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STUDY ON INJECTION MOLDING PROCESS & PARAMETER OPTIMIZATION

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Abstract—*: *Determining the optimal process parameter Is routinely performed in plastic injection molding industry as It has a direct and dramatic influence on product quality and cost Using the trial and errorapproach to détermine the process parameter for injection molding no longer good enough. Factor that affect the quality of a molded part CanBe classified in to four categories 1)Part design 2) Mold design 3) machine performance 4) Processing conditions. The part and mold design are assumed as established and fixed. During production, quality characteristics may deviate due to drifting or shifting of processing conditions caused by machine wear, environmental changes or operator fatigue. This paper aim to review the research of the practical use of Taguchi method in the optimisations of processing parameter for injection molding. The Taguchi robust parameter design has been widely used over the past decade to solve many signal response process parameter design.

The review will on the Taguchi methods with various approaches including Signal to noise ratio. Mould analysis based on two level fractional designs. Orthogonal arrays of Taguchi, the signal to noise ratio are utilized to find the optimal levels and the effect of process, parameters are determined by many researches on shrinkage and warpage.

I. INTRODUCTION

Now a day injection molding bears the responsibility of mass production plastic components to meet the rapidly rising market demand as a multitude of different types of consumer products including products are made of injection molding parts.The product quality depends on mould design material selection and process parameters. Settings such as filling, cooling, packaging and injection molding process. Incorrect input parameters setting will cause bad quality of surface roughness decrease dimensional precision, warpage, unacceptable wastes increase lead time and cost. The trial- and error process is costly and time consuming, thus not suitable for complex manufacturing processes. In order to minimize such defects in plastic injection molding design of experiment, the Taguchi method is applied. In experimental design there are many variable factors that affect the functional characteristic of the product .In order to find optimum levels, fractional factorial designs using orthogonal arrays are used. In this way an optimal set of process can be obtained from various approaches

II. OBJECTIVE

The main objectives of the process are to reduce cycle time by process parameters optimization to ensure high quality parts. The aim of this project work is to identify the factors affecting cycle time and to reduce cycle time to optimize process. Hence the objectives of the present experimental work are

A. To review the literature on injection molding process parameters

B. To design the experiment for assessment of injection molding process parameters

C. To Select appropriate injection molding machine and suitable material

D. To select the major process parameters that will affect the cycle time and quality of the product

E. To select the major process parameters that will affect the cycle time and quality of the product

F. To optimize selected injection molding process parameters

III. Taguchi Method

Taguchi methods provide a systematic approach to a better understanding of the process and assist industrial engineers to discover the key process variables which affect the critical process or product characteristics. Taguchi's philosophy is more relevant in terms of working towards a target performancewhich essentially reflects the continuous improvement attitude. The objective of the Taguchi methods is to obtain more robust processes/products under varying environmental variables. Unlike the full factorial design method that investigates every possible combination of processes parameters, the Taguchi method studies the entire parameter space with a minimum number of experiments. Accordingly, the studied process should be characterized by a number of parameters which are signal factors, control factors and noise factors [1]

IV. STEPS IN TAGUCHI PARAMETER DESIGN

Taguchi parameter design was used for identifying thesignificant processing parameters and optimizing the minimum shrinkage. Two important tools used in parameter design are orthogonal arrays and signal-to-noise (S/N) ratios. Fig.1. demonstrates the steps of Taguchi parameter design.

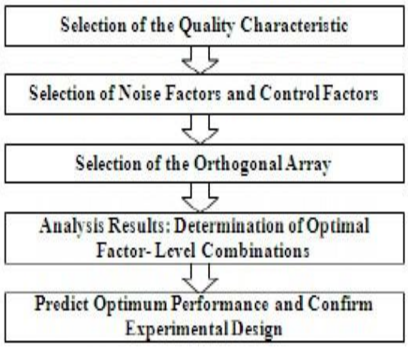

Figure 1Steps of Parameter design

teps Involved in Taguchi method

The use of the parameter design of the Taguchi method to optimize a process with multiple performance characteristics includes the following Steps:

1. Define the problem.
2. Selection of factors and number of levels.
3. Selection of appropriate Orthogonal Array (OA).
4. Performing the experiments
5. Statistical analysis and interpretation of Experimental results.
6. Determination of optimal condition.
7. Confirmation run or experiment.

