Simultaneous optimization of variable injection velocity profile and process parameters in plastic injection molding for minimizing weldline and cycle time

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Abstract
Weldline that is formed when two or more melt fronts meet is one of the major defects in plastic injection molding (PIM), which has an influence on not only the appearance but also the strength of a plastic product. Consequently, it is preferable to reduce it as much as possible for high product quality. On the other hand, high productivity is always required in the PIM. In other words, cycle time should be minimized. To achieve the high product quality and productivity, process parameters such as melt temperature, cooling time and so on plays an important role. In this paper, the process parameters in PIM are optimized for minimizing the weldline and the cycle time simultaneously. In particular, variable injection velocity that the injection velocity varies during the PIM process is adopted and optimized. A novel weldline evaluation is also proposed. Numerical simulation in PIM is so intensive that a sequential approximate optimization (SAO) using radial basis function (RBF) network is adopted for the design optimization. It is found from the numerical result that the trade-off between the weldline reduction and the cycle time is observed. Based on the numerical result, the experiment using the PIM machine (GL100, Sodick) is carried out. Through the numerical and experimental result, the validity of the proposed approach is examined.

Keywords: Plastic injection molding, Engineering optimization, Multi-objective optimization, Weldline reduction, Computer aided engineering

1. Introduction

Plastic injection molding (PIM) is a major manufacturing technology to produce plastic products. The PIM consists of three processes: filling, packing and cooling process. In the filling process, the melt plastic is filled into the cavity. Conventionally, the melt plastic is packed with a constant pressure in the packing process. Finally, the melt plastic is cooled down for solidification in the cooling process. High product quality is required in the PIM, and major defects such as warpage, volume shrinkage, short shot and weldline should be minimized or avoided, whereas high productivity is always required. In other words, cycle time is minimized in the PIM. Trade-off between the product quality and the productivity is generally observed, and process parameters such as melt temperature, injection velocity, packing pressure, packing time, cooling temperature and cooling time should be adjusted and optimized for the high product quality and productivity. Recently, computer-aided engineering (CAE) coupled with design optimization technique has been recognized as one of the powerful tools available and many papers have been published (Kurtaran
Weldline that is formed when two or more melt fronts meet is one of the major defects, which has an influence on not only the gloss appearance but also the strength of product. Then, it is important to reduce it for the high product quality. Li et al. optimized the melt temperature and the injection velocity for weldline reduction using Taguchi method (Li et al., 2007). Kim et al. also optimized several process parameters (the melt temperature, the mold temperature and the injection velocity) for weldline reduction using Taguchi method (Kim et al., 2017). Deng et al. optimized several process parameters (mold temperature, melt temperature, and injection time) for minimizing warpage, weldline and air trap of a power outlet plastic product using multi-objective particle swarm optimization (Deng et al., 2008). Shayfull et al. and Ozcelik pointed out that the melt temperature and the injection velocity were effective parameter to the weldline strength (Shayfull et al., 2011; Ozcelik, 2011). Liu et al. determined the melt temperature, the mold temperature, the injection velocity, the injection time and the packing pressure to maximize the weldline strength using Taguchi method (Liu et al., 2000). It is found from the above brief review that the process parameters optimization is still a crucial issue, and that a high injection velocity will be effective to weldline reduction. However, the high injection velocity results in short shot that the melt plastic is not filled into the cavity. On the other hand, a low injection velocity is valid for avoiding the short shot (Moayyedian et al., 2017), which makes the weldline long. A constant injection velocity is conventionally used, but an innovative approach using variable injection velocity is proposed in order to reduce the weldline without short shot. Let us explain this approach using Fig. 1, in which a high injection velocity is used at the beginning for weldline reduction, and the injection velocity gradually decreases for avoiding the short shot. To conduct the variable injection velocity in the experiment, the plunger position is updated during the injection process. To reduce the weldline without the short shot, it is important to determine the optimal injection velocity profile ($v_{inj1}$, $v_{inj2}$, and $L$ in Fig. 1) with an intelligent manner.

Next, let us consider the weldline evaluation. The weldline length is conventionally used to evaluate the weldline in the literature (Kim et al., 2017; Shayfull et al., 2011; Deng et al., 2008), but this method completely depends on the finite element analysis model (mesh size). Unlike them, Kitayama et al. focused on the weldline temperature for weldline reduction (Kitayama et al., 2018a), in which the weldline temperature was maximized. However, for further weldline reduction, a novel weldline evaluation considering the weldline temperature should be developed.

