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Multi-objective process parameter optimization for energy saving in injection molding process*

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Abstract: This paper deals with a multi-objective parameter optimization framework for energy saving in injection molding process. It combines an experimental design by Taguchi's method, a process analysis by analysis of variance (ANOVA), a process modeling algorithm by artificial neural network (ANN), and a multi-objective parameter optimization algorithm by genetic algorithm (GA)-based lexicographic method. Local and global Pareto analyses show the trade-off between product quality and energy consumption. The implementation of the proposed framework can reduce the energy consumption significantly in laboratory scale tests, and at the same time, the product quality can meet the pre-determined requirements.

Key words: Injection molding process, Energy saving, Multi-objective optimization, Genetic algorithm, Lexicographic method
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1 Introduction

Energy savings and emissions reduction have become key state policy in China. Improving energy efficiency and reducing energy consumption are the attentive focuses for almost all industrial processes, especially for the manufacturing industry, as it accounted for more than 85.2% of the final industrial energy use in China in 2003 (Abdelaziz *et al*., 2011). Injection molding is a major manufacturing process in the polymer processing industry for the transformation of plastic materials into various products. It has six main operation stages, including mold clamping, injection, packing, cooling, mold opening, and ejection. As the plastic material needs to be heated, forced into the mold at high pressure and then cooled, the injection molding is obviously an energy intensive process. The rapidly increasing scale of the injection molding industry in China has a significant impact on the environment, even a slight increase in the efficiency of the injection molding process could lead to substantial energy savings and emissions reduction (Mattis *et al*., 1996).

Energy saving technologies for the injection molding process can be roughly divided into two branches. The first branch mainly focuses on machine improvement and new molding technologies, such as an all-electric power system, new clamping technology, low-pressure-high-speed technology, multi-shot hot runner design, a variable speed drive, and automatic V/P switch-over, etc. (Zhang, 2008). The second branch focuses on the examination of the relationship between process parameters and energy consumption, which leads to the development of energy consumption models and parameter optimization methods for energy saving. Apparently, the first branch is mainly based on hardware technologies, some of which have been equipped in the new

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generation injection molding machines. When an injection molding enterprise expects to reduce energy consumption using those hardware-based energy saving technologies, it usually needs to buy the new generation injection molding machines, or to rebuild the old machines by equipping them with new energy saving devices. Whatever the strategy is, it requires a heavy purchase or rebuild expense. Considering that plastics manufacturing is a narrow margin of profit industry, and there is a huge amount of low-end injection molding machines in China (Peng and Yang, 2008), the process optimization-based approach may be an attractive choice, as it requires only experimental data and can indeed reduce energy use at low cost. Thus, this paper attempts to develop a data-driven process optimization-based technology to achieve energy saving in injection molding process.

Although in practice, energy saving via process optimization is not a novel exercise, only a few theoretical studies have been reported. The pioneering work of reducing the energy use in injection molding was reported in the early 1980s, focusing on qualitative discussion on the parameter selection to minimize energy usage (Lafreninere, 1981; Ames, 1982), or quantitative examination on the amounts of energy consumed by various machine components in a typical molding machine (Nunn and Ackerman, 1981). In the mid of 1990s, Munoz and Sheng (1995), Sheng and Sutanto (1995) and Mattis *et al*. (1996) developed a framework for analyzing the influence of component, mold design decision and process parameter selection on the process energy efficiency. A set of energy-oriented process models was presented that can describe the modes of energy utilization in injection molding processes. The total energy consumption includes not only the energy used for melting and pushing the plastic into the mold cavity, but also some additional energy terms for mold movements, clamping and part ejection. With those theoretical models, Thiriez (2006) explored the relationship between the energy consumption and the process parameters, yielding a system-level environmental analysis of the injection molding process. The above efforts for energy reduction in the injection molding process remained at the stage of process analysis and modeling, until Lin (2008) made an attempt to obtain the optimal parameter combination to minimize energy consumption. The non-linear relationship between the process parameters and the energy consumption was modeled by an artificial neural network (ANN); then an increment scouting method was used to obtain the optimal injection parameters. The deficiency in Lin (2008) is clear, that is, it did not consider the requirements on product quality when attempting to obtain the optimal process parameters for minimizing energy consumption.

For practical application, striving merely for energy efficiency without considering product quality is unrealistic. It is desirable to develop a framework to optimize process parameters with minimum energy consumption, as well as satisfactory product quality. The process of optimizing systematically and simultaneously a collection of objective functions is called multi-objective optimization problem (MOP) (Marler and Arora, 2004), also called multi-response optimization (MRO) or multi-criteria decision-making (MCDM) in different application areas (Montgomery, 2001). Multiple objectives may be incommensurable and often competing. There is rather a set of alternative trade-offs, generally known as Pareto-optimal solutions. In the example of this paper, product quality and energy consumption are generally competing, since high performance quality control substantially increases control effort and results in more energy use. Classical methods for generating the Pareto-optimal set aggregate the objectives into a single, parameterized objective function, such as the weighting method and the constraint method. The weighting method converts an MOP into a single optimization problem (SOP) by forming a linear combination of the objectives. This technique is simple, but cannot generate all Pareto-optimal solutions with non-convex trade-off surfaces. The constraint method transforms $k-1$ of the k objectives into constraints, where the emphasis is usually laid on the formulation of the objective function and the handling of constraints. The constraint method is suitable for the case where a prior preference on the multiple objectives is available (Marler and Arora, 2004). Although some advanced MOP methods such as the evolutionary algorithms (Zitzler *et al*., 2003; Carlos *et al*., 2008) have become available in recent years, the aforementioned traditional approaches are still attractive and popular because many well-studied algorithms for SOPs can be used directly.

