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Multiobjective Optimization Design of Heating System in Electric Heating Rapid Thermal Cycling Mold for Yielding High Gloss Parts

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ABSTRACT: An optimization design method is developed for the electric heating system in rapid thermal cycling molding (RTCM) mold. First, a multiobjective optimization model is established, in which the distance between the mold cavity surface and the center of heating elements and the number and power density of heating elements are the design variables, the required heating time t_h and the highest cavity surface temperature T_{max} at time t_h are the objective functions. Then, an optimization strategy consisting of design of experiment, finite element analysis, artificial neural network (ANN) and response surface methodology (RSM) models, and Pareto-based genetic algorithm is proposed to solve the multiobjective optimization model. Finally, the optimization strategy is applied for the design of the heating system for an automotive spoiler blow mold. The results show that the temperature distribution uniformity on the blow mold cavity surface is obviously improved and high heating efficiency is also ensured with the optimized design parameters. Moreover, the ANN model exhibits its superiority over the RSM model in terms of modeling and predictive abilities. A RTCM blow mold with the optimized electric heating system is constructed and successfully utilized to mold high gloss automotive spoiler. © 2013 Wiley Periodicals, Inc. J. Appl. Polym. Sci. **2014**, *131*, 39976.

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INTRODUCTION

In the plastics injection and blow molding, the mold temperature is an important processing parameter because it not only has a great influence on cycle time but also significantly affects the surface quality of molded parts. Lower mold temperature is usually preferred in molding process to shorten the cycle time, whereas this will lead the plastics melt to solidify prematurely and thus result in poor part surface quality, such as roughness, sunken points and orange peel on the blow molded part surface as well as welding line, flowing mark and jetting on the injection molded part surface. If the plastics parts have high gloss appearance requirement, the surface defects have to be eliminated via some secondary operations including sanding, polishing, and spraying. These operations not only significantly increase the production cost but also are harmful to the operators' health. Raising the mold temperature to a high level can be a good way to improve the part surface quality, but this will extend the cycle time to a great extent in regular molding process. In recent years, the rapid development of the automobile, household appliance and consumer electronic industries greatly promotes the applications of industrial plastics parts, and also puts forward much higher performance requirement on the parts, e.g., good appearance qualities. For this reason, a new molding technology called rapid thermal cycling molding (RTCM) is developed recently to meet the increasingly strict requirement on plastics parts. In this new molding process, the mold cavity temperature is alternately changed via rapid heating and cooling in each molding cycle. Owing to the high mold cavity temperature, the filled plastics melt or inflated parison melt can easily replicate the glossy mold cavity surface and thus high-gloss parts can be molded. At the same time, rapid heating and cooling can also keep the cycle time at an acceptable level.

To alternately change the mold cavity temperature without a great increase in cycle time, a rapid mold heating technique is required. In recent years, some rapid mold heating methods have been proposed. These methods can be mainly divided into two categories: external heating and internal heating. The former category mainly include induction heating,[1] gas-assisted heating,[2] high-frequency proximity heating,[3] infrared heating,[4] etc. As to the latter category, the steam-assisted heating,[5] hot water or oil heating,[6] and electric heating[7] are the most commonly used methods. The external heating methods do have high heating efficiency, but the high cost, complex mold structure or low temperature uniformity limits their applications in actual production. In practical applications, the internal heating methods are much more preferable in terms of their better adaptability and stability, particularly for the mold with a relatively large volume. Some heating channels are drilled within the mold with the internal heating to transport the hot medium or install the electric-heating elements. To acquire the best performance of the heating system in terms of the temperature distribution on mold cavity surface and the heating efficiency, it is quite necessary to optimize the layout of heating channels in the mold. To solve this problem, some optimization design methods have been proposed. Li et al.[8] proposed the optimization strategy combining response surface methodology (RSM) with genetic algorithm (GA) to optimize the layout of heating channels for a RTCM injection mold with steam-assisted heating. In addition, an optimization strategy coupling RSM with particle swarm optimization (PSO) was also proposed by Wang et al.[9,10] The RSM model is usually constructed for the defined variables of a process or system by fitting a polynomial equation. Artificial neural network (ANN) can be considered as an alternative to the polynomial regression. Among various kinds of ANN models, the error back propagation (BP) feed-forward neural network is the most widely utilized one, and it has been used for modeling in many processes.[11–15] Moreover, stochastic search procedure based on the GA can be an efficacious manner for process optimization. The GA is capable of exploring large solution space in parallel. The GA coupling with the ANN model has been successfully applied in many process optimization problems.[16–18]

The present work aims to develop an effective optimization design method for the heating system in the RTCM mold with electric heating. First, a multiobjective optimization model for both mold cavity temperature uniformity and heating efficiency is established. Then, a multiobjective optimization strategy is proposed, which consists of design of experiment (DOE), finite element analysis (FEA), RSM and ANN models, and Pareto-based GA. Finally, the developed optimization method is then used to design the heating system for an industrial blow mold.

MULTIOBJECTIVE OPTIMIZATION MODEL AND ALGORITHM

In general, many optimization problems in engineering domains have multiple objectives. In this work, the heating system design of the RTCM mold has the objectives of uniform temperature distribution on cavity surface as well as high heating efficiency. For this purpose, the design of heating system must be optimized.

