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Parameter Optimization of Injection Molding of Polypropylene by using Taguchi Methodology

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Abstract : *Injection molding is an important polymer processing operation in the plastic industry. In this process, polymer is injected into a mold cavity, and solidifies to the shape of the mold. Optimizing the parameters of the injection molding process is critical to enhance productivity. For process optimization, parameters must operate at optimum levels for acceptable performance. Taguchi method is one of the methods of optimization, in which orthogonal array is generated based on experimental design. Optimization of injection molding process parameters will be carried out using polypropylene (PP) as the molding material*

Keywords – *Coolant Flow rate, Injection Molding Optimization, Taguchi methodology,*

I. Introduction

Injection Molding is a cyclic process for producing identical articles from a mold, and is the most widely used for polymer processing. The main advantage of this process is the capacity of repetitively fabricating parts having complex geometries at high production rates. Complexity is virtually unlimited and sizes may range from very small to very large. Most polymers may be injection molded, including thermo plastics, fiber reinforced thermo plastics, thermosetting plastics, and elastomers. Critical to the adoption of this high volume, low cost process technology is the ability to consistently produce quality parts.

Table No. 1 Parameters Considered by Various Authors for Process Optimization

REFERANCE NUMBER	PARAMETERS CONSIDERED											OPTIMIZATION METHOD	RESPONSE STUDIED	NOTATIONS USED
	a	b	c	d	e	f	g	h	i	j	k			
1			*	*	*	*	*	*	*		*	PCA& REGRESSION ANALYSIS	QUALITY	a – FILLING TIME
2	*				*	*	*				*	DOE & KRIGING ALGORITHM	WARPAGE	b – INJECTION TEMPERATURE
3	*				*	*	*				*	ANN & GENETIC ALGORITHM	PARAMETER LEVELS	c – INJECTION SPEED
4			*	*	*	*	*	*		*	*	TAGUCHI METHOD	TENSILE STRENGTH	d – INECTION PRESSURE
5	*				*	*	*	*			*	GENETIC ALGORITHM	RUNNER DESIGN	e – BARREL TEMPERATURE
6	*				*	*	*					TAGUCHI METHOD	WARPAGE	f – HOLDING PRESSURE
7	*	*									*	3D-SIMULATION	FLOW ANALYSIS	g – HOLDING TIME
8	*		*	*								3D-SIMULATION	GATE DESIGN	h– COOLING TIME
9			*			*	*			*		FEM MODELLING	DIMENSIONAL STABILITY	i – SCREW STROKE
*- INDICATES PARAMETERS CONSIDERED AT VARIED LEVELS														j – NOZZLE TEMPERATURE
														k –MOLD TEMPERATURE

The above Table highlights the importance of selection of parameters and the significance of their optimum levels to achieve a robust process or parameter design [1-9]. The parameters like screw stroke, injection temperature have been found out less important and nozzle temperature has been substituted for barrel temperature. Filling time is dependent on injection speed and injection pressure and hence, need not be considered. Most of the researchers have considered mold temperature as a very important parameter [1-5, 7]. A module called Mold Temperature Controller (MTC), used to control mold temperature; is very expensive and generally not incorporated in the basic control system. This constrains the effective control of the output of injection molding.In absence of mold temperature controller (MTC), optimization of process parameters can be achieved considering the coolant flow rate along with other process parameters [10]. In cooling system design, design variables typically include the size, location and layout of cooling channels, and the thermal properties, temperature and flow rate of the coolant. The mold temperature modulation can be achieved and in turn the consideration of coolant flow rate as an input parameter for robust process optimization of injection molding. Basic Injection Molding process will be studied, and monitored. Optimization of injection molding process parameters will be carried out using polypropylene (PP) as the molding material, due to its universality as the most common injection molding material.

The design of experiment (D.O.E.) chosen for the Injection Molding of Polypropylene is Taguchi L_{18} (2^1 x 3^7) orthogonal array, by carrying out a total number of 18 experiments along with a verification experiment. The parameters to be considered for the robust parameter design of polypropylene material are:

a) Barrel Temperature b) Injection Pressure c) Injection Speed d) Holding Pressure
e) Holding Time f) Cooling Time g) Coolant Flow Rate

Weight will be the output response to study the variation in output due to changes in the levels of process parameters. The work material used is (Polypropylene with Impact Copolymer variant) and is recommended for use in Injection Molding processes where high flow and medium impact strength are required. It is an ideal material for rigid packaging, automotive components, housewares and parts of appliances.