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.[2]

Table 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

he 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. 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.[2]

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 Barrel Temperature, Injection Pressure, Injection Speed, Holding Pressure, HoldingTimeCoolingTime, and Coolant FlowRate.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.[3]

Input Factors with Units & Notation:-

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

V. Design of Experiment

The 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. 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. [2]

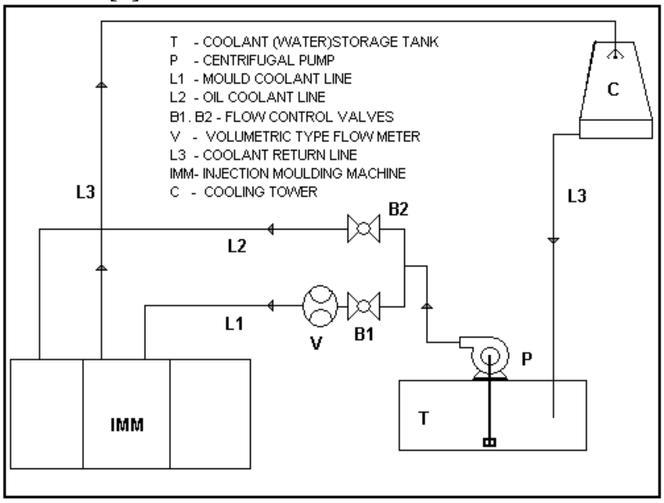

Figure 2 Injection Molding Experimental Set Up

Notations used in the calculations are as given:-

S/N ---- Signal to Noise ratio for given response Weight and its unit is dB

kq ---- level for the factor denoted by subscript q. q ϵ {A,B,C,D,E,F,G}

vq ---- degree of freedom for the factor denoted by subscript q. q ϵ {A,B,C,D,E,F,G}

vm ---- degree of freedom for associated with the mean {always equal to 1}

ve ---- degree of freedom associated with the error

N ---- total number of observations

Table 4 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%	

T ---- sum of all observations
Tm ---- average of all observations
Vq ---- variance for the factor denoted by subscript q. q ϵ {A,B,C,D,E,F,G}
Se ---- Pooled Error Standard Deviation
SSm ---- Sums of Squares due to Mean
SST ---- Total Sums of Squares of Weights,
SSq ---- Sums of Squares for Factors denoted by subscript q. q ϵ {A,B,C,D,E,F,G}
SSe ---- Sums of Squares of ErrorNotations used in the calculations are as given:-
S/N ---- Signal to Noise ratio for given response Weight and its unit is dB
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SSe ---- Sums of Squares of ErrorSS ---- 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;

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

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,

$$SS_T = \sum_{i=1}^{N} w_i^2$$

For any Factor the Sums of Squares is given by the equation

$$SS_q = \left[\sum_{i=1}^{k_q}\left(\frac{q_i^2}{n_{q_i}}\right)\right] - \frac{T^2}{N}$$

given below: -
The part showed excellent surface texture and specifically gloss in terms of commercial terms ofproduct value.

Table 2 DOF

Sr.No.	Factors-	Levels-kq	DOF-vq
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 -vt	18

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
∑									1736.8156	167585.957	
MEAN									96.48976		

Table 3 S/N Ratio

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.
Delta = (Maximum S/N Ratio – Minimum S/N Ratio)

Delta of Barrel Temperature (A) = (-39.68035+ 39.70691) = 0.026556

Table No. 5 Rank of Factors[2]

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

Regression modeling is used to determine the relation between input and output variables of the injection molding process. For modeling the process different mathematical functions including linear polynomial, Quadratic polynomial and logarithmic are used. These models are modified using step backward elimination method with 95% CL in Minitab software. Terms with CL of higher than 95% (P-value less than 0.05) are selected. These terms with their corresponding P-values are reported in Tables 2 and 3. One criterion for choosing the model is correlation coefficient [11]. Therefore, correlation coefficients (R2 value) of the equationsfor shrinkage are calculated. As shown in Table 4, based on their R2 test, quadratic polynomial models are best fitted for bothoutputs. The R^2 values indicate that the predictors explain 90.1% and 92.7% of the PP and PS variances, respectively.[2]

