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Automated Molding Design Methodology to Optimize Multiple Defects in Injection Molded Parts

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ABSTRACT

Plastic molding designers are frequently faced with optimizing multiple defects in injection molded parts. These defects are usually in conflict with each other, and thus a tradeoff needs to be made to reach a final compromised solution. In this study, an automated injection molding design methodology has been developed to optimize multiple defects of injection molded parts. Two features of the proposed methodology are as follows: one is to apply the utility theory to transform the original multiple objective optimization problem into single objective optimization problem with utility as objective function, the other is an implementation of a direct search-based injection molding optimization procedure with automated consideration of process variation. The modified complex method is used as a general optimization tool in this research. The developed methodology was applied to an actual molding design and the results showed that the methodology was useful through the CAE simulation using a commercial injection molding software package. Applied to production, this study will be of immense value to industry in reducing the product development time and enhancing the product quality.

Key Words: Injection molded parts, multiple objective optimization, utility theory, modified complex method

1. Introduction

1.1 Objective

The injection molding process, carried out by a consecutive five-stage with plastication, filling, packing, cooling, and ejection, is one of the most commonly used methods of processing polymers[1]. This process is a complex but highly efficient means of producing a wide variety of three-dimensional thermoplastic parts in a large production volume.

Many parts manufactured by injection molding suffer from a wide range of defects. These defects may include warpage, shrinkage, weld and meld lines, flow mark, flash, sink mark, and void[1]. However, the design against defects in injection molded parts is very difficult. Molded part quality is related to molding parameters of the design space such as material, mold, part, and process conditions, through the complex multi-dimensional and nonlinear relationships[2]. In this multi-dimensional and nonlinear design domain, the design procedure is multifaceted and thus a number of technically feasible design solutions may coexist for the same application. Moreover, designers are frequently faced with multiple defects in injection molded parts. These defects are usually in conflict with each other, and thus a tradeoff should be made to obtain a compromised solution. The design difficulty is further increased with the addition of process variation that is inherently inevitable. Since the variation of process variables induces variation of rheological and thermal behavior of the melt and hence change the filling and postfilling characteristics, the process variation can result in significant quality variation in the molded part[2]. Due to these difficulties, traditional efforts for injection molding design focus on a trial-and-error approach.

Currently, injection molding CAE simulation is widely accepted as a design tool for predicting the defects in molded parts without actually fabricating a mold. However, the contemporary CAE simulation requires the mold designer still to run the simulation, perform the design evaluation, and redesign based on experience, until a satisfactory design is obtained. This manual design process appears ineffective and does not guarantee the optimal design solution and so has led to an increasing interest in the automated injection molding design.

The objective of this study is to develop a methodology to obtain optimal robust design solutions automatically, minimizing the conflicting multiple defects in injection molded parts. In this study, a combined consideration of optimality and robustness of design solution is of great importance because the injection molding process inherently has significant process variability as described earlier. The optimal robust solution is defined as a solution with possible highest functional value and lowest deviation against this value.

The significance of the developed methodology is the synthesis of a computer simulation of injection molding process, a multiple objective optimization technique, Taguchi method, and a direct search-based optimization scheme into a monolitic part quality system. As a multiple objective optimization technique, a utility theory is introduced that provides an effective means to achieve the designer's subjective preferences for the conflicting multiple defects in molded parts and a tradeoff between the part defects in order to obtain a desired optimal solution. By implementing this theory, a performance of a design, called utility, or desirability, is obtained, which is regarded as the objective function value to be optimized in the methodology. In addition, a performance measure called signal to noise(S/N) ratio[3,4], which is proposed by Taguchi[3,4], is incorporated in the methodology to select the optimal robust design that aims to meet the possible highest objective function value, or optimality, but to minimize the expected variability in the value, or robustness. Furthermore, a modified complex method based on direct search procedure is developed and implemented to automatically search for the optimal robust solutions in design space.

For the purpose of applying the proposed methodology to an actual injection molding design, the Cavallero's capacitor can part[2] was chosen for the warpage and weld line optimization. The results showed that the methodology was useful through the CAE simulation using a commercial injection molding software package. Applied to production, this research will be of immense value to industry in reducing the product development time and enhancing the product quality.