Input Factors with Units & Notation:-

1) Barrel Temperature, °C - [A]
2) Injection pressure , MPa - [B]
3) Injection speed, % - [C]
4) Coolant flow rate, l/m - [D]
5) Holding pressure, MPa - [E]
6) Holding time, second - [F]
7) Cooling time, second - [G]

Response Measured with Unit & Notation:-

1) Weight, gram - [W]

Any surface defect during the trials will be noted as an attribute data.

In Taguchi L_{18} (2^1 x 3^7) orthogonal array 18 rows represent the 18 experiments to be conducted with 7 columns at, 3 levels of the corresponding factors. ANOVA will be used for statistical evaluation of experimental observations. F- Ratio will be used to determine the confidence intervals.

Table No. 2 : Level Values of Input Factors

Sr.No	Factors	Levels		
		1	2	3
1	Barrel Temperature [A]	215	225	235
2	Injection Pressure [B]	30	40	45
3	Injection Speed [C]	40	45	50
4	Coolant Flow Rate [D]	4	7	11
5	Holding Pressure [E]	35	40	45
6	Holding Time [F]	1.5	1.75	2.0
7	Cooling Time [G]	5.5	5.75	6.0

II. Design of Experiment

Fig. No. 1 shows schematic diagram of the experimental set-up. The flow control valves (B1, B2), were used to control the coolant flow to the mold and the flow was measured by the flow meter, (V). The control parameters were varied according to the orthogonal array design and the weight of the molded parts were measured with the help of a Weighing Machine. The cycle time was also noted. The surfaces of molded pieces were studied for any defects related to molding and none was observed.

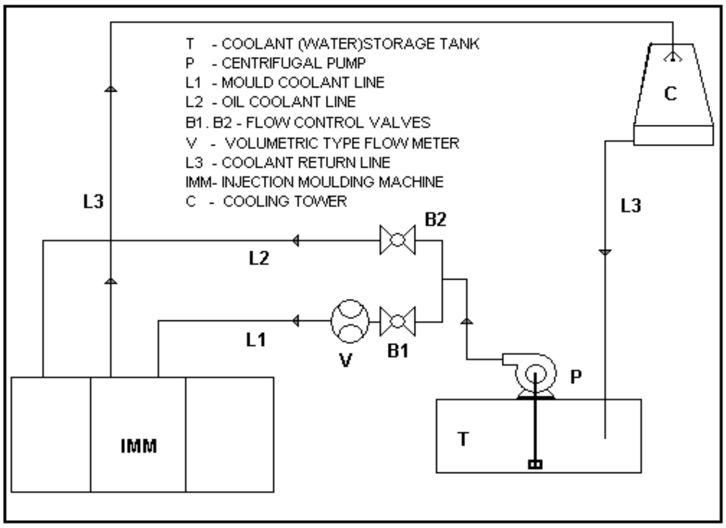

Figure. No. 1 Injection Molding Experimental Set Up

Table No: 3 Taguchi L$_{18}$ Orthogonal Array

Expt No.	A	B	C	D	E	F	G
1	215	30	40	4	35	1.50	5.50
2	225	40	45	7	40	1.75	5.50
3	235	45	50	11	45	2.00	5.50
4	235	30	45	4	40	2.00	5.50
5	215	40	50	7	45	1.50	5.50
6	225	45	40	11	35	1.75	5.50
7	225	30	50	7	35	2.00	5.75
8	235	40	40	11	40	1.50	5.75
9	215	45	45	4	45	1.75	5.75
10	225	30	45	11	45	1.50	5.75
11	235	40	50	4	35	1.75	5.75
12	215	45	40	7	40	2.00	5.75
13	235	30	40	7	45	1.75	6.0
14	215	40	45	11	35	2.00	6.0
15	225	45	50	4	40	1.50	6.0
16	215	30	50	11	40	1.75	6.0
17	225	40	40	4	45	2.00	6.0
18	235	45	45	7	35	1.50	6.0

