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ORIGINAL ARTICLE

Optimization of injection molding process parameters using integrated artificial neural network model and expected improvement function method

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Abstract In this study, an adaptive optimization method based on artificial neural network model is proposed to optimize the injection molding process. The optimization process aims at minimizing the warpage of the injection molding parts in which process parameters are design variables. Moldflow Plastic Insight software is used to analyze the warpage of the injection molding parts. The mold temperature, melt temperature, injection time, packing pressure, packing time, and cooling time are regarded as process parameters. A combination of artificial neural network and design of experiment (DOE) method is used to build an approximate function relationship between warpage and the process parameters, replacing the expensive simulation analysis in the optimization iterations. The adaptive process is implemented by expected improvement which is an infilling sampling criterion. Although the DOE size is small, this criterion can balance local and global search and tend to the global optimal solution. As examples, a cellular phone cover and a scanner are investigated. The results show that the proposed adaptive optimization method can effectively reduce the warpage of the injection molding parts.

Keywords Injection molding · Warpage · Optimization · Design of experiment · Artificial neural network · Expected improvement function

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1 Introduction

Injection molding is the most widely used process for producing plastic products. The entire injection molding cycle can be divided into three stages: filling, post-filling, and mold opening [1]. During production, warpage is one of the most important quality problems, especially for the thin-shell plastic products. Several researches have been devoted to the warpage optimization of thin-shell plastic parts [2–9]. Warpage can be reduced by modifying the geometry of parts, or changing the structure of molds, or adjusting the process parameters. The part design and mold design are usually determined in the initial stage of product development, which cannot be easily changed. Therefore, optimizing process parameters is the most feasible and reasonable method.

It is an important issue in plastic injection molding to predict and optimize the warpage before manufacturing takes place. Many literatures have been devoted to warpage optimization. Lee and Kim [10] optimized the wall thickness and process conditions using the modified complex method to reduce warpage and obtained a reduction in warpage of over 70%. Sahu et al. [11] optimized process conditions to reduce warpage by a combined implementation of the modified complex method and design of experiments. Their results showed that these methods can effectively reduce warpage.

Although these methods can reduce warpage effectively, they are costly and time-consuming because they perform lots of expensive function evaluations. Compared to these methods, the Taguchi method [12–14] is easier to perform and can analyze the effective factors, but it can only obtain the better combination of process parameters, not the optimal solution in the design space.

The warpage is a nonlinear and implicit function of the process parameters, which is typically estimated by the

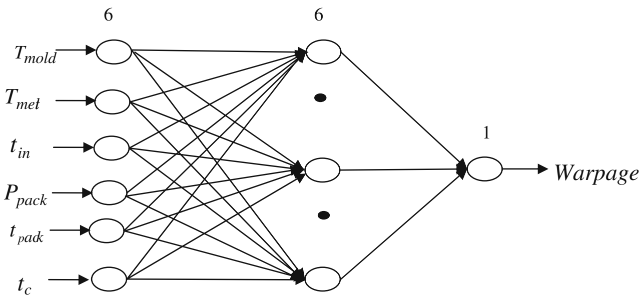


Fig. 1 Configuration of the ANN model

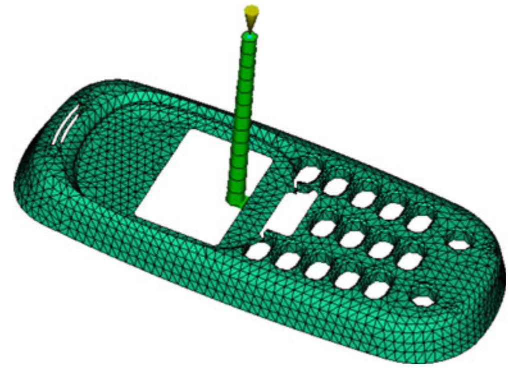


Fig. 3 Mid-plane model of a cellular phone cover

solution of finite element equations. In general, a complicated task often requires huge computational cost. Hence, in order to reduce the computational cost in warpage optimization, many researchers have introduced some surrogate models, such as Kriging surrogate model, artificial neutral network (ANN), response surface method, and support vector regression. Gao et al. [15–17] optimized process conditions to reduce the warpage by combining the kriging surrogate model with modified rectangular grid approach or expected improvement (EI) function method. Kurtaran et al. combined the genetic algorithms with a neural network or response surface method to optimize the process parameters for reducing the warpage of plastic parts [18, 19]. Zhou et al. [20] optimized injection molding process using support vector regression model and genetic algorithm. Their results have shown that the methods based on the surrogate model can reduce the high computational cost in the warpage optimization, and the genetic algorithm can be used to approach to the global optimal design effectively.