Here, let us summarize several issues to resolve in this paper.

1. Variable injection velocity that the injection velocity varied during PIM is adopted for the weldline reduction without the short shot (See Fig. 1).

Next, let us consider the weldline evaluation. The weldline length is conventionally used to evaluate the weldline in the literature (Kim et al., 2017; Shayfull et al., 2011; Deng et al., 2008), but this method completely depends on the finite element analysis model (mesh size). Unlike them, Kitayama et al. focused on the weldline temperature for weldline reduction (Kitayama et al., 2018a), in which the weldline temperature was maximized. However, for further weldline reduction, a novel weldline evaluation considering the weldline temperature should be developed.

Fig. 1 Illustrative example of variable injection velocity.

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2. A novel weldline evaluation considering the weldline temperature and the injection time is proposed, which is maximized for weldline reduction. On the other hand, the cycle time is minimized for high productivity.

3. A multi-objective optimization is performed, in which the variable injection velocity profile as well as several process parameters are optimized. The SAO using radial basis function (RBF) network is adopted for the design optimization tool (Kitayama, et al., 2011).

4. To examine the validity of the proposed approach, the experiment based on the numerical result is carried out.

The rest of paper is organized as follows. In section 2, the numerical simulation model is described. In section 3, the multi-objective optimization is explained. In section 4, the numerical and experimental result is shown. Moldex3D (R16) is used for the PIM numerical simulation.

2. Numerical simulation model

A target product shown in Fig. 2 is considered in this paper, in which the thickness of side wall is 0.35 mm and the height of the product is 30.7 mm. Figure 3 shows the flow process of melt front and weldline. As shown in Fig. 3(a), the melt plastic flows into side wall. Then, the melt front meets as shown in Fig. 3(b), and finally the weldline is produced as shown in Fig. 3(c). Liquid Crystal Polymer resin (LCP) is used as the material, and the material property is listed in Table 1. Conformal cooling channel is used for improving the productivity and the product quality (weldline), and the overview is shown in Fig. 4, in which the enlarged view enclosed by the black circle is shown in Fig. 4(b). The diameter of conformal cooling channel is 8.00 mm.

![Fig. 2 Overview of target product and the dimensions.](image)

![Fig. 3 Flow process and weldline.](image)

![Fig. 4 Conformal cooling channel used in this paper.](image)

| Table 1 Material property of LCP resin. |
|----------------------------------------|
| Density [g/cm$^3$] | 1.61 |
| Eject temperature [℃] | 247 |
| Elastic module [GPa] | 15 |
| Poisson ratio | 0.3 |
| Material characteristic | Crystalline |
| Recommend mold temperature [℃] | 80-120 |
| Recommend melt temperature [℃] | 325-345 |
3. Multi-objective optimization for weldline reduction and short cycle time

3.1 Multi-objective optimization

A multi-objective optimization is generally formulated by Eq. (1) (Miettinen, 1998).

\[
\begin{align*}
    (f_1(x), f_2(x), \ldots, f_k(x)) & \rightarrow \min \\
    x_i^l \leq x_i \leq x_i^u & \quad i = 1, 2, \ldots, n \\
    g_j(x) & \leq 0 \quad j = 1, 2, \ldots, n_{con}
\end{align*}
\]

(1)

where \(f_i(x)\) is the \(i\)th objective function to be minimized, \(k\) represents the number of objective functions, \(x = (x_1, x_2, \ldots, x_n)^T\) is the design variables, \(x_i\) denotes the \(i\)th design variable, \(x_i^l\) and \(x_i^u\) are the lower and upper bounds of the \(i\)th design variable, \(n\) represents the number of design variables, \(g_j(x)\) denotes the \(j\)th design constraint, and \(n_{con}\) represents the number of design constraints. When the \(j\)th objective function \(f_j(x)\) is to be minimized, it is equivalent to minimize the function \(-f_j(x)\).

