Parameter Study in Plastic Injection Molding Process using Statistical Methods and IWO Algorithm

Alireza Akbarzadeh and Mohammad Sadeghi

***Abstract*—Dimensional changes because of shrinkage is one of the most important problems in production of plastic parts using injection molding. In this study, effect of injection molding parameters on the shrinkage in polypropylene (PP) and polystyrene (PS) is investigated. The relationship between input and output of the process is studied using regression method and Analysis of Variance (ANOVA) technique. To do this, existing data is used. The selected input parameters are melting temperature, injection pressure, packing pressure and packing time. Effect of these parameters on the shrinkage of above mentioned materials is studied using mathematical modeling. For modeling the process, different types of regression equations including linear polynomial, Quadratic polynomial and logarithmic function, are used to interpolate experiment data. Next, using step backward elimination and 95% confidence level (CL), insignificant parameters are eliminated from model. To check validity of the PP model, correlation coefficient of each model is calculated and the best model is selected. The same procedure is repeated for the PS model. Finally, optimum levels of the input parameters that minimize shrinkage, for both materials are determined. Invasive Weed Optimization (IWO) algorithm is applied on the developed mathematical models. The optimization results show that the proposed models and algorithm are effective in solving the mentioned problems.**

***Index Terms*—IWO algorithm, Optimization, Plastic injection molding, Regression, shrinkage.**

I. Introduction

Nowadays, competitive market requires producers to produce high quality parts, with lower price in the least possible time. Injection molding is known as an effective process for mass production of plastic parts with complicated forms and high dimensional precision. In this method, high pressure fluid polymer is injected to the cavity with desired form. Next, under high pressure, fluid solidifies. During the process, plastic materials are under high pressure and temperature. Materials are cooled to get desired form. Injection molding process can be divided into four stages:
Plasticization, injection, packing and cooling. Although molding process may seem simple, the molded polymers are effected by many machine parameters and process condition [1-2].

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Alireza Akbarzadeh is with the Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.Tel/Fax: 98-511-876-3304; E-mail: Ali_Akbarzadeh_T@ yahoo.com.
Mohammad Sadeghi is with the Department of Mechanical Engineering, Ferdowsi University of Mashhad, Mashhad, Iran.E-mail: H.Sadeghi@ymail.com.

Incorrect input parameters settings will cause bad quality of surface roughness,decreases dimensional precision, Warpage, unacceptable wastes, increases lead time and cost [3].Therefore, finding the optimized parameters is highly desirable. In past scientists used trials and error to find good process conditions but this method is time and cost consuming. In addition, when there are a large number of input parameters, these methods can't be used. Nowadays, the model of the process and optimal condition are developed using analytic methods and heuristic algorithms [4-8].

In previous studies, critical parameters that affect the quality of the parts are investigated. Hang et al. [4] considered six input parameters as; mold temperature, melting temperature, packing pressure, packing time and injection time. They studied effects of these parameters on surface quality of the thin molded parts. Li yang et al. [5] investigated effect of the same parameters with the addition of injection speed, injection acceleration on width of the segregation line. Chang et al. [6] studied effects of melting temperature, injection temperature, packing time and packing pressure on the surface quality of the produced parts using fuzzy logic. Sue et al. [7] used Artificial Neural Network (ANN) and SA algorithm to optimized surface quality of produced parts. Shi et al. [8] used numerical simulation and Genetic Algorithm (GA) to achieve best shear stress. Warpage in plastic parts due to anti-symmetric shrinkage is one of the most important defects caused by residual stress. These stresses are usually due to the one directional anti-symmetric shrinkage. As the shrinkage decreases, shrinkage in 3 directions decrease and therefore warpage decreases [9]. Prediction of shrinkage is very difficult because of the number of parameters and complexities of the process. Despite huge studies on modeling and optimizing of injection molding process, a few researches deal with PP and PS produced parts. Altan [10] utilized Taguchi method to optimize shrinkage of plastic, PP and PS, injection molding parts. He also applied neural network to model the process and was able to achieve 0.937% and 1.224% shrinkage in PP and PS, respectively. In this paper, we extend the Design of Experiment (DOE) study performed by Altan [10] by developing a regression model and applying IWO algorithm to obtain the optimum levels. We show that our method results in slight improvement in lowering shrinkage.