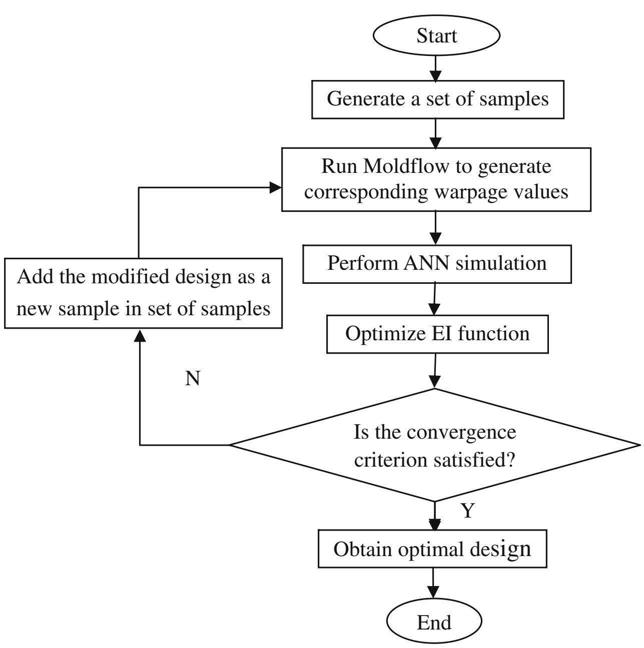


Fig. 2 Flowchart of combining ANN/EI optimization

In this study, the mold temperature, melt temperature, injection time, packing pressure, packing time, and cooling time are considered as process parameters. A small-size design of experiment is obtained by Latin hypercube design (LHD), and the warpage values are evaluated by MoldFlow Plastic Insight software. An adaptive optimization based on artificial neural network model is proposed. The adaptive process is performed by an EI function, which can adaptively select the additional sample points to improve the surrogate model and find the optimum value [17]. This method has been viewed as effective global optimization [21]. The numerical results show that this method can reduce warpage efficiently.

2 Artificial neural network

ANN is a powerful tool for the simulation and prediction of nonlinear problems. A neural network comprises many highly interconnected processing units called neurons. Each neuron sums weighted inputs and then applies a linear or nonlinear function to the resulting sum to determine the output, and all of them are arranged in layers and combined through excessive connectivity.

The typical ANN is a back propagation network (BPN) [22–26] which has been widely used in many research fields. A BPN has hierarchical feed-forward network architecture, and the output of each layer is sent directly to each neuron in the layer above. Although a BPN can have many layers, all pattern recognition and classification tasks can be accomplished with a three-layer BPN [27].

Table 1 Ranges of the process parameters

Parameter	T_{mold} (°C)	T_{melt} (°C)	t_{in} (s)	P_{pack} (%)	t_{pack} (s)	t_c (s)
Lower limit	50	260	0.2	60	1	5
Upper limit	90	300	0.8	90	5	15

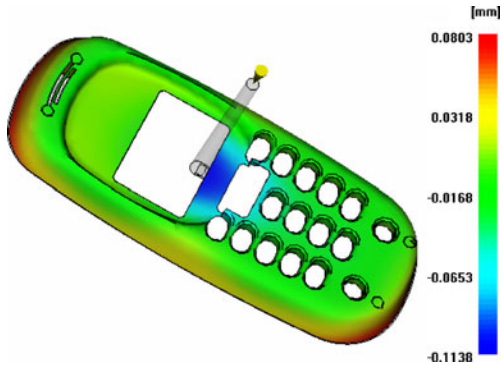


Fig. 4 Warpage of the cover before optimization

A BPN is trained by repeatedly presenting a series of input/output pattern sets to the network. The neural network gradually "learns" the input/output relationship of interest by adjusting the weights between its neurons to minimize the error between the actual and predicted output patterns of the training set. After training, a separate set of data which is not in the training set is used to monitor the network's performance. When the mean squared error (MSE) reaches a minimum, network training is considered complete and the weights are fixed.

