Approximate Model and Clonal Selection Algorithm Based Optimization of Heating Channels for Variotherm Injection Mold

X. P. Li*
College of Engineering,
Zhejiang Normal University, China
E-mail: xpl2005@163.com
*Corresponding author

T. W. Ji
Center for Engineering and Scientific Computation,
Zhejiang University, China
E-mail: newtime2010@sina.com

Received: 7 February 2013, Revised: 5 May 2013, Accepted: 15 September 2013

Abstract: The integration of an approximate model and a clonal selection algorithm (CSA) is considered as one of the most effective ways to solve complex optimization design problems in engineering. In this study, first, a process for developing an approximate model and the principles of clonal selection algorithms is presented. Second, a variotherm temperature injection mold was used to produce a large liquid crystal display (LCD) TV panel. Next, an approximate model for optimizing the layout of the heating channels in the mold was established. Third, the clonal selection algorithm program was coded according to the aforementioned principles to solve the established approximate model. Finally, the layout of the heating channels was optimized and the optimal solutions were obtained. Finite element simulation and industrial injection production indicated that the integration of the approximate model and clone selection algorithm used in this study to optimize the layout of the heating channels for the injection mold was very effective.

Keywords: Clonal Selection Algorithm, Mold Optimal Design, Variotherm Injection

Reference: Li, X. P., and Ji, T. W., "Approximate Model and Clonal Selection Algorithm Based Optimization of Heating Channels for Variotherm Injection Mold", Int J of Advanced Design and Manufacturing Technology, Vol. 6/ No. 4, 2013, pp. 31-39.

Biographical notes: X. P. Li received his PhD in School of Materials Science and Engineering of Shandong University. He is currently Associate Professor at the College of Engineering, Zhejiang Normal University, China. His current research interest includes CAD and intelligent control in materials processing. **T. W. Ji** is Associate Professor of Engineering and Scientific Computation Center at Zhejiang University, China. He received his PhD in School of Materials Science and Engineering of Shandong University. His current research focuses on metal forming and Finite Element Method.

1 INTRODUCTION

With a relatively short molding cycle time, high automation, high molding accuracy, and flexibility to produce various geometrical shapes, injection molding technology has become one of the most widely used processing technologies for mass production in the plastics industry. In recent years, with the development of 3C (computer, communication, and consumer electronics) industries, the performance requirements of plastic products, including good surface appearance, high mechanical strength, close dimensional tolerances, etc., have become much higher. To meet these high requirements, a variotherm injection molding technology called rapid heat cycle molding technology [1-3] was developed.

In this new injection technology, the temperature of the mold cavity surface must be heated to a high and uniform temperature before melt injection. This temperature is usually above the glass-transition temperature of the injected plastic material. In the filling and packing stages, the temperature is still kept in the high state; then, the mold is rapidly cooled to solidify the shaped resin melt in the post-packing stage for demolding. Owing to such a high and uniform mold temperature, variotherm injection technology can effectively eliminate the frozen layer resulting from the low mold temperature in conventional injection methods and greatly improve the flow of the resin melt. Thus, the surface appearance of the cast part is significantly improved; the surface defects such as weld marks, flow marks, sinks, and floating fibers of fiber-reinforced plastics are eliminated. At the same time, rapid cooling can constrain the total cycle time to an acceptable level.

Variotherm injection technology has also the potential to eliminate post-processing processes such as spraying and coating, which are used to cover the defects of conventional injection parts. Thus, the pollution resulting from spraying and coating processes can be avoided, and production costs can also be reduced. Therefore, variotherm injection is considered to be a green manufacturing technology. During the variotherm injection process, the cavity surface of the mold must be rapidly heated and cooled to designated temperatures. The production efficiency and part quality are seriously affected by the heating temperature and the uniformity of its distribution over the mold cavity surface. Defects such as weld marks and flow mark are easily formed if the temperature is low or distributed unevenly after heating.

As a result, the heating/cooling channels in the mold must be specially designed. The temperature distribution over the mold cavity surface must be as uniform as possible. At the same time, the heating time must be short enough to maintain high production efficiency. Therefore, it is very necessary to determine the layout of heating channels in the mold properly. Wang et al. [4] developed a numerical model to analyze the heat transfer during the heating and cooling stages. The effect of the heating/cooling medium employed, mold structure, etc. on heating/cooling efficiency and temperature uniformity was studied. However, the layout of the channels in the mold was not optimized.