This paper is organized as follows. First experimental data and selected material is introduced. Regression analysis is performed and 1st and 2nd orders as well as logarithmic models are developed. ANOVA is used to determine significant model parameters. Finally, IWO algorithm is used to optimize input parameters to achieve desired output, minimum shrinkage.

II. Experimental Method

Existing experimental data is used [10]. The data is based on a modified orthogonal array in Taguchi method. The selected input parameters include, melting temperature, packing pressure, packing time and injection pressure. Shrinkage, which is one of the most important criteria, is selected as output. Selected materials are PP and PS. Grade of the PP MH-418 with melting index of 4.5g/10min and grade of the PS is LGH-306 with melting index of 7.5g/10min. Level of input parameters in each experiment and the measured results are shown in Table 1.

III. Modeling the Process

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 (R^2 value) of the equations for shrinkage are calculated. As shown in Table 4, based on their R^2 test, quadratic polynomial models are best fitted for both outputs. The R^2 values indicate that the predictors explain 90.1% and 92.7% of the PP and PS variances, respectively. Furthermore, to check the validity of the models normal probability plot of residuals, Fig. 1 and Fig. 2 are investigated.

Based on Fig. 1 and Fig. 2, both models are normally distributed. Low dispersion of the points from the reference line indicates high quality of the models. The selected models are shown in Table 5. These two models will later be used by the IWO algorithm to obtain the optimum input variable settings.

TABLE 1. EXPERIMENTAL RESULTS [10]

Parameters	*Melting temperature*	Injection pressure	*Packing pressure*	*Packing time*	Polypropylene shrinkage (%)	Polystyrene shrinkage (%)
Unit	*C°*	*Mpa*	*Mpa*	*Sec*	-	-
Symbol	T	P_i	P_p	t_p	*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 3. P-VALUE RESULTS FOR POLYSTYRENE MODEL

Predictor	P-value
Constant	0.001
T	0.006
p_i	0.028
P_p	0.000
t_p	0.040
T^2	0.009
p_i^2	0.045
t_p^2	0.048
P_i*t_p	0.027
P_p*t_p	0.016

TABLE 4. R^2 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

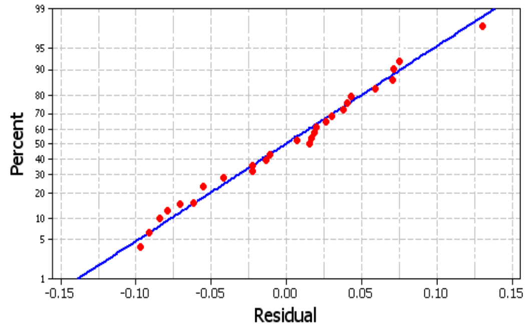

Figure 1. Normal test for Polypropylene shrinkage results

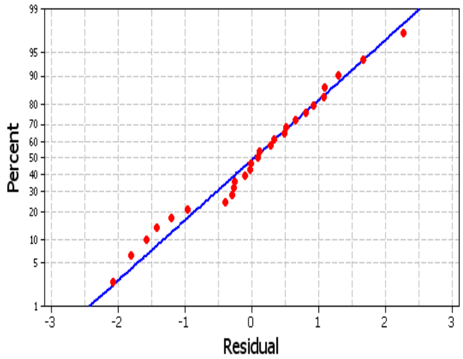

Figure 2.Normal test for Polystyrene shrinkage rsults

A graphical representation depicting the effect of the critical parameters on output is also explored. In the present

TABLE 5. REGRESSION MODELS

Output Parameter	Fitted Function
Polypropylene	***PP=*** $3.63 - 0.0732\times PP + 0.0880\times t_p + 0.000402\times P_i^2 - 0.000187\times T\times p_i + 0.000221\times T\times PP - 0.000283\times T\times t_p - 0.000693\times P_i\times t_p$
Polystyrene	***PS=*** $45.7 - 0.274\times T - 0.223\times P_i - 0.0550\times PP - 0.186\times t_p + 0.000540\times T^2 + 0.00166\times P_i^2 - 0.00531\times tp^2 + 0.00255\times P_i\times t_p + 0.00281\times PP\times t_p$

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 $\bar{y}$, we can write,

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

where SS_i is sum of squared deviations from the mean. MS_i is mean of squares and defined as,

$$MS_i = \frac{SS_i}{DF_i} \qquad (2)$$

where DF_i for i=1,…,4 denotes degree of freedom which is the number of levels for each factor minus 1. DF_T is the number of experiments minus 1. Meanwhile, DF_e is DF_T minus sum of DF_i for i=1,…,4. F_{value} is the ratio between the mean of squares effect and the mean of squares error.

$$F = \frac{MS_i}{MS_e} \qquad (3)$$

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,

$$\rho(\%) = \left(\frac{SS_i - DF_i \times MS_e}{SS_T}\right) \times 100 \qquad (4)$$

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 PS.