3.2 Design variables (Process parameters)

In this paper, the melt temperature \((T_{melt} [\degree C])\), the packing pressure \((P [\text{MPa}])\), the packing time \((t_{pack} [\text{s}])\), the cooling temperature \((T_{cool} [\degree C])\) and the cooling time \((t_{cool} [\text{s}])\) are taken as the design variables. High injection velocity is effective to the weldline reduction, that results in the short shot. On the other hand, to avoid the short shot, low injection velocity is useful, that makes the weldlines long (Li et al., 2007; Moayyedian et al., 2017). For the weldline reduction without the short shot, variable injection velocity approach that the injection velocity \(v_{inj}\) varied is adopted. The illustrative example has been given in Fig. 1. At the beginning of injection process, high injection velocity is used for the weldline reduction. After that, to avoid the short shot, the injection velocity gradually decreases. The profile is unknown in advance, and this optimal profile is determined. The design variables in the variable injection velocity profile are the injection velocity \((v_{inj} [\text{mm/s}])\) and the plunger position \((L [\text{mm}])\). \(L_{max} [\text{mm}]\) in Fig. 1 denotes the maximum distance of plunger. As the result, the design variables \(x\) is given as \(x = (T_{melt}, P, t_{pack}, T_{cool}, t_{cool}, L, v_{inj}^1, v_{inj}^2)^T\). The lower and upper bounds of design variables are given by Eq. (2).

\[
\begin{align*}
    325 & \leq T_{melt} \leq 360 \\
    50 & \leq P \leq 80 \\
    1.0 & \leq t_{pack} \leq 10 \\
    80 & \leq T_{cool} \leq 120 \\
    3.0 & \leq t_{cool} \leq 20 \\
    1.5 & \leq L \leq 6.5 \\
    100 & \leq v_{inj}^1 \leq 250 \\
    10 & \leq v_{inj}^2 \leq 100
\end{align*}
\]

(2)

The lower and upper bounds of design variables are determined as follows:

The melt temperature \((T_{melt})\), the cooling temperature \((T_{cool})\) and the cooling time \((t_{cool})\): The recommended value in Moldex3D is used.

The packing pressure \((P)\): The recommended value in Moldex3D is used for the lower bound. On the other hand, the mold will be damaged when over 80 MPa is applied, and then the upper bound is set to 80 MPa.

The packing time \((t_{pack})\): The lower and upper bounds are determined by considering the gate seal time.

The variable injection velocity profile \((v_{inj}^1, v_{inj}^2\) and \(L)\): Through the trial and error method, the relationship between \(v_{inj}^1\) and \(v_{inj}^2\) show in Fig. 1 was clarified. Consequently, they are determined through the process.

3.3 Objective functions

Shayfull et al. suggested that the injection time was one of the important factors for weldline reduction (Shayfull et al., 2011), and Kitayama et al. reported that it was possible to reduce the weldline by maximizing the weldline temperature (Kitayama et al., 2018a). Based on their works, a novel weldline evaluation is proposed in this paper.

First, let us examine the effect of injection time on the weldline. Note that the symbol \(t_{inj} [\text{s}]\) denotes the injection time. Figure 5 shows the numerical result using different injection time under fixed process parameters, which are listed in Table 2.
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Table 2 Process parameters to examine the effect on weldline

| $T_{melt}$ [°C] | $P$ [MPa] | $t_{pack}$ [s] | $T_{cool}$ [°C] | $t_{cool}$ [s] |
|-----------------|-----------|--------------|----------------|--------------|
| 325             | 50.0      | 3.00         | 100            | 10.0         |

Fig. 5 Weldline using different injection time

It is clear from Fig. 5 that the shorter the injection time is, the shorter the weldline is. However, it should be noted that the shorter injection time will lead to the short shot. A constant injection velocity is widely used in the literature, but the variable injection velocity is used, in which the injection time is given by Eq. (3).

$$t_{inj} = \frac{L}{v_{inj}} + \frac{2(L_{max} - L)}{v_{inj} + v_{2}}$$

Next, let us examine the effect of weldline temperature on the weldline. Note that the minimum weldline temperature is simply called the weldline temperature in this paper, and the symbol $T_{weld}$ [°C] is used. Figure 6 shows the relation between the weldline and the weldline temperature, from which it is found that the higher the weldline temperature is, the shorter the weldline is.