In our previous research, the heat transfer process of the variotherm mold during the injection process was analyzed, and the factors that influence the temperature distribution were also discussed [3], [5]. However, the methods that can be used to quantify these factors were not discussed. Therefore, to optimize the channel layout in a mold, an optimization system featuring an integrated approximate model and clonal selection algorithm was developed in this study. First, the approximate model was established by experiment and finite element simulation. Then, the clonal selection algorithm was coded to optimize the design variables, and the optimal results were obtained. Finally, the effectiveness of the optimization method presented in this paper was demonstrated by using finite element simulation and conducting an industrial production experiment.

2 ESTABLISHMENT OF APPROXIMATE MODEL AND CLONAL SELECTION ALGORITHM

2.1. Establishment of approximate model

Due to the fact that the values of design variables are nonlinear, it is usually difficult to establish a real and accurate mathematical model to solve complex problems in engineering. Approximate models based on experimental design and statistical analysis can be used to replace real and accurate models. The number of iteration runs during calculations and the nonlinearity of a given problem can be reduced by using an approximate model. Thus, using approximate models is considered to be an effective method for solving complex optimization design problems. There are various types of approximate models available for solving optimization problems.

Huang et al. [6] proposed kriging surrogate models to optimize the shape of an aero-engine turbine disc. V. Nasrollahi et al. [7] used a neural networks model and finite element simulation to predict the spring back of bending area in sheet metals. Takassi et al. [8] applied a fuzzy model to predict the product composition of CH_4, CO_2, and CO in the Fischer-Tropsch process for natural gas synthesis. Although the aforementioned models have proved to be very effective in optimization problems, the theory and construction process are complex.

In this study, a response surface model was employed. The basic concept of the response surface method

(RSM) is to construct an approximation of an implicit limit state using an appropriately simple and explicit polynomia1 function. A fairly accurate estimate of the solutions to engineering problems could be obtained if the selected response surface function fits the actual implicit limit state function well [9-11]. However, if there are too many random variables in an engineering problem, it is very difficult to construct an appropriate polynomia1 function, and it will possibly cost much time. Even if only a few design variables are used, the RSM still works very well. A response surface model is usually formulated as shown in Eq. (1).

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \sum_{i=1}^{n} \beta_{ii} x_i x_i + \sum_{i=1}^{n} \sum_{i<j}^{n} \beta_{ij} x_i x_j \tag{1}$$

Where β_0, β_i, β_{ii}, and β_{ij} represent regression coefficients, x_i ($i = 1, 2, \cdots, n$) are design variables, y is the response and n is the total number of the design variables. If the number of experiments is m, the canonical equation of Eq. (1) can be expressed as follows.

$$\begin{bmatrix} (\phi_0,\phi_0)(\phi_1,\phi_0)\cdots(\phi_n,\phi_0) \\ (\phi_0,\phi_1)(\phi_1,\phi_1)\ldots(\phi_n,\phi_1) \\ \vdots \quad \vdots \quad \cdots \quad \vdots \\ (\phi_0,\phi_m)(\phi_1,\phi_m)\ldots(\phi_n,\phi_m) \end{bmatrix} \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_m \end{bmatrix} = \begin{bmatrix} (y,\phi_0) \\ (y,\phi_1) \\ \vdots \\ (y,\phi_n) \end{bmatrix} \tag{2}$$

$$\text{subject to:} \begin{cases} (\phi_k,\phi_l) = \sum_{i=0}^{m} w_i x_i^{k+1} & k,l = 0,1,\cdots,n \\ (y,\phi_l) = \sum_{i=0}^{m} w_i y_i x_i^{l} & l = 0,1,\cdots,n \end{cases}$$

Where w_i is a weight coefficient that is usually set to 1. The regression coefficients matrix $\beta^* = (\beta_0^*, \beta_1^*, \cdots \beta_n^*)^T$ can be obtained by solving Eq. (2).

2. 2.Clonal selection algorithm

Stochastic search algorithms such as simulated annealing (SA) [12], genetic algorithms (GA) [13], [14] and particle swarm optimization techniques [15] have been successfully employed in solving injection molding problems. These algorithms are powerful optimization techniques analogous to the natural selection process in genetics. They have the capability to converge to a globally optimum with the highest probability with relatively low computational effort. Although these heuristic methods do not always guarantee the globally optimal solution, they will provide a reasonable solution in a short CPU time.

The clonal selection technique is a new member of modern heuristics algorithms and has been applied to optimize a few engineering problems that are found to be exciting. Gan et al. [16] proposed a clonal selection programming based fault detection system for performing induction machine fault detection and analysis; the results proved to be extremely useful for practical industrial applications. Ulutas et al. [17] used a clonal selection algorithm for optimizing the dynamic facility layout problem.