Notations used in the calculations are as given:-
S/N ---- Signal to Noise ratio for given response Weight and its unit is dB
k_q ---- level for the factor denoted by subscript q. q □ {A,B,C,D,E,F,G}
v_q ---- degree of freedom for the factor denoted by subscript q. q □ {A,B,C,D,E,F,G}
v_m ---- degree of freedom for associated with the mean {always equal to 1}
v_e ---- degree of freedom associated with the error
N ---- total number of observations
T ---- sum of all observations
T_m ---- average of all observations
V_q ---- variance for the factor denoted by subscript q. q □ {A,B,C,D,E,F,G}
S_e ---- Pooled Error Standard Deviation
SS_m ---- Sums of Squares due to Mean
SS_T ---- Total Sums of Squares of Weights,
SS_q ---- Sums of Squares for Factors denoted by subscript q. q □ {A,B,C,D,E,F,G}
SS_e ---- Sums of Squares of Error

SS ---- Sums of Squares
%P ---- percent contribution
F ---- F- Ratio
CI ---- Confidence Interval
α ---- risk

For Weight, the calculation of S/N ratio follows “Smaller the Better” model.
For smaller the better, S/N is given by;

$$\begin{aligned} \mathbf{S/N} &= -10\log(\mathrm{MSD}) \quad \text{where} \quad \mathrm{MSD} = \frac{1}{n}\sum_{i=1}^{n} w_i^2 \\ &= -10\log\left(\frac{1}{n}\sum_{i=1}^{n} w_i^2\right) \end{aligned} \qquad \text{------------------- (1)}$$

where MSD is the mean square deviation,
w (the observation) Weight, and i is the iterant
n is the number of tests in a trial.

Total Sums of Squares of Weights,

$$\mathbf{SS_T} = \sum_{i=1}^{\mathbf{N}} w_i^2 \qquad \text{------------------------ (2)}$$

For any Factor the Sums of Squares is given by the equation given below: -

$$\mathbf{SS_q} = \left[\sum_{i=1}^{\mathbf{k_q}} \left(\frac{\mathbf{q}_i^2}{\mathbf{n}_{\mathbf{q}_i}}\right)\right] - \frac{\mathbf{T}^2}{\mathbf{N}} \qquad \text{------------------------ (3)}$$

III. Experimental Result

The part showed excellent surface texture and specifically ‘gloss’ in terms of commercial terms of product value. The experimental observations and calculated S/N ratios are shown in TABLE No. 4.

Table. No. 4- S/N Ratios

Expt No.	A	B	C	D	E	F	G	CT	W	W^2 =(W * W)	S/N (dB)
1	215	30	40	4	35	1.50	5.50	29.6	96.378	9288.71888	-39.6796
2	225	40	45	7	40	1.75	5.50	29.6	96.742	9359.01456	-39.7123
3	235	45	50	11	45	2.00	5.50	30.1	96.339	9281.20292	-39.6760
4	235	30	45	4	40	2.00	5.50	30.2	96.697	9350.23245	-39.7082
5	215	40	50	7	45	1.50	5.50	30	96.534	9318.81316	-39.6936
6	225	45	40	11	35	1.75	5.50	30.1	96.164	9247.51490	-39.6603
7	225	30	50	7	35	2.00	5.75	29.8	96.626	9336.58388	-39.7019
8	235	40	40	11	40	1.50	5.75	30.1	96.585	9328.66223	-39.6982
9	215	45	45	4	45	1.75	5.75	28.9	96.048	9225.21830	-39.6498
10	225	30	45	11	45	1.50	5.75	29.4	96.425	9297.78063	-39.6838
11	235	40	50	4	35	1.75	5.75	29.2	96.806	9371.40164	-39.7180
12	215	45	40	7	40	2.00	5.75	29.3	96.240	9262.13760	-39.6671
13	235	30	40	7	45	1.75	6.0	29.8	96.826	9375.27428	-39.7198
14	215	40	45	11	35	2.00	6.0	29.4	96.480	9308.39040	-39.6887
15	225	45	50	4	40	1.50	6.0	28.7	96.260	9265.98760	-39.6689
16	215	30	50	11	40	1.75	6.0	28.3	96.642	9339.67616	-39.7033
17	225	40	40	4	45	2.00	6.0	28.4	96.184	9251.36186	-39.6621
18	235	45	45	7	35	1.50	6.0	28.4	96.840	9377.98560	-39.7211
$\sum$									1736.8156	167585.957	
MEAN									96.48976		

Table. No. 5- Degrees of Freedom

Sr. No.	FACTOR	LEVELS- k_q	DOF - v_q
1	A	3	2
2	B	3	2
3	C	3	2
4	D	3	2
5	E	3	2
6	F	3	2
7	G	3	2
8	Error	-	3
9	Mean	-	1
		TOTAL - v_T	18

