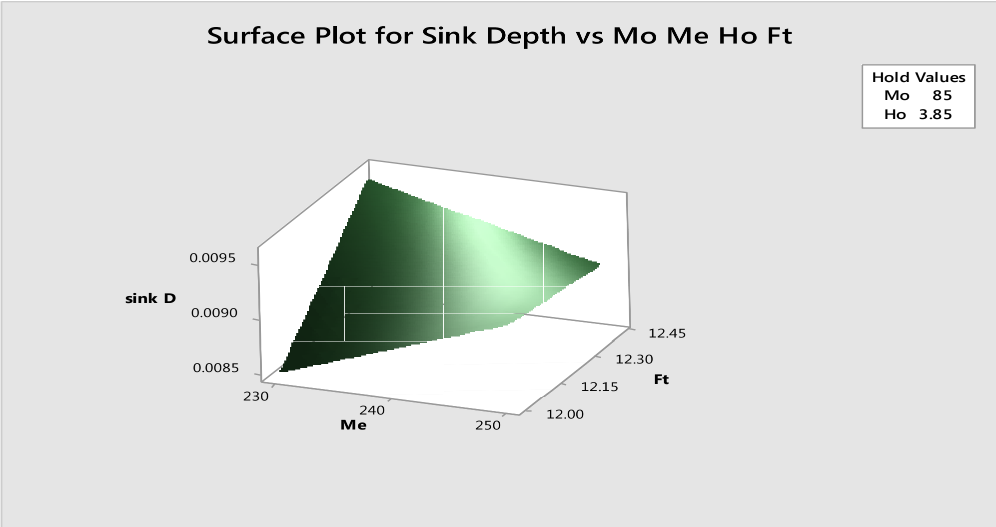


Figure 11: Contour plot for Sink Depth vs. the Mold temp, Melt Temp, Fill Time and Holding Pressure Time




Surface Plot for Sink Depth vs Mo Me Ho Ft
Hold Values
Me 240
Ft 12.2
sink D
0.012
0.011
0.010
0.009
50
60
70
80
Mo
3.5
4.0
4.5
Ho


Surface Plot for Sink Depth vs Mo Me Ho Ft
Hold Values
Ft 12.2
Ho 3.85
sink D
0.011
0.010
0.009
230
240
250
Me
50
60
70
80
Mo



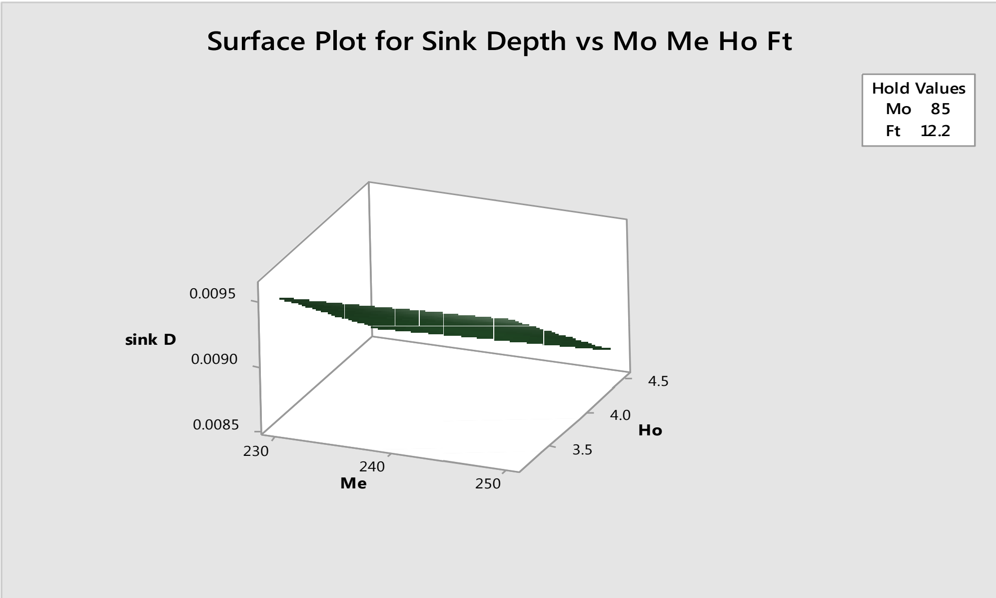


Figure 12: Surface Plots for Sink depth Vs the Mold Temperature, Melt Temperature, Fill time and Holding pressure Time

