Optimizing Performance of Injection Molding Process Using Fuzzy Goal Programming

Abbas Al-Refaie, Ghaith Bani-Domi, Ammar Essa, Issam S. Jalham

***Abstract*—This research aims to enhance the performance of Injection molding production line (IMPL) using process analytical technology (PAT) framework. The main quality response is can's weight. At initial factor levels, the process capability index value of 1.22 for weight indicates that the IMPL is incapable. Designed experimentation followed by fuzzy goal programming is carried out to determine the combination of optimal factor settings. Confirmation experiments were then conducted at optimal factor settings, where it is found that the IMPL capability is enhanced 1.44. Finally, control charts were established for monitoring future IMPL production. In conclusions, the tools used in the PAT framework are found effective for improving the performance of IMPL.**

Keywords: Fuzzy goal programming; Injection molding; Control charts.

I. INTRODUCTION

Globally, the demand for plastic products has increased rapidly. In plastics manufacturing, there are three types of blow molding; extrusion, injection and stretch. Injection molding production line (IMPL) is widely used for bottle production applied in food beverage, cosmetics and pharmaceutical field. This technology boasts with full automation, stable functioning, high intelligence and efficiency, low cost, no contamination in production, and up to National Hygienic Standard.

Typically, IMPL begins with a plastic resin hot tube called pre-form. The pre-form is placed within a split mold with a hollow cavity. The mold sides are then clamped together, pinching and sealing the pre-form tube. Air is blown into the tube, which expands the hot resin wall into the shape of the cavity.

Then, the mold is cooled with water solidifying the resin into the shape of the part. Finally, the part is ejected from the mold and trimmed.

Producing quality plastic cans, shown in Figure 1, is the main challenge that faces product/process engineers. A manufacturer aims at improving the performance of IMPL, shown in Figure 2, for a plastic can. Variations in can weight may result in production and quality losses. The PAT framework is a combination of tools that, when used within a system, can provide useful means for acquiring information resulting in process continual improvement. Most popular PAT tools are multivariate tools for design, data acquisition and analysis, process analyzers, process control tools, and continuous improvement and knowledge management tools.

The Taguchi method is applied used for obtaining robust design at minimal experimentation effort in a wide range of industrial applications [1]-[3]. However, this method does not consider process engineers' preferences about process settings [4]-[9]. Several formulations of goal programming (GP) models were introduced for solving the fuzzy GP (FGP) problems taking into account the decision maker's preferences. FGP was used for optimal process performance in various fields [10]-[15]. In the IMPL, process engineers seek to determine the combination of process settings while considering preferences on process settings as well as can's weight. Therefore, this paper aims at optimizing the performance of IMPL using PAT framework.

Manuscript received Feb. 20, 2017; revised April,10, 2017.

A. Al-Refaie is with the University of Jordan (corresponding author e-mail: abbas.alrefai@ ju.edu.jo).

G. Domi received master degree in industrial Engineering from the University of Jordan.

A. Essa received master degree in industrial Engineering from the University of Jordan.

I. S. Jalham is a professor with is with the University of Jordan

II. PAT Framework

The PAT framework was implemented to improve the performance of injection treatment process and is described as follows.

A. Identifying critical process attributes

Based on process knowledge, the three main controllable process factors of the IMPL are current torque (x_1) of 67.7%, screw speed (x_2) 64.7rev/min, pressure (x_3) of 70 bars.

B. Control Charts and process capability analysis

The can's weight is considered the nominal-the-best response type. The lower and upper specification limits, LSL and USL, are 30.3 and 29.7 g, respectively. Twenty five samples, each of sample size of two, are collected at the current process settings. The $\bar{x}$ -*R* control charts are established as shown in Figure 3, where both indicate that the IMPL is in statistical control The estimated mean and standard deviation, $\hat{\mu}$ and $\hat{\sigma}$, are 29.863 g and 0.04469g, respectively

.

C. Process Capability Analysis

Capability analysis is used to assess whether a process is statistically capable to meet a set of customer desired product specifications. In practice, the process standard deviation, σ, is unknown and is frequently estimated by Eq. (1).