TABLE 6.ANOVA RESULTS FOR POLYPROPYLENE

Source	Degree of Freedom (DF_i)	Sum of Square (SS_i)	Mean Square (MS_i)	F Value	P value
T	2	0.19215	0.09608	*7.18	0.005
$\boldsymbol{P_i}$	2	0.08941	0.04471	*3.34	0.058
$\boldsymbol{P_p}$	2	0.60066	0.30033	*22.43	0.000
$\boldsymbol{t_p}$	2	0.21046	0.10523	*7.86	0.004
Error	18	0.24099	0.01339		
Total	26	1.33367			

F value in 90% C.I is 2.63 , *Significant factor

TABLE 7.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
$\boldsymbol{P_i}$	2	0.16539	0.08270	1.57	0.236
$\boldsymbol{P_p}$	2	1.35027	0.67513	*12.78	0.000
$\boldsymbol{t_p}$	2	0.40681	0.20341	*3.85	0.041
Error	18	0.95057	0.05281		
Total	26	4.80252			

F value in 90% C.I is 2.63, *Significant factor

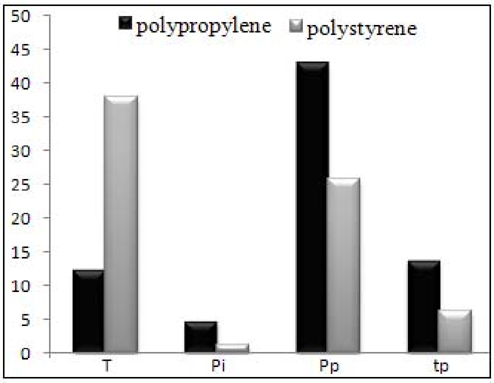

Figure 3.Contribution percentage for parameters

As Fig. 4 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.

IV. OPTIMIZATION METHOD

Invasive Weed Optimization (IWO) is a probabilistic search algorithm inspired by the behavior 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.

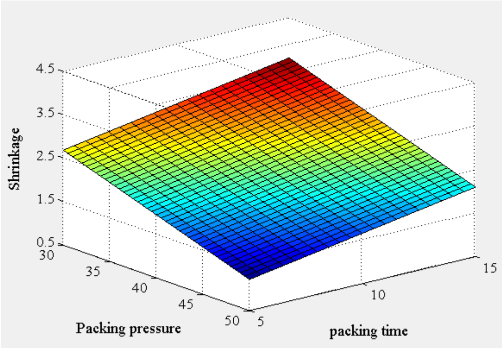

Figure 4.Estimate Polypropylene shrinkage in regard to packing pressure and packing time.

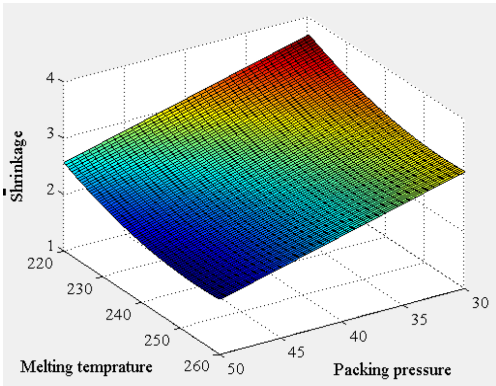

Figure 5.Estimate Polystyrene shrinkage in regard to melting temprature and packing pressure.

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:

$$\sigma_{iter} = [\frac{(iter_{\max} - iter)}{iter_{\max}}]^n \times (\sigma_{initial} - \sigma_{final}) + \sigma_{final} \quad (5)$$

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 $\sigma_{initial}$ 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 [12-14].

In this study, proposed algorithm is coded in Matlab 7.1 software and is used to optimize the problem. Optimized parameters settings and predicted output are shown in Table 8. As shown in this Table, by settings the input parameters at the stated values, shrinkage percentage of less than 1% for both materials is achieved. As indicated in Table 9, these values represent 35.7% and 25.7% improvements in shrinkage of PP and PS parts, respectively.