The results showed that the presented algorithm reached the best known solutions and even found better solutions for large-sized problems in 88% of the instances, whereas each of the other methods used was successful only for a small fraction of a total of 50 problems. Currently, the use of the clonal selection algorithm (CSA) is becoming increasingly widespread for engineering applications; however, the application of the CSA to the injection molding process has not been reported. In the view of the foregoing discussion, the main objective of the present work was to verify the effectiveness of the clonal selection technique in solving the injection molding process problem.

In the CSA, the objective function to be optimized is represented by "antigen" and the solution candidates are represented by "antibodies". During the algorithm, antibodies will be cloned and mutated according to their affinity to antigen in each generation, and a new mutational population will be created. If $A(k)$ is defined as the antibody population at time k and is represented by the time-dependent variable matrix $A(k) = \{a_1(k), a_2(k) \cdots, a_n(k)\}$. The evolution process of the algorithm can be described as follows:

$$A(k) \xrightarrow{T_c^C} Y(k) \xrightarrow{T_g^C} Z(k), Z(k) \cup A(k) \xrightarrow{T_s^C} A(k+1)$$

Where, $A(k)$ is the initial antibody population; $Y(k)$ is the population after clonal proliferation; $Z(k)$ is the population after affinity maturation; $A(k+1)$ is the next population after clonal selection; T_c^C, T_g^C, and T_s^C are the clonal proliferation operator, affinity maturation operator and clonal selection operator, respectively. Thus, after the process, the search space for solving problems is expanded due to the increase in the diversity of antibodies; as a result, premature convergence during the process of evolution is prevented. The local minimum value of the search space can also be avoided. At the same time, through clonal selection, the convergence rate is accelerated.

Generally, the CSA procedure can be defined as follows:

Step 1: Define the problem. The form of encoding the antigen and antibodies will be decided. The parameters needed for the algorithm will be determined, including the size of the antibody population, the clone times, the mutation rate, etc.
Step 2: The objective function and constraints must be represented by antigens and the initial antibody population could be randomly generated.
Step 3: Evaluate the affinity of the antibodies to the antigen based on the former's objective function value and potential constraint violations. Antibodies with high affinity will be placed at the front of the order.
Step 4: The antibodies with high affinity are selected to create a new population and they will be cloned and mutated according to the clone times and the mutation rate in this new population. Then, the next new antibody population will be formed.
Step 5: If the termination criterion is satisfied, the computation procedure is terminated; otherwise, new complementary antibodies are added, and the procedure returns to Step 3.
According to the principles introduced in this paper, the program for the CSA was coded by the authors using the C++ language. It can be used for the optimization problem proposed in section 3.

3 APPROXIMATE MODEL FOR OPTIMIZING THE LAYOUT OF HEATING CHANNELS IN A TV PANEL INJECTION MOLD

3.1. Structure of the LCD TV and the layout of heating channels in the mold

The panel of an LCD TV is a large plane part that must possess a high-quality appearance. Fig. 1-a) shows a 3D CAD model of an LCD TV panel. The conventional injection molding process does not satisfy the requirement for the product's surface appearance, because it produces obvious weld marks, flow marks and other surface defects indicative of poor quality. Variotherm injection has recently been successfully applied to the production of LCD TV panels, and good products with excellent appearance are obtained. Figure 1-b) shows the distribution of the heating channels above the cavity surface in the mold cavity plate.
From the two figures shown above, it can be observed that the heating channels are linearly distributed along the products in the mold. To make sure the mold is heated and cooled rapidly, the cavity plate is usually heat-insulated with the other mold plates, because there is thermal insulating material around the cavity plate. Therefore, in the heating stage of the injection process, heat transfer occurs only in the cavity plate. Additionally, a major focus of this study was the temperature and the uniformity of its distribution throughout the mold cavity surface.

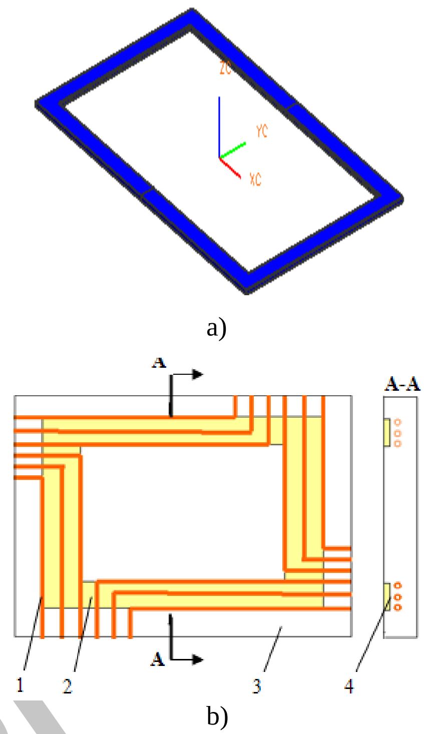

Fig. 1 Panel shape and heating channel layout in the variotherm mold, a) the shape of an LCD TV panel, b) heating channel layout for the TV panel, 1-heating channels, 2- TV panel, 3- mold cavity plate, 4- cavity surface