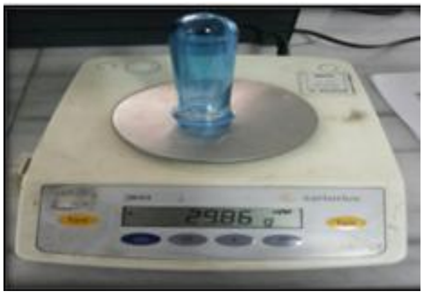
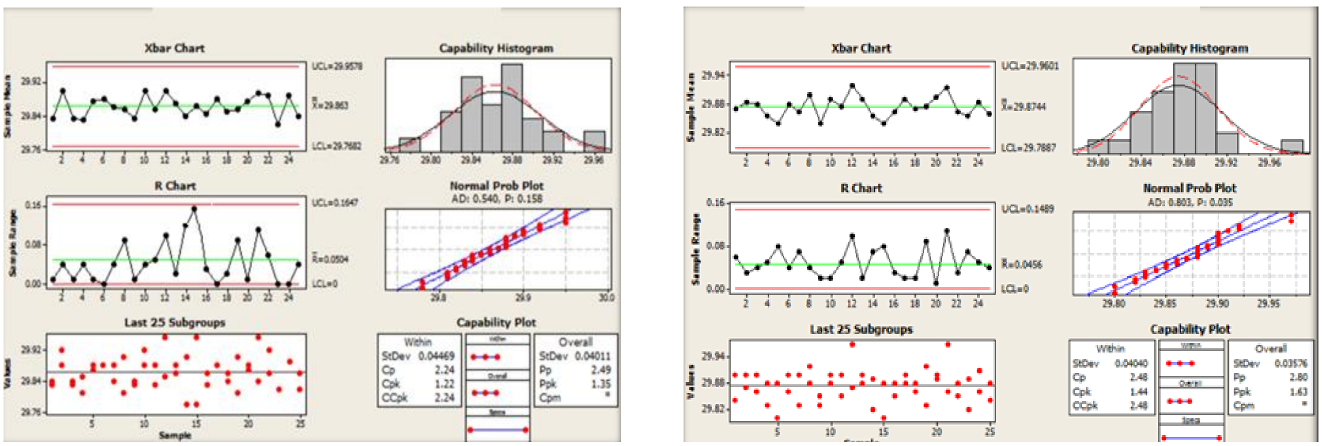


Figure 1. Plastic can.

Figure 2. Injection molding machine.



(a) Initial IMPL settings. (b) Optimal IMPL settings.

Figure 3. The $\bar{x}$ -R charts for can's weight and capability analysis.

$$\hat{\sigma} = \frac{\bar{R}}{d_2} \tag{1}$$

where d_2 is a constant related to the sample size, while $\bar{R}$ is the center line of the R chart. The actual process capability index, C_{pk}, attempts to take the target into account. The C_{pk} estimator, $\hat{C}_{pk}$, can be expressed mathematically by:

$$\hat{C}_{pk} = \min\left\{\frac{\hat{\mu} - LSL}{3\hat{\sigma}}, \frac{USL - \hat{\mu}}{3\hat{\sigma}}\right\} \tag{2}$$

Applying Eq. (2), the estimated process capability is 1.22, which is smaller than the minimal recommended values of 1.33. As a result, the IMPL is concluded incapable of producing conforming cans within weight specifications. Therefore, improvement is needed in IMPL performance by reducing weight variations.

C. Designed experiments

Based on process knowledge, the main factors affecting the wastewater quality characteristics are current torque (%, x_1), screw speed (1/min, x_2) and back presser (bar, x_3). For the present process with three two -level factors, the proper experimental design is the 2^3 full factorial design. Eight experiments will be conducted with two replications. In each experiment, a sample of ten cans is randomly selected and then the weight observations are recorded as shown in Table 1

D. Modeling and prediction

The regression model for can's weight is formulated as follows:

$$\begin{aligned} y = {} & 343 - 4.25x_3 - 4.88x_2 - 4.43x_1 + 0.0662x_3x_2 + 0.0602x_3x_1 \\ & + 0.0691x_2x_1 - 0.000938x_3x_2x_1 \end{aligned} \tag{3}$$