In this paper, a three-layer ANN model with one hidden layer was used. The mold temperature (T_{mold}), melt temperature (T_{melt}), injection time (t_{in}), packing pressure (P_{pack}), packing time (t_{pack}), and cooling time (t_{c}) are regarded as input variables, and warpage is regarded as output variable. So the neuron numbers of the input layer and output layer of ANN are determined. The neuron number of the middle layer was determined by trials. The transfer function between the input layer and the hidden layer is "Logsig," and the transfer function between the hidden layer and the output layer is "Purelin." The train function is trainlm, performance function is MSE, learning cycle is 50,000, learning rate is 0.05, and momentum factor is 0.9. The configuration of ANN used in this paper is shown in Fig. 1.

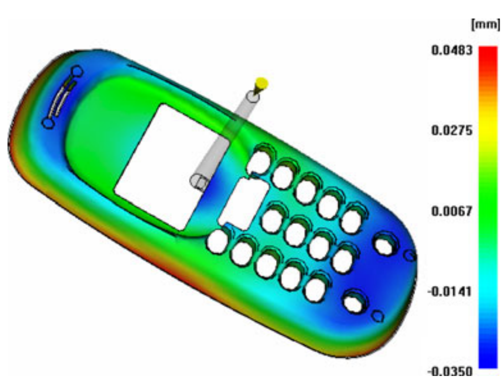


Fig. 5 Warpage of the cover after optimization

Table 2 Optimization results

Parameter	T_{mold} (°C)	T_{melt} (°C)	t_{in} (s)	P_{pack} (%)	t_{pack} (s)	t_{c} (s)	Warpage (mm)
Before optimization	75.57	288.31	0.57	63.96	1.22	5.70	0.1941
After optimization	73.86	298.99	0.20	60.00	1.00	9.48	0.0833

3 EI method

ANNs can be used as an arbitrary function approximation mechanism which "learns" from observed data. ANN is here used to build an approximate function relationship between the warpage and the process parameters, replacing the expensive analysis and reanalysis of simulation programs in the optimization process. In general, the approximate function may have many extremum points, making the optimization algorithms employing such functions converge to a local minimum. EI algorithm is here introduced to close to the global optimization solution.

EI involves computing the possible improvement at a given point. It is a heuristic algorithm for a sequential design strategy for detecting the global minimum of a deterministic function [17, 21]. It can balance local and global search. Before sampling at some point $\boldsymbol{x}$, the value of $Y(\boldsymbol{x})$ is uncertain. $Y(\boldsymbol{x})$ at a candidate point $\boldsymbol{x}$ is normally distributed with $\widehat{\mathbf{y}}(x)$, and variance σ^2 given using the ANN predictor. If the current best function value is $Y_{\min}$, then an improvement $I = Y_{\min} - y(x)$ by the ANN predictor can be achieved. The likelihood of this improvement is given by the normal density:

$$\frac{1}{\sqrt{2\pi}\sigma(\mathbf{x})}\exp\left[-\frac{(Y_{\min}-I-\widehat{y}(\mathbf{x}))^2}{2\sigma^2(\mathbf{x})}\right]. \tag{1}$$

Then, the expected value of the improvement is found by integrating over this density:

$$E(I) = \int_{I=0}^{I=\infty}\left\{\frac{1}{\sqrt{2\pi}\sigma(\mathbf{x})}\exp\left[-\frac{(Y_{\min}-I-\widehat{y}(\mathbf{x}))^2}{2\sigma^2(\mathbf{x})}\right]\right\}\mathrm{d}I. \tag{2}$$

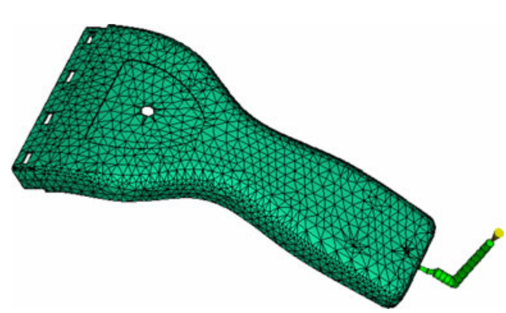


Fig. 6 Model of a scanner

Table 3 Ranges of the process parameters

Parameter	T_{mold} (°C)	T_{melt} (°C)	t_{in} (s)	P_{pack} (%)	t_{pack} (s)	t_c (s)
Lower limit	80	260	0.2	60	1	5
Upper limit	120	300	0.8	90	5	15