Design Variables for Optimization

For the RTCM mold with electric heating, the heating elements installed in the mold are usually located closely and conformally to the mold cavity surface to improve the heating efficiency. Moreover, the distance between the adjacent heating elements should be kept the same for uniform mold cavity heating. Thus, the distance between the center of heating elements and cavity surface (H), and the number (N) and power density (q) of heating elements are the three main parameters affecting the heat transfer process of the mold. Therefore, parameters H, N, and q are selected as the design variables in the optimization design of the heating system.

Objective Functions

In RTCM, the mold cavity surface is required to be heated to a designated temperature, usually above the thermal distortion temperature of the used plastics. The heating efficiency and the temperature distribution uniformity on the mold cavity surface are two main concerns in RTCM. This is because that they directly affect the production efficiency and part surface quality. In this work, the required heating time, t_h, for the whole mold cavity surface to be just heated to the designated temperature, is used as an objective function to evaluate the heating efficiency; whereas the highest cavity surface temperature, T_{max}, at time t_h is used as another objective function to evaluate the temperature uniformity on the mold cavity surface.

Multiobjective Optimization Model

The objective of the optimization design of heating system is to find the optimum values of the design variables (H, N, q) for simultaneously minimizing the required heating time t_h and highest cavity surface temperature T_{max} within design space. This multiobjective optimization model can be formulated as the following expressions:

$$\begin{gathered}\text{Find} : H, N, q \\ \text{Make} : t_h(H, N, q), T_{max}(H, N, q) \rightarrow \min \\ \text{Within the ranges} : \\ H^{(l)} \leq H \leq H^{(u)}, N^{(l)} \leq N \leq N^{(u)}, q^{(l)} \leq q \leq q^{(u)}\end{gathered} \tag{1}$$

where $H^{(l)}$, $H^{(u)}$, $N^{(l)}$, $N^{(u)}$, $q^{(l)}$, and $q^{(u)}$ represent the lower and upper limits of design variable H, N, and q, respectively. The limits of these parameters can be determined based on the size and mechanical strength of the mold investigated and the actual power density of heating elements available.

Pareto Solution and Multiobjective GA

It is impossible to find a unique optimal solution that makes all the objective functions to be the best simultaneously due to the fact that the objectives under consideration usually conflict with each other. Most of the multiobjective optimization problems give rise to a set of optimal solutions known as Pareto solutions. The Pareto solutions are some compromise solutions in the feasible regions.[19–21] That is, these solutions capture the trade-offs among the objectives and each Pareto solution satisfies the objectives at a reasonable level. Each point in Pareto solution set can be selected as the best one according to the designer's consideration for the requirements of a practical problem. In light of this, the ultimate goal of a multiobjective optimization algorithm is to identify the Pareto solution set. In this work, the multiobjective GA based on Pareto ranking approach is adopted to search the Pareto solutions for the multiobjective optimization problem. The detailed developing procedure of this algorithm can be found in Ref. 22.

OPTIMIZATION STRATEGY

Before achieving optimum design of the heating system, the quantitative relationships between objective functions and design variables must be created first. For this reason, the DOE

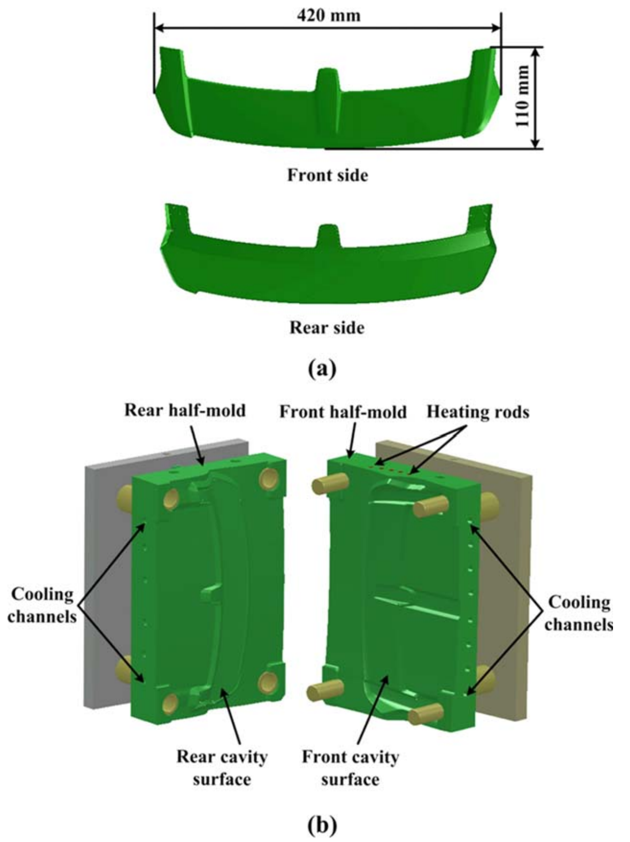


Figure 1. Schematic of (a) automotive spoiler and (b) corresponding electric heating RTCM blow mold. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

method is adopted to evaluate the influence of design variables on objective functions. The FEA program is used to simulate the heat transfer process and then to acquire the corresponding values of objective functions for different combinations of design variables arranged through the DOE. Using the obtained DOE patterns, the RSM and ANN models are developed to establish the quantitative relationships between objective functions and design variables.