In this paper, the lexicographic method (Carlos *et al*., 2007) is adopted to find the optimal process parameter settings for both quality assurance and energy saving. The lexicographic method requires a list of objectives in decreasing order of preferences and the bounded objective functions method. It starts from a single most preferred objective function and transforms the remaining objectives into constraints with fixed bounds chosen by the decision-maker. From a practical viewpoint, it is easy to solve an MOP by requiring the decision-maker to rank the objectives in order based on one's preferences from best to worst. Even if the decision-maker does not provide ranking information for the objectives, it is also possible to select randomly an objective to be optimized at each time. In this paper, the relative importance of the objective functions is clear. Product quality is more important than energy consumption. A lexicographic method is a perfect choice. The original lexicographic method was developed to solve MOP problems with equality constraints; however, many widely-used intelligent optimization methods such as evolutionary algorithms (EAs) can not directly solve problems with equality constraints (Mezura-Montes, 2009). Therefore, a variation of lexicographic method with relaxed inequality constraints is used in this paper.

Considering the complex and nonlinear relationships among process parameter settings, product quality and energy consumption, many studies of injection molding processes have investigated the application of ANNs (Mok and Kwong, 1999). In fact, ANNs have been frequently combined with genetic algorithms (GAs) in finding the optimal parameter settings to improve product quality of injection molding processes (Mok *et al*., 2001; Ozcelik and Erzurumlu, 2006; Shen *et al*., 2007; Chen *et al*., 2009; Altan, 2010). In this paper, ANN is used to develop a quality and energy prediction model; based on the ANN prediction model, a GA-based lexicographic method is used to solve the multi-objective optimization problem. In fact, the effectiveness of the whole optimization process is strongly dependent on the performance of the quality and energy prediction model.

2 Injection molding process

Injection molding is a typical multi-stage process, among which, injection (or filling), packing-holding, and cooling are the most important phases. During filling, the screw moves forward and pushes the molten polymer into the mold cavity. Once the mold is completely filled, the process then switches to the packing-holding stage, during which additional polymer is "packed" at high pressure to compensate for the material shrinkage associated with the material cooling and solidification. The packing-holding continues until the gate freezes off, which isolates the material in the mold from that in the injection unit. The process enters the cooling stage; the part in the mold continues to solidify until it is rigid enough to be ejected from the mold without damage. Concurrently, with the early cooling phase, plastication takes place in the barrel where polymer is melted and conveyed to the front of barrel by screw rotation, preparing for the next cycle.

The primary concern in the injection molding process is always to produce high quality parts. Recently, however, with increasing attention to energy savings and emissions reduction, it is desirable to reduce energy consumption and guarantee product quality at the same time. To achieve this aim, it is important to evaluate the feasibility of a multi-objective process optimization procedure in injection molding process.

In injection molding, product quality can be described by mechanical properties (such as part strength and stiffness), dimensional conformity (such as weight, length and thickness) and surface appearance (such as sink mark, record groove and jetting) (Yang and Gao, 2006). To simplify quality-oriented process optimization, part weight (PW) is often selected for determining the optimal process parameter settings under single quality characteristic consideration because PW has a close relation to other quality properties (Yang and Gao, 2006; Chen *et al*., 2009; Sun *et al*., 2010). Previous studies have shown that, the control of PW involves many process parameters, and significant interactions exist among the parameters. For example, Srinivasan *et al*. (1991) developed a regression model that relates PW (y) to the setpoints for mold temperature (x_1), nozzle-melt temperature (MT) (x_2), packing time (PT) (x_3) and packing pressure (PP) (x_4):

$$y = \sum_{i=1}^{3}\sum_{j=1}^{3} B_{ij} x_i x_j + B_p x_4, \tag{1}$$

where x_ix_j (i,j=1,2,3) are the quadratic terms of independent variables; B_{ij} and B_p are the corresponding coefficients for x_ix_j and x_4.

Sun *et al.* (2010) presented another multiple regression model for PW (y) that involves the injection velocity (IV) (x_1), injection pressure (x_2), PT (x_3) and MT (x_4):

$$y=\alpha_0+\sum_{i=1}^{4}\left(\alpha_i x_i+\beta_i x_i^2\right)+\sum_{i=1}^{4}\sum_{j=1}^{4}\gamma_{ij}x_ix_j, \quad (2)$$

where α_0, α_i, β_i and γ_{ij} are the corresponding coefficients for the constant, linear, quadratic and interact terms, respectively.

Although the above two models involve slightly different process parameters, the common fact is, PW is a complex nonlinear model involving multiple process parameters. There will be a cluster of combinations of process parameters for a specified PW. The model that relates energy consumption and process parameters is also a complex nonlinear model as described in Section 3, which is generally different from the quality model. This implies that, different process parameter settings corresponding to a certain product quality can result in differing amounts of energy consumption. Without a theorem-proof format, a conclusion can be drawn that it is possible to obtain multi-objective optimization for both quality assurance and energy saving in injection molding process.

3 A multi-objective parameter optimization framework

As a pure data-based energy saving technique, the initial settings of experimental condition are very important for the following process analysis, modeling and optimization. There are two basic ways to collect data, by selecting historical data or by running designed experiments. In the illustrative example of this study, no energy consumption measurements are available in the historical database. Thus, Taguchi's orthogonal design is performed first to provide initial experimental data for process analysis. Fractional factor design is also used to provide necessary additional experimental data for nonlinear modeling.