Therefore, we can select a cross section of the variotherm mold cavity plate as a simplified model for heat transfer analysis and channel layout optimization. In this way, the optimization analysis model for the heating channels can be established as shown in Fig. 2.

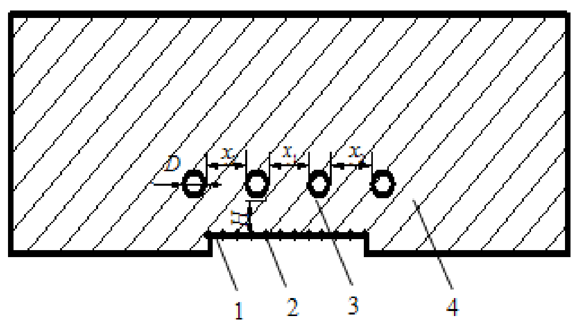

Fig. 2 Optimization model for the heating channels 1-cavity surface 2- temperature-tracking points 3-heating channels 4-mold cavity plate

The number of channels, diameter of the channels (D), distances between the channels (x_1, x_2) and distance from the channels to the cavity surface (H) shown in Fig. 2 are all parameters affecting the heat transfer in the mold. Of course, their effects on the temperature of the

cavity surface are different. Twelve temperature-tracking points along the cavity surface were selected to study the temperature distribution over the cavity surface. They are also shown in Fig. 2.
In an initial simulation, the channel number was set to 4 according to the width of the panel, and the geometric parameters were set as follows: $x_1 = 14$ mm, $x_2 = 14$ mm, $H = 11$ mm, $D = 8$ mm. The width of the panel was 55 mm, and the total heating time was 30 s. The properties of the cavity plate material used in this paper are listed in Table 1.

Table 1 Properties of mold material and heat transfer coefficients

Density, $g \cdot cm^{-3}$	Specific heat, $J \cdot Kg^{-1} \cdot C^{-1}$	Thermal conductivity, $W \cdot m^{-1} \cdot ℃^{-1}$	Heat transfer coefficients	
			Cavity surface, $W \cdot m^{-2} \cdot K^{-1}$	Between vapor and channels, $W \cdot m^{-2} \cdot K^{-1}$
7.78	460	30	20	5200

Figure 3 shows the results for the temperature distribution over the cavity surface, as indicated by the 12 temperature-tracking points after heating the mold for approximately 30 s. As shown in Fig. 3, the temperature of the cavity surface is not the same after the heating stage. The temperature is distributed unevenly. On both sides of the cavity plate, heat dissipates more quickly to the lateral areas, and the central area of the plate is heated more quickly than other areas. This leads to a higher temperature distribution in the central part of the model. If a polymer melt is injected, the surface temperature of the melt becomes non-uniform, and the cooling rate becomes inevitably inconsistent as well. This non-uniform heating and cooling temperature distribution will degrade the surface quality of the polymer product. Thus, it is very important to determine the number of channels, the distance between them, the diameter of the channels and the distance from the channels to the cavity surface.

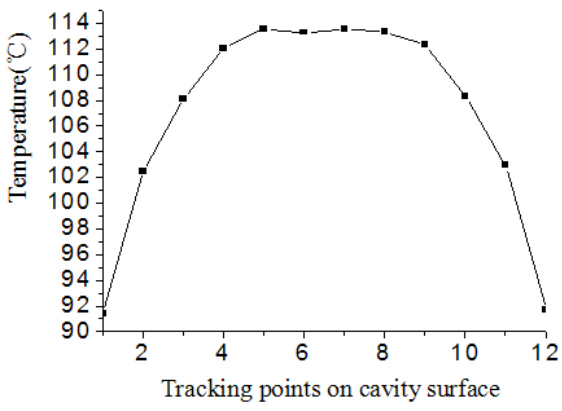

Fig. 3 Temperature distribution over the cavity surface of cavity plate

Generally, high heating/cooling efficiency and a uniform temperature distribution over the mold cavity surface are the ultimate goals for ensuring high mold strength, good product appearance and strong mechanical properties. Therefore, it is necessary to construct an appropriate mathematical model to optimize the layout of the channels in the mold.