1.2 Related work

Recent researches in the optimization of the defects in injection molded parts have been extensively carried out[2,5,6-13]. Pandelidis and Zou[8] presented a method to solve an injection molding problem using an optimization approach. They used the sequential unconstrained minimization technique (*SUMT*) integrated with flow simulation software. The objective function was the sum of a temperature difference term, an overpack term and a frictional heating term with an weighting factor. Kim[9] described a method for optimizing molding conditions, which consist of temperature difference, melt temperature, and filling time, based on the results from flow simulation. He used the genetic algorithm, as a optimization tool. However, neither of Pandelidis etc.[8] and Kim[9] took into account the packing and cooling process in the optimization process. Lee and Kim[12] made an attempt to reduce the part warpage using the concept of deliberately varying part wall thicknesses. In that research, the wall thicknesses were optimized first, and then the process conditions were optimized, based on the modified complex method. Lee and Kim[13] showed that varying wall thicknesses within dimensional tolerances could considerably reduce the part warpage. They showed that the varying wall thickness design model obtained by Taguchi method had better warpage characteristics, compared with constant wall thickness design model. Yao and Kim[14] developed an automated design methodology for minimization of weld lines by optimizing the part and mold design. A combined implementation of the complex method and injection molding simulation was done to reduce and relocate the weld line.

2. Multiple objective optimization techniques

As described in the section 1.1, multiple defects in injection molded parts are usually in conflict with each other, and thus a tradeoff should be made to find a compromised solution. Hence, a problem of optimizing such multiple defects in injection molded parts belongs to the multiple objective optimization problem.

Multiple objective optimization techniques can be broadly classified into generating methods and preference based methods[15,16]. Generating methods have been developed to enumerate the exact non-inferior (Pareto-optimal) or an approximation of it. However, a major drawback of all the methods is that most realistic problems are too large to allow the exact non-inferior set to be found and, even if it were generated, the set would include too many alternatives for the designer's consideration.

Preference based methods, on the other hand, attempt to quantify the designer's preference for each criterion and use this associated information to obtain a single super criterion that results in a single optimal preference based design. The utility theory is such a method widely used in decision analysis in engineering design. Originally devised for economic applications and later developed for design purposes, the utility theory provides a formal analytical method for obtaining the utility, or the goodness, of a design with the rule of "the larger the better"[17]. This approach permits design to pend conditions of uncertainty as well as the designer to enter his own subjective preferences into the design problem in a quantitative fashion. Thus it simplifies decisions such as making complex tradeoffs among conflicting attributes. Recent works showing its potential usefulness to mechanical design can be found in literatures [15,18,19]. With these backgrounds, the utility theory is used in this study to optimize the conflicting defects, or attributes, in injection molded parts. By implementing the utility theory, the multiattribute utility function that will provide a utility for overall design characterized by multiple attributes is developed. This utility is a single performance of a design with all attributes considered and it is regarded as the objective function value to be optimized in the methodology. In the following section, a new procedure for determining the multiattribute utility function is developed and presented.

3. Determination of utility function

The utility function can be defined as a function describing the utility of a design alternative which characterized by multiple attribute values, whose utility has a numerical value between 0 and 1 according to the designer's preference[15,17,19].

The overall multiattribute utility (*MAU*) is calculated from equation (1) derived by Keeney and Raiffa[17], given conditions of utility independence of attributes. Utility independence means that the degree of nonlinearity of utility over each attribute range is not affected by other attribute levels.

$$U(\boldsymbol{x})=\frac{1}{K}\left[\ \left[\ \prod_{i=1}^{n}(Kk_iU_i(x_i)+1\ \right]-1\ \right] \quad (1)$$

where

$U(\boldsymbol{x})$ = *MAU* of an alternative characterized by attribute vector $\boldsymbol{x}=(x_1, x_2, \ldots, x_n)$,

x_i = performance level of attribute i,

$U_i(x_i)$ = single attribute utility (*SAU*) function for attribute i,

i = $1,\ 2, \ldots, n$ attributes,

k_i = single attribute scaling constant, and

K = normalizing constant, derived from

$$1+K=\prod_{i=1}^{n}(1+Kk_i) \quad (2)$$

General assumptions on the utility independence are appropriate in many realistic problems, and they are operationally evident in practice[17]. The *MAU* function for the simplest case of the problem with two attributes, which are utility independent, is presented from the equation (1) and (2) as follows:

$$MAU = k_1 \cdot U_1 + k_2 \cdot U_2 + (1 - k_1 - k_2) \cdot U_1 \cdot U_2 \tag{3}$$

In order to evaluate the *MAU* function of the equation (1) or (3), the *MAU* function variables, i.e., *SAU* functions for each attribute and scaling constants should be defined first.