Table. No. 6- ANOVA - Unpooled

SOURCE	SS	v	VARIANCE V	F-RATIO	%P	CONFIDENCE INTERVAL
A	0.333488	2	0.1667438	50.79233	31.93268	99%
B	0.2800781	2	0.140039	42.65772	26.81853	99%
D	0.1947309	2	0.0973654	29.65879	18.64621	95%
E	0.0862102	2	0.0431051	13.13037	8.254946	95%
C	0.07888	2	0.0394402	12.01399	7.55309	95%
F	0.03831	2	0.0191531	5.834277	3.667958	90%
G	0.0228038	2	0.0114019	3.47316	2.183545	-
Error	0.009849	3	0.0032829	-	0.943	
T	1.0445	17			100%	

3.1 Pooling of Error

The combining of column effects to get better estimate error variance is referred to as pooling. The pooling up strategy entails F-test the smallest column effect against the next larger one to see if significance exists. If no significant F-ratio exists, then these two effects are pooled together to test the next larger column effect until some significant F ratio exists.

Pooling-up will tend to maximize the number of columns judged to be significant, and it will be used by us to lead us to the verification experiment.

Table. No. 7- ANOVA - Unpooled

SOURCE	SS	v_q	VARIANCE V	F-RATIO	%P	CONFIDENCE INTERVAL
A	0.333488	2	0.1667438	50.79233	31.93268	99%
B	0.2800781	2	0.140039	42.65772	26.81853	99%
D	0.1947309	2	0.0973654	29.65879	18.64621	95%
E	0.0862102	2	0.0431051	13.13037	8.254946	95%
C	0.07888	2	0.0394402	12.01399	7.55309	95%
F	0.03831	2	0.0191531	5.834277	3.667958	90%
E_p	0.032652	5	0.00653	-	3.1266	
T	1.0445	17			100.00	

The percent contribution and F-ratio of cooling time (D) were insignificant and hence they were pooled with the error estimates along with the degrees of freedom, sums of squares, variance to regenerate the table as result of pooling up strategy employed.

3.2 Delta

Delta = (Maximum S/N Ratio – Minimum S/N Ratio)
Delta of Barrel Temperature (A) = (-39.68035+ 39.70691) = 0.026556
The Delta values and corresponding Ranks are tabulated in the TABLE No. 8.

Table. No. 8 Rank of Factors

LEVEL	BARREL TEMP [A]	INJECTION PRESSURE [B]	INJECTION SPEED [C]	COOLANT FLOW RATE [D]	HOLDING PRESSURE [E]	HOLDING TIME [F]	COOLING TIME [G]
LEVEL 1	-39.68035	-39.69944	-39.68117	-39.68109	-39.69493	-39.69086	-39.68833
LEVEL 2	-39.68153	-39.69549	-39.69399	-39.70264	-39.69301	-39.69392	-39.68647
LEVEL 3	-39.70691	-39.67386	-39.69363	-39.68506	-39.68085	-39.68401	-39.69400
DELTA	0.026556	0.025571	0.01282	0.0215445	0.014078	0.00991	0.00753
RANK	1	2	5	3	4	6	7