3.2. Construction of objective function

In the variotherm injection process, the mold suffers great thermal stress due to its high working temperature. Thus, fatigue cracks may be easily generated on the cavity plate, and the lifetime of the mold is usually lower than that of a conventional injection mold. Therefore, to ensure the strength of the cavity and improve the mold lifetime, the distance from different channels to the cavity surface, H, shown in Fig. 2 could be kept the same. Moreover, the experimental results obtained in this study indicate that the diameter of the channels affects the heating efficiency of the mold cavity. The larger the diameter is, the more quickly the mold cavity is heated.
The channel diameter also affects the uniformity of the temperature distribution over the mold cavity under the same other conditions. Although the diameter of the channels affects the heat transfer through the mold cavity, it is better to retain the same given value in terms of mold strength and manufacturing cost. In this study, the diameters of the channels were identical and the number of channels was 4. Only the distances x_1, and x_2 shown in Fig. 2 were set as the design variables. Twelve points spaced evenly over the mold cavity surface were used to track the temperature. The variance between the temperatures detected at the tracking points and the average temperature were used to formulate the objective function. The model showed a uniform temperature distribution over the cavity surface of the mold cavity plate. The value of the objective function was inversely proportional to the uniformity of the temperature distribution. Therefore, the optimization problem can be expressed as follows:

$$\min_{X \in R} F(X) = \min \sum_{i=1}^{n} (T_i - \bar{T})^2 = \min_{X \in R} (OBJ_f(x_1, x_2)) \tag{3}$$

Subject to: $a_1 \le x_1 \le b_1, a_2 \le x_2 \le b_2$ (4)

Where T_i is the temperature at tracking point i when the heating process is finished, $i = 1,2,...,n$, and n is the total number of temperature-tracking points. $\overline{T}$ is the average temperature of all the tracking points. $F(X)$ or $OBJ_f(x_1, x_2)$ is the objective function. $X = [x_1, x_2]^T$ is the vector of the design variables. x_1, x_2 are the design variables. a_1, a_2, b_1, b_2 are the lower and upper limits of the design variables x_1, x_2, respectively. Different values of x_1 and x_2 will generate different values of T_i and $\overline{T}$. Therefore, T_i and $\overline{T}$ are the functions of the design variables x_1 and x_2. The value of the objective function $\sum_{i=1}^{n}(T_i - \overline{T})^2$ also varies with x_1 and x_2. To minimize the value of the objective function, an approximate model relating the objective function to the variables should be established.

3.3. Establishment of approximate model

As described above, the response surface method was used to establish an approximate model. To obtain the response surface equation, experiment samples should be selected and determined. The different values of the design variables x_1 and x_2 correspond to different experiment samples. The design variable x_1 is selected from the range of a_1 to b_1, and the design variable x_2 is selected from the range of a_2 to b_2. At the same time, the finite element method is used to solve the temperature field of the cavity plate for different values of the experiment samples. Different experiment samples correspond to different finite element models. For different experiment samples x_1 and x_2, the temperature field of the mold cavity plate has different distributions and values. The finite element simulation software program was used to solve the temperature field in this study. The objective response values for the experiment samples were obtained using the solved temperature field. Then, the response surface equation could be established according to the objective response values and the experiment samples.

In the mold design process, x_1 and x_2 are not allowed to be too large to ensure high heating efficiency, especially because x_1 has an obvious effect on heating efficiency. In engineering applications, x_1 usually is less than 18 mm. Moreover, according to the heat transfer analysis results presented in Fig. 3, if $x_1 = x_2$, there is a concentration of heat in the central part of the cavity surface. Thus, x_1 must be selected to be larger than x_2. In this study, the ranges of x_1 and x_2 were determined to be $14 \le x_1 \le 18$ and $13 \le x_2 \le 17$. The Latin Hypercube Design (LHD) experimental method was used to determine the experiment samples. According to the principles of LHD and to preserve the accuracy of the results, ten experiment samples were selected and arranged. The details of the experiment samples of LHD are shown in Table 2.