The conventional development of the utility function for engineering design applications often requires two major steps of first determining *SAU* functions, and using this information as the basis to build the *MAU* function. With utility values of $U_{best} = 1$ defined to the best preference for an attribute function and $U_{worst} = 0$ for the least preference, the *SAU* is developed to describe the designer's compromise between two extremes based on one's priority reflected answers on the lottery questions[15,17,19]. Finally, the combination of the assessed *SAU*'s by scaling constants yields the *MAU*. Here, scaling constants reflect the designer's preferences on attributes and can be acquired based on scaling constant lottery questions[15,17,19]. With such an intuitive approach, however, preference data are not usually provided by the designer in a consistent way due to a lack of precise knowledge regarding the gradient directions of the value functions and thus subjected to considerable preference errors[19, 20]. Therefore, there exists a need to provide an efficient measurement technique assisting the designer in identifying and eliminating any inconsistent preference information, and finally in obtaining the *MAU* function with more accurate preference reflection among attributes.

In order to obtain the *MAU* function, a new procedure for determining the *MAU* function variables, i.e., all the variables defining *SAU*'s and scaling constants, is established in this study. A feature of this procedure includes an integration of a preference learning process based on the *Analytic Hierarchy Process* (*AHP*)[21], an optimization technique and its employment in the estimation of those variables. The *AHP*, developed by Satty[21], is a decision-aiding method which aims at quantifying relative priorities for a given set of design alternatives on a ratio scale[22]. The method links the design alternatives to a hierarchy of attributes and elicits from the designer a set of pairwise comparisons of the attributes at each level of the hierarchy. These pairwise comparisons are used to compute relative weights of the attributes. After synthesized these relative weights, they are aggregated up the hierarchy to obtain a rank of the preferential order of the alternatives. Fig. 1 represents a sample hierarchy model of evaluating the alternatives. More detailed informations of the *AHP* are presented in literatures [21,22].

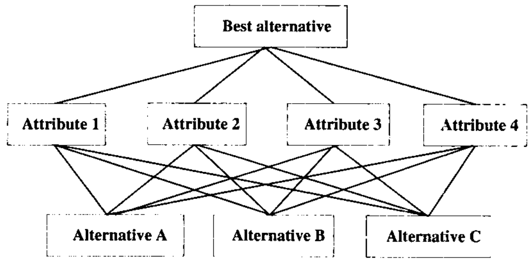


Fig. 1 Sample *AHP* model for three alternatives.

Along with the equation (3), the procedure for evaluating the *MAU* function in this research can be explained as follows:

[Step 1] Model the function form to employ the *SAU* function of attributes and its variables. Among the several forms of *SAU* functions for attributes commonly used in practice, Bezier curve[23] is chosen in this research because of its generality and potential to reflect the designer's nonlinear preference. Mathematically, for *n+1* control points, the Bezier curve is defined by the following polynomial of degree *n*:

$$P(u) = \sum_{i=0}^{n} \frac{n!}{i!(n-i)!} u^i (1-u)^{n-i} P_i \tag{4}$$

where u is the parameter, $P(u)$ any point on the curve, and P_i the control point. Fig. 2 shows an example of cubic Bezier curve used in this study as a form of the *SAU* function. In the figure, x_0 and x_3 denote the best preferred value and the worst value of the attribute *X*, respectively, then $[x_0, x_3]$ represents the overall acceptable design space. The design space is given through Taguchi's orthogonal array based experiments and designer's judgements. Here, the end control points, P_0 and P_3, are fixed at $U_{best}=1$ and $U_{worst}=0$, respectively, and hence the shape of curve is controlled by only the interior points, P_1 and P_2. However, we intend to determine the shape of curve using only the y-coordinate of the interior points, while setting the x-coordinates at constant attribute values, x_1 and x_2, respectively, in the overall acceptable design space. Coordinates, x_1 and x_2, are selected such that they are located with the same interval in the overall acceptable design space. For another attribute, the form of the *SAU* function can be defined through a procedure similar to the above. Therefore, the *MAU* function for two attributes is uniquely defined by six unknowns, i.e., y-coordinates of the interior control points to reflect each *SAU* function and two scaling constants.

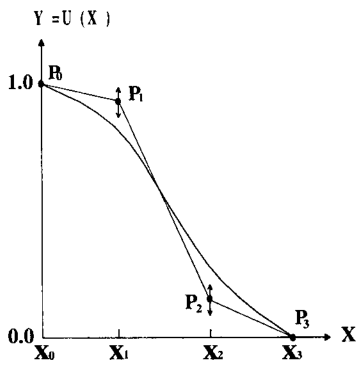


Fig. 2 Example of Bezier curve of degree 3.