RSM Model

RSM model is a useful analytical function to describe the quantitative correlation between the responses and independent variables. There are many types of RSM models that can be employed to establish the functions, but the full second-order polynominal model is the commonly used one. The second-order RSM model can be represented as the following expression:

$$y=\beta_0+\sum_{i=1}^{k}\beta_i x_i+\sum_{i=1}^{k}\beta_{ii}{x_i}^2+\sum_{i=1}^{k-1}\sum_{j>i}^{k}\beta_{ij}x_i x_j \tag{2}$$

where y is the response; x_i and x_j are the independent variables; β_0 is the model constant; β_i, β_{ij}, and β_{ii} represent the coefficients of linear, interaction and quadratic terms, respectively; k is total number of independent variables. The RSM model can be fitted using the patterns from the aforementioned DOE by least-square method.

ANN Model

ANN model is a data modeling tool that is able to capture and represent the complex relationship of the input and output data. It is well known that the BP neural network with three layers can approximate any nonlinear functions with arbitrary accuracy. Therefore, a three layer BP feed-forward neural network is used to build the predictive model using the aforementioned patterns from the DOE as the training patterns. The neural networks toolbox in MATLAB is used to generate the neural network. Before presenting the patterns to the BP network, the input and output data are normalized in the range of [−1, 1] to train the network more efficiently. The hyperbolic tangent and purely linear functions are chosen as the activation functions for the neurons in the hidden and output layers of network, respectively. To improve the generalization abilities of the network, a matlab function (TRAINBR) developed based on Bayesian regularization technique is selected as the training algorithm.

Before using the developed RSM and ANN models to predict the values of objective functions in design space, it is quite necessary to assess the fitting and prediction accuracies of these models. For this reason, three evaluation parameters including correlation coefficient (R^2), mean absolute error (MAE) and root mean square error ($RMSE$) are employed in this work:

$$R^2=1-\frac{\sum_{j=1}^{p}\left(T_j-O_j\right)^2}{\sum_{j=1}^{p}\left(T_j-O_j\right)^2+\sum_{j=1}^{p}\left(T_j-T_e\right)^2} \tag{3}$$

$$MAE=\frac{100}{p}\times\left[\sum_{j=1}^{p}\left(|T_j-O_j|/O_j\right)\right] \tag{4}$$

$$RMSE=\left[\frac{\sum_{j=1}^{p}\left(T_j-O_j\right)^2}{p}\right]^{1/2} \tag{5}$$

where p is the number of simulations, O_j is the values of the objective functions obtained in the jth simulation, T_j is the corresponding predicted values of the objective functions in the jth simulation using the models, and T_e is the average values of the objective functions in p number of simulations. Additionally, five validated simulations are also carried out using the design variable values chosen randomly in design space to check the generalization abilities of the constructed models.

Both developed models with high prediction and generalization accuracies are solved using the multiobjective GA to optimize the design variables. Then, the FEA is conducted to simulate the t_h and T_{max} using the optimized variables as the design parameters of heating system to validate the effectiveness of its optimal design.

APPLICATION OF OPTIMIZATION STRATEGY IN MOLD HEATING SYSTEM DESIGN

In this section, the RTCM blow mold for molding the automotive spoiler is taken as an example to illustrate the application

Table I. Full Factorial Design Matrix with Simulated and Predicted Responses

	Design variable			Response 1			Response 2		
				t_h (s)			T_{max} (°C)		
					Predicted			Predicted	
No.	H (mm)	N (–)	q (W cm^{-2})	Simulated	RSM	ANN	Simulated	RSM	ANN
1	16	5	25	22.70	22.97	22.67	134.93	134.37	135.07
2	16	5	30	19.60	19.58	19.57	138.67	138.25	138.64
3	13	4	20	26.20	26.45	26.88	127.35	128.59	128.76
4	10	5	20	15.20	15.16	14.88	133.14	132.93	133.30
5	10	4	20	20.40	20.23	20.73	139.46	138.23	136.95
6	13	5	20	20.30	20.66	20.36	126.50	127.06	126.52
7	16	4	25	28.40	28.55	28.53	132.38	131.91	132.32
8	13	5	30	14.10	13.83	14.17	132.34	131.84	132.33
9	10	4	30	12.90	13.01	12.90	140.27	139.35	140.28
10	10	4	25	15.70	15.85	15.71	139.55	138.90	139.53
11	13	5	25	16.50	16.47	16.39	129.60	129.55	129.62
12	13	6	20	16.90	16.91	16.94	129.84	129.22	129.82
13	13	6	25	14.00	13.66	13.97	133.69	131.95	133.70
14	16	5	20	27.70	27.90	27.78	131.16	130.27	131.07
15	13	4	25	21.10	21.33	21.26	129.22	130.86	130.96
16	16	6	30	16.90	16.98	16.92	143.07	144.64	143.32
17	16	4	30	24.20	24.23	24.14	136.03	135.56	136.05
18	13	4	30	17.90	17.75	17.87	132.00	132.91	132.54
19	10	6	20	12.10	12.14	12.07	130.63	131.33	130.62
20	16	4	20	35.00	34.41	34.89	128.03	128.04	128.07
21	10	5	25	12.00	11.71	11.72	133.12	133.83	134.45
22	16	6	25	19.50	19.43	19.54	139.74	140.53	139.68
23	10	6	30	8.20	8.66	8.19	133.49	133.37	133.49
24	10	6	25	9.70	9.63	9.70	132.09	132.46	132.26
25	16	6	20	23.50	23.43	23.41	135.73	136.20	135.80
26	13	6	30	12.00	11.95	12.08	135.85	134.46	137.10
27	10	5	30	10.00	9.81	10.01	133.12	134.51	134.53
Validated simulations									
1	12	4	20	23.60	24.19	23.61	128.84	130.79	128.87
2	12	5	25	15.00	14.70	14.82	130.08	129.97	128.50
3	14	5	30	15.80	15.56	16.12	133.86	132.96	134.75
4	15	4	30	22.00	21.88	21.96	134.13	133.67	135.12
5	15	5	20	25.00	25.29	25.06	130.20	128.19	130.21