According to the experimental results of the LHD method shown in Table 2, a response surface approximate model could be established by using a regression or fitting method such as the least squares method to solve Eq. (1) and Eq. (2). Then, the approximate model would be obtained as shown in Eq. (5).

$$\sum_{i=1}^{12}(T_i - \bar{T}) = F(x_1, x_2) = 6656.0125 - 444.3103x_1 - 245.0992x_2 + 9.8469x_1^2 + 6.8952x_2^2 + 2.2638x_1x_2 \quad (5)$$

Table 2 LHD experiments

Experiment numbers	x_1 ,mm	x_2 ,mm	$\overline{T}$,℃	$\sum_{i=1}^{n}(T_i - \bar{T})^2$
1	14	14	106.9219	734.0212
2	15	16	104.0749	610.1488
3	16	15	104.4103	489.5587
4	17	13	105.296	436.5687
5	18	17	110.5349	365.2348
6	17	14	104.3144	398.8779
7	18	16	102.1627	346.8291
8	16	13	106.1919	512.7566
9	15	15	105.1049	576.5804
10	14	17	104.2511	725.2938

Figure 4 compares the objection function values obtained by the approximate model using selected sample points with the actual function values obtained by the finite element simulation.

Fig. 4 shows that the experimental results closely agree with the simulated results. Thus, the approximate model generated may be used for optimization. According to Eq. (5), the objective function $\sum_{i=1}^{n}(T_i - \overline{T})^2$ can be optimized with respect to the design variables x_1 and x_2 by using a clonal selection algorithm. The design variables minimizing the objective function are the desired ones.

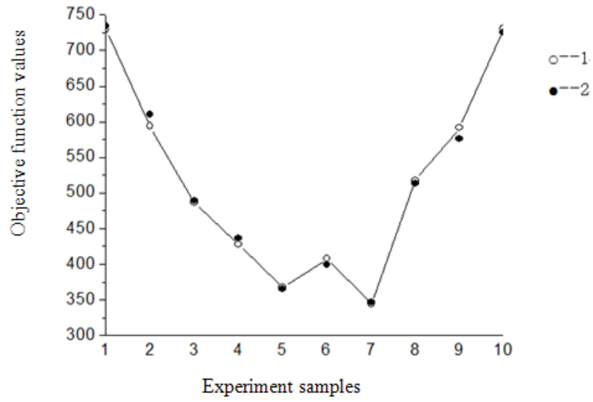

Fig. 4 Comparison of approximate model and experimental results
1- calculated values by approximate model
2- calculated values by finite element simulation

4 OPTIMIZATION PROCESS USING CLONAL SELECTION ALGORITHM

First, the objective function and constraints used as antigens are defined in the program for the clonal selection algorithm and all the parameters needed for the algorithm are determined. Then the optimization process is carried out according to the parameters defined above. When the optimization process reaches the 1000th generation, the process is terminated, where the minimum value of the objective function, 334.78, is obtained. The design variables corresponding to the minimum objective function value are $x_1 = 18.00$ and $x_2 = 14.82$.

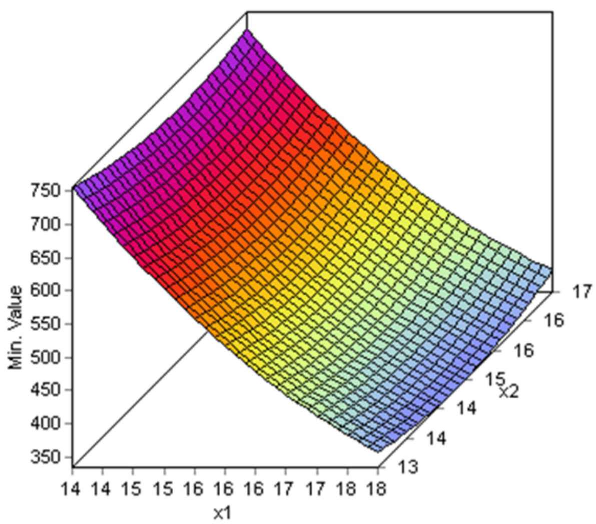

Fig. 5 Effects of x_1 and x_2 on the objective function in space

The effects of the design variables x_1, x_2 on the objective function in the search space are illustrated in Fig. 5.
Fig. 5 shows that the value of the objective function $\sum_{i=1}^{12}(T_i - \bar{T})^2$ decreases with an increase in x_1. However, with the increase in x_2, the value of the objective function first decreases and then increases. Therefore, it can be concluded that in the range of $14 \le x_1 \le 18$, the larger the distance x_1 between the central channels above the mold cavity is, the more uniform the temperature of the mold cavity surface becomes. However, if the distance is too large, the heating efficiency will be greatly reduced. The distance x_2 on both sides of the channels has a parabolic effect on the uniformity of the temperature distribution over the mold cavity surface. There is an optimal value of x_2 for the uniformity of the temperature distribution. For this problem, the optimal value of x_2 is 14.82 mm and the optimal value of x_1 is 18.00 mm. For convenience, the values of x_1 and x_2 are rounded to the integers 18 mm and 15 mm, respectively.