[Step 2] Generate a set of non-inferior design alternatives given in form of the combination of multiple attribute values, which will be later ranked through the *AHP*. To ensure a fairly good approximation accuracy in the overall acceptable design space, design alternatives are selected such that their attribute values are located in the overall acceptable design space as uniformly as possible. Also, the number of alternatives to be chosen is constrained. In this problem, there are six unknowns, and accordingly at least seven non-inferior design alternatives are needed.

[Step 3] Apply the *AHP* to the selected design alternatives, and rank the preferential order of the alternatives.

[Step 4] The *MAU* function variables are optimized using an optimization technique. With the ranked results, the *MAU* function variables are optimized at a time in such a way that the rank obtained from the calculation of the equation (3) for the selected design alternatives coincides with the rank of same alternatives resulted from the *AHP*. In the optimization process, a preference order of any two design alternatives, $\boldsymbol{A}$ and $\boldsymbol{B}$, is realized when the following condition is satisfied:

$$|MAU(\boldsymbol{A}) - MAU(\boldsymbol{B})| \geq \delta \tag{5}$$

where δ is a small positive constant, called indifference level, defining the hardness of the comparison relationship.

4. Realization of the optimality and robustness

In optimization of the injection molding process, a combined consideration of optimality and robustness is very important since the injection molding process inherently has significant process variability all the time even though the process conditions are tightly controlled by sophisticated devices during the molding operation. Optimality means the accessibility of the objective response to the target value, and robustness the sensitivity of the objective response to the uncontrollable variation of the process. Accordingly, the optimal robust solution is defined as a solution with the possible highest functional value and the lowest deviation against this value. To realize the optimality and robustness of a design, the Taguchi method[3,4] is employed in this study, which is a statistical technique to make use of the orthogonal arrays and signal to noise (S/N) ratio analysis. To perform the Taguchi design, appropriate orthogonal arrays for the design factors that are controllable or/and for the noise factors that are uncontrollable must be defined first. Orthogonal arrays provide guidelines on experimental plans to obtain more information with less experiments for a given set of factors. In this work, the noise array, which is orthogonal array for the noise factors, is constructed to model and simulate variations of the uncontrollable process variables around the nominal process setup values of current design. Fig. 3 shows an L_4 noise array, as a sample array for explanation. In the array, R_1 to R_4 represent four different noise factor settings, while the columns represent the noise factors. Each array entry is level 1 or 2 which corresponds to the lower or upper limit of the noise factors, respectively. For the current design, four noise factor settings in the noise array are evaluated to make a total of four replications.

Noise Factors			
Run	N_1	N_2	N_3
R_1	1	1	1
R_2	1	2	2
R_3	2	1	2
R_4	2	2	1

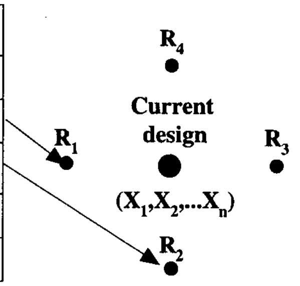


Fig. 3 Noise array (L_4) and its experiments for the current design.

In practice, meanwhile, improvement of the optimality and improvement of robustness may conflict with each other, and thus a tradeoff needs to be made between these two attributes. This problem is simplified by introducing the Taguchi's S/N ratio that represents both function improvement and deviation minimization. By using the S/N ratio, the problem changes to a single criterion maximization problem. Among the common types of S/N ratios, the larger-the better type is employed in this research because the design desirability is maximized when the MAU is also maximized. The S/N ratio of the larger-the better type is calculated as follows:

$$S/N_L = -10 \log \left\{ \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_i^2} \right\} \tag{6}$$

where y_i is the ith response, i.e., MAU_i, to the process variation with the current design, and n the number of replications given by the noise orthogonal array.

As the S/N ratio gets larger, the mean of function values gets larger but the deviation of function value around the mean smaller[3,4]; in other words, optimality is improved and robustness is minimized. Correspondingly, the design with the largest S/N ratio of the MAU is required to be searched in the design space using an appropriate search algorithm to choose it as the best optimal robust design solution.