Based on the above examination, a novel weldline evaluation of the target product shown in Fig. 2 is given by Eq. (4), which is selected as the first objective function $f_1(x)$ to be maximized.

$$f_1(x) = \frac{T_{weld}}{t_{inj}} \rightarrow \text{max}$$

Next, let us consider the cycle time for the productivity. The cycle time is simply evaluated by the sum of the injection time $t_{inj}$, the packing time $t_{pack}$ and the cooling time $t_{cool}$, which is given by Eq. (5) and is selected as the second objective function $f_2(x)$ to be minimized.

$$f_2(x) = t_{inj} + t_{pack} + t_{cool} \rightarrow \text{min}$$

3.4 Design constraint

Short shot that the melt plastic is not filled into the cavity is a fatal defect in the PIM, and this should strongly be avoided. This is then taken as the design constraint. The illustrative example of short shot in the numerical simulation...
and the experiment is shown in Fig. 7. The target product has the thin wall, and then the inappropriate process parameters easily cause the short shot. In addition, high injection velocity for weldline reduction easily leads to the short shot. Equation 6 is used to numerically evaluate the short shot.

\[ V_s = 1 - \frac{V}{V_c} \]  

(6)

where \( V \) and \( V_c \) denote the melt plastic volume shown in Fig.7(a) and the cavity volume, respectively. Equation 6 represents the ratio of the unfilled volume to the cavity volume, and the positive value of Eq. (6) indicates the occurrence of short shot. The design constraint \( g_1(x) \) is then evaluated as follow.

\[ g_1(x) = \begin{cases} V_s & V_s > 0 \\ 0 & \text{Otherwise} \end{cases} \]

![Melt plastic volume (V)](image)

![Unfilled volume](image)

(a) Numerical simulation

(b) Experiment

Fig. 7 Illustrative example of short shot in numerical simulation and experiment.

### 3.5 Sequential approximate optimization

In this paper, the multi-objective design optimization is formulated, and the main aim is to identify the pareto-frontier between objectives with a small number of simulation. The SAO using the RBF network is adopted for the design optimization, and see the detailed procedure is described in (Kitayama, et al., 2011). In this section, the procedure to identify the pareto-frontier is briefly described.

**STEP1** The Latin hypercube design (LHD) is used to generate initial sampling points.

**STEP2** The numerical simulation using Moldex3D (R16) is carried out at the sampling points. The objective functions and the design constraint is numerically evaluated.

**STEP3** The objective functions and the design constraint are approximated by the RBF network. Here, the approximated objective functions are denoted as \( \hat{f}_k(x) \) \((k = 1, 2, \ldots, k)\), and the approximate design constraint is denoted as \( \hat{g}_1(x) \).

**STEP4** The pareto-optimal solutions are determined by the weighted \( lp \) norm method formulated as follows.

\[
\min \left[ \sum_{k=1}^{k} \left( \alpha_g \hat{f}_k(x) \right)^{\frac{1}{p}} \right] \\
\text{s.t.} \quad x_i^L \leq x_i \leq x_i^U \quad i = 1, 2, \ldots, n \\
\hat{g}_1(x) \leq 0
\]  

(8)

where \( \alpha_g(q = 1, 2, \ldots, k) \) represents the weight of the \( k \)th objective function, and \( p \) is the parameter, which is set to 4 referring to (Kitayama et al., 2017b). To obtain a set of pareto-optimal solutions, various weights are assigned.

**STEP5** If a terminal criterion is satisfied, the SAO algorithm will be terminated. Otherwise, the pareto-optimal solutions are added as the new sampling points for improving the accuracy of the pareto-frontier. As the result, the number of sampling points is updated. Then, return to STEP2.

The flow is shown in Fig. 8. The average error between the response surface and the numerical simulation at the pareto-optimal solutions is taken as the terminal criterion. The SAO algorithm will be terminated when the average error is within 5%.
4. Numerical and experimental result

To examine the validity of the proposed approach, at first, numerical optimization using the SAO is carried out and the pareto-frontier is identified. Then, based on the numerical result, the experiment is also carried out. Therefore, the validity of the proposed approach is examined through the numerical simulation and the experiment. \( L_{\text{max}} \) in Fig. 1 is set to 7.5 mm by considering the shape of the target product.

4.1 Numerical result

Twenty initial sampling points are generated by the LHD and the pareto-frontier between Eqs. (4) and (5) is identified by using the SAO described in section 3.5. The pareto-frontier is shown in Fig. 9 with the weldline, in which the black dots denote the pareto-optimal solutions using the variable injection velocity and the white squares denote the ones using the constant injection velocity, respectively. To identify the pareto-frontier, 33 simulations are required. The aim of multi-objective optimization is to identify the pareto-frontier between conflicting objectives given by Eqs. (4) and (5), and all solutions in Fig. 9 are effective under the two objectives and the selected process parameters given by Eq. (2). To determine the optimal process parameters with a small number of simulations, the SAO is adopted.