Using integration by parts, Eq. 2 can be written as:

$$E(I) = \sigma(x)[u\Phi(u) + \phi(u)] \tag{3}$$

where Φ and ϕ are the normal cumulative distribution function and density function, respectively, and

$$u = \frac{Y_{\min} - \widehat{y}(\mathbf{x})}{\sigma(\mathbf{x})}. \tag{4}$$

The first term of Eq. 3 is the difference between the current minimum response value $Y_{\min}$ and the predicted value $\widehat{y}(x)$ at $\boldsymbol{x}$, penalized by the probability of improvement. Hence, the first term is large when $\widehat{y}(x)$ is small. The second term is a product of predicted error $\sigma(x)$ and normal density function $\phi(u)$. The normal density function value is large when the error $\sigma(x)$ is large and $\widehat{y}(x)$ is close to $Y_{\min}$. Thus, the expected improvement will tend to be large at a point with the predicted value smaller than $Y_{\min}$ and/or with much predicted uncertainty.

This infilling sampling method has some advantages: (1) It can intelligently add sample points to improve the ANN, so it allows "learns" from observed data with a small size; (2) it can avoid searching the areas with relative large function values and reduce the computational cost; (3) it can also avoid adding some points close to each other in the design space and keep the stability of ANN prediction.

4 Warpage optimization based on improved ANN method

4.1 Warpage optimization problem

A warpage minimum design problem can be described as follows:

$$\begin{array}{lll} \text{Find} & x_1, x_2, \cdots, x_m & \\ \text{maxmize} & E[I(x_1, x_2, \cdots, x_m)] & \\ \text{Subject to} & \underline{x}_j \le x_j \le \overline{x}_j & j = 1, 2, \cdots, m \end{array} \tag{5}$$

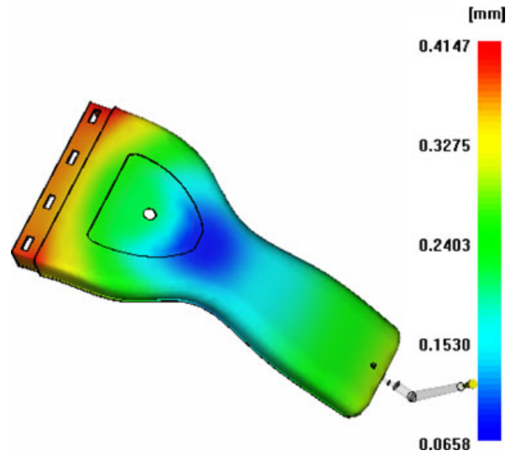


Fig. 7 Warpage of the scanner before optimization

where the process parameters $x_1, x_2, \cdots, x_m$ are the design variables and $\underline{x}_j$ and $\overline{x}_j$ are the lower and upper limits of the jth design variable. The objective function $E[I(x_1, x_2, \cdots, x_m)]$ is given by Eqs. 3 and 4 in which $Y_{\min}$ and $\overline{y}(x)$ are the current minimum value and the predicted value of warpage, respectively.

4.2 Convergence criterion

The convergence criterion is here to satisfy:

$$\frac{E[I(x)]}{Y_{\min}} \le \Delta r \tag{6}$$

where Δr is a given convergence tolerance and $Y_{\min}$ is the minimum function value in samples. The left-hand side is a ratio between the maximum expected improvement and the minimum function value. Thus, Δr can be given without consideration of the magnitudes, and Δr=0.1%.

4.3 Implementation of optimization procedure

Implementation of integrated ANN model and EI function method is given in Fig. 2.