IV. Analysis of Result

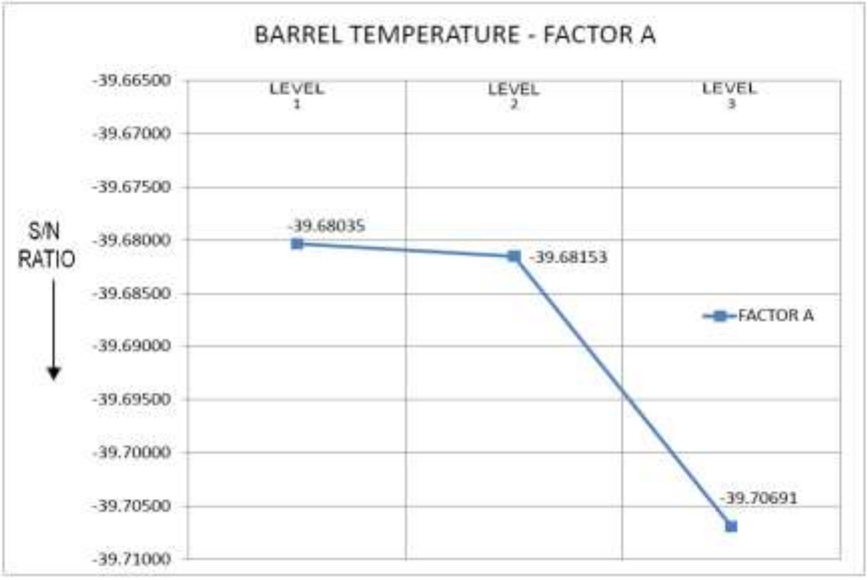

Figure No. 2 S/N Ratio Curve for Barrel Temperature

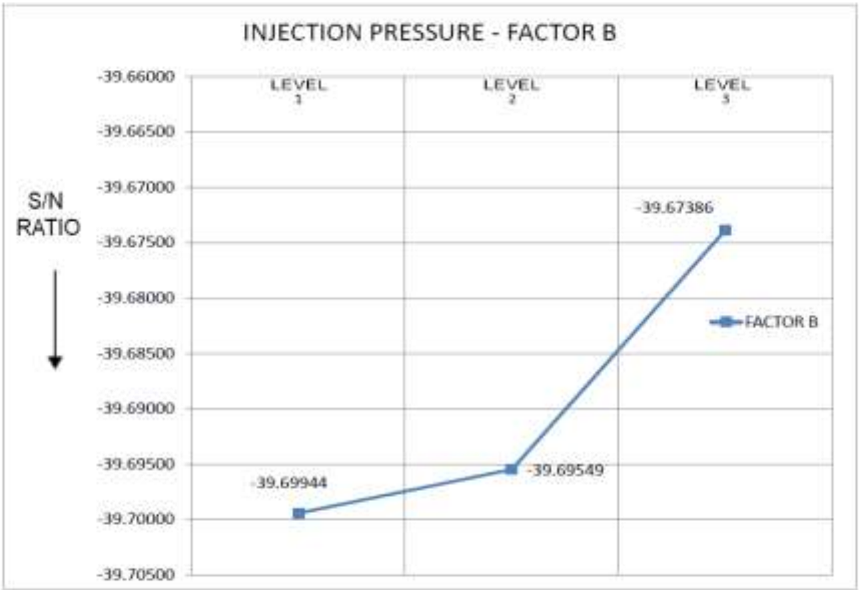

Figure No. 3 S/N Ratio Curve for Injection Pressure

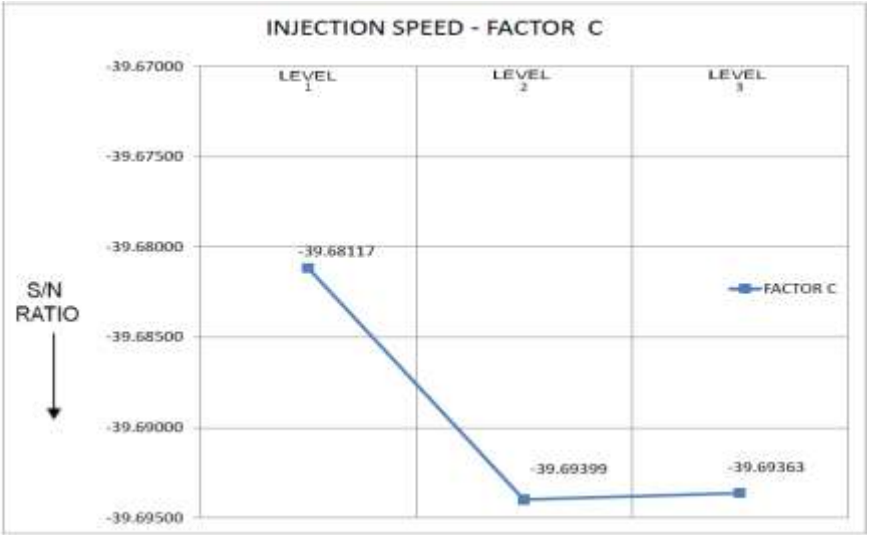

Figure No. 4 S/N Ratio Curve for Injection Speed

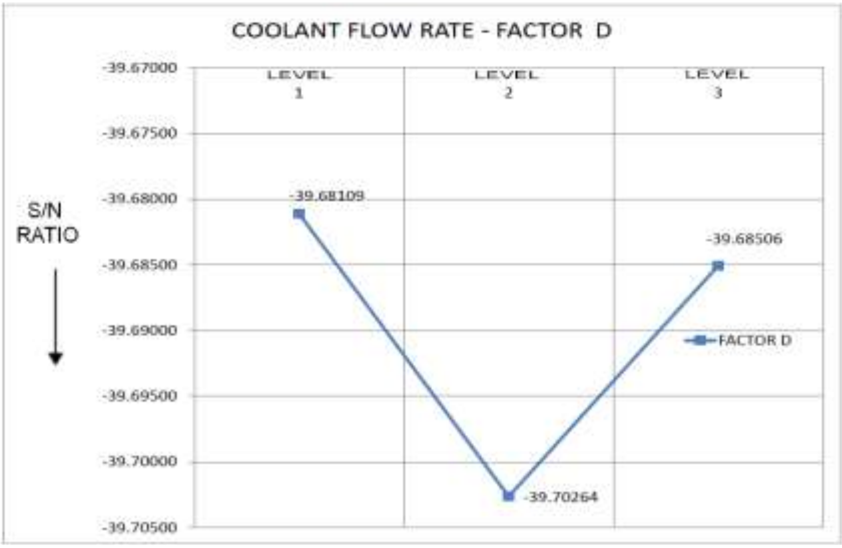

Figure No. 5 S/N Ratio Curve for Coolant Flow Rate

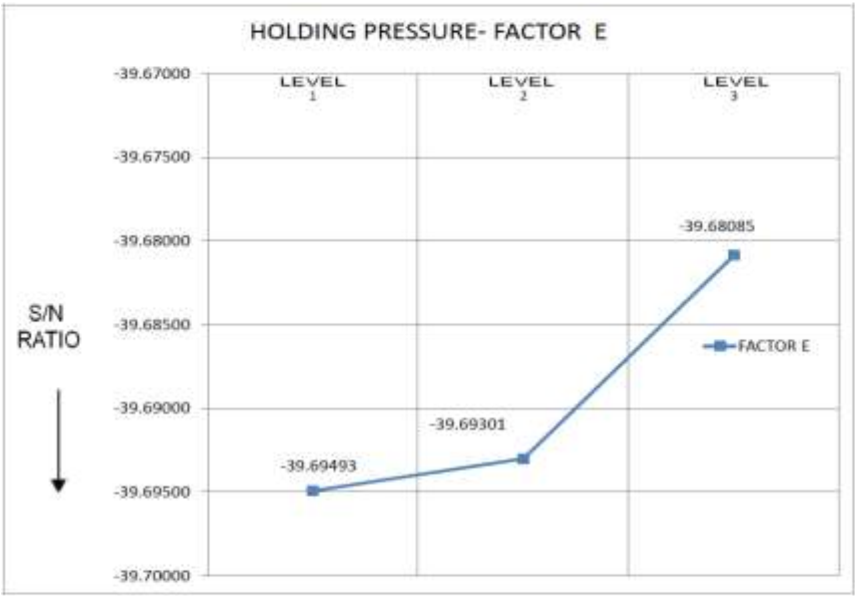

Figure No. 6 S/N Ratio Curve for Holding Pressure

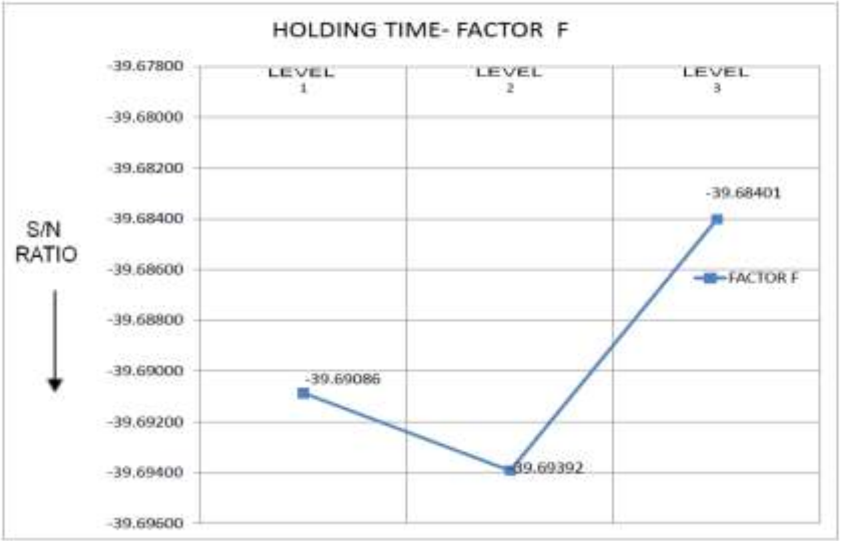

Figure No. 7 S/N Ratio Curve for Holding Time

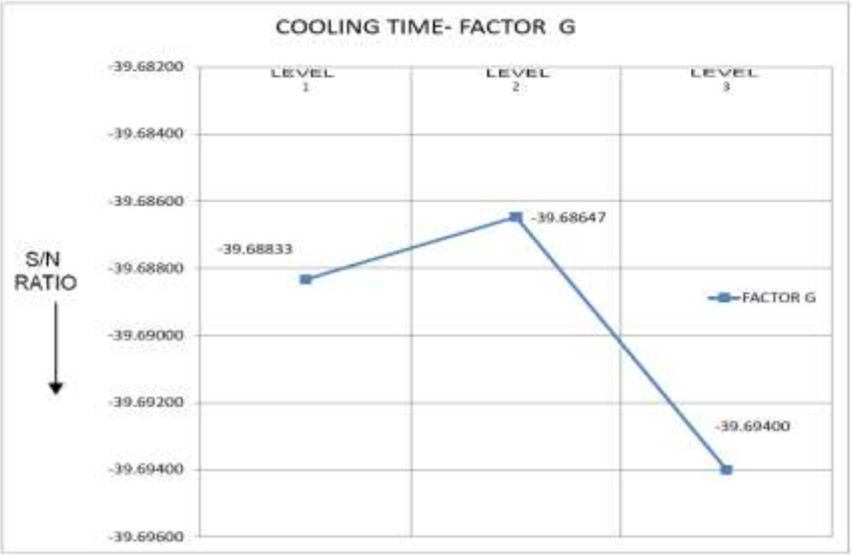

Figure No. 8 S/N Ratio Curve for Cooling Time

1) The Barrel Temperature contributes the maximum 31.93 % to the output response Weight and is most significant at Level 3 which corresponds to 235 °C and F- ratio of 50.792 at 99% Confidence Interval (Fig. 2)