4.4) Optimization Engineering

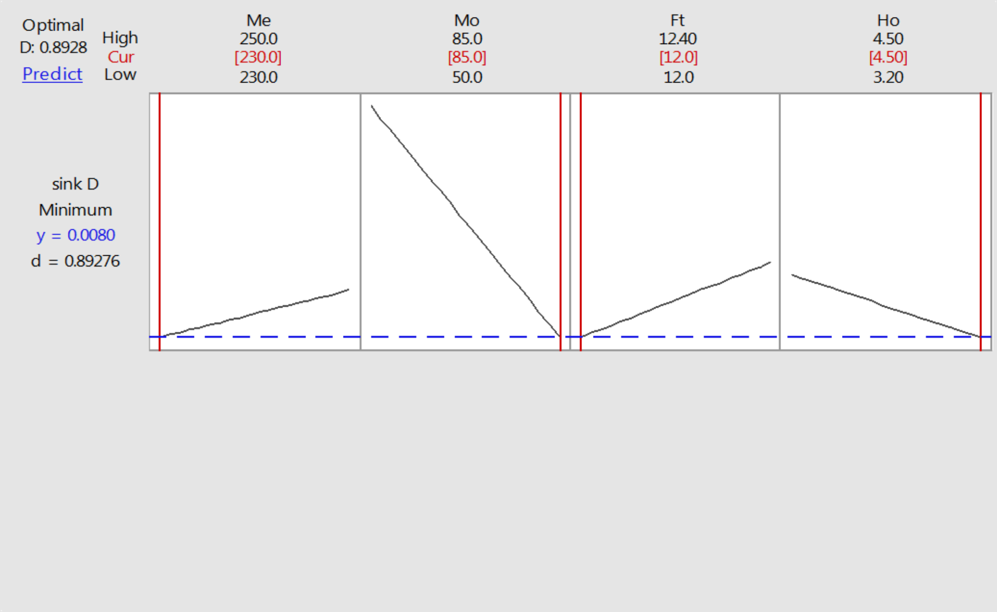


Figure 13: Optimizer Response for Sink Depth

A constrained non-linear approach was selected and used to solve a numerical objective oriented optimization for obtained regression model. The response surfaces of the Linear + Interaction model between the response and the variables were depicted after analysis of the data. Via these response surfaces, the relations between the percentage of sink depth and the effective factors are graphically given in Figure 11 & 12. The optimized ranges for each factor that leads to the best response (the lowest minimum sink depth) were extracted from these surfaces. Figure-13 shows the optimal parameter composition and the predicted response acquired by the Desirability Function, where y is the minimum response of the Sink depth, d is the individual Desirability Function, and D is the Composite Desirability Function for the best opportunity to achieve the objective. This study includes single response, so the composite desirability (D) and the individual Desirability Function (d) are the same. With RSM, it was determined that the optimal conditions that should be applied to achieve the objective are A (Melting Temperature) equal to 230◦C and B (Mold temperature) equal to 85◦C; C (Holding Pressure Time) equal to 4.5 Sec, and Fill time equals to 12.0 sec ,these settings will yield a minimum Sink Depth equal to 0.0080.

5) CONCLUSION

This paper showed the effective integration of both optimizations tools for development of experimental models towards process optimization. The experimental design methods evade the experiential rules and Trial-and-Error methods that are traditionally used for improvement of part's quality. The experimental cost needed to achieve a robust, high-quality process, and improve the production throughput is also reduced. Following results were found:

a) The result shows that the optimization in terms of minimum sink marks obtained from integrated approach as 0.0080, is better than the optimized figure of sink marks obtained with the Taguchi Method as stand alone.

b) Three linear parameters (Mold Temperature, pressure Holding Time and filling time) and 01 interaction ((Mo*Ho) have significant effect on minimum sink mark's optimization. The results also show that square terms between the parameters have insignificant effect on sink marks.

This study can provide relevant practitioners with a reference for applying these techniques in practical and academic research. The result predicts the required standard for plastic part's production, and provided the practical assistance to manufacturers in choosing suitable parametric combinations for injection molding. This methodology can also be applied while designing parts and could significantly contribute in terms of valuable input for product designers in developing designing alternatives as well as to give effective and corrective solutions.

5.1) Future Aspects

Being the effective method for development of experimental models towards process optimization, there are certain concerns regarding RSM/Taguchi application for multi-response optimization and may not find the global optimization in a process having large number of variables highly correlated non-linearly with multiple outputs. To perform multi-objective optimization such that multiple conflicting objectives are simultaneously optimized is required to be searched more for potential and feasible combination of process control parameter values. Furthermore research may also be aimed for global optimization of plastic injection molded parts requiring minute dimensional accuracies by applying optimization in all three aspects of process robust design i.e. process parameters and mold design and process tolerances.

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