Table 6.EXPERIMENTAL RESULTS[2]

Parameters	Melting temperature	Injection pressure	Packing pressure	Packing time	Polypropylene shrinkage (%)	Polystyrene shrinkage (%)
Unit	C°	Mpa	Mpa	Sec	-	-
Symbol	T	Pi	Pp	tp	PP	PS
1	220	50	30	5	1.844	3.125
2	220	60	40	10	1.313	2.281
3	220	70	50	15	1.125	2.125
4	220	50	30	10	1.688	2.563
5	220	60	40	15	1.563	1.549
6	220	70	50	5	1.438	1.875
7	220	50	30	15	1.688	2.031
8	220	60	40	5	1.469	2.031
9	220	70	50	10	1.250	1.844
10	240	60	50	5	1.344	1.375
11	240	70	30	10	1.625	2.281
12	240	50	40	15	1.375	1.344
13	240	60	50	10	1.094	1.438
14	240	70	30	15	1.313	1.813
15	240	50	40	5	1.406	1.625
16	240	60	50	15	1.063	1.313
17	240	70	30	5	1.813	1.875
18	240	50	40	10	1.625	1.719
19	260	70	40	5	1.250	1.781
20	260	50	50	10	1.313	1.375
21	260	60	30	15	1.219	1.406
22	260	70	40	10	1.250	1.531
23	260	50	50	15	1.000	1.250
24	260	60	30	5	1.563	1.844
25	260	70	40	15	1.156	1.656
26	260	50	50	5	1.313	1.344
27	260	60	30	10	1.469	1.844

Table 7.P-Value Results For Polystyrene Mode

Predictor	P-value
Constant	0.001
T	0.006
pi	0.028
Pp	0.000
tp	0.040
T2	0.009
pi2	0.045
tp2	0.048
Pi*tp	0.027
Pp*tp	0.016

Table 8 R2 Test for regression models

Output parameter	**Function type**		
	Linear polynomial	**Quadratic polynomial**	**Logarithmic**
Polypropylene	88.9	90.1	89.3
Polystyrene	82.4	92.7	85.3

Study, there are four main input parameters. However, the simultaneous effect of all four parameters on output cannot be displayed graphically. Therefore a linear ANOVA study, considering only the four main input parameters for each material is performed.F-test is used by ANOVA to identify the important variables. For n values of y_i and the mean value y , we can write,

$$SS = \sum_{i=1}^{n} (y_i - y)^2$$

where SSi is sum of squared deviations from the mean. MSi is mean of squares and defined as,

$$\mathrm{MS} = \frac{\mathrm{SS}}{\mathrm{d.f.}}$$

where DFi for i=1,…,4 denotes degree of freedom which is the number of levels for each factor minus 1. DFT is the number of experiments minus 1. Meanwhile, DFe is DFT minus sum of DFi for i=1,…,4. Fvalue is the ratio between the mean of squares effect and the mean of squares error.

$$F = \frac{\mathrm{M.S.\ effect}}{\mathrm{M.S.\ error}}$$

F-test determines the significance of each factor on the response variable. ANOVA results are shown in Tables 6 and 7. According to these two Tables, injection pressure in both materials has the least effect on shrinkage. At 90% CL, according to its F-value, shown in Table 7, injection pressure has no significant effect on output for PS.
The ANOVA results can also be used to determine the contribution percentage of each output by,
Results are tabulated in Fig. 3. As shown in this Figure, packing pressure and melting temperature are the most important parameters affecting the shrinkage of the PP and PS, respectively
Upon identifying the two most important input parameters, the quadratic polynomial regression models, Table 5, are used to plot the pair-wise effects in 3D charts. To do this, the two most important main parameters, identified by contribution percentages, are varied while the other two main parameters are held constant at their mid-levels. Fig. 4 shows the simultaneous effect of packing pressure and packing time on shrinkage of PP and Fig. 5 shows the effect of melting temperature and packing pressure on shrinkage of PSF value in 90% C.I is 2.63, *Significant factor[1]