2) The Injection Pressure contributes the second highest 26.81% to the output response Weight and is most significant at Level 1 which corresponds to 30 MPa and F-ratio of 42.65 at 99% Confidence Interval (Fig. 3)The Injection speed contributes 7.55% to the output response Weight and is most significant at Level 2 which corresponds to 45 % and F-ratio of 12.01 at 95% Confidence Interval. (Fig. 4)The Coolant Flow Rate contributes 18.64 % to the output response Weight and is most significant at Level 2 which corresponds to 7 LPM and F-ratio of 29.66 at 95% Confidence Interval. (Fig. 5)
3) The Holding Pressure contributes 8.25% to the output response Weight and is most significant at Level 1 which corresponds to 35 MPa and F-ratio of 13.13 at 95% Confidence Interval. (Fig. 6)
4) The Holding Time contributes 3.66 % to the output response Weight and is most significant at Level 2 which corresponds to 1.75 second and F-ratio of 5.843 at 90% Confidence Interval. (Fig. 7)
5) The Cooling Time was considered insignificant due to lower F-ratio and hence was pooled with experimental error value. The pooled error (E_p) contributes 3.1266 % to the output response Weight. (Fig. 8)

V. Experimental Verification

After performing the statistical analysis on the experimental data, it has been observed that there is one particular level for each factor for which the responses are minimum. Considering these levels as optimal levels a verification experiment is designed and process reliability is verified along with the capability estimate [11].