5 Warpage optimization for a cellular phone cover and a scanner

5.1 The optimization problem

In this section, the results of two warpage optimization examples are presented. These are intended to show the

Table 4 Optimization results

Parameter	T_{mold} (°C)	T_{melt} (°C)	t_{in} (s)	P_{pack} (%)	t_{pack} (s)	t_c (s)	Warpage (mm)
Before optimization	92.95	298.38	0.25	85.49	2.83	10.30	0.4805
After optimization	119.32	300.00	0.20	90.00	4.92	15.00	0.2896

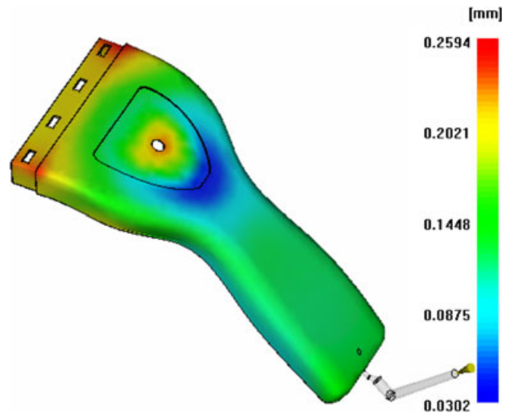


Fig. 8 Warpage of the scanner after optimization

efficiency and accuracy of the integrated ANN model and EI function method.

The first example is a cellular phone cover. It is discretized by 3,780 triangle elements, as shown in Fig. 3. Its length, width, height, and thickness are 130, 55, 11, and 1 mm, respectively. The material is polycarbonate (PC)/acrylonitrile-butadiene-styrene.

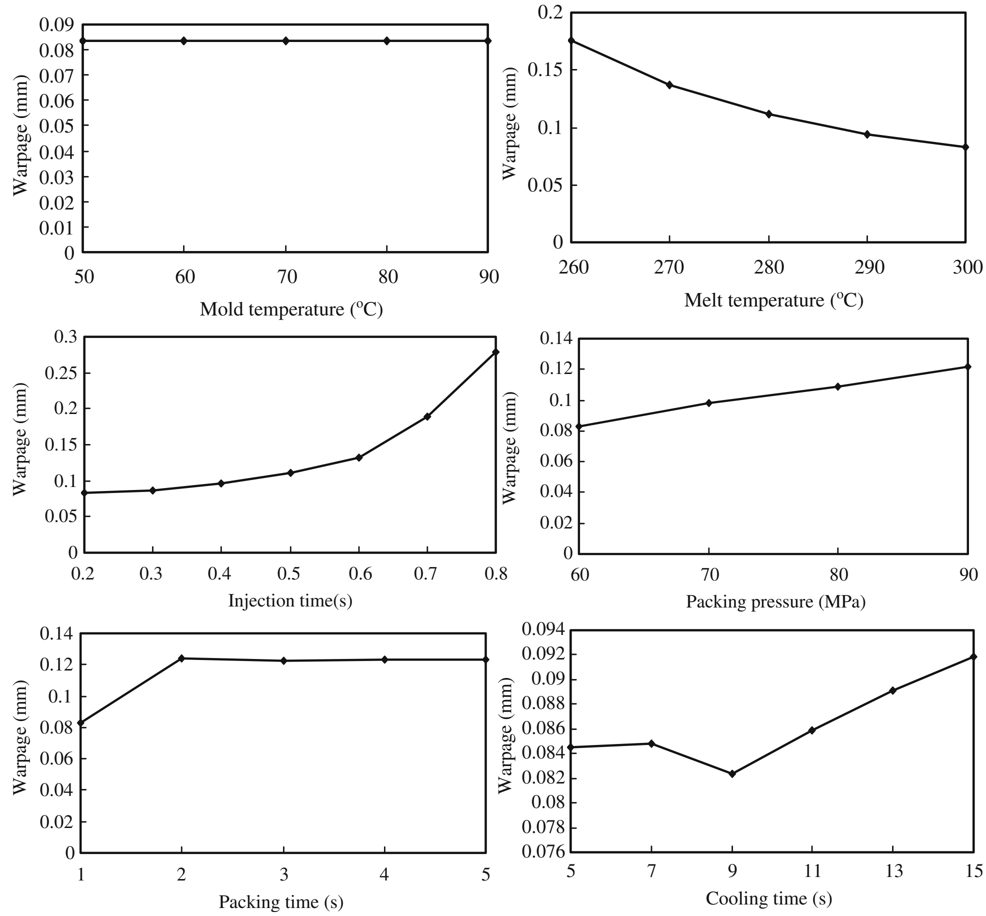
The mold temperature (T_{mold}), melt temperature (T_{melt}), injection time (t_{in}), packing pressure (P_{pack}), packing time (t_{pack}), and cooling time (t_c) are considered as design variables. The objective function warpage($\mathbf{x}$) is quantified by the out-of-plane displacement, which is the sum of both maximum upward and downward deformations with reference to the default plane in Moldflow Plastics Insight software. The constraints consist of the lower and upper bounds on the design variables given in Table 1. ANN model is here used to approximate warpage($\mathbf{x}$), i.e., $\widehat{y}(\mathbf{x})$ in Eq. 2.