5 FINITE ELEMENT SIMULATION AND ENGINEERING APPLICATION

5.1. Finite element simulation

Through the above optimization and analysis, the optimal design variables were obtained. To verify the optimization results, the heating process of the variotherm mold with the optimal values of x_1 and x_2 was simulated by using the finite element software. Table 3 compares the uniformity of the temperature distribution and the average temperature of the mold cavity surface for different design variable values.

Table 3 shows that the uniformity of the temperature distribution and the average temperature of the mold cavity surface are 734.0℃ and 106.9℃, respectively. When using the optimal values of the design variables, the uniformity of the temperature distribution and the average temperature of the mold cavity surface are 334.48℃ and 102.7℃. When using the rounded optimal values of the design variables, the uniformity of the temperature distribution and the average temperature of the mold cavity surface are 335.5℃ and 102.6℃.
It can be observed that the temperature results for the optimal design variables and rounded optimal design

variables are very similar. Through the optimization design, the uniformity of the temperature distribution is increased by 54.5%. Therefore, the optimization design is very effective. We also found that the average temperature over the variotherm mold cavity surface after optimization decreased slightly. It is clear that there is a balance between the heating efficiency and the uniformity of the temperature distribution. Therefore, for the optimal design of the layout for the heating channels in the mold, a multi-objective optimization design that considers heating efficiency and the uniformity of the temperature distribution should be considered. This multi-objective optimization design will be subject of further research conducted by the authors.

Table 3 Comparison of results for different designs

Parameters	Initial values	Rounded design variables and obtained results	Optimal results
x_1,mm	14	18	18.00
x_2,mm	14	15	14.82
$\sum_{i=1}^{12}(T_i-\overline{T})^2$	734.0	335.5	334.48
$\overline{T}$ ( )	106.9	102.6	102.7

5.2. Engineering application

Based on the optimization design described above, a variotherm mold for an LCD TV panel was designed. The heating channels of the mold were designed by using the optimized design variables. Production showed that sound panel products were produced very successfully. The product's surface is bright and mirror-smooth. There are no weld marks, flow marks or other defects on the surface.

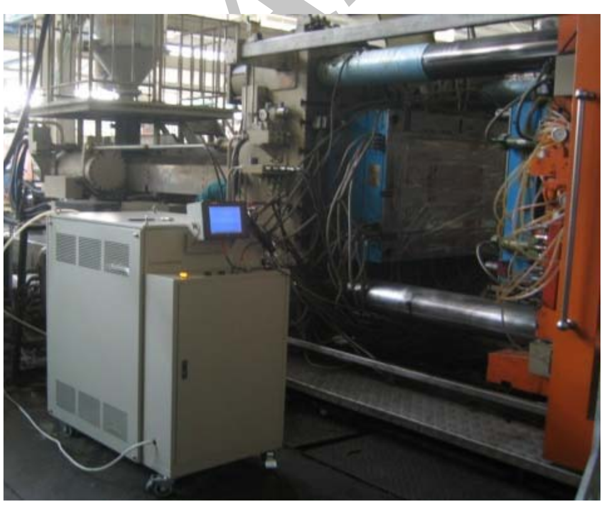

Fig. 6 Variotherm injection production line

Fig. 7 LCD TV panel variotherm mold in open state

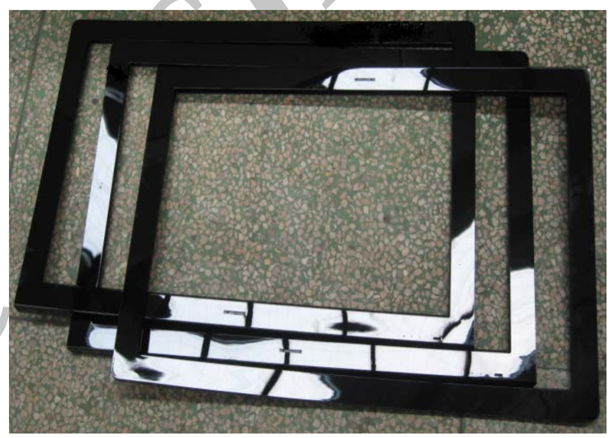

Fig. 8 TV Panel fabricated using variotherm injection technology

6 CONCLUSION

With the goal of achieving a uniform temperature distribution on a variotherm mold cavity surface, an approximate model for optimizing the layout of the heating channels in a mold was established. The established model was optimized by using the clonal selection algorithm which was coded by the authors. The layout of the heating channels was optimized by using the approximate model and the algorithm. The optimal results greatly improved the uniformity of the temperature distribution over the variotherm mold cavity surface.