The proposed optimization framework is illustrated in Fig. 1. With the designed experimental data, analysis of variance (ANOVA) is applied to quantitatively determine the major factors that affect the part quality and energy consumption. A nonlinear process model is developed using ANN, which will be used to build the fitness functions in the GA-based optimization procedures. A lexicographic method based multi-objective optimization, is adopted to search for the optimal process settings for both product quality and energy consumption. Finally, validation experiments are conducted. When the obtained process settings do not satisfy the pre-specified requirements, the whole optimization procedures should be repeated after updating the data sets and the prediction model.

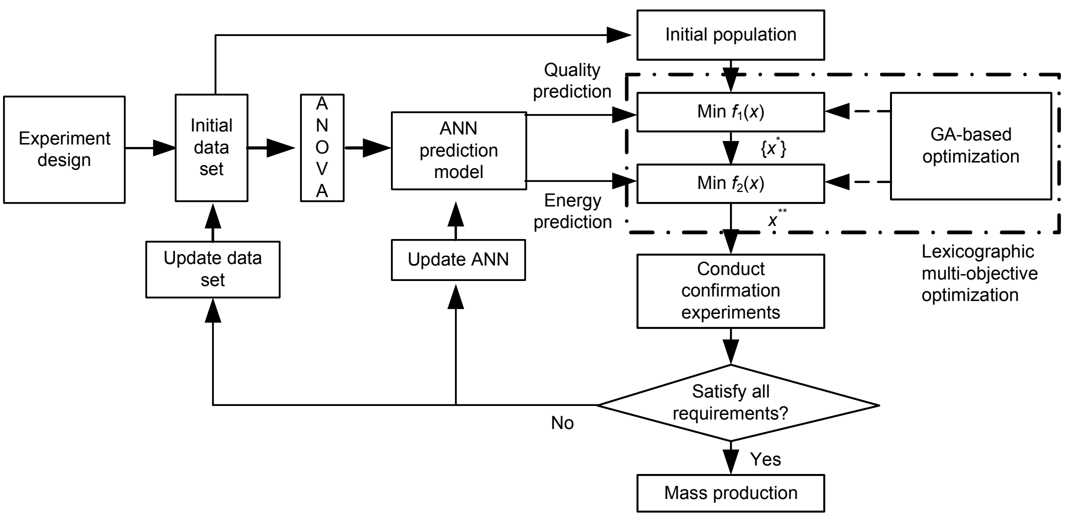

Fig. 1 Diagram of the proposed multi-objective parameter optimization framework

3.1 Experimental setup and process analysis

All the experiments are conducted on a Chen Hsong reciprocating-screw injection molding machine, Model type MJ55, located in the Center for Polymer Processing and Systems (CPPS) at the Fok Ying Tung Graduate School, Hong Kong University of Science & Technology (HKUST). The material is high-density polyethylene (HDPE). The mold is a customized mold with flat cavity. PW is selected as the quality response, which is measured by a Dertork high precision electronic scale (Tianjian, China; precision: 0.001 g); and energy consumption per cycle (ECC) is considered as the evaluating standard of energy consumption, which is measured by a high precision electric energy meter (Huayuan DTS151, Nanjing, China; accuracy class: 0.02).

In authors' previous work (Yang and Gao, 2006), seven process variables including MT, coolant water (or mold) temperature (CWT), IV, PP, injection stroke, screw rotation speed, and plastication back pressure, were considered in analyzing their influences on PW. Previous results showed that MT, CWT, IV, and PP are the most significant factors. In this example, to avoid unnecessary overwhelming amount of experiments, only PT, IV, PP and MT are selected as control factors. The mold temperature is excluded because it is not closed-loop controlled on the machine, while the PT is included because it indeed influences both PW and energy consumption by theoretical analysis. During the experimental design, PT and IV take three levels, while PP and MT take four levels, as listed in Table 1.

A L_{12} ($3^2 \times 4^2$) orthogonal array is applied, resulting in 12 treatments with different level combinations of the four factors. Each replicates for three times, to reduce experimental errors. The order of the experiment is arranged randomly to avoid unexpected noises. The responses of PW and ECC are listed in Table 2.

To gain more insight into the mechanism of the injection molding process, ANOVA is used for process analysis. The influence of all parameters on PW and ECC is shown in Table 3. PT and MT are more important than IV and PP for both PW and ECC under the above-mentioned experimental conditions. The degrees of sensitivity of PW and ECC to each parameter are shown in Figs. 2a–2d.

From Fig. 2a, it can be seen that an increase of the PT setting leads to increases of both PW and ECC

Table 1 Factors and levels for experimental design

Level	Factor			
	PT (s)	IV (mm/s)	PP ($\times 10^5$ Pa)	MT (°C)
1	4	30	25	190
2	5	35	30	200
3	6	40	35	210
4			40	220

Table 3 Factors influence on PW and ECC by one-way ANOVA

Factor	Contribution (%)	
	PW	ECC
PT	44.58	39.75
IV	18.20	10.95
PP	13.37	5.83
MT	23.85	43.47

Table 2 Results of L_{12} ($3^2 \times 4^2$) experiment design

Treatment	PT (s)	IV (mm/s)	PP ($\times 10^5$ Pa)	MT (°C)	Average PW (g)	Average ECC (kJ)
1	4	30	25	190	20.973	64.35
2	4	30	40	220	20.850	67.86
3	4	35	30	200	20.869	63.18
4	4	40	35	210	20.872	64.35
5	5	30	40	190	21.151	65.61
6	5	35	30	210	20.974	69.26
7	5	35	35	200	20.990	66.34
8	5	40	30	220	21.031	68.04
9	6	30	25	200	21.090	68.04
10	6	35	40	210	21.068	65.52
11	6	40	25	220	21.143	69.55
12	6	40	35	190	21.201	68.04

linearly; while in Figs. 2b, 2c and 2d, the relationships between the control factors (IV, PP, and MT) and the response variables (PW and ECC) show clear nonlinear patterns, indicating that nonlinear modeling techniques are necessary to map the complex relationships. In addition, the confliction between quality and energy can be observed (Fig. 2d).