5. Automatic search of optimal robust design

A modified complex method (*MCM*) based on the direct search scheme is implemented as a tool for automated search of optimal robust design solution. This method provides solutions to many practical engineering problems where derivative information is relatively expensive to calculate. The complex method, proposed by Box[24], starts with the simplex, the vertices of which consist of randomly generated *2n* trial points, where *n* is the number of design variables. The mechanism used to search for the minimum is based on a distortion of the simplex, by which the point with the highest function value is expanded toward the centroid of the remaining points, so as to generate a new design point. The new point is tested for feasibility and acceptability. If the point is not acceptable, the point is sequentially retracted half the distance to the centroid of the current set of points until a newly generated point is acceptable. This expansion and retraction process is repeated until certain stop conditions are satisfied. The topology of the simplest case of the complex method with two design variables is illustrated in Fig. 4. The process to automatically search for optimal robust design solution using the modified complex method in this study is presented by the following, where the symbol * stands for modifications to the complex method:

[Step 1] Design factors, noise factors, and their extreme values or levels are defined. As such, the

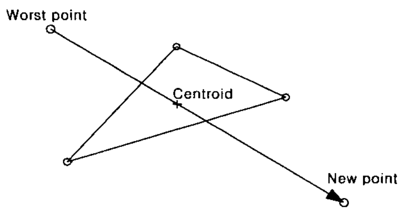


Fig. 4 Topology of the complex method.

overall design space, where optimal robust design solution is searched, is defined by specifying the lower and upper limit of the design factors. And the extent of the variations of the noise factors is defined by their levels.

[Step 2] Initial design points C_p $(p=1,2,\ldots,2n)$ are generated at random.

[Step 3] At each design point, the S/N ratio is calculated with the *MAU*s obtained by evaluating the settings in the noise array and the equation (6). These S/N ratios correspond to the objective function at each design point, $f_p(p=1,2,\ldots,2n)$.

[Step 4] Among *2n* design points, C_m with the lowest (or the worst) function value f_m is selected.

[Step 5] Calculate the centroid C_c of the remaining points and the new point C_r with the function value f_r as follows:

$$C_r = C_c + \alpha(C_c - C_m) \tag{7}$$

where α is reflection factor. Box[24] recommended the use of $\alpha=1.3$.

(a) * If C_r is feasible and $f_r < f_m$, retract C_r half the distance to the centroid C_c. It continues until $f_r > f_m$ for the complex method. However, this is an impractical and time-consuming process, due to extensive computing time required for the simulation. Based on numerical experiments, we assume that the functional evaluations at up to four trial points in the retraction procedure are sufficient. If it is still true that $f_r < f_m$, then let $C_c = C_m$ and $f_c = f_m$. Otherwise, go to step 6.

(b) If C_r is feasible and $f_r > f_m$, then replace C_r by C_m. Go to step 6.

(c) * If C_r is not feasible, C_r is retracted toward the centroid with a retraction step of 0.95 times α; $\alpha=0.95\alpha$, until C_r is feasible. In doing so, the trial points can be searched on the same retraction track.

[Step 6] Check the stop condition imposed to properly terminate the search process. If the condition is satisfied, terminate the procedure. Otherwise, go to step 4. For the present study, the maximum number of function evaluations is used to stop unexpected excessive iteration in the search process.

6. Case study

The Cavallero's capacitor can[2] was used to demonstrate the proposed methodology, aided by the *C-MOLD*[25] injection molding software package. *PP/HUNTSMAN CHEM/P4-011*, tool steel, and water are employed as the polymer material, mold material, and coolant, respectively. The part used here is identical to the one considered previously by Yao[2]. As shown in Fig. 5 and Table 1, the original design of the part had the weld line and warpage problem: the weld line of *15.5mm* accompanied by air trap and the warpage of *0.52mm*. In particular, since the weld line caused an unacceptable esthetic problem, Yao[2] made an attempt to minimize the weld line by optimizing

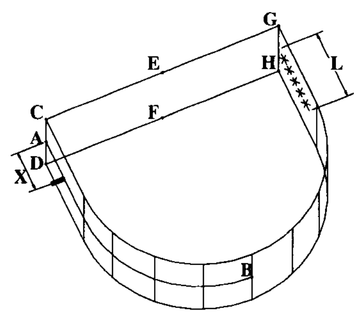


Fig. 5 3-D view of the capacitor can, in which X is the gate location located on the line *AB* and L the weld line length.

Table 1 Results of the original design for the can.

