Journal of Computational Design and Engineering Vol. 1, No. 4 (2014) 256~265
www.jcde.org

Optimization of injection molding process for car fender in consideration of energy efficiency and product quality

Hong Seok Park* and Trung Thanh Nguyen

Lab for Production Engineering, School of Mechanical and Automotive Engineering, University of Ulsan, San29, Mugeo 2-dong, Namgu, Ulsan, 680-749, Korea

(Manuscript Received June 30, 2014; Revised August 25, 2014; Accepted September 1, 2014)

Abstract

Energy efficiency is an essential consideration in sustainable manufacturing. This study presents the car fender-based injection molding process optimization that aims to resolve the trade-off between energy consumption and product quality at the same time in which process parameters are optimized variables. The process is specially optimized by applying response surface methodology and using non-dominated sorting genetic algorithm II (NSGA II) in order to resolve multi-object optimization problems. To reduce computational cost and time in the problem-solving procedure, the combination of CAE-integration tools is employed. Based on the Pareto diagram, an appropriate solution is derived out to obtain optimal parameters. The optimization results show that the proposed approach can help effectively engineers in identifying optimal process parameters and achieving competitive advantages of energy consumption and product quality. In addition, the engineering analysis that can be employed to conduct holistic optimization of the injection molding process in order to increase energy efficiency and product quality was also mentioned in this paper.

Keywords: Multi-objective optimization; Injection molding process; Energy efficiency; Plastic car fender

1. Introduction

Injection molding has been the most popular method for making plastic products due to high efficiency and manufacturability. The injection molding process includes four important stages: filling, packing, cooling, and ejection. A primary traditionally concern in injection molding has been that of the extent to which high-quality products with strong mechanical properties can be manufactured, in the absence of any undesired defects. Many previous studies have sought to eliminate defects in plastic products. To minimize temperature deviation for an automotive product, cooling circuit parameters were optimized using CAE program [1]. In the case of reducing warpage, the combination of the response-surface method or neural network with a genetic algorithm was conducted in order to obtain optimal parameters [2, 3]. The deficiency of these studies was the lack of consideration for the energy consumption of the injection molding process. Consumer pressure, rising energy cost and environmental legislation have combined to increase the importance of reducing energy consumption in the industrial plastic industry.

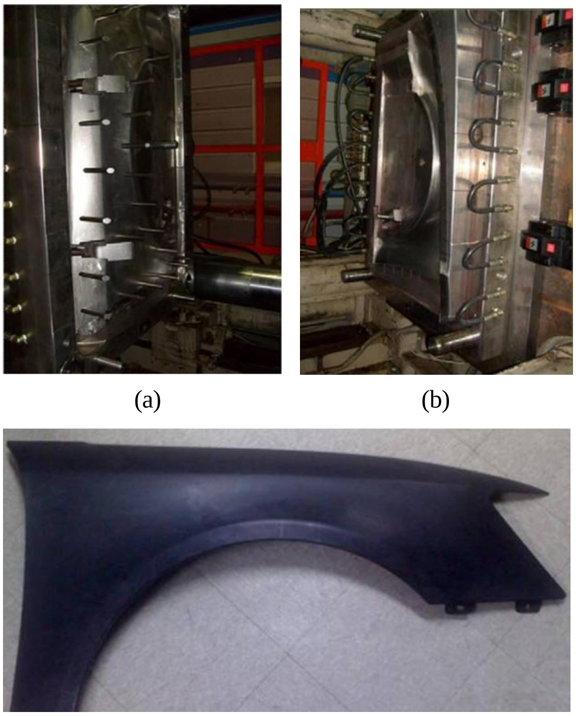
To enhance practical application, both energy consumption and product quality should be taken into consideration. Energy saving for the injection molding process can be divided into two sub-aims. In the first sub-aim, companies and manufacturers focus on machine improvement and manufacturing technologies related to injection molding machine hardware and auxiliