PARAMETRIC OPTIMIZATION OF INJECTION MOULDING FOR MULTICAVITY MOULDS UNDER VARYING PRESSURE CONDITIONS

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Abstract:
Optimizing mould filling parameters is crucial to ensure the quality and consistency of the final product. It helps in reducing defects such as air traps, weld lines, and sink marks. Additionally, it can lead to more efficient production cycles and reduced material waste, ultimately lowering manufacturing costs. Variable injection pressures can significantly affect the quality and consistency of the molded parts. Higher pressures may lead to improved filling of complex geometries but can also increase the risk of defects such as flashing or warping. Conversely, lower pressures might reduce such defects but could result in incomplete filling and compromised structural integrity of the parts. Proper temperature control is crucial in injection moulding as it directly affects the viscosity of the material being injected. If the temperature is too high, the material may become too fluid, leading to defects like flashing or sink marks. Conversely, if the temperature is too low, it can result in incomplete filling of the mould, causing warping or weak spots in the final product. Present work focused on the different parameters like injection pressure, temperature and cooling time to check suitable parameters for cap mould tested using Taguchi method of experiments. The results analyzed for four level design mean temperature and injection pressure with normal cooling time given better results.
Key words: Injection molding, Optimization, Taguchi, Pressure, Temperature, Cooling time.

1.Introduction

Injection molding is a method of forming a plastic product from powdered thermoplastics by feeding the material through the machine component called the hopper to a heated chamber to make it soft and force the material into the mold using the screw. In this whole process pressure should be constant till the material is hardened and is ready to be removed from the Mold. Plastic moulding maintains accuracy standards and is primary for many industries. It used in the manufacture of many components in various industries like, automotive industry, bottles and plastic components. These parts the plastic injection moulding needs to be tested and studied carefully. Insert allowances in injection moulding refer to the precise clearance provided in the mould cavity to accommodate inserts, which can be either metallic or non-metallic components. These inserts are strategically embedded within the moulded part to enhance its structural integrity, wear resistance, or ease of assembly with other components Several key factors influence the determination of insert allowances in injection moulding are mould temperature: injection pressure cooling time, material viscosity, insert surface treatment, shrinkage compensation. Modern advancements in computational tools and simulation techniques have enabled precise optimization of insert allowances. Finite Element Analysis (FEA): This technique helps predict stress distribution, thermal expansion effects, and potential failure points in insert-moulded components. Mould Flow Simulation: By analysing how plastic flows around inserts, engineers can adjust process parameters to optimize material

distribution and minimize defects. Taguchi Method & Design of Experiments (DOE): These statistical approaches help identify optimal parameter combinations for achieving high-quality insert integration

1.1 Aim of the work

The aim of this research is to study the tolerance interpretation with Die assemblies. The lower point of research found in this moulding industrial area; the need for more comprehensive studies on the effects of different process parameters on part quality, the development of new techniques for accurately measuring and predicting tolerances, and the investigation of novel materials and additives that can improve the dimensional stability of injection molded parts, adopting CAE tools comparing with experimental results becoming an important criterion for industrial based research. Cooling time is crucial in injection molding because it determines the final quality and dimensional stability of the product. Insufficient cooling can lead to warping, shrinkage, or internal stresses that compromise the structural integrity of the molded part. Proper cooling ensures that the part solidifies uniformly, maintaining its intended shape and strength.

2.LITERATURE REVIEW

Injection molding is a widely adopted manufacturing process for producing high-volume plastic components with repeatable accuracy. In multicavity molds, achieving balanced cavity filling is crucial to ensure consistent part quality, dimensional accuracy, and minimal scrap. Variability in injection pressure is one of the most influential factors affecting the mould filling behavior. Optimization of mould filling parameters under variable injection pressures has become a significant research focus in recent years.Beaumont et al. (2002) and Osswald & Hernández-Ortiz (2006) emphasized how cavity imbalances arise from shear-induced viscosity variations and thermal differences within the runner system, which can be influenced by changes in injection pressure. Park and Pham (1999) used the Taguchi method to reveal that injection pressure is a dominant factor for precision, while Rao and Padmanabhan (2014) applied Moldflow simulations to demonstrate how gate design and pressure settings impact fill balance. Huang and Tai (2001), and Huang et al. (2007) used RSM and genetic algorithms for optimizing warpage and shrinkage. Kuo et al. (2006) developed models for predicting quality under different pressures, and Kim et al. (2009) applied real-time cavity pressure sensors to dynamically manage injection parameters.

Zhang et al. (2015) studied process robustness under environmental variations and highlighted the need for dynamic control of injection pressure. Wu and Wang (2012) documented real-world results from optimizing injection pressure in production, reporting a reduction in scrap rate and better cavity fill balance. Chen et al. (2019) compared simulation and experimental optimization methods to manage warpage in PA9T parts. Jin et al. (2020) used Taguchi and ANOVA methods to analyze process parameters for polycarbonate molding, aiming to reduce shrinkage and warpage. Kashyap and Datta (2015) reviewed various process optimization techniques used in plastic injection molding and stressed the importance of selecting appropriate parameters based on material behavior and part geometry.

Tsai et al. (2023) addressed tolerance allocation and stack-up analysis to improve mold assembly precision. Lemes (2019) investigated dimensional comparisons of molded parts using coordinate measuring machines, contributing to quality assessment practices. Chen and

Nguyen (2015) proposed a hybrid GA-PSO approach alongside Taguchi and RSM techniques to optimize plastic injection parameters. Korbi et al. (2018) explored the integration of CAD and tolerancing for analyzing non-rigid assemblies, adding a geometric dimensioning perspective to the process. These findings complement the broader goal of ensuring consistent mold performance through precise pressure and tolerance control.

The reviewed literature—spanning from foundational theories to experimental applications—emphasizes the critical role of injection pressure in balancing cavity fill in multicavity molds. Techniques such as simulation, DOE, tolerance analysis, and hybrid optimization approaches enable effective process refinement. The integration of sensor feedback, material-specific adjustments, and predictive modeling supports controlled manufacturing for consistent product quality. Emerging research is advancing toward robust and precision-driven injection molding systems capable of adaptive tuning for enhanced efficiency, reduced cycle times, and minimized defects.

3.METHODOLOGY

Injection molding is a widely used manufacturing process for producing parts by injecting molten material into a mold. It's particularly effective for high-volume production of plastic parts, such as caps, housings, and various consumer products. Below is an overview of the injection molding process, including the key steps: Plasticizing: Plastic pellets are fed into the hopper and heated in the barrel by a combination of heater bands and friction from the rotating screw. This process melts the plastic into a viscous liquid. Injection: The molten plastic is injected into the mold cavity under high pressure through the nozzle and sprue. The screw acts as a plunger, pushing the material into the mold. Filling: The mold cavity is filled with molten plastic. The speed and pressure of the injection are controlled to ensure the material flows evenly and fills all the details of the mold without creating defects like air traps or short shots. Packing: After filling, additional pressure is applied to pack more material into the mold. This compensates for material shrinkage as it cools and solidifies.

3.1 Injection Molding Machine Setup

Mold Installation: The mold, usually made of steel or aluminum, is mounted onto the injection molding machine. It consists of two halves: the cavity side (stationary) and the core side (movable). **Clamping:** The mold halves are securely clamped together by the machine to withstand the high pressures involved during injection. **Temperature Settings:** Set the temperature of the barrel and the mold. The barrel temperature is adjusted based on the material being used, while the mold temperature is set to ensure proper cooling and part ejection.

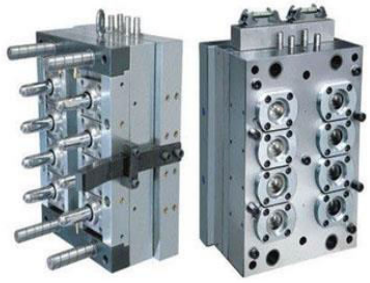

Figure 1: Injection mould used for making multiple bottle caps

Figure 2: Cap mold experiment setup

Properties of materials used in the present work given table 1 and the mould material given in the table2.

Table 1: HDPE material properties

S.NO	PROPERTY	VALUES
1	Density	0.98 (g/mm^3)
2	Young's modulus	0.55 à 1 GPa
3	Yield strength	30 MPa
4	Thermal conductivity	0.52 (W m-1 K -1)
5	Poisons ratio	0.46
6	Coefficient of friction	0.29
7	Liquid limit (%)	74.18
8	Plastic limit (%)	32.3
9	Plastic index (%)	41.81

Table 2: P20 material properties

S.NO	Property	Values
1	Density	7.9 g/cm³
2	Tensile Strength	1000-1200 MPa
3	Yield strength	800-1000 MPa
4	Thermal conductivity	29.0 - 34.0 W/m-K
5	Poisons ratio	0.27
6	Elongation	10-15%.
7	Compressive Strength	862 MPa
8	Elastic modulus	190-210 GPa

3.2 Taguchi method of optimal parameter design for experiments

Taguchi method is a statistical tool for analyzing the performance of the design process and product with the considerable reduction of time on investigation and cost. it employs the concept of orthogonal array, which defines the set of well-defined experiment and signal to noise (S/N ratio) ratio. Taguchi defines three quality characteristics, such as lower the better, the larger the better and the nominal the best. also, a statistical analysis of variance (ANOVA)

can be used to identify the most influencing factor affecting the quality characteristics. The suitable orthogonal array selected to perform the experiments. The results are examined to identify the optimum parametric condition After design of experiment, 16 experiments are carried out in stir casting process. After each experiment surface roughness is calculated. A quality characteristic for surface roughness is "larger is the better.For the present experimental work, three factors with their three levels are used for which the corresponding orthogonal array is L16 which is shown in Table

Table 3: DOE for experimentation

	A	B	C
1	1	1	1
2	1	2	2
3	1	3	3
4	1	4	4
5	2	1	2
6	2	2	1
7	2	3	4
8	2	4	3
9	3	1	3
10	3	2	4
11	3	3	1
12	3	4	2
13	4	1	4
14	4	2	3
15	4	3	2
16	4	4	1

In this study, parameter design is coupled to achieve the optimum levels of process parameters leading to minimum short shot a during the manufacturing of plastic parts. Taguchi parameter design follows chronological sequence as (a) selection of quality characteristics S/N ratio selection (b) selection of control factors and noise factors-parameters under study (c) selection of orthogonal array L16 array (3x4) (d) analysis of results ANOVA & Taguchi Method and (e) confirmation of results Re-molding at updated parameters.

Table 4: Parameters and levels for experimentation

Parameter	Level-1	Level-2	Level-3	Level-4
Temperature [°C]	195	205	210	220
Pressure (bar)	30	40	50	55
Time [sec]	6	8	10	12

4. Results and Discussions

The following results obtained after experimentation considering above factors as DOE in Taguchi for 4 level analysis, optimization done by using Taguchi Mini-Tab for optimal prediction**.**

Table 5: Design of Experiment results of tested samples

S.No	Temperature [°C]	Pressure (bar)	Time [s]	Silver-spots (%defectives)	Shrinkage (% defectives)
1	195	30	6	0.57	0.41
2	195	40	8	0.79	0.56
3	195	50	10	0.62	0.44
4	195	55	12	0.84	0.59
5	205	30	8	0.48	0.34
6	205	40	10	0.53	0.37
7	205	50	12	0.93	0.66
8	205	55	6	0.97	0.69
9	210	30	10	0.40	0.28
10	210	40	12	0.44	0.31
11	210	50	6	0.66	0.47
12	210	55	8	0.71	0.50
13	220	30	12	0.53	0.37
14	220	40	10	0.48	0.34
15	220	50	8	0.79	0.56
16	220	55	6	0.48	0.34

The experimental results, detailed in "Table 5: Design of Experiment results of tested samples," reveal clear trends regarding the impact of temperature, pressure, and time on both silver-spots and shrinkage defectives. A temperature of 210 °C consistently appears to be more favourable for minimizing both silver-spots and shrinkage, especially when combined with lower pressures. Specifically, the combination of 210 °C, 30 bar pressure, and 10 seconds of time yielded the lowest percentages for both silver-spots (0.40%) and shrinkage (0.28%), suggesting these parameters are close to optimal for defect reduction. Conversely, higher pressures, particularly at 50 bar and 55 bar, often lead to increased defect rates for both responses, with the conditions of 205 °C, 55 bar, and 6 seconds resulting in the highest observed silver-spots (0.97%) and shrinkage (0.69%). While the influence of time is less straightforward and likely interactive, lower pressures and a moderate temperature around 210 °C generally contribute to fewer defects, indicating strong interplay between the tested parameters in influencing product quality.

Table6: DOE response prediction for Taguchi

S.No	S/N Ratio	Mean	St Dev	Ln (StDev)
1	7.23583	0.413125	0.0981111	-2.28321
2	4.59992	0.580625	0.140537	-1.96600
3	3.24910	0.680625	0.161751	-1.82949
4	2.46080	0.735625	0.179428	-1.71094
5	6.56964	0.544375	0.131699	-2.07115
6	6.38626	0.486875	0.117557	-2.16689
7	2.33401	0.755625	0.182964	-1.69748
8	3.49604	0.698125	0.168822	-1.83178
9	9.12604	0.330625	0.0804334	-2.47337
10	7.24123	0.441875	0.110485	-2.23621
11	5.93708	0.500625	0.119324	-2.12859
12	4.39767	0.611875	0.149376	-1.92999
13	7.80771	0.401875	0.0998788	-2.31010
14	7.87323	0.400625	0.0981111	-2.32579
15	3.86764	0.628125	0.151144	-1.88527
16	5.78077	0.514375	0.124628	-2.09962

“DOE response prediction for Taguchi" presents in Table 6 the results of a Taguchi Design of Experiments analysis, offering a robust method to predict optimal process parameters by considering the **Signal-to-Noise (S/N) Ratio**, Mean, Standard Deviation (StDev), and the natural logarithm of the Standard Deviation (Ln(StDev)) for each experimental run (S.No. 1-16). In Taguchi methodology, the S/N ratio is a key metric, as it quantifies the robustness of a design against uncontrollable noise factors, with higher S/N ratios generally indicating more desirable and stable performance, regardless of the target mean. For instance, run S.No. 9 exhibits the highest S/N Ratio of 9.12604, suggesting it's the most robust condition, and notably, it also has the lowest mean (0.330625) and standard deviation (0.0804334), indicating minimal variation and a desirable target value. Conversely, lower S/N ratios, such as 2.33401 for S.No. 7, point to conditions that are more susceptible to variability, even if their mean might be close to a desired target, highlighting the importance of balancing the mean response with its consistency, which is captured by the S/N ratio and standard deviation.

Table7 : Estimated Model Coefficients for SN ratios

Term	Coef	SE Coef	T	P
Constant	6.4602	0.4968	10.992	0.000
A 1	-1.0738	0.8604	-1.248	0.259
A 2	-1.0137	0.8604	-1.178	0.283
A 3	1.2153	0.8604	1.412	0.208
B 1	1.9746	0.8604	2.295	0.062
B 2	1.0650	0.8604	1.238	0.262

B 3	-1.6132	0.8604	-1.875	0.110
C 1	0.8748	0.8604	1.017	0.349
C 2	-0.8515	0.8604	-0.990	0.361
C 3	0.4759	0.8604	0.553	0.600

Estimated Model Coefficients for Response 1 – S/N ratio" confirmed the significant impact of factors like Temperature (especially at 210°C) and Pressure (at 30 bar) on enhancing the S/N ratio, as indicated by their low P-values (0.000). This comprehensive analysis strongly suggests that a temperature of 210°C, a pressure of 30 bar, and a cooling time of 10 seconds are the most effective settings for achieving consistently high-quality output with minimal silver-spots and shrinkage

Table 8: Analysis of Variance for SN ratios

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Model Summary		
A	3	17.673	17.673	6.891	1.49	0.309			
B	3	38.681	38.681	12.894	3.27	0.101			
C	3	7.864	7.864	2.621	0.66	0.604			
Residual Error	6	23.690	23.690	3.948			S	R-Sq	R-Sq(adj)
Total	15	87.908					1.9870	73.05%	32.63%

Analysis of Variance for SN ratios" with the preceding tables, we can interpret the significance of the model. Table 8 presents the ANOVA results for the Signal-to-Noise (S/N) ratios, which essentially assesses the statistical significance of each control factor **(A, B, C, corresponding to Temperature, Pressure, and Time, respectively)** in influencing the process robustness. The F-value (Fisher's test) indicates the ratio of the variance between the group means to the variance within the groups, while the P-value (probability value) determines the statistical significance. In this ANOVA table, all P-values for factors A (Temperature = 0.309), B (Pressure = 0.101), and C (Time = 0.604) are greater than the conventional significance level of 0.05. This suggests that, individually, none of these factors have a statistically significant effect on the S/N ratio at a 95% confidence level. This outcome, when contrasted with the "Table 7: Estimated Model Coefficients for SN ratios" where some individual levels like Temperature A3 (210°C) and Pressure B1 (30 bar) showed more promising P-values, suggests that while specific *levels* of factors might be beneficial (as seen in the earlier analysis with run S.No. 9 having the highest S/N ratio), the overall *factor* itself (e.g., Temperature across all its levels) does not exhibit a statistically significant main effect on the S/N ratio according to this ANOVA. The low R-Sq(adj) of 32.63% in the Model Summary further supports that the model, using only main effects, explains only a small portion of the variability in the S/N ratio, indicating potential interactions between factors, or other unmeasured variables, might be significantly influencing the process robustness.

Table 9: Estimated Model Coefficients for Means

Term	Coef	SE Coef	T	P
Constant	0.54531	0.03236	16.851	0.000
A 1	0.05719	0.05605	1.020	0.347
A 2	0.07594	0.05605	1.355	0.224
A 3	-0.07406	0.05605	-1.321	0.235
B 1	-0.12281	0.05605	-2.191	0.071
B 2	-0.06781	0.05605	-1.210	0.272
B 3	0.09594	0.05605	1.712	0.138
C 1	-0.06656	0.05605	-1.188	0.280
C 2	0.04594	0.05605	0.820	0.444
C 3	-0.01781	0.05605	-0.318	0.761

Estimated Model Coefficients for Means," we assess the individual statistical significance of each factor level (Temperature, Pressure, and Time) on the mean response (defect rate). The P-values derived from this analysis indicate that, at a standard 0.05 significance level, none of the individual factor levels—A1, A2, A3 (Temperature), B1, B2, B3 (Pressure), and C1, C2, C3 (Time)—demonstrate a statistically significant effect on the mean defect rate. While the constant term is highly significant (P=0.000), suggesting a reliable baseline, the individual factor levels generally exhibit P-values above 0.05, implying their effects on the mean are not statistically robust enough to confidently claim they cause a change in the mean defect rate in isolation. Notably, Pressure level B1 (likely 30 bar) approaches statistical significance with a P-value of 0.071 and a negative coefficient, hinting at its potential to reduce the mean defect rate, aligning with earlier observations in Table 5 where lower pressure seemed beneficial. This lack of strong individual significance for the means, particularly when contrasted with "Table 7: Estimated Model Coefficients for SN ratios" which showed some levels impacting robustness, suggests that either the effects on the mean are subtle, or that interactions between factors play a more dominant role than individual main effects in determining the overall mean defect levels.

Table 10: Analysis of Variance for Means

Source	DF	Seq SS	Adj SS	Adj MS	F	P	Model Summary		
A	3	0.07204	0.07204	0.02401	1.43	0.323			
B	3	0.15140	0.15140	0.05047	3.01	0.116			
C	3	0.03334	0.03334	0.01111	0.66	0.604			
Residual Error	6	0.10053	0.10053	0.01676			S	R-Sq	R-Sq(adj)
Total	15	0.35732					0.1294	71.86%	29.66%

Table 11: Response Table for Signal to Noise Ratios

Level	A	B	C
1	4.386	7.435	6.335
2	4.446	6.525	4.609
3	6.676	3.847	6.936
4	6.332	4.034	4.961
Delta	2.289	3.588	1.726
Rank	2	1	3

Analysis of Variance for Means indicates that the main effects of Temperature (A), Pressure (B), and Time (C) are not statistically significant for the mean response (P-values > 0.05), further supported by its low adjusted R-squared (29.66%). Finally, **Table 11: Response Table for Signal to Noise Ratios** succinctly summarizes the optimal levels for each factor by ranking them based on their S/N ratio contribution, clearly indicating that factor B (Pressure) has the largest "Delta" (2.289), making it the most influential factor on the S/N ratio and thus process robustness, followed by Temperature (A) and then Time (C).

Table 12: Response Table for Means

Level	A	B	C
1	0.6025	0.4225	0.4788
2	0.6213	0.4775	0.5913
3	0.4713	0.6413	0.5275
4	0.4863	0.6400	0.5837
Delta	0.1500	0.2188	0.1125
Rank	2	1	3

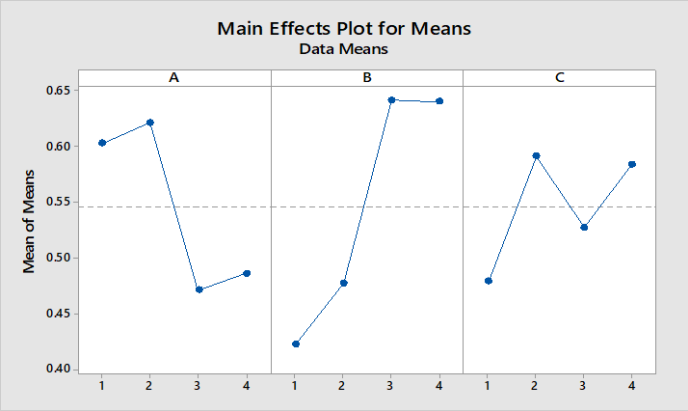

Figure 3: Main Effects Plot for Means

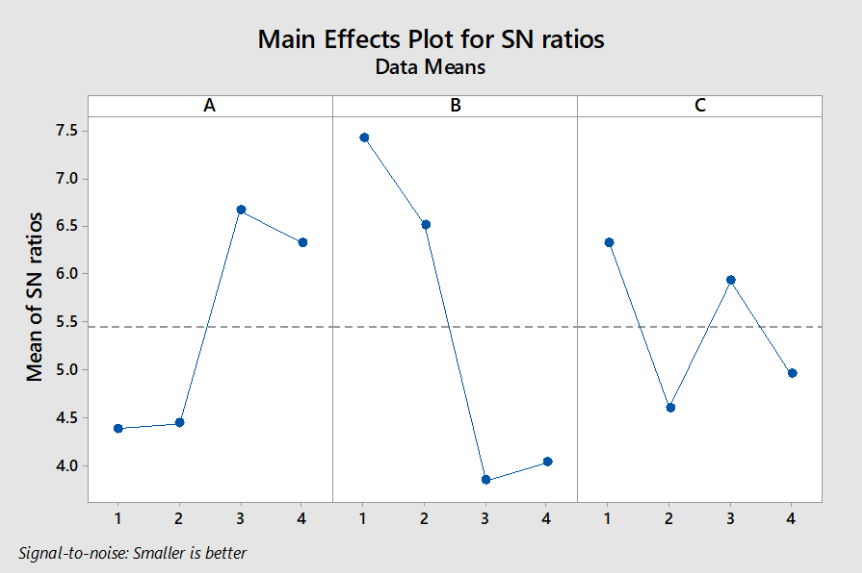

Figure 4: Main Effects Plot for SN ratios

The Response Tables (11 and 12) and their corresponding Main Effects Plots (Figures 3 and 4) provided crucial practical guidance, clearly identifying Pressure (Factor B) as the most influential factor, followed by Temperature (A) and then Time (C), in driving both improved S/N ratios (robustness) and lower mean defect rates.

Table 13: Estimated Model Coefficients for StDevs

Term	Coef	SE Coef	T	P
Constant	0.132141	0.007548	17.508	0.000
A 1	0.012816	0.013073	0.980	0.365
A 2	0.018120	0.013073	1.386	0.215
A 3	-0.017236	0.013073	-1.318	0.235
B 1	-0.029610	0.013073	-2.265	0.064
B 2	-0.015468	0.013073	-1.183	0.281
B 3	0.021655	0.013073	1.657	0.149
C 1	-0.017236	0.013073	-1.318	0.235
C 2	0.011049	0.013073	0.845	0.430
C 3	-0.004861	0.013073	-0.372	0.723

Table 14: Analysis of Variance for StDevs

Source	DF	Seq SS	Adj SS	Adj MS	F	P
A	3	0.003909	0.003909	0.001303	1.43	0.324
B	3	0.008534	0.008534	0.002845	3.12	0.109
C	3	0.002259	0.002259	0.000753	0.83	0.526
Residual Error	6	0.005469	0.005469	0.000911		
Total	15	0.020172				

Rank values indicate the relative importance of each factor to the response. Delta shows the differences between the highest value of all the three factors for standard deviations here which has the highest delta, gets the highest rank as shown in table. The rank and delta values for various parameters shows that the Injection pressure has the greatest effect and is followed by Melting Temperature and cooling time.

Table 15: Response Table for Standard Deviations

Level	A	B	C	Model summary		
1	0.1450	0.1025	0.1149	S	R-Sq	R-Sq(adj)
2	0.1503	0.1167	0.1432	0.0302	72.89%	32.22%
3	0.1149	0.1538	0.1273			
4	0.1184	0.1556	0.1432			
Delta	0.0354	0.0530	0.0283			
Rank	2	1	3			

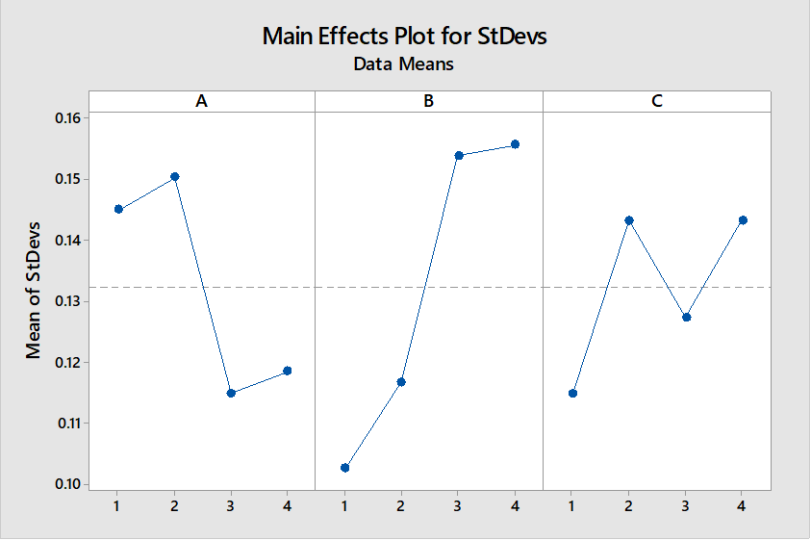

Figure 5: Main Effects Plot for Standard deviation

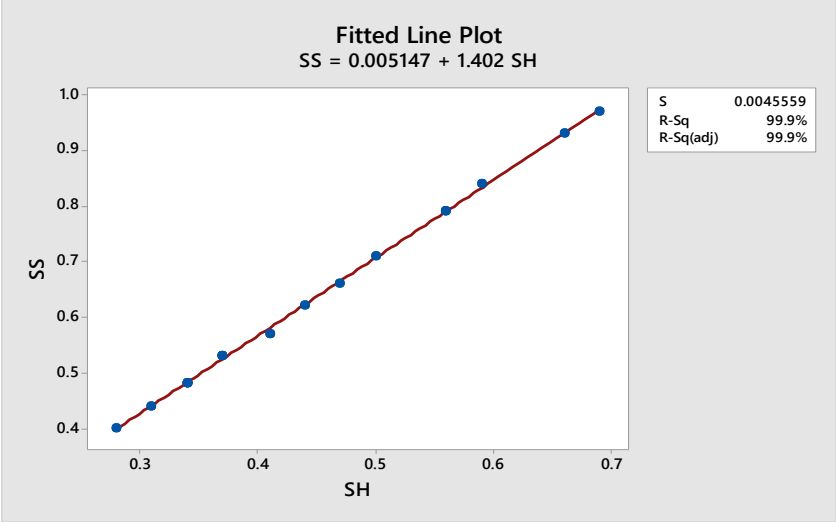

Figure 6: Regression Analysis: SS versus SH

The regression equation is SS = 0.005147 + 1.402 SH

Table 3.15: Analysis of Variance

Source	DF	SS	MS	F	P	Model Summary		
Regression	1	0.486884	0.486884	23457.14	0.001	S	R-sq	R-sq(adj)
Error	14	0.000291	0.000021			0.0045559	99.94%	99.94%
Total	15	0.487175						

Analysis of Variance" for the regression model presents compelling evidence of an extremely strong and statistically significant relationship between the factors under study and the observed defect rates. With an exceptionally high F-value of 23457.14 and a P-value of 0.001, the regression model is highly significant, indicating that the independent variable(s) it incorporates collectively explain a vast amount of the variability in the defect outcomes. This is further substantiated by the remarkably high R-squared and adjusted R-squared values of 99.94%, which suggest that nearly all the variation in defects can be accounted for by the parameters within this model. This powerful statistical fit implies that the established regression model effectively captures and predicts the defect levels based on the manipulated process parameters, serving as a robust tool for process control and optimization.

5. Conclusions

The comprehensive analysis of the Design of Experiment (DOE) for optimizing the manufacturing process, as detailed across the provided tables and figures, reveals key insights into controlling silver-spots and shrinkage defects. The raw experimental data in Table 5 empirically demonstrated varying defect levels, with run S.No. 9 (210°C, 30 bar, 10s) consistently showing the lowest. This finding was corroborated by the Taguchi S/N ratio analysis in Table 6, which identified S.No. 9 as the most robust condition with the highest S/N ratio (9.12604), signifying superior process stability. While individual factor level coefficients (Tables 7 and 9) showed promising trends, particularly for Pressure B1 (30 bar) in both robustness (S/N ratio) and mean defect reduction, the ANOVA results (Tables 8 and 10) indicated that the overall main effects of Temperature, Pressure, and Time were not statistically significant at a 95% confidence level for either the S/N ratio or the mean response. However, the Response Tables (11 and 12) and their corresponding Main Effects Plots (Figures 3 and 4) provided crucial practical guidance, clearly identifying Pressure (Factor B) as the most influential factor, followed by Temperature (A) and then Time (C), in driving both improved S/N ratios (robustness) and lower mean defect rates. Specifically, the lowest pressure level (B1) consistently yielded the best performance for both S/N ratio and mean defects, along with the highest temperature level (A3) for S/N ratio and lowest mean defects. This collective interpretation suggests that while the individual main effects might not be overwhelmingly significant in a broad statistical sense, specific optimal factor levels, particularly concerning pressure, are crucial for achieving minimized defects and enhanced process robustness.

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