of the optimization strategy proposed above in electric-heating system design.

Figure 1 shows the three dimensional (3D) CAD model of the automotive spoiler and corresponding RTCM mold with electric heating. To cut the manufacturing cost, the dimensions of the molded spoiler in this work are reduced relative to the actual automotive spoiler. The length and width of the spoiler are ∼420 and 110 mm, respectively, and its average wall thickness is about 3 mm. In the practical applications, excellent surface appearance in the front side of the spoiler is required. So, the front half-mold needs to be thermally cycled in the RTCM process. The electric heating rods are selected as the heating elements to heat the mold cavity surface and water is used to cool the mold in each molding cycle.

In this work, the full factorial experimental design is selected as the DOE method. In the experimental design, three levels are set for each design variable. The results of the full factorial experimental design are detailed in Table I. The transient thermal analysis module of the commercial finite software ANSYS is used to conduct the heat transfer analysis to obtain the

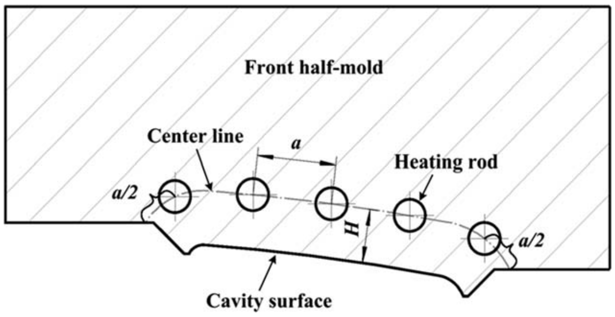


Figure 2. Geometrical model for heating system design.

corresponding values of the objective functions for different sets of design variables. Because the heating system is installed only in the front half-mold, the heat transfer analysis and optimal design of the heating system are only conducted on the front half-mold. Strictly speaking, the heat exchange between the heating rods and front half-mold base is a 3D heat transfer problem. But, taking into account the fact that the front half-mold exhibits nearly the same cross-section, it is reasonable to simplify the 3D FEA problem to be a 2D one during heat transfer analysis. Figure 2 shows the geometry model for the 2D analysis. Figure 3 illustrates the mesh model and boundary conditions for the thermal response analysis. The heat flux, the value of which equals to the power density of the heating rods used, is loaded at the interface between the heating rods and mold base. The initial mold temperature, environmental temperature and air free convection coefficient are set to be 30°C, 30°C and 15 W $m^{-2\circ}C^{-1}$, respectively. The properties of the mold steel (AISI P20) and electric heating rod filler are listed in Table II. The diameters of all heating rods are 8 mm. The designated temperature of the mold cavity surface is 120°C.

The patterns obtained from the aforementioned full factorial experimental design is used to develop the RSM and ANN models. Because there is no definite rule available to determine the appropriate number of neurons in the hidden layer for the ANN model, it is determined by trial and error method. The result shows that the ANN model with 10 neurons in hidden layer can give smaller mean square error (MSE) and better converging rate. The architecture of the ANN model used in this work is shown in Figure 4. The tolerance of MSE and maximum number of training iterations are set at 10^{-4} and 100, respectively.