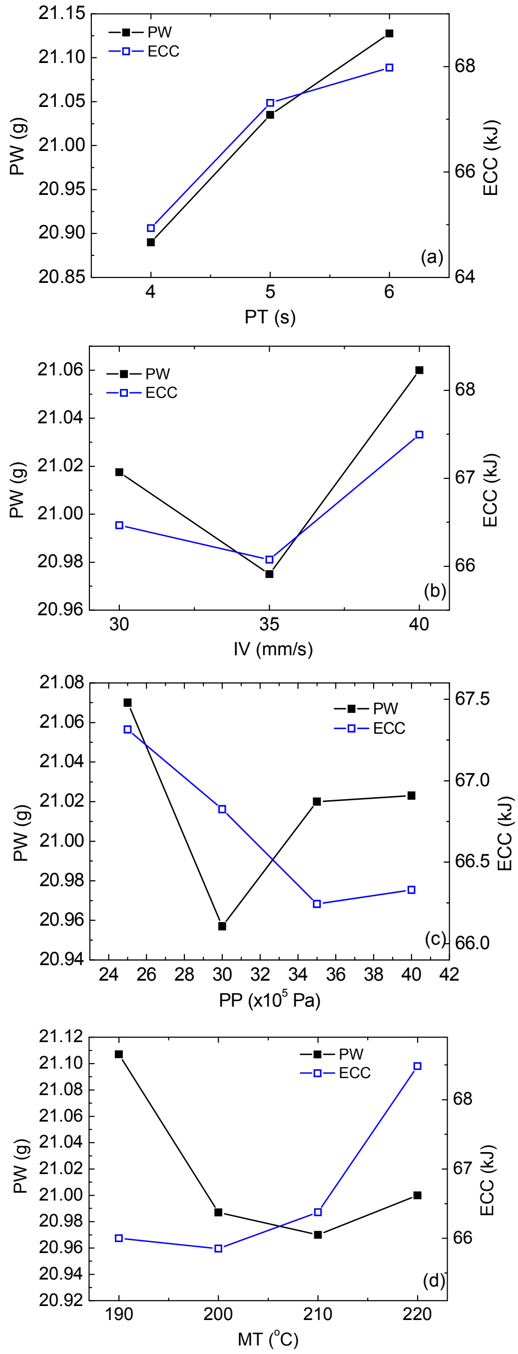

Fig. 2 Illustration of the effects of (a) PT, (b) IV, (c) PP and (d) MT on the PW and the ECC

According to Table 3, PT and MT are the two most significant factors on both the PW and ECC. Thus, the overlaid contour plot can be used to visually illustrate the relationships between the two control factors and the two response variables, as shown in Fig. 3.

Although the overlaid contour plot can roughly determine the optimal region for multiple response variables, it is limited to only two experimental factors. Fig. 3 is used to graphically illustrate the feasibility of the proposed multi-objective optimization for energy saving in injection molding. It is clear that, different combinations of the two control factors can generate constant PW, while a PW contour line intersects different energy consumption contour lines. It implies that the energy consumption can be reduced by choosing proper process settings without affecting the product quality.

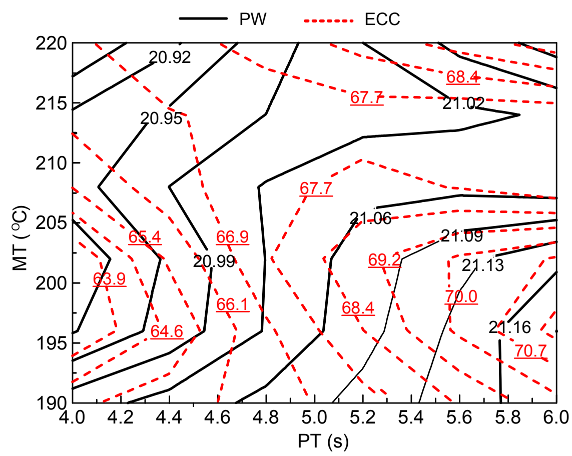

Fig. 3 Overlaid contour plots for PW and ECC

3.2 ANN-based quality and energy consumption prediction

To construct an efficient objective function is critical in an optimization problem. As substantiated by many researchers, the complex relationships between quality or energy indexes and process parameters cannot be accurately expressed by any analytic model. Traditional modeling methods are mostly reliant on assumptions for model simplifications, and thus may lead to inaccurate results (Shen *et al.*, 2007). On the other hand, neural networks have been widely used for extracting information from data in the form of predictive input-output models. They provide a general framework, which can, in principle, approximate any type of nonlinearity in the data. The characteristics of the ANN technique make it suitable for modeling the quality or energy consumption in injection molding process. Therefore, it is used in this study as the modeling tool. As shown in Fig. 1, the objective functions in the subsequent GA-based multi-objective optimization are built by the ANN technique. The performance of the prediction model determines whether or not the true optimal solution can be found.