Table 9 ANOVA Results For Polystyrene

Source	Degree of Freedom (DF_i)	Sum of Square (SS_i)	Mean Square (MS_i)	F Value	P value
T	2	1.92948	0.96474	*18.27	0.000
P_i	2	0.16539	0.08270	1.57	0.236
P_p	2	1.35027	0.67513	*12.78	0.000
t_p	2	0.40681	0.20341	*3.85	0.041
Error	18	0.95057	0.05281		
Total	26	4.80252			

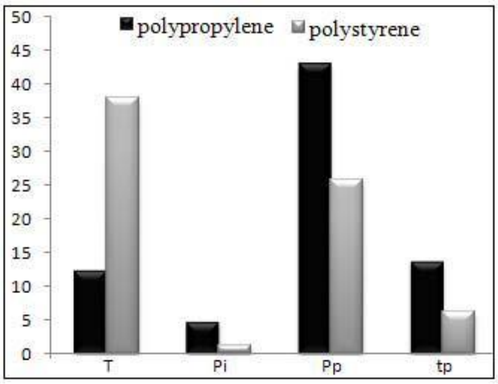

Figure 3 Contribution percentage for parameters

The Figure shows by increasing packing pressure and decreasing packing time, shrinkage is minimized. As Fig. 5 shows by increasing melting temperature and decreasing packing pressure, shrinkage reaches its minimum. As stated earlier, effect of no more than two inputs can be displayed graphically. If the output space is not too complicated, it may be possible to use such graphs to identify the settings resulting in optimum output. However, as in the present study, the number of inputs is four and graphical techniques are no longer effective. This is why IWO algorithm is used to identify the optimum levels.[5]

VI. Optimization Method

Invasive Weed Optimization (IWO) is a probabilistic search algorithm inspired by the behaviour of invasive weeds colonizing in opportunity spaces in their natural habitats. Basically, weeds are plants whose vigorous, invasive habits of growth pose a serious threat to cultivated plants, making them a hazard to agriculture. Weeds have shown to be very robust and adaptive to the changes of environment. The algorithm starts with an initial population of weeds dispersed randomly on the solutions space. The fitness of Each weed is then determined by evaluating it against the object function. To simulate the natural survival process, any given weed in the colony produces seeds based on three criteria: its fitness, the colony's lowest fitness and the highest fitness. The seeds are randomly distributed within a limited distance around their parent plant. Usually as the colony gets denser the dispersions of seeds become closer. All weeds in the colony, including new offspring, are then evaluated. In this stage, if the population has reached its maximum allowable number, the lesser fitted ones are eliminated. This competitive exclusion results in evolution of the colony in consecutive generations.[3]

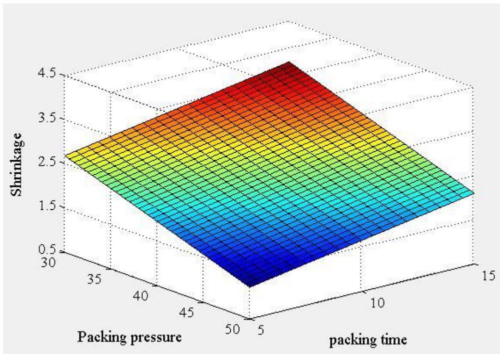

Figure 4 Estimate Polypropylene shrinkage in regard topacking pressure and packing time.

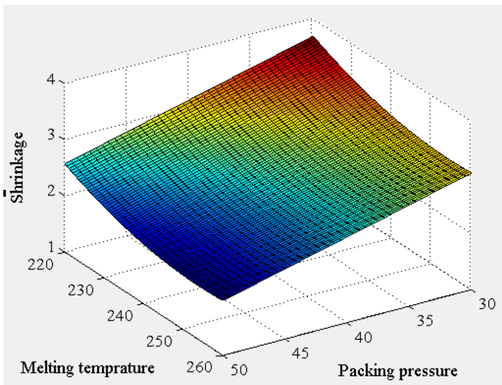

Figure 5 Estimate Polystyrene shrinkage in regard to melting temperature and packing pressure.

IWO attempts to make use of the robustness, adaptation and randomness of colonizing weeds. Using such properties, the algorithm is able to converge towards optimal solution. In IWO, a weed represents a solution to the problem; in our case a response for each regression model in a special parameter setting. A set of random level of parameters creates the initial population of seeds. Since the goal is minimizing shrinkage then a weed having lesser shrinkage has more fitness. A new seed is produced by exchanging the level of two parameters within the all parameters in the regression model. At each iterations, the transposition range (the distance) between two levels must be less than the standard deviation (SD) of seeds distribution given by following equation

$$\sigma_{iter} = [\frac{(iter_{max} - iter)}{iter_{max}}]^n \times (\sigma_{initial} - \sigma_{final}) + \sigma_{final}$$

In this formula, σ_{iter} is the current iteration SD, $iter_{max}$ is the maximum number of iterations, iter is the current iteration number and σinitial and σ_{final} are the initial and final value of SD. The main steps of IWO algorithm is schematically illustrated in Fig. 6. The details of this technique and its various applications are well documented in literature[6]

VII.CONCLUSIONS

Warpage is one of the main defects in injection molding process which appears due to anti-symmetric shrinkage. In ``

key process input variables on shrinkage for PP and PS materials are investigated.

Several regression models are investigated. Step backward elimination method, at 95% CL, is used to eliminate insignificant terms from the models. R2 and P-value statistics are used to identify the best models. Results indicate that quadratic polynomial is better than the other models. Next, ANOVA is used to determine the most effective parameters for the selected model. Based on ANOVA, for PP packing pressure is the most effective while injection pressure is the least important. The other two variables, melting temperature and packing time are significant and have approximately the same effect. Again, based on ANOVA, for PS, melting temperature is the most influential variable while packing pressure and packing time are next the influential parameters.

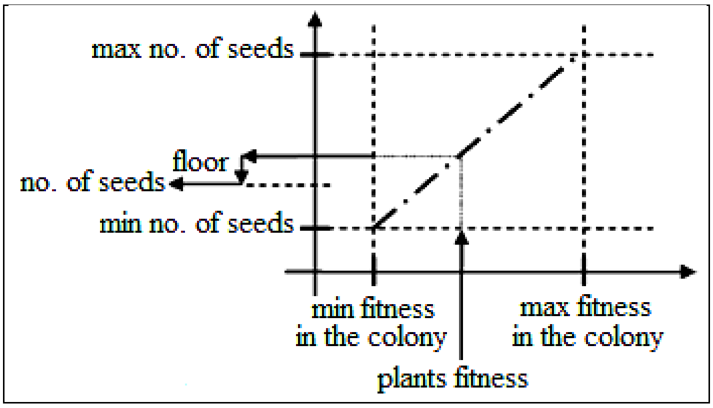

Figure 6 Seed production procedure in a colony of weeds

Table 10 Optimization Levels

Optimunn levels of each parameter				% Shrinkage	
Melting temperature	Injection pressure	Packing pressure	Packing time	PP	PS
C°	Mpa	Mpa	Sec		
260	60	50	5	%0.88	-
260	60	40	15	-	%0.95

Table 11 Comparison Results

Output parameter	Initial Machine settings	After Optimization	Improvement
Polypropylene	% 1.37	% 0.88	% 35.7
Polystyrene	% 1.28	% 0.95	% 25.7

Additionally, injection pressure is not statistically significant. Finally, IWO optimization method is applied to determine optimum input levels to minimize shrinkage. Results indicate that shrinkage is reduced to below 1% which is slightly better than the previous study [10]. Therefore, the present study demonstrates the effectiveness of models and proposed optimization method.

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.Since the material is a polymer of specific grade, parallels cannot be drawn in results with analogical experimentations. [7]

Advantages Of 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.

APPENDIX

Abbreviation

ANN	artificial neural network
ANOVA	analysis of variance
CL	Confidence level
GA	genetic algorithm
IWO	invasive weed optimization
PP	polypropylene
PS	polystyrene
RSM	response surface methodology
SD	standard deviation

Notation

DF_i	degree of freedom
F	f-value
$iter_{max}$	maximum number of iterations
Ms_e	mean square of error
MS_i	mean square
P_i	injection pressure
P_p	packing pressure
ρ	percentage contribution
SS_i	sum of square
SS_T	total sum of square
T	melting time
t_p	packing time
Ybar	mean of outputs
Y_i	output
$\sigma_{initial}$	initial value of standard deviation
σ_{final}	final value of standard deviation
σ_{iter}	current iteration of standard deviation

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