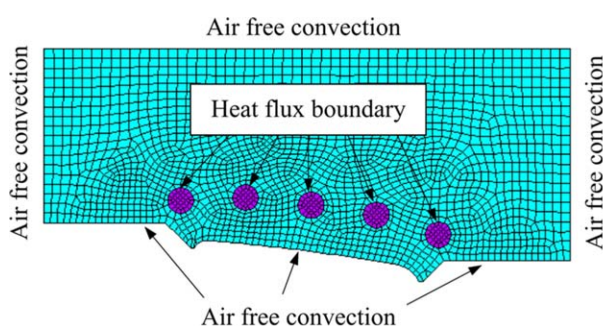


Figure 3. Mesh model and boundary conditions for thermal response simulation. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

Table II. Properties of Mold Material and Heating Rod Filler

Material	ρ (kg m^{-3})	λ (W $m^{-1\circ}C^{-1}$)	C (J $kg^{-1\circ}C^{-1}$)
Mold steel	7850	33.5	470
Heating rod filler	2700	5.5	1100

Once the models with good generalization are developed, the models can be used as the fitness functions of GA to solve the multiobjective optimization models [eq. (1)]. In the hybrid RSM-GA and ANN-GA optimizations, the population size is initialized as 90. Adaptive feasible mutation is adopted. Scatter crossover is selected and the crossover fraction is set at 0.75. The average change in the spread of Pareto solutions <0.0001 is used as the stopping criteria for the algorithm.

RESULTS AND DISCUSSION

Model Fitting and Analyses

The simulated values of the t_h (response 1) and T_{max} (response 2) obtained from the full factorial experiments are given in Table I. The data are used to fit the full second-order RSM model [eq. (2)]. The fitted two quadratic polynomial models are expressed as follows:

$$t_h = 81.128 + 1.800H - 15.580N - 2.518q - 0.241HN - 0.049Hq + 0.187Nq + 0.097H^2 + 1.022N^2 + 0.031q^2 \quad (6)$$

$$T_{max} = 364.491 - 21.983H - 35.388N - 0.920q + 1.255HN + 0.107Hq + 0.046Nq + 0.505H^2 + 1.848N^2 - 0.004q^2 \quad (7)$$

Analysis of variance (ANOVA) is used to check the significance of the regression models for both t_h and T_{max} at a 95% confidence level, and the results are given in Tables III and IV, respectively. The F value is calculated from a term mean square divided by a residual mean square. The P value (probability) is used as a tool to examine the significance of model terms. The term with P value <0.05 is significant, or else it is insignificant. As shown in Table III, the P value for the model of the t_h is <0.0001, which implies that the regression model is significant.

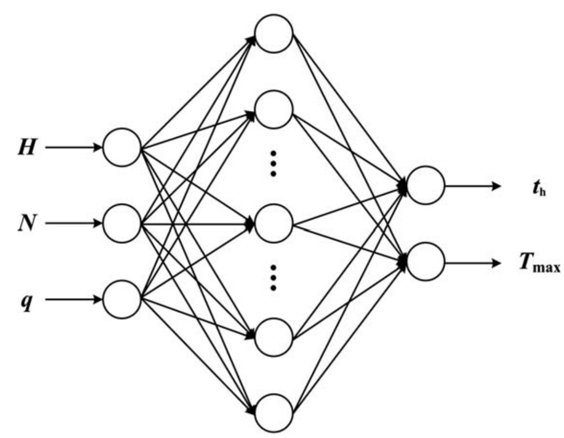


Figure 4. ANN architecture (3–10–2) used in this work.

Table III. ANOVA Results for Required Heating Time

Source	Sum of squares	DOF	Mean square	*F*-value	*P*-value
Model	1082.49	9	120.28	1509.42	<0.0001
H	570.09	1	570.09	7154.43	<0.0001
N	264.50	1	264.50	3319.36	<0.0001
q	210.13	1	210.13	2636.98	<0.0001
HN	6.31	1	6.31	79.16	<0.0001
Hq	6.60	1	6.60	82.84	<0.0001
Nq	10.45	1	10.45	131.18	<0.0001
H^2	4.56	1	4.56	57.28	<0.0001
N^2	6.27	1	6.27	78.68	<0.0001
q^2	3.58	1	3.58	44.90	<0.0001
Residual	1.35	17	0.08		
Total	1083.85	26			
$R^2 = 0.998$					

In addition, the single terms of *H*, *N*, and *q*, interaction terms of *HN*, *Hq*, and *Nq* and quadratic terms of H^2, N^2, and q^2 are significant model terms indicated by their *P* values. In Table IV, the *P* value <0.0001 indicates the significant nature of the model of the $T_{\max}$. Among the model terms, the single term of *q*, interaction terms of *HN* and *Hq* and quadratic terms of H^2 and N^2 are significant model terms. The regression models are also evaluated via the correlation coefficient R^2 [eq. (3)], the values of which are found to be 0.998 and 0.954 for the models of t_h and $T_{\max}$, respectively. Higher R^2 value for the constructed regression model of the t_h implies that it is able to give better estimate of the t_h in the design space.

For the ANN approach, the normalized training patterns are used to train the neural network. The weight and threshold values for each neuron in hidden and output layers of the network are updated iteratively in the training process. Once the MSE or the maximum number of training iterations for the network reaches the set value, the network-training process is stopped. Figure 5 shows the evolution of the MSE for the ANN model during training. After 60 iterations, the MSE is decreased to the predetermined value of 10^{-4}, then the training process is terminated and the trained network is obtained. The values of R^2 for the models of the t_h and $T_{\max}$ are 0.999 and 0.962, respectively. The small magnitude of MSE (10^{-4}) and high values of R^2 demonstrate that the constructed ANN model possesses good approximation characteristics.