Neural networks offer distinct advantages in some areas but have other limitations. One of the main and well-known disadvantages of neural network training is that it requires a large quantity of experimental data. The experimental data listed in Table 2 are insufficient to obtain an accurate, robust neural network prediction model. Fractional factorial design is thus performed to generate necessary additional experimental data for ANN modeling. Finally, 39 pairs of experiments were conducted as listed in Table 4. The data are also used to generate an initial population for the GA-based optimization procedures.

A 4-8-2 three-layered back-propagation neural network (BPNN) is employed to map the nonlinear patterns between the process parameter settings and the response variables. The inputs of the network are the settings of PT, IV, PP and MT, while the outputs are PW and ECC. The nonlinear function in the hidden nodes is tansig.

The experimental data listed in Table 4 are randomly divided into two parts, a training set and a test set. The training set consists of 33 input-output data pairs, while the test set consists of the remaining six data pairs. The Levenberg-Marquardt back-propagation training algorithm is adopted to train the BPNN. The prediction performances of the developed BPNN are shown in Figs. 4 and 5.

The predicted values almost overlap with the actual values, indicating the good performance of the ANN model. Absolute percentage error (APE) is used as an error index to measure the prediction performance:

$$\mathrm{APE}=\left|\frac{\hat{y}-y}{y}\right|, \tag{3}$$

Table 4 Experimental data for ANN-based nonlinear modeling

No.	Input				Output	
	PT (s)	IV (mm/s)	PP ($\times10^5$ Pa)	MT (°C)	Average PW (g)	Average ECC (kJ)
1	4	30	25	190	20.971	64.44
2	4	40	30	190	21.089	68.40
3	4	35	35	190	20.955	62.64
4	4	35	30	200	20.870	63.36
5	4	35	35	200	20.901	62.64
6	4	40	25	210	20.943	65.52
7	4	30	35	210	20.887	65.52
8	4	35	40	210	21.002	66.60
9	4	35	25	220	20.921	68.04
10	4	30	30	220	20.814	64.80
11	4	40	30	220	20.800	66.60
12	4	30	35	220	20.839	65.52
13	4	30	40	220	20.843	68.04
14	4	35	40	220	20.844	68.04
15	5	40	30	190	21.070	66.96
16	5	30	35	190	21.064	65.52
17	5	35	35	190	21.111	68.04
18	5	35	25	200	21.159	73.08
19	5	30	30	200	21.021	65.52
20	5	35	30	200	20.989	68.04
21	5	30	40	200	21.018	66.24
22	5	40	25	210	21.090	67.32
23	5	30	30	210	20.980	68.04
24	5	40	35	210	20.947	66.24
25	5	35	40	210	21.083	68.04
26	5	40	25	220	21.032	67.32
27	5	35	40	220	20.957	69.12
28	6	30	25	190	21.144	70.56
29	6	40	35	190	21.201	68.04
30	6	35	40	190	21.206	70.56
31	6	35	25	200	21.333	75.60
32	6	40	30	200	21.151	70.56
33	6	35	35	200	21.060	68.76
34	6	40	25	210	20.938	65.52
35	6	30	35	210	21.042	68.40
36	6	35	40	210	21.071	65.52
37	6	30	25	220	21.103	69.84
38	6	30	40	220	21.055	68.76
39	6	40	40	220	21.172	72.36

where $\hat{y}$ is the predicted value of the real measurement y by the ANN model.

The maximum APEs for PW and ECC of the test data set are 0.08% and 1.23%, respectively. The developed BPNN model has good interpolation capability. It can be used as an efficient predictive tool for both product quality and energy consumption

3.3 GA-based lexicographic optimization

With the lexicographic method, the objective functions are ranked in order of importance by the decision-maker. The optimum solution is then obtained by minimizing the objective functions, starting with the most important one and proceeding according to the order of importance of the objectives (Carlos *et al.*, 2008). Let the subscripts of the objectives indicate not only the objective function number, but also the priority of the objective. Suppose there are K objectives in an MOP problem:

$$\begin{aligned} &\text{Min } \{f_1(x),\cdots,f_k(x),\cdots,f_K(x)\},\\ &\text{s.t.}\\ &g_j(x)\le 0,\ j=1,2,\cdots,m, \end{aligned} \tag{4}$$

where $f_1(x)$ and $f_K(x)$ denote the most and the least important objective functions, respectively. The first problem is formulated as

$$\begin{aligned} &\text{Min } f_1(x)\\ &\text{s.t.}\\ &g_j(x)\le 0,\ j=1,2,\cdots,m, \end{aligned} \tag{5}$$

and its solution x_1^* ($f_1^*=f_1(x_1^*)$) is obtained. Then the second problem is formulated as

$$\begin{aligned} &\text{Min } f_2(x)\\ &\text{s.t.}\\ &g_j(x)\le 0,\ j=1,2,\cdots,m,\\ &f_1(x)=f_1^*. \end{aligned} \tag{6}$$

The solution of this problem is obtained as x_2^* ($f_2^*=f_2(x_2^*)$). This procedure is repeated until all the K objectives have been considered.