(unit: mm)

Design	Gate location X	Experimentation	
		Weld line	Warpage
Original	3.5	15.5	0.52

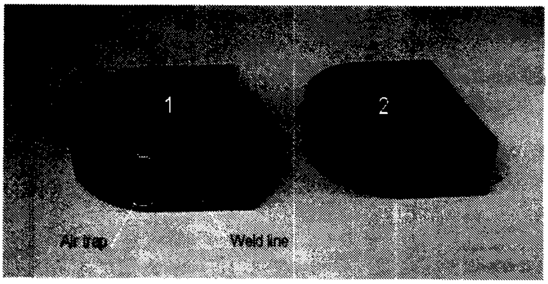


Fig. 6 Comparisons of part quality between the original design (1) and the design optimized by Yao (2) for the can[2].

Table 2 Results of the design optimized by Yao for the can.

(unit: mm)

Design	Gate location X	Simulation		Experimentation	
		Weld line	Warpage	Weld line	Warpage
Optimized	11.5	0.0	0.664	0.0	0.70

only the gate location X and by remaining both part thickness ($=1.524mm$) and process variables as the original design values. As a result, the weld line including air trap was completely eliminated by using the optimized gate location, $X=11.5mm$, as shown in Fig. 6 and Table 2; on the contrary, the warpage was more increased to $0.70mm$ from $0.52mm$. This indicates that the weld line and the warpage in this part conflict with each other, which provides a necessity of applying the proposed methodology to optimizing them simultaneously. Fig. 7 represents a function chosen in both designs to evaluate the weld line and the warpage for the can.

The methodology starts with determining the *MAU* function of the weld line and warpage in the part. Based on the assumption that the weld line and the warpage of the part are utility independent, the

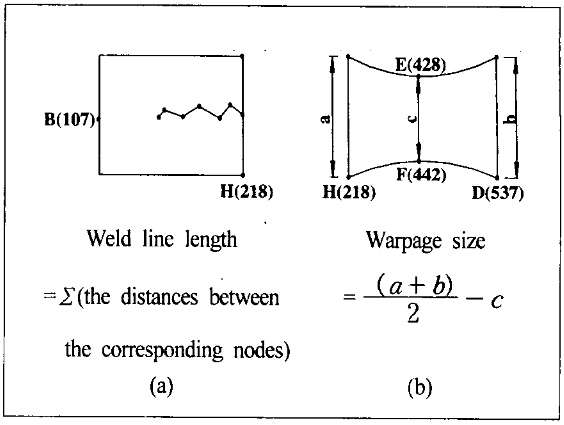
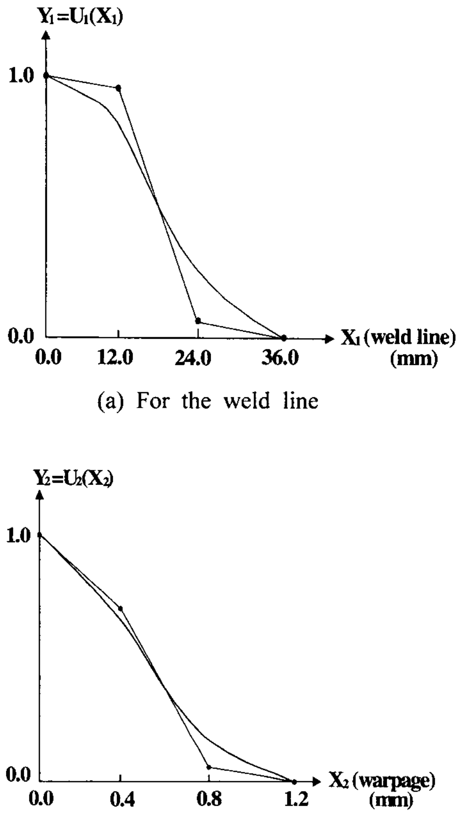


Fig. 7 Evaluation function of the weld line(a) and warpage(b) for the can, in which the numbers in parentheses are the node numbers on the real mesh model.

equation (3) was employed as the *MAU* function form, and the Bezier curve of degree 3 was adopted as the form of each *SAU* function. Six unknowns, i.e., $P_1^y, P_2^y, Q_1^y, Q_2^y, k_1$ and k_2, of the *MAU* function was optimized in such a way that the preference rank obtained from the calculation of the equation (3) for selected design alternatives coincides with the rank resulted from the *AHP*. Table 3 represents a set of non-inferior design alternatives selected for the *AHP* and the rank result of preference order of the alternatives. Table 4 shows the *MAU* function variables optimized with $\delta=0.01$, and Fig. 8 illustrates the *SAU* function curves configurated for the weld line and the warpage.