Table IV. ANOVA Results for Highest Cavity Surface Temperature

Source	Sum of squares	DOF	Mean square	*F*-value	*P*-value
Model	455.36	9	50.60	39.27	<0.0001
H	1.32	1	1.32	1.02	0.3260
N	5.38	1	5.38	4.18	0.0568
q	102.72	1	102.72	79.73	<0.0001
HN	170.03	1	170.03	131.98	<0.0001
Hq	30.72	1	30.72	23.85	<0.0001
Nq	0.63	1	0.63	0.49	0.4938
H^2	124.00	1	124.00	96.25	<0.0001
N^2	20.49	1	20.49	15.90	0.0010
q^2	0.07	1	0.07	0.06	0.8170
Residual	21.90	17	1.29		
Total	477.26	26			
$R^2 = 0.954$					

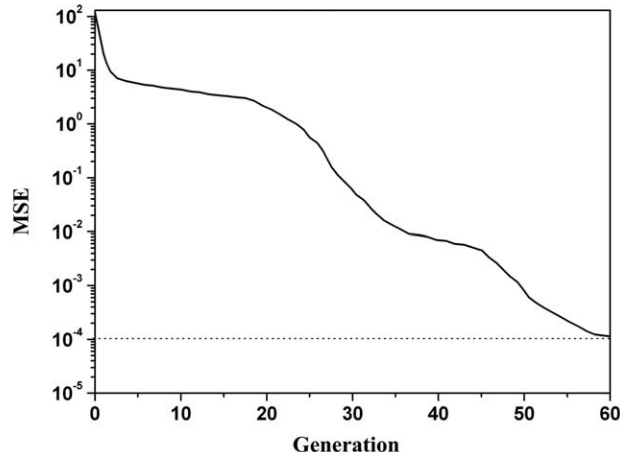


Figure 5. Variation of MSE with generation during ANN training.

Comparison of Predictive and Modeling Abilities of RSM and ANN

The responses predicted by the constructed RSM and ANN models for the designed and validated simulations are listed in Table I. It can be found that the predicted responses agree with the simulated data well, which indicates that both constructed RSM and ANN models can yield accurate responses and possess good generalization abilities. The R^2, *MAE*, and *RMSE* calculated by eqs. (3)−(5) are listed in Table V. As can be seen, for the designed and validated simulations, the ANN model shows higher R^2 values than the RSM model. Moreover, the values of the *MAE* and *RMSE* of the ANN model are lower than those of the RSM model. That is, the ANN model predicts more accurate responses than the RSM model for the t_h and $T_{\max}$ within the design space.

Generation of the RSM model needs only a single step calculation and so the computation cost is low. However, it is noteworthy that the search process of the RSM model highly depends upon search space because only quadratic nonlinear correlation is usually assumed. To make use of RSM more effectively, the search space needs to be narrowed down appropriately. This requires either more extra experiments or good prior knowledge of the process or system to determine the search space. For the ANN model, the generation may require a large number of iterative calculations and so higher computation cost depending on the nonlinearity of the process and the number of parameters. Fortunately, the ANN can capture inherently almost any form of nonlinear relationship and its search space can be chosen 2more liberally.

Table V. Comparison of Predictive Abilities of RSM and ANN Models for Designed and Validated Simulations

Parameter	Designed simulation				Validated simulation			
	t_h		T_{max}		t_h		T_{max}	
	RSM	ANN	RSM	ANN	RSM	ANN	RSM	ANN
R^2	0.9987	0.9992	0.9541	0.9621	0.9939	0.9983	0.6916	0.9062
MAE	1.0749	0.5551	0.5686	0.3161	1.5449	0.7379	0.8314	0.5297
RMSE	0.2248	0.1785	0.9007	0.7956	0.3447	0.1674	1.3324	0.9241

GA-based Multiobjective Optimization and Confirmative Simulations

The previously developed RSM and ANN models are used as the fitness functions for GA to optimize the design variables within design space. On the basis of the hybrid RSM-GA and ANN-GA optimizations, the optimal Pareto solutions of the t_h and T_{max} are obtained, and the results are shown in Figure 6. As can be seen, there is a compromising relationship between the t_h and T_{max}. When the heating efficiency is increased, the temperature uniformity is decreased, and vice versa. In practical applications, the designer can select one point from the Pareto optimal solutions as the optimal design according to the different requirements on part surface quality and productivity. Compared with the conventional blow molding process, the production efficiency can be significantly enhanced due to the fact that the secondary operations can be eliminated in the RTCM process for the molded parts with high surface quality requirement. Therefore, the T_{max}, representing the temperature distribution uniformity of the mold cavity surface, is selected as the major consideration in this work. Based upon the above analyses, the optimized results by using the hybrid RSM-GA and ANN-GA optimization methods are obtained and given in Table VI. It can be found that there is little difference between the optimized results obtained by the two hybrid optimization methods. This is because that both the RSM and ANN models developed in this work are quite significant.