The ranges of mold temperature and melt temperature are based on the recommended values in Moldflow Plastics Insight, and the ranges of injection time, packing pressure, packing time, and cooling time are determined by the experience of the manufacturer.

First, ten samples are selected by LHD, then the warpage value corresponding to every sample design is obtained by running Moldflow Plastics Insight software, and finally, an approximate function relationship between warpage and the process parameters is constructed by means of ANN model simulation, replacing the expensive simulation analysis in the optimization iterations.

The optimization problem based on EI function is solved here using the sequential quadratic programming [28]. The expected improvement surface may be highly multimodal

Fig. 9 Each factor's individual effect on the warpage of a cellular phone cover



and thus difficult to optimize reliably. Firstly, 1,000 random points are selected, and EI function values computation are performed by means of the constructed approximate mathematical function. The point with maximum EI function value is then selected to be one initial design. In addition, the point with minimum warpage value in sample points is selected to be another initial design, i.e., two optimization processes are executed at each iteration. In comparison with simulation analysis, these processes consume very short time and can be ignored.

Only 20 iterations were needed to obtain the optimization solution; the results are given in Table 3. Figures 4 and 5 show the warpage values before and after optimization, respectively (Table 2).

The second example is a scanner. The cover is discretized by 8,046 triangle elements, as shown in Fig. 6. It is made of PC. The mold temperature (T_{mold}), melt temperature (T_{melt}), injection time (t_{in}), packing pressure (P_{pack}), packing time (t_{pack}), and cooling time (t_{c}) are considered as design variables. The objective function warpage($\mathbf{x}$) is quantified by the out-of-plane displacement, which is the sum of both maximum and minimum deformations with reference to the default plane in Moldflow Plastics Insight software. The constraints consist of the lower and upper bounds on the design variables given in Table 3.

The ranges of mold temperature and melt temperature are based on the recommended values in Moldflow Plastics Insight, and the ranges of injection time, packing pressure, packing time, and cooling time are determined by the experience of the manufacturer.

Initial ten samples are selected by LHD; the optimal solution was obtained after 25 iterations. The results are given in Table 4. Figures 7 and 8 show the warpage before and after optimization, respectively.

6 Discussions

Tables 2 and 4 show that several process parameters are lying in the boundaries of the limits. Figures 9 and 10 show each factor's effect on the warpage when all other factors are kept at their optimal level, respectively.

Figures 9 and 10 show that high melt temperature and short injection time are desirable. The warpage value decreases nonlinearly as melt temperature changes from260°C to 300°C. This is because lower melt temperature has bad liquidity and can lead to early formation of frozen skin layer, which can generate higher shear stress and block flow. If there is no enough time to release the shear stress, the warpage will increase. However, the