In practice, the equality constraint $f_k(x)=f_k^*$ is too strong to find an optimal solution. To overcome such

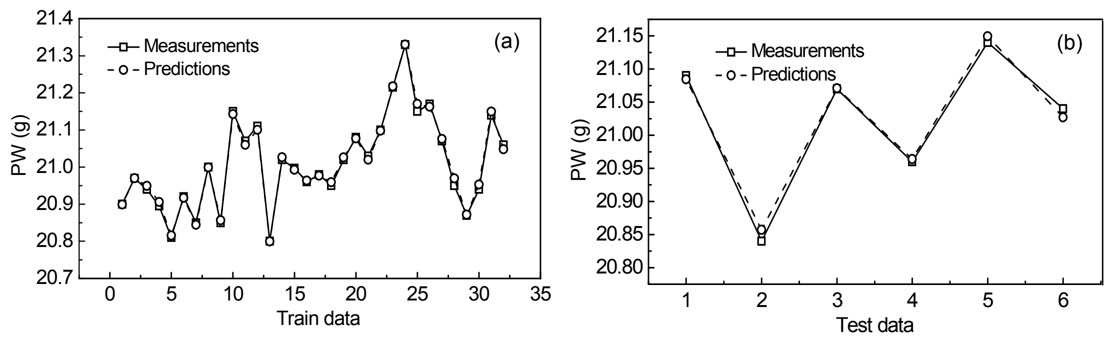

Fig. 4 ANN prediction results for PW
(a) Training data; (b) Test data

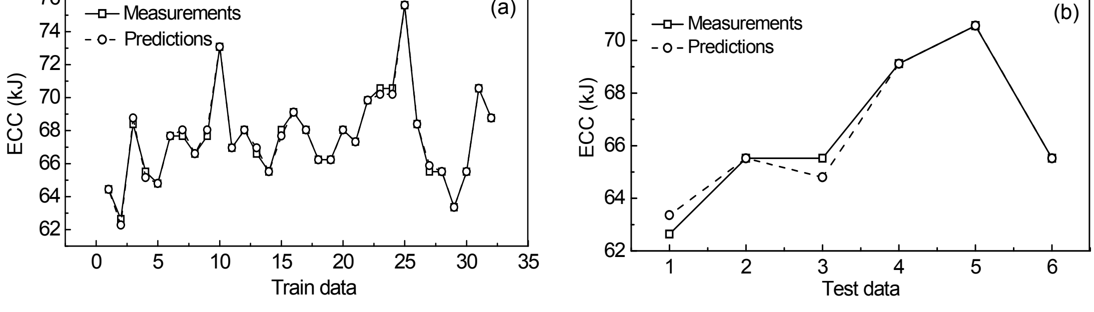

Fig. 5 ANN prediction results for ECC
(a) Training data; (b) Test data

a problem, the above lexicographic procedures can be modified by converting equality constraints into relaxed inequality constraints (Mezura-Montes, 2009), i.e., $f_k(x) \le f_k^*$. For further relaxation, one can introduce slacks to the inequality constraints, e.g., $f_k(x) \le f_k^* + \delta_k$, where δ_k is a pre-established bound and varying δ_k generates different weakly Pareto optimal points (Ruzika and Wiecek, 2005).

In the BPNN prediction model, $f_1(x)$ denotes the objective function of product quality (i.e., PW), $f_1(x)=\sqrt{(\mathrm{PW}-\mathrm{PW}_{\mathrm{des}})^2}$, where $\mathrm{PW}_{\mathrm{des}}$ is the desired PW specified by the customer. $f_2(x)$ denotes the objective function of energy consumption, $f_2(x)$=ECC. $\boldsymbol{x}$=[PT, IV, PP, MT]$^{\mathrm{T}}$ is the vector of control factors. Then the first layer optimization problem is obtained:

$$\begin{aligned}&\text{Min } f_1(x),\\&\text{s.t.}\\&4\text{ s} \le \mathrm{PT} \le 6\text{ s},\\&30\text{ mm/s} \le \mathrm{IV} \le 40\text{ mm/s},\\&2.5\times10^6\text{ Pa} \le \mathrm{PP} \le 4\times10^6\text{ Pa},\\&190\text{ °C} \le \mathrm{MT} \le 220\text{ °C},\end{aligned} \tag{7}$$

where the ranges of control factors are selected based on the experience of the manufacturer of the application work.

There are a plenty of numerical optimization algorithms available to solve the above single-objective optimization problem. In this study, GA is used. The solution of the optimization problem with GA begins with a set of potential solutions (or chromosomes in the biological evolutionary process) that is randomly generated. The entire set of these solutions comprises a population. The chromosomes evolve during generations. New generations are obtained after applying the selection, crossover and mutation operations. The chromosomes are then evaluated using a certain fitness criteria and the best ones are kept while the others are discarded. This process is repeated until the termination criterion is met.

The implementation of GAs includes the determination of a number of parameters. The population size, the probabilities of selection, crossover and mutation, the scaling window, and several other parameters definitely affect the convergence rate and the global optimality. Recommended in those previous works on GA (Alander, 1992; Srinivas and Patnail, 1994; Tan *et al*., 2001), population size ranges from 30 to100, crossover rate ranges from 0.5 to 0.9, and mutation rate ranges from 0.005 to 0.05. According to the experimental results in this study, the population size of 70, crossover rate of 0.6, and mutation rate of 0.02 have the best convergence performance.

With respect to the termination criterion, there are three kinds of termination conditions commonly used in GAs (Safe *et al*., 2004): (1) An upper limit on the number of generations is reached; (2) An upper limit on the number of evaluations of the fitness function is reached; and (3) The chance of achieving significant changes in the next generations is excessively low.