Next, an experiment plan, such as the choice of design factors and noise factors and the definition of their extreme values or levels, is made. In the current research, to deal with the design space including part design, mold design and process conditions, the factors such as gate location X, side wall thickness Th_{side}, top and bottom wall thickness $Th_{top\&bottom}$, fill time t_{fill}, hold time t_{hold}, postfill time $t_{postfill}$, melt temperature T_{melt}, coolant temperature $T_{coolant}$, and pack profile percent P_{pack} are considered as the candidate design factors. To identify significant design factors on the warpage or the weld line of the part among the candidate design factors, the L_{12} orthogonal array based experiment



(a) For the weld line

(b) For the warpage

Fig. 8 SAU function curves for the can.

and the *Analysis of Variance* (*ANOVA*)[3,4] were performed. Table 5 shows the design factors and their extreme values chosen from the *ANOVA* results and designer's judgements. However, three factors such as the fill time, the postfill time and the coolant temperature are excluded from such design factors, instead, each of them is set at the medium values between its two limits used in the L_{12} array. Table 6 illustrates the noise factors and their levels.

Finally, an automatic search process for optimal robust designs is carried out by the modified complex method. In the present study, the search process was separately performed for two different initial design points; the design points generated arbitrarily in the overall design space, referred to as *case 1*; the design points produced at random in the neighborhood of a design point with the highest S/N ratio from the Taguchi's cross-product experiment, or $L_{18} \times L_8$, by the design factors and the noise factors, referred to as *case 2*. Once the initial design points are given, for each design point, a set of experiments in the noise array L_8 shown in Table 7 is run, and then the warpages and weld lines, the *MAU* values, and the S/N ratios

Table 3 Selected non-inferior design alternatives and the preferred rank estimated by the *AHP*.

Alternatives	Weld line (mm)	Warpage (mm)	Preferred rank
A_1	2.0	1.01	5
A_2	4.1	0.57	4
A_3	6.5	0.36	2
A_4	8.0	0.24	1
A_5	13.2	0.19	3
A_6	22.7	0.12	6
A_7	30.5	0.08	7

Table 4 Variables optimized for the MAU function.

Design coefficients		Estimated result
$SAU_{weld\ line}$	P_1^y	0.9377
	P_2^y	0.0883
	k_1	0.5432
$SAU_{warpage}$	Q_1^y	0.6694
	Q_2^y	0.0740
	k_2	0.3734

Table 5 Design factors and their limits.

Design factor	Lower limit	Upper limit
X (mm)	0.0	33.0
Th_{side} (mm)	1.0	2.0
$Th_{top\&bottom}$ (mm)	1.0	2.0
t_{hold} (sec)	1.25	2.75
T_{melt} (°K)	505.0	545.0
P_{pack} (%)	30.0	90.0

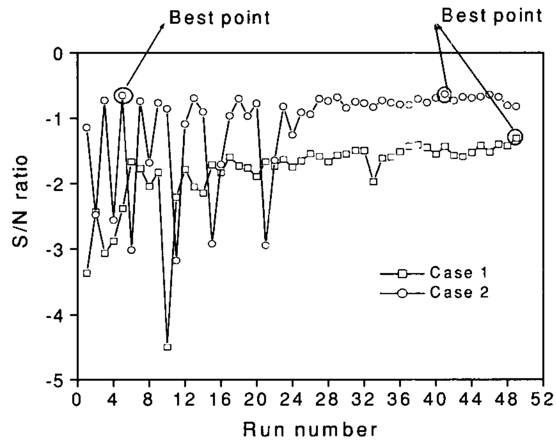
Table 6 Noise factors and their levels.

Noise factor	Level 1	Level 2
t_{fill} (sec)	-0.1	+0.1
t_{hold} (sec)	-0.25	+0.25
$t_{postfill}$ (sec)	-1.0	+1.0
T_{melt} (°K)	-5.0	+5.0
$T_{coolant}$ (°K)	-5.0	+5.0
P_{pack} (%)	-10.0	+10.0

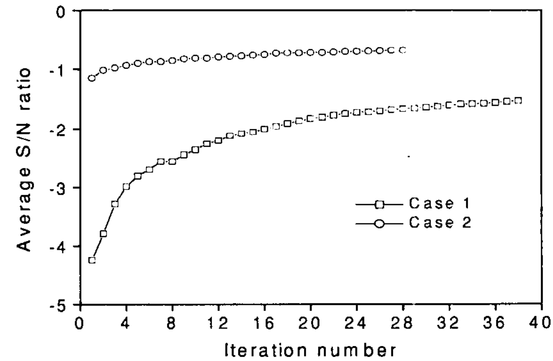
Table 7 Noise factor array for experiment.