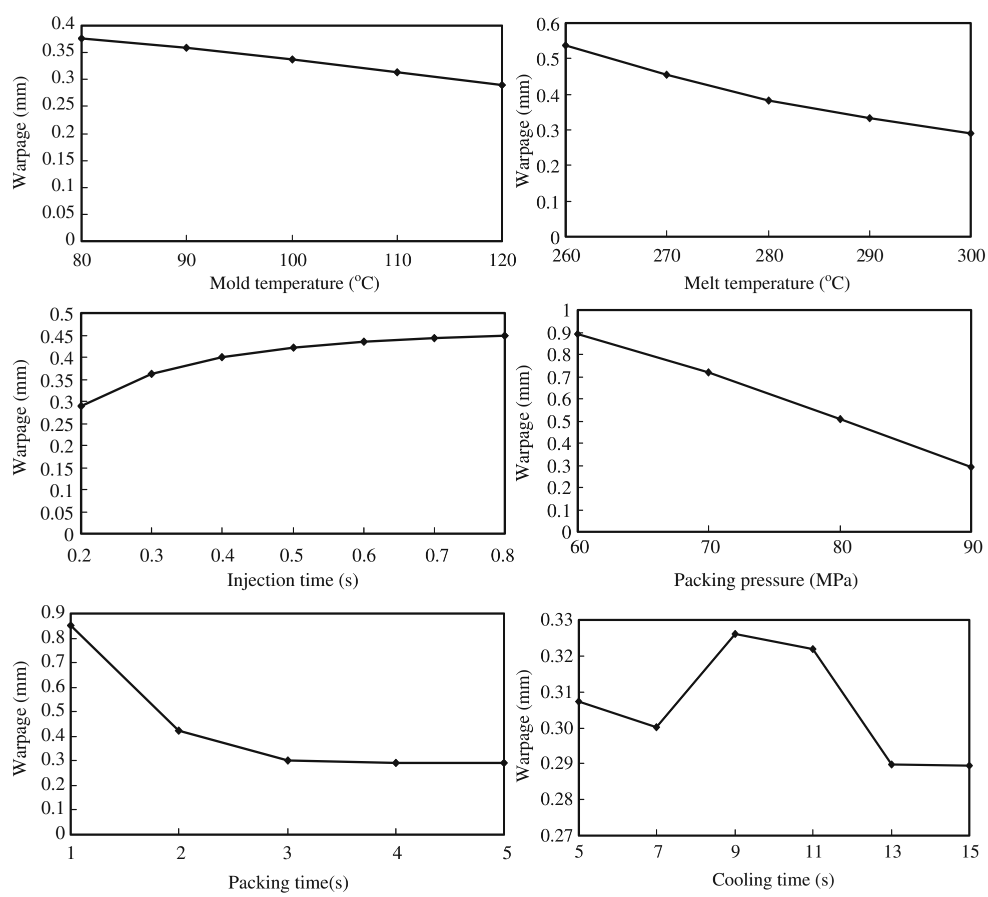


Fig. 10 Each factor's individual effect on the warpage of a scanner

warpage value increases nonlinearly with the injection time. For the thin-wall injection molded parts, long injection time can increase the ratio of the frozen skin layer to the molten core layer. This can block badly the flow and lead to higher shear stress and more molecular orientation in the material. The warpage value changes only a period of packing time and almost is constant when packing time is longer than some values. Figures 9 and 10 also show that the variation of warpage values is irregular when changing other process parameters such as packing pressure, cooling time, and mold temperature. The warpage value depends on the combined efforts of all process parameters, and all these process parameters should be provided by means of optimization.

7 Conclusions

In this study, an integrated ANN model and EI function method is proposed to minimize the warpage of the injection molding parts. This method aims at optimizing some approximate functions trained by the ANN model. The optimization process can be started from an approximate function trained by a set of a few sample points, then adding the best sample point into the training set by means of EI function. Every iteration of the optimization consists of training the approximate function and optimizing the EI function. The EI function can take the relatively unexpected space into consideration to improve the accuracy of the ANN model and quickly approach to the global optimization solution. As the applications, a cellular phone cover and a scanner, are investigated, only a small number of Moldflow Plastics Insight analysis are needed in optimizations because the first iterations for both examples need a set of a few sample points (only ten sample points) and follow-up of every iteration adds one sample point into the set only. Numerical results show that the proposed optimization method is efficient for reducing warpage of injection molded parts and can converge to the optimization solution quickly. Although the design variables of these relatively examples are limited to the mold temperature, melt temperature, injection time, packing pressure, packing time, and cooling time, the present method is also applicable to more process parameters.

However, there still are two problems. The first one is the development of an efficient optimization algorithm. Because the EI function is multimodal with sharp peaks, so it would be difficult to find the optimum solution. The second one is developed for some optimization methods to determine some network parameters, such as learning cycle, learning rate, momentum factor, and number of hidden neuron in the learning framework of the BPN, making the convergence speed of the network quick and steady. Further developments are planned.

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