In the first-layer optimization problem, the settling boundary, $f_1(x) \le \delta$, is defined as the termination criterion, where δ is the user-defined threshold. In this study, δ takes the value of 0.01. When all the fitness values in a population are less than the threshold δ, the GA process stops and all individuals $\{x^*\}$ in that population are selected to generate the initial population for the second-layer optimization.

The second-layer optimization problem is

$$\begin{aligned}&\text{Min } f_2(x),\\&\text{s.t.}\\&4\text{ s} \le \mathrm{PT} \le 6\text{ s},\\&30\text{ mm / s} \le \mathrm{IV} \le 40\text{ mm / s},\\&2.5\times10^6\text{ Pa} \le \mathrm{PP} \le 4\times10^6\text{ Pa},\\&190\text{ °C} \le \mathrm{MT} \le 220\text{ °C},\\&f_1(x) \le \delta,\end{aligned} \tag{8}$$

where $f_1(x) \le \delta$ is just the termination condition in the first optimization problem because the objective function extremum is obviously $f_1^* = f_1(x_1^*) = 0$.

GA is used to solve this problem again. The maximum number of iterations is used as the termination criteria to avoid excessive computation time, which is set as 50 in this study. The solution obtained at the end, x^{**}, is taken as the desired solution of the multi-objective optimization problem.

3.4 Verification of the optimization result and model updating

Before mass production, it is necessary to thoroughly validate the optimization results by conducting several additional verification experiments. In some situations, the obtained process parameter settings may not satisfy the pre-specified requirements on product quality or energy consumption. The possible reasons may be that (1) inadequate training data results in an inaccurate ANN prediction model; or (2) pre-mature phenomenon occurs in GA resulting in unsuccessful optimum searching. Whatever, the entire multi-objective optimization procedures should be repeated after updating the data set and re-training of the BPNN prediction model. Even when the obtained process parameter can meet all the requirements, it is desirable to accumulate new experimental data to update the prediction model and adjust the operating conditions if necessary. This updating procedure can gradually improve the performance of the BPNN prediction model and ensure the proposed multi-objective optimization method to be a global search methodology for determining a true optimal solution.

4 Results and discussion

Suppose that there are eight product specifications on PW specified by different customers, i.e., 20.85, 20.90, 20.95, 21.00, 21.05, 21.10, 21.15, and 21.20 g, respectively, which can be covered in the operation space of the injection molding machine under the experimental conditions given in Section 3.1. To demonstrate the effectiveness of the proposed multi-objective optimization framework, two groups of comparative experiments were conducted. In the first group, the process parameter settings are determined by a single objective parameter optimization procedure (Chen *et al*., 2009), i.e., the design method is under only PW consideration (Method A in Table 5). In the second group, the parameters are determined by the proposed dual-objective optimization method (Method B in Table 5).

From Table 5, it is clear that the proposed energy saving oriented dual-objective optimization method (Method B) can confidently reduce the energy use for all quality specifications, compared with the single-objective quality-oriented optimization method (Method A). The average improvement rate of energy consumption is about 10% in laboratory scale tests, indicating its potential for application in the molding shop floor environment for energy consumption reduction. However, it is worth mentioning that, the product quality obtained by Method B has a relatively large bias to its target value as shown in Table 5.

For further explanation, Fig. 6 and Table 6 show the local Pareto front for PW_{des}=21.00 g, where the dots are the final solutions of GA after the second-layer optimization, and the triangles are the Pareto

Table 5 Energy saving results for the eight comparative experiments

Experiment	Method	Process parameter setting				PW	ECC	Energy
		PT (s)	IV (mm/s)	PP ($\times10^5$ Pa)	MT (°C)	(g)	(kJ)	saving
1. PW_{des}=20.85 g	A	4.4	31	26	217	20.850	64.85	5.5%
	B	5.0	35	32	213	20.847	61.27	
2. PW_{des} =20.90 g	A	4.1	36	40	214	20.900	69.63	17.9%
	B	5.2	36	40	212	20.902	57.14	
3. PW_{des} =20.95 g	A	5.2	39	26	194	20.950	63.61	10.9%
	B	5.3	37	35	204	20.949	56.62	
4. PW_{des} =21.00 g	A	5.9	39	30	207	21.000	68.54	19.1%
	B	5.2	35	31	213	20.998	55.40	
5. PW_{des} =21.05 g	A	5.0	38	37	200	21.050	61.63	10.7%
	B	4.3	38	33	197	21.047	55.02	
6. PW_{des} =21.10 g	A	5.2	37	36	194	21.099	62.91	10.1%
	B	4.1	39	33	197	21.109	56.61	
7. PW_{des} =21.15 g	A	4.4	40	34	200	21.150	61.60	10.0%
	B	4.3	39	34	192	21.153	59.18	
8. PW_{des} =21.20 g	A	5.7	35	40	198	21.201	63.88	3.5%
	B	5.6	35	40	197	21.205	61.65	

optimal solutions. There are seven Pareto optimal solutions. The first row in Table 6 turns out to be the final solution in Method B that has the minimum energy consumption; while the seventh row is the final solution in Method A that has the minimum quality deviation (i.e., the fourth group of experimental results in Table 5). The two solutions are both Pareto optimal, indicating that there is a clear trade-off between product quality and energy consumption.