$R^2_{adjusted} = 93.9$, s=000239792, p-value <0.0001

For the average can weight, which is the nominal-the-best type response, the triangular membership function, μ_y, is represented by:

$$\mu_y = \begin{cases} 0, & y < g_y - \Delta_y^- \\ 1 - \dfrac{g_y - y}{\Delta_y^-}, & g_y - \Delta_y^- \le y \le g_y \\ 1 - \dfrac{y - g_y}{\Delta_y^+}, & g_y \le y \le g_y + \Delta_y^+ \\ 0, & y > g_y + \Delta_y^+ \end{cases} \tag{4a}$$

The corresponding constraints are expressed as:

$$y+\rho_y^- - \rho_y^+ = g_y \quad (4b)$$

$$\mu_y + \frac{\rho_y^-}{\Delta_y^-} + \frac{\rho_y^+}{\Delta_y^+} = 1 \quad (4c)$$

$$0 \le \rho_y^+ \le \Delta_y^+ \quad (4d)$$

$$0 \le \rho_y^- \le \Delta_y^- \quad (4e)$$

Then, for can's weight the membership function with the corresponding constraints are formulated as follows:

$$\mu_y = \begin{cases} 0, & y < 29.7 \\ 1-\frac{30-y}{0.3}, & 29.7 \le y < 30, \\ 1-\frac{y-30}{0.3}, & 30 \le y < 30.3, \\ 0, & y \ge 30.3 \end{cases}$$

Let ρ_y^- and ρ_y^+ denote the negative and positive deviation from the can's weight target, then the corresponding constrains are:

$$y+\rho_y^- - \rho_y^+ = 30, \quad (5a)$$

$$\mu_y + \frac{\rho_y^-}{0.3} + \frac{\rho_y^+}{0.3} = 1, \quad (5b)$$

$$0 \le \rho_y^- \le 0.3, \quad (5c)$$

$$0 \le \rho_y^+ \le 0.3, \quad (5d)$$

Since process engineers have no prior information on the exact targets of x_1, x_2, and x_3, the trapezoidal membership function, μ_{x_j}, is chosen to express each process factor and is defined as:

$$\mu_{x_j} = \begin{cases} 0, & x_j < g_{x_j}^l - \partial_{x_j}^-, \\ 1-\frac{g_{x_j}^l - x_j}{\partial_{x_j}^-}, & g_{x_j}^l - \partial_{x_j}^- \le x_j < g_{x_j}^l, \\ 1, & g_{x_j}^l \le x_j < g_{x_j}^u, \\ 1-\frac{x_j - g_{x_j}^u}{\partial_{x_j}^+}, & g_{x_j}^u \le x_j < g_{x_j}^u + \partial_{x_j}^+, \\ 0, & x_j \ge g_{x_j}^u + \partial_{x_j}^+, \end{cases} \quad (6)$$

$$x_j + \omega_x^- \ge g_x^l, \quad (7a)$$

$$x_j - \omega_x^+ \le g_x^u, \quad (7b)$$

$$\mu_x + \frac{\omega_x^-}{\partial_x^-} + \frac{\omega_x^+}{\partial_x^+} = 1, \quad (7c)$$

$$0 \le \omega_x^- \le \partial_x^-, \quad (7d)$$

$$0 \le \omega_x^+ \le \partial_x^+, \quad (7e)$$

where $g_{x_j}^l$ and $g_{x_j}^u$ are the lower and the upper limits of x_j, respectively. The $\partial_{x_j}^-$ and $\partial_{x_j}^+$ are the maximal negative and positive admissible violations from $g_{x_j}^l$ and $g_{x_j}^u$, respectively.

$$x_1 + \omega_{x1}^- \ge 67.5, \quad x_1 - \omega_{x1}^+ \le 74.2, \quad (8a)$$

$$x_2 + \omega_{x2}^- \ge 63.3, \quad x_2 - \omega_{x2}^+ \le 64.7, \quad (8b)$$

$$x_3 + \omega_{x3}^- \ge 70, \quad x_3 - \omega_{x3}^+ \le 75, \quad (8c)$$

$$\mu_{x1} + \frac{\omega_{x1}^-}{0.2} + \frac{\omega_{x1}^+}{0.2} = 1, \quad (8d)$$

$$\mu_{x2} + \frac{\omega_{x2}^-}{0.2} + \frac{\omega_{x2}^+}{0.2} = 1, \quad (8e)$$

$$\mu_{x3} + \frac{\omega_{x3}^-}{1.0} + \frac{\omega_{x3}^+}{1.0} = 1, \quad (8f)$$