The uniformity of the temperature distribution is one of most important factors that affect product quality. Through optimization, the uniformity of the temperature distribution over the mold cavity plate was increased by 54.5% and high-performance products for engineering applications were obtained.

ACKNOWLEDGMENTS

The research work was supported by the Natural Science Foundation of Zhejiang Province (Grant No. LQ12E05007) and the National Natural Science Foundation of China (Grant No. 51175478).

REFERENCES

[1] Chen, S. C., Minh, P. S., Chang, J. A., Huang, S. W., and Huang, C. H., "Mold temperature control using high-frequency proximity effect induced heating", International Communications in Heat and Mass Transfer, Vol. 24, No. 2, 2012, pp. 216-223.

[2] Xie, L., and Ziegmann, G., "A visual mold with variotherm system for weld line study in micro injection molding", Microsystem Technologies, Vol. 14, No. 6, 2008, pp. 809-814

[3] Li, X. P., Gong, N. N., Guan, Y. J., and Cheng, G. M., "Thermal and stress analysis of rapid electric heating injection mold for a large LCD TV panel", Applied Thermal Engineering, Vol. 31, No. 17-18, 2011, pp. 3989-3995.

[4] Wang, G. L., Zhao, G. Q., Li, H. P., and Guan, Y. J., "Research on a new variotherm injection molding technology and its application on the molding of a large LCD panel", Polymer - Plastics Technology and Engineering, Vol. 48, No. 7, 2009, pp. 671-681.

[5] Li, X. P., Zhao, G. Q., Guan, Y. J., and Li, H. P., "Research on thermal stress, deformation, and fatigue lifetime of the rapid heating cycle injection mold", The International Journal of Advanced Manufacturing Technology,November, Vol. 45, No. 3-4, 2009, pp. 261-275

[6] Huang, Z, J., Wang. C. G., Chen, J., and Tian, H., "Optimal design of aeroengine turbine disc based on kriging surrogate models", Vol. 89, No. 1-2, 2011, pp. 27-37.

[7] Nasrollahi, V., and Arezoo, B., "Prediction of springback in sheet metal components with holes on the bending area, using experiments, finite element and neural networks", Materials & Design, Vol. 36, 2012, pp. 331-336.

[8] Takassi, M. A., Salooki, M. K., and Esfandyari, M., "Fuzzy model prediction of Co (III)/Al2O3 catalytic behavior in Fischer-Tropsch synthesis", Journal of Natural Gas Chemistry, Vol. 20, No. 6, 2011, pp. 603-610.

[9] Zhou, L. Z., and Zhao, J., "Advanced response surface method for mechanical reliability analysis", Applied Mathematics and Mechanics, Vol. 28, No. 1, 2007, pp. 19-26.

[10] Ekren, O., and Ekren, B. Y., "Size optimization of a PV/wind hybrid energy conversion system with battery storage using response surface methodology", Applied Energy, Vol. 85, No. 11, 2008, pp. 1086-1101.

[11] Wang, G. G., "Adaptive Response Surface Method Using Inherited Latin Hypercube Design Points", Journal of Mechanical Design, Vol. 125, No. 2, pp. 210-220.

[12] Yang, Y. K., Yang, R. T., and Tzeng, C. J., "Optimization of mechanical characteristics of short glass fiber and polytetrafluoroethylene reinforced polycarbonate composites using the neural network approach", Expert Systems with Applications, Vol. 39, No. 3, 2012, pp. 3783-3792 .

[13] Chen, W. C., Fu, G. L., Tai, P. H., and Deng, W. J., "Process parameter optimization for MIMO plastic injection molding via soft computing", Vol. 36, No. 2, 2009, pp. 1114-1122 .

[14] Ratle, F., Achim, V., and Trochu, F., "Evolutionary operators for optimal gate location in liquid composite moulding", Applied Soft Computing, Vol. 9, No. 2, 2009, pp. 817-823.

[15] Wang, G. L., Zhao, G. Q., Li, H. P., and Guan, Y. J., "Multi-objective optimization design of the heating/cooling channels of the steam-heating rapid thermal response mold using particle swarm optimization", International Journal of Thermal Sciences, Vol. 50, No. 5, 2011, pp. 790-802.

[16] Gan, Z. H., Zhao, M. B., and Chow, T. W. S., "Induction machine fault detection using clone selection programming", Expert Systems with Applications, Vol. 36, No. 4, 2009, pp. 8000-8012.

[17] Ulutas, B. H., and Islier, A. A., "A clonal selection algorithm for dynamic facility layout problems," Journal of Manufacturing Systems", Vol. 28, No. 4, 2009, pp. 123-131.