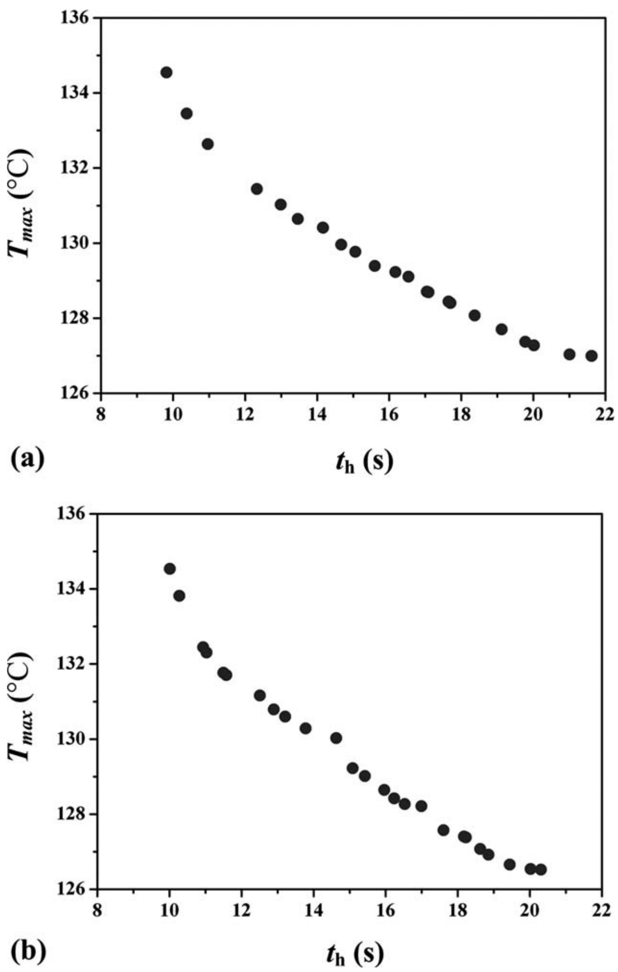


Figure 6. Pareto optimal solutions of design variables based on (a) RSM-GA and (b) ANN-GA optimizations.

Using the aforementioned optimized design variables as the design parameters of the heating system, the simulations are performed to obtain the objective functions (t_h and T_{max}) and the results are listed in Table VI. As can be seen, the errors between the simulated and optimized results are quite small (<1.5%), which demonstrates the effectiveness of both hybrid optimization methods. Moreover, the hybrid ANN-GA method shows higher accuracy in finding optimum design parameters and predicting optimum responses than the hybrid RSM-GA one. Figure 7 shows the temperature contour plots on the analyzed cross-section of the front half-mold with the optimal heating system design. Corresponding temperature distribution across the mold cavity surface is shown in Figure 8. It can be observed that the maximum cavity surface temperature difference is within 8°C and the required heating time is about 20 s. As a result, it can be speculated that the spoilers molded using the RTCM with the optimal heating system design have much glossy and uniform surface appearance, and the heating efficiency can be ensured as well.

Molding Experiments and Results

The above comparative analyses demonstrate that the optimized values of the design variables obtained by the hybrid ANN-GA method are more reasonable in terms of shorter required heating time and more uniform temperature distribution on the mold cavity surface. Therefore, an electric heating system is designed for the automotive spoiler mold according to the optimized values obtained by the hybrid ANN-GA method. The constructed RTCM blow mold of automotive spoiler is shown in Figure 9. The molding experiments for the spoiler are conducted on an industrial extrusion blow molding machine, which has a screw diameter of 55 mm and a length-diameter-ratio of

Table VI. Optimized Values of Design Variables and Objective Functions Using Hybrid Optimization Methods and Confirmation Simulations

	Design variable			Objective function	
	H (mm)	N (–)	q (Wcm^{-2})	t_h (s)	T_{max} (°C)
RSM-GA	13.44	5	20	21.62	126.99
Simulated	13.44	5	20	21.30	127.27
Error (%)	–	–	–	1.50	0.22
ANN-GA	12.98	5	20	20.33	126.52
Simulated	12.98	5	20	20.20	126.32
Error (%)	–	–	–	0.64	0.16

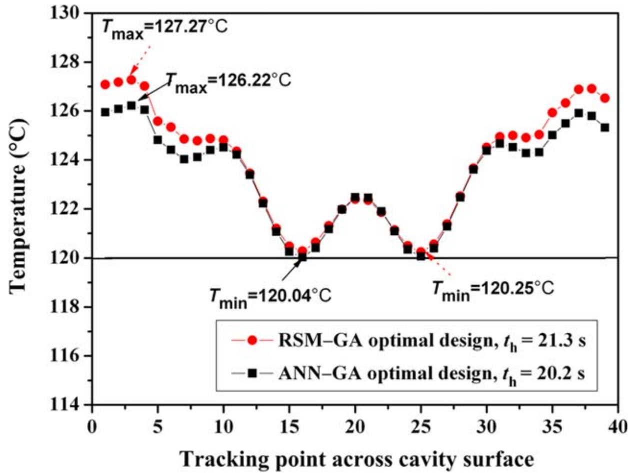


Figure 8. Comparison of temperature distributions across cavity surface of mold with optimal heating system designs. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

25:1. The material used is ABS (grade BM5602, TechnoPolymer, Japan) with a melt index of 1.7 g/10 min (240°C, 10 kg) and a thermal distortion temperature of 115°C. So the designated mold cavity surface temperature is set at 120°C in the experiments. The extruder is operated at 170°C in the feeding zone and at 240°C toward the parison die. The parison is formed through a diverging die having an outer diameter of 80 mm and a lip gap of 3 mm. The blowing pressure is set at 1.0 MPa.