$$0 \le \omega_{x1}^{-,+} \le 0.2, \quad (8g)$$

$$0 \le \omega_{x2}^{-,+} \le 0.2, \quad (8h)$$

$$0 \le \omega_{x3}^{-,+} \le 1.0, \quad (8i)$$

The objective function of the model is to minimize the sum of deviations of response and process variables. Accordingly, the objective function is to minimize:

$$Z=3.3(\rho_y^- + \rho_y^+) + 5(\omega_{x1}^- + \omega_{x1}^+) + 5(\omega_{x2}^- + \omega_{x2}^+) + 5(\omega_{x3}^- + \omega_{x_3}^+) \quad (9)$$

Solving the model, the obtained optimal process conditions found are: current torque (x_1) of 67.5%, screw speed (x_2) of 63.3 rev/min, pressure (x_3) of 75 bars. These parameters yield optimal value of weight response 30.03g. The membership values for y, x_1, x_2, and x_3 are 90.099 %, 100 %, 100 %, and 100 %, respectively.

E. Production Control

The $\bar{x}$ -*R* charts are constructed for validation as shown in Figures 3. It is noted that both charts are concluded in statistical control for can's weight and hence, they can be used for monitoring future production. The calculated $\hat{\mu}$ and $\hat{\sigma}$ values are found to be 29.8744 g and 0.0404g, respectively.

III IMPROVEMENT ANALYSIS

Table 2 displays the improvement analysis, where it is noted that:

i. The estimated process mean, $\hat{\mu}$, at the combination of optimal factor settings is 29.8744, which becomes closer to the target value (= 30 gm) than its corresponding value of 29.863 at the combination of initial factor levels.

ii. The estimated variation, $\hat{\sigma}$, reduced from 0.04469gm at initial settings to 0.0404gm at optimal settings.

iii. The process capability index, $\hat{C}_{pk}$, value is improved from 1.22 to 1.44. This result indicates that the IMPL becomes capable.

IV. CONCLUSIONS

The PAT framework is successfully implemented to improve the performance of IMPL. In this framework, the $\bar{x}$ -*R* charts control charts are employed to assess IMPL performance at initial factor settings followed by process capability analysis. A fuzzy goal programming model is then formulated and applied to optimize process settings based on process-engineer's preferences for factor settings and quality response. Results showed that the IMPL capability index is improved from 1.22 to 1.42, and thereby it becomes capable. In conclusion, the PAT framework efficiently optimized IMPL performance.

REFERENCES

[1] G. Taguchi, "Taguchi Methods. Research and Development," Vol. 1, 1991, (American Suppliers Institute Press, Dearborn, Michigan.

[2] J. J. Pignatello, "Strategies for robust multiresponse quality engineering,". IIE Transactions, Vol. 25, 1993, pp. 5–15.

[3] H-C. Lin, C-T. Su, C-C. Wang, B-H. Chang and R-C. Juang, "Parameter optimization of continuous sputtering process based on Taguchi methods, neural networks, desirability function, and genetic algorithms," *Expert Systems with Applications*, Vol. 39(17): 2012, pp. 12918–12925.

[4] A. Al-Refaie, "Optimizing SMT performance using comparisons of efficiency between different systems technique in DEA," *IEEE Transactions on Electronics Packaging Manufacturing*, Vol. 32(4), 2009, pp. 256–264.

[5] A. Al-Refaie, "Super-efficiency DEA approach for optimizing multiple quality characteristics in parameter design. *International Journal of Artificial Life Research*, Vol. 1(2), 2010a, pp. 58–71.

[6] A. Al-Refaie, "A Grey-DEA approach for solving the multiresponse problem in Taguchi Method. Journal of Engineering Manufacture, " Vol. 224(1), 2010b, pp. 147–158.

[7] A. Al-Refaie, "Optimizing correlated QCHs using principal components analysis and DEA techniques. *Production Planning & Control*, " Vol. 22(07), 2011, pp. 676–689.

[8] A. Al-Refaie, and M. Al-Tahat, "Solving the multi-response problem in Taguchi method by benevolent formulation in DEA. *Journal of Intelligent Manufacturing*, Vol. 22(4), 2011, pp. 505–521.