Run	t_{fill}	t_{hold}	$t_{postfill}$	T_{melt}	$T_{coolant}$	P_{pack}
R_1	1	1	1	1	1	1
R_2	1	1	1	2	2	2
R_3	1	2	2	1	1	2
R_4	1	2	2	2	2	1
R_5	2	1	2	1	2	1
R_6	2	1	2	2	1	2
R_7	2	2	1	1	2	2
R_8	2	2	1	2	1	1

are evaluated systematically. The search process continues according to its rule, until the number of S/N ratio evaluations make a total of *50*. Fig. 9 shows the search procedure of the S/N ratio, which is plotted in two ways, i.e., value versus run number and average versus iteration number. Table 8 shows the search results obtained for two different initial design points; *case 1* and *case 2*. From Fig. 9 and Table 8, it is shown that the search results for *case 2* is superior to those for *case 1*, in terms of both the total computing time and the quality of searched designs; for *case 2*, two best S/N ratios were *-0.6560* and *-0.6361* obtained in the *5th* and *41st* evaluation, respectively; for *case 1*, however, the best S/N ratio was merely *-1.3120* found in the *49th* evaluation. Particularly, for the best solutions for *case 2*, the mean values of the *MAU* were *0.9277* and *0.9295*, respectively, while the standard deviations *0.0196* and *0.0097*, respectively; in other words, it ensures that both of the best solutions have considerably high quality for both optimality and robustness. Furthermore, Table 8 shows that the weld line and the warpage of all the best optimal robust designs were adequately compromised, compared with the original design and Yao's design, which is a result in case of application of the utility theory as a multiple objective optimization technique. Table 9 represents molding variables obtained for the best optimal robust designs for two cases in Table 8.



(a) Value versus run number



(b) Average versus iteration number

Fig. 9 Optimization procedure of the S/N ratio for the can.

7. Conclusions and future works

An automated injection molding design methodology

Table 8 Best optimal robust designs selected for different initial design points.

Design	S/N ratio	MAU		Weld line		Warpage	
		Average	Standard deviation	Average	Standard deviation	Average	Standard deviation
Case 1	-1.3120	0.8599	0.0105	1.9470	1.2017	0.2964	0.0207
Case 2^1	-0.6560	0.9277	0.0196	2.2715	0.6008	0.1438	0.0381
Case 2^2	-0.6361	0.9295	0.0097	1.6225	0.6008	0.1511	0.0176

Table 9 Results of molding variables for the best optimal robust designs.

Design	X mm	Th_{side} mm	$Th_{top\&bottom}$ mm	t_{hold} sec	T_{melt} °K	P_{pack} %	t_{fill} sec	$t_{postfill}$ sec	$T_{coolant}$ °K
Case 1	27.4	1.34	1.97	1.37	521.9	49.7	1.0	10.0	303.0
Case 2^1	32.3	1.07	1.93	1.82	512.8	58.3	1.0	10.0	303.0
Case 2^2	31.5	1.10	1.94	1.97	511.4	57.0	1.0	10.0	303.0

has been developed to optimize multiple defects in injection molded parts. In the methodology, a tradeoff between conflicting multiple defects of injection molded parts was successfully made by an overall mutiattribute utility function based on the designer's preference, which was derived from an integration of the utility theory, the *Analytic Hierarchy Process* (*AHP*) and an optimization technique. The concept of the orthogonal arrays and signal to noise (S/N) ratio in the Taguchi method was incorporated in the methodology to consider both optimality and robustness of a design. In addition, a combined implementation of the modified complex method and injection molding simulation was developed to search for optimal robust designs within a limited number of simulation runs. Based on the present study, however, it is concluded that well-prepared initial design points need to be given to obtain optimal design solutions of high quality faster.

The methodology was successfully applied to the actual molding design problem, as an example, for the weld line and warpage optimization. From the application, it was seen that the obtained optimal robust designs exhibited high quality characteristics in terms of both quality mean and quality deviation, and consequently the methodology was expected to be also applied to other actual injection molding designs. Applied to production, the proposed methodology will be of immense value to industry in maintaining the competitiveness through the enhancement of product quality and reduction of product development time. As future work, new decision making methods, including advanced utility functions, may need to be developed to obtain the designer's preference more accurately and more consistently than the current approach. Additionally, the cost issues of parts are planned to consider as other attributes to be optimized in the methodology in the future, even though the issues have not been included in the current methodology.

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