Fig. 7 shows the global Pareto curve front (represented by the triangles) for all quality specifications and Table 7 gives the corresponding optimal parameter combinations. From Fig. 7, an interesting phenomenon can be observed. Different PW specifications result in different minimum energy consumption. There exists a global minimum value for energy consumption where PW is around 20.90 g. The utility of this "global optimal point" is limited; however, it is helpful for gaining deeper insight into the relationship between product quality and the consumed energy in an injection molding process.

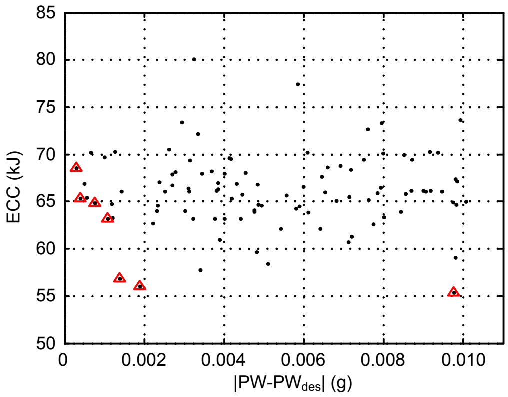

Fig. 6 Local Pareto front analysis for PW_{des}=21.00 g

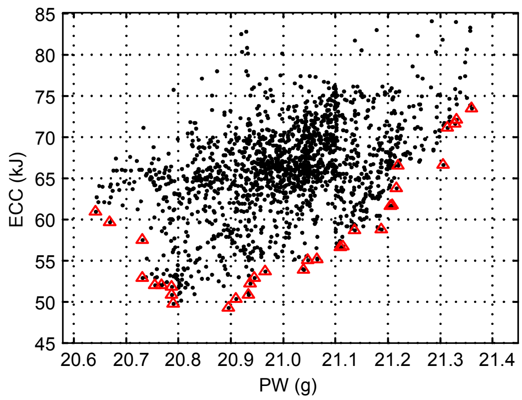

Fig. 7 Global Pareto front analysis

Table 6 Part of GA results for PW_{des}=21.00 g

No.	PT (s)	IV (mm/s)	PP (×10^5 Pa)	MT (°C)	PW (g)	ECC (kJ)	Front*
1	5.2	35	31	213	20.990	55.40	1
2	5.2	35	30	213	20.998	56.08	1
3	5.2	35	30	212	21.001	56.84	1
4	4.0	38	34	199	21.001	63.23	1
5	5.3	38	34	200	21.001	64.85	1
6	5.5	37	27	194	21.000	65.38	1
7	5.9	39	30	207	21.000	68.54	1
8	5.3	32	35	194	20.991	66.08	0
9	4.8	39	30	195	20.991	66.17	0
10	5.0	32	35	193	20.991	66.13	0
11	4.8	32	35	193	20.991	66.14	0
12	4.8	40	26	197	20.991	66.20	0
13	4.8	38	32	200	20.991	65.87	0
14	5.0	34	30	211	20.992	63.92	0
15	5.4	38	26	193	20.992	63.37	0
16	4.5	36	38	208	20.992	65.96	0
17	5.1	34	32	211	20.992	65.19	0
18	5.9	31	36	198	20.992	72.71	0
19	4.8	35	30	198	20.993	69.51	0
20	4.7	32.6	33	206	21.000	68.83	0

* 1 means that the corresponding parameter combination is a Pareto optimal solution; while 0 means that the parameter combination is not an optimal solution

Table 7 Local Pareto optimal solution sets for the four quality specifications

PW_{des} (g)	PT (s)	IV (mm/s)	PP (×10^5 Pa)	MT (°C)	PW (g)	ECC (kJ)
20.90	5.2	36	30	212	20.902	57.14
	5.2	35	30	208	20.901	57.54
	5.0	35	30	207	20.901	58.44
	4.1	36	40	214	20.900	69.63
21.00	5.2	35	31	213	20.990	55.40
	5.2	35	30	213	20.998	56.08
	5.2	35	30	212	21.001	56.84
	4.0	38	34	199	21.001	63.23
	5.3	38	34	200	21.001	64.85
	5.5	37	27	194	21.000	65.38
21.10	5.9	39	30	207	21.000	68.54
	4.1	39	33	197	21.110	56.61
	4.1	39	33	198	21.103	56.75
	4.2	39	33	198	21.101	57.15
	4.3	39	33	198	21.099	58.78
	5.2	37	36	194	21.099	62.91
	5.7	34	28	218	21.100	73.98
	5.9	34	29	206	21.100	75.28
21.20	5.6	35	40	197	21.205	61.65
	5.6	35	40	198	21.202	61.71
	5.7	35	40	198	21.201	63.88

5 Conclusions and future work

In this paper, an effective dual-objective optimization framework is presented for energy saving in injection molding process. It is the first attempt focusing on the simultaneous optimization of both product quality and energy consumption, and the implementation of the proposed framework can reduce the energy consumption significantly in laboratory scale tests, at the same time, the product quality can meet the pre-determined requirement. The average improvement rate of energy consumption is about 10%, indicating its potential for application in the molding shop floor environment for energy consumption reduction.

The local and global Pareto analyses show the relationship between product quality and energy consumption. Higher requirement on product quality can result in higher energy consumption. There indeed exists the trade-off between quality and energy. The decision-makers have to make a choice according to the actual need.

The proposed framework is applicable for determining the optimal process parameter settings for the mass production of a certain product. The future work will focus on the energy saving issue for the injection molding process with multiple products, for which, it is required to determine the optimal production sequence, as well as the optimal process parameter settings for each product, to achieve the global minimum energy consumption.

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