Figure 10 shows the comparison of the spoilers molded with conventional and electric heating RTCM blow molding processes. As can be clearly seen, the spoiler molded with the former process has low surface gloss and obvious sunken points; whereas high gloss surface and no sunken points appear on the spoilers molded using the latter process, and so the sanding, polishing or spraying processes can be eliminated completely. The molding cycle time for the electric heating RTCM process is about 62 s, which is only 6−8 s longer than that for the conventional blow molding process. Moreover, for the spoiler mold investigated in this work, the electric heating process consumes about 0.1 kWh more electric energy than that of the conventional process for each molding cycle in the mold heating stage. The cycle time and energy consumption for the RTCM process is thought in accepted ranges considering the benefits in part surface appearance. Therefore, the electric heating RTCM technology for producing the automotive spoiler with high gloss appearance is feasible.

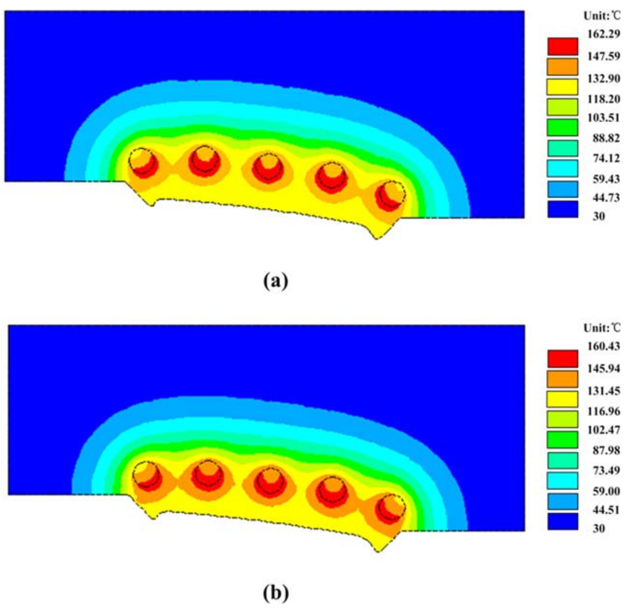


Figure 7. Temperature contour plots on analyzed cross-section of front half-mold with optimal heating system designs obtained using (a) RSM-GA and (b) ANN-GA optimizations. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

CONCLUSIONS

In the present work, the RTCM technology with electric heating and water cooling is developed to improve the surface quality of molded plastics parts. A multiobjective optimization strategy consisting of DOE, FEA, ANN, and RSM models, and Pareto-based GA is proposed to optimize the design of electric heating

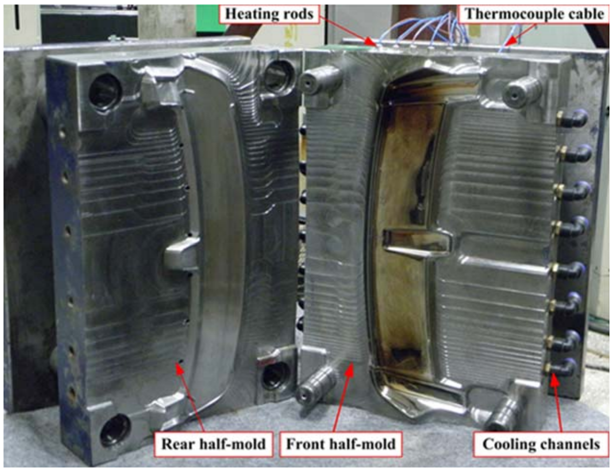
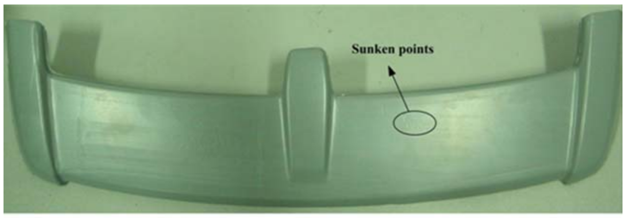


Figure 9. RTCM blow mold of automotive spoiler. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]



(a)

(b)

Figure 10. Comparison of automotive spoilers molded with (a) conventional blow molding and (b) electric heating RTCM methods. [Color figure can be viewed in the online issue, which is available at wileyonlinelibrary.com.]

system in RTCM mold. By performing this optimization strategy to design the electric heating system for an actual blow mold of automotive spoiler, its effectiveness is verified. With the optimized design parameters, the maximum temperature difference across the blow mold cavity surface is within 8°C and the required heating time is also maintained at an acceptable level. It is also found that the ANN model exhibits superior over RSM model. The blow molding experiments show that the automotive spoilers molded with the electric heating RTCM process possess high gloss appearance and no sunken points, and thus the secondary processes can be eliminated completely. The optimization method can also be used to design the heating system for other RTCM molds.

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