V. Conclusions

Warpage is one of the main defects in injection molding process which appears due to anti-symmetric shrinkage. In this study, mathematical models for determining effects of 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. R^2 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.

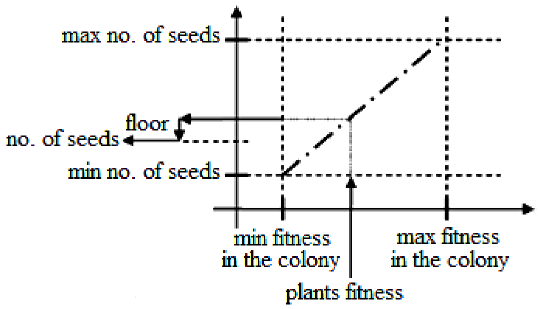

Figure 6.Seed production procedure in a colony of weeds

TABLE 8.Optimization Results

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

TABLE 9.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.

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

REFERENCES

[1] G. Pötsch and W. Michaeli, "Injection molding: An introduction", *Munich: Hanser Publishers, 1995.*

[2] J.A. Brydson, "Plastic materials", *Butterworth-Heinmann: Oxford, 1995.*

[3] D.V. Rosato, M.G. Rosato, "Injection molding handbook" *Massachusetts: Kluwer Academic Publishers, 2000.*

[4] M.C. Huang and C.C. Tai , "The effective factors in the warpage problem of an injection-molded part with a thin shell feature", *J. Mat. Proc. Tech.*, vol. 110, 2001, pp. 1–9.

[5] J.M. Liang and P.J. Wang , "Multi-objective optimization scheme for quality control in injection molding", *J. Inject. Mold. Tech. Career and Technical Education,* vol. 64, 2002, pp. 331–342.

[6] K.T. Chiang and F.P. Chang , "Application of grey-fuzzy logic on the optimal process design of an injection-molded part with a thin shell feature", *International Communications in Heat and Mass Transfer, April* 2006, pp. 94–101.

[7] C.T. Su and H.H. Chang , "Optimization o f parameter design: an intelligent approach using neural network and simulated annealing", *Int. J. Systems Science*, vol. 31, 2000, pp. 1543–1549.

[8] F. Shi, Z.L. Lou, J.G. Lu and Y.Q. Zhang , "Optimization of plastic injection molding process with soft computing", *Int. J. Adv. Manuf. Tech*. vol. 21, 2003, pp. 656–661.

[9] R.A. Malloy, "Plastic part design for injection molding", *Munich: Hanser Publishers, 1994.*

[10] M. Altan, "Reducing Shrinkage in Injection Moldings via the Taguchi, ANOVA and Neural Network Methods", *j. Mat. & Design*, vol. 31, 2010, pp. 599–604.

[11] D.C. Montgomery, "Design and analysis of experiments" 7th ed., N*ew York: John Wiley & Sons, 2008.*

[12] A.R. Mehrabian and C. Locas, "A novel numerical optimization algorithm inspired from weed colonization", *Ecological Informatics*, vol. 1, 2006, 355-366.

[13] A.R.Mehrabian, Aghil Yousefi-Koma, "optimal positioning of piezoelectric actuators on a smart fin using bio-inspired algorithms", *Aerospace Science and technology*, vol. 11, 2007, 174-182.

[14] H. Sepehri-Rad and C. Lucas, "A recommender system based on invasive weed optimization algorithm," in Proc. *IEEE Congress on Evolutionary Computation, 2007,* pp. 4297–4304.

Alireza Akbarzadeh was born in July of 1960 in Mashhad, Iran. He received his PhD in Mechanical Engineering in 1997 from University of New Mexico in USA. He worked at Motorola USA for 15 years where he led R&D as well as Automation teams. He joined Ferdowsi University of Mashhad in 2005 and is currently associate professor of M.E. Department. He has over 18 Journal publications and over 50 conference papers.

His areas of research include Robotics (Parallel Robots, Biologically inspired Robots, Biped), Dynamics, Kinematics, Automation, Optimization, Design and Analysis of Experiments.

Mohammad Sadeghi was born in September of 1984 in Mashhad, Iran. He received his B.Sc. degree in Manufacturing Engineering from Birjand University, Iran in 2008. He is currently an M.S.c student at the Department of Mechanical Engineering, Ferdowsi University of Mashhad in Iran.