It is found from Fig. 9 that the trade-off between the objective functions is observed. Among the pareto-optimal solutions, three points (points A, B and X in Fig. 9) are selected for the comparison. It is found from Fig. 9 that the weldline by the proposed approach (points A and B) is shorter than the one by the conventional one (point X). Therefore, the weldline can drastically be reduced by the proposed approach. The variable injection velocity profiles at points A and B are shown in Fig. 10 with the constant injection velocity at point X, from which it is confirmed that our assumption that high injection velocity would be effective to the weldline reduction and the injection velocity gradually decreases for avoiding the short shot is valid. The pareto-optimal solutions at points A, B and X are listed in Table 3, from which it is found that the injection time \( t_{\text{inj}} \) by the proposed approach is much short. The melt temperature \( T_{\text{melt}} \) by the proposed approach is higher that by the conventional one, but the cooling time \( t_{\text{cool}} \) among three points is so close. When the melt temperature is high under same cooling time, it is assumed that the weldline temperature would be high. This result indicates that Eq. (4) is valid for the weldline reduction.

![Fig. 9 Pareto-frontier and weldline.](image_url)
Fig. 10 Optimal variable injection velocity profile at points A and B.

Table 3 Optimal process parameters at point A, B and X in Fig. 8.

|       | $v_{inj1}$ [mm/s] | $v_{inj2}$ [mm/s] | L [mm] | $T_{melt}$ [°C] | P [MPa] | $I_{pack}$ [s] | $T_{cool}$ [°C] | $t_{cool}$ [s] | $t_{inj}$ [s] |
|-------|-------------------|-------------------|--------|-----------------|--------|----------------|-----------------|----------------|---------------|
| A     | 225.3             | 95.2              | 3.22   | 353             | 51.8   | 4.9            | 89.5            | 15.2           | 0.032         |
| B     | 203.2             | 97.5              | 3.84   | 355             | 55.2   | 4.7            | 91.5            | 13.5           | 0.039         |
| X     | 122.9             | -                 | 339    | 76.6            | 6.5    | 93.8           | 15.0            | 0.061         |

Finally let us examine the temperature distribution of target product, which is shown in Fig. 11. It is found from Fig. 11 that the temperature is uniformly distributed due to the conformal cooling channel, but the lower temperature distribution can be achieved by the proposed approach. This will be useful for high product quality such as warpage reduction (Kitayama et al., 2017a).

Fig. 11 Temperature distribution of target product after cooling process at points A, B and X.

4.2 Experimental result

The numerical result shows the validity of the proposed approach. To examine the validity of the proposed approach, the experiment using the PIM machine (GL-100, Sodick) in Fig. 12 is carried out. Note that, in the experiment, the weldline temperature is not measured and we cannot evaluate the value of objective function correctly. Therefore, the experiment is carried out using the optimal process parameters listed in Table 3.

Points A, B and X in Fig. 9 are selected for the experiment. The experimental result is shown in Fig. 13 with the numerical result, in which the red line represents the weldline in the experiment. The weldline length in the experiment is approximately measured and the comparison is listed in Table 4, from which it is found that the weldline length in the experiment does not coincide with the numerical result. However, it is found from Fig. 13 that the weldline at point A is shorter than the others, whereas the one at point X is long. This completely coincides with the numerical result. Figure 14 shows the variable injection velocity at points A and B, in which the red line denotes the injection velocity in the experiment and the blue line denotes the one in the numerical result. It is found from Fig. 14 that, due to the short injection time, it is difficult to control the injection velocity exactly in the experiment like the numerical result. However, it is confirmed that the weldline can be reduced by the proposed approach.
5. Conclusions

In this paper, the simultaneous design optimization of variable injection velocity profile and process parameters in PIM for minimizing weldline and cycle time has been performed. In addition, the novel evaluation for weldline using the minimum weldline temperature and the injection time has been proposed. The optimal variable injection velocity profile as well as other several process parameters have been determined by the SAO using the RBF network. As the result, the pareto-frontier between weldline and cycle time has been identified. In addition, it has been found that the variable injection velocity was effective to the weldline reduction without the short shot. Based on the numerical result, the experiment using the PIM machine (GL100, Sodick) has been conducted. Through the numerical and experimental
result, the validity of the proposed approach has been confirmed.

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