Table No. 9 Optimal Parameter Settings of Input Factors

	Parameters					
	A	B	C	D	E	F
Factor Levels	235	30	45	7	35	2.0

$$CI = \sqrt{F_{\alpha;1;\nu_e} \cdot V_{ep} \cdot [(1/n_{eff}) + (1/r)]} \quad \text{------------ (4)}$$

$$n_{eff} = \frac{N}{1 + \text{DOF used in } \alpha \text{ estimate}} \quad \text{------------ (5)}$$

r = sample size used for verification= 5

μ_{est}= estimated Mean

$\mu_{est} = \mu_{A3B1C3D3E1F3}$ = the estimate of average weight at the optimum levels of each factors

$= [\sum A3/6+\sum B1/6+\sum C2/6+\sum D2/6+\sum E1/6+\sum F3/6] - 5 \text{ x } T_m$

$\mu_{est} = \mu_{A3B1C3D3E1F3}$ = 96.82578 gram

$F_{0.01;1;5;}$ = 16.8; ----F Value at 99% Confidence Interval

V_{ep} = 0.00653; ---- Value of pooled error from TABLE No. 7

r = 5;

n_{eff} =[1+ (Degrees of Freedom of six factors in verification)]

n_{eff} = N/[1+ (2+2+2+2+2+2)]

n_{eff} = 18/13 = 1.3846

$CI = \sqrt{[F_{0.01;1;5;} V_{ep} [(1/ n_{eff}) +(1/r)]]}$

$CI = \sqrt{[16.8 *0.00653* [(1/1.3846)+ (1/5)]]}$

CI = 0.3181 =0.318

$\mu_{est} \pm CI = \mu_{A3B1C3D2E1F2} \pm CI$

$\mu_{est} - CI < \mu < \mu_{est} + CI$

$96.922 - 0.318 < \mu < 96.922 + 0.318$

$96.5077 < \mu < 97.1437$

Since the value of μ_{est} falls within the above range, the parameter settings and design is reliable.

The USL for given part is 98 grams.

The LSL for given part is 96.04 grams with 2% tolerance on USL

S_e =Pooled Error Standard Deviation= $(V_{ep})^{1/2}$

S_e = 0.0808

5.1 Capability Estimates (6s process variation)

Typically, process variation is defined as 6s, where s is the standard deviation, as an estimate of σ. When data are normally distributed, approximately 99.73% of the data fall within 6 standard deviations (± 3 standard deviations from the mean), and approximately 99% of the data fall within5.15 standard deviations (± 2.575 standard deviations from the mean).

Therefore process capability C_p = (USL-LSL)/ (6 S_e)

C_p = 4.042

C_{pu} = (USL- μ_{est})/(3 S_e) = 4.8444

C_{pl} = (μ_{est} -LSL)/(3 S_e) = 3.241

Minimum of C_{pu} and C_{pl} is compared with C_p and since, $C_{pl} < C_p$ it means the process is off-centered.

5.2 Verification Result

The verification experiment was conducted and the cooling time was maintained at 6 sec with all other parameters at their optimal levels from TABLE No. 9.

The part weight measured at this setting was 96.539 grams with a cycle time of 28 .1 second.

The optimal setting results in a part weight which falls within the process limits defined by the Confidence Level Equation used to verify predictions. Hence the values obtained from the Capability Estimates and the output of the Confirmation Experiment prove that the defined levels of parameters have significant contribution in making the system reliable. it has been observed that the part weight is within the acceptable range. So it can be concluded that the combinations of parameters tend to reach towards optimum settings.

Table No. 10 Verified Optimal Parameter Levels of Input Factors

	Parameters Values					
	A	B	C	D	E	F
Pre Experimental Values	230	35	40	11	30	2.5
Optimal Parameter values for Min.Weight	235	30	45	7	35	1.75

5.3 Highlights of the Experiment

1) Cycle Time was reduced by 4 second as against the cycle time prior to experimentation recorded was 32.4 second. The percent saving in production was 12.5%, we can reasonably comment that productivity was enhanced by 12.5 %.
2) The reduced injection pressure lessens the clamping force required and in turns results in reduced power consumption per part weight due to reduction in power required for clamping.
3) Reduced part weight contributes to material savings.

VI. Conclusion

1) In search of an optimal parameter combination, (favorable process environment) capable of producing desired quality of the product in a relatively lesser time (enhancement in productivity), the Taguchi methodology has been characteristically successful.
2) The study proposes a consolidated optimization approach using Taguchi's robust design of optimization .The Methodology could serve in minimizing the cost to customer by enhancing quality and production aspects.
3) In Taguchi L_{18} orthogonal matrix experiment, no interactions between the input factors are considered. But some interaction effect may be present during the experiment. This may result in some observations which do not go with the theoretical belief though not observed during the course of experimentation.
4) Since the material is a polymer of specific grade, parallels cannot be drawn in results with analogical experimentations. But, the experimental method can be analogically applied to most of the polymers with some minor deviations.

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