[9] A. Al-Refaie, T. Chen, R. Al-Athamneh, H.C. Wu , " Fuzzy neural network approach to optimizing process performance by using multiple responses," *Journal of Ambient Intelligence and Humanized Computing*, Vol. 7 (6), 2016, pp. 801-816.

[10] A. Al-Refaie, "A proposed satisfaction function model to optimize process performance with multiple quality responses in the Taguchi method. *Journal of Engineering Manufacture*, 2013. doi: 10.1177/0954405413498583.

[11] A. Al-Refaie, "A proposed weighted additive model to optimize multiple quality responses in the Taguchi method with applications," *Journal of Process Mechanical Engineering*, Vol. 228(2), 2014a, pp. 291–301.

[12] A. Al-Refaie, "Optimizing multiple quality responses in the Taguchi method using fuzzy goal programming: modeling and applications," *International Journal of Intelligent Systems*, Vol. 30(6), 2015a, pp. 651–675.

[13] A. Al-Refaie, "Optimal performance of plastic pipes' extrusion process using Min-Max model in fuzzy goal programming," *Journal of Process Mechanical Engineering*, 2015b. doi: 10.1177/0954408915620988.

[14] Al-Refaie A., " FGP model to optimize performance of tableting process with three quality responses," *Transactions of the Institute of Measurement and Control*, Vol. 36(3), 2014b, pp. 336–346.

[15] A. Al-Refaie, M. H. Li, M. Jarbo, C. H.Yeh, and N. Bata, " Imprecise data envelopment analysis model for robust design with multiple fuzzy quality responses," *Advances in Production Engineering & Management*, Vol. 9(2), 2014a, pp. 83–94.

TABLE 1. EXPERIMENTAL DATA.

Exp. *i*	***Process factor***			**Replicate I**										
	x_3	x_2	x_1	1	2	3	4	5	6	7	8	9	10	Average
1	70	63.3	74.4	29.84	29.92	29.83	29.85	29.88	29.9	29.78	29.83	29.88	29.86	29.857
2	70	63.3	67.7	29.87	29.88	29.9	29.85	29.85	29.92	29.95	29.88	29.83	29.83	29.876
3	70	64.7	74.4	29.9	29.88	29.95	29.86	29.82	29.89	29.82	29.84	29.84	29.9	29.87
4	70	64.7	67.7	29.85	29.9	29.86	29.87	29.84	29.83	29.85	29.81	29.86	29.87	29.854
5	75	63.3	74.4	29.87	29.91	29.88	29.81	29.87	29.85	29.9	29.87	29.78	29.91	29.865
6	75	63.3	67.7	29.83	29.82	29.87	29.9	29.8	29.85	29.9	29.88	29.83	29.86	29.854
7	75	64.7	74.4	29.85	29.89	29.8	29.87	29.83	29.87	29.81	29.88	29.81	29.84	29.845
8	75	64.7	67.7	29.76	29.83	29.84	29.93	29.85	29.88	29.83	29.9	29.82	29.87	29.851
Replicate II														
1	70	63.3	74.4	29.9	29.84	29.86	29.87	29.86	29.81	29.86	29.9	29.82	29.88	29.86
2	70	63.3	67.7	29.88	29.92	29.87	29.84	29.88	29.87	29.91	29.87	29.86	29.89	29.879
3	70	64.7	74.4	29.91	29.79	29.86	29.83	29.85	29.89	29.9	29.86	29.84	29.91	29.864
4	70	64.7	67.7	29.83	29.8	29.87	29.94	29.8	29.85	29.9	29.84	29.85	29.86	29.854
5	75	63.3	74.4	29.84	29.96	29.85	29.85	29.94	29.77	29.84	29.88	29.83	29.84	29.860
6	75	63.3	67.7	29.84	29.92	29.83	29.85	29.88	29.9	29.78	29.83	29.88	29.86	29.857
7	75	64.7	74.4	29.93	29.89	29.8	29.88	29.81	29.84	29.87	29.79	29.85	29.81	29.847
8	75	64.7	67.7	29.8	29.82	29.84	29.92	29.84	29.88	29.83	29.9	29.81	29.87	29.851

TABLE 2. IMPROVEMENT SUMMARY.

Process settings	$\hat{\mu}$	$\hat{\sigma}$	$\hat{C}_{pk}$	Process condition
Initial	29.863	0.04469	1.22	incapable
Optimal	29.8744	0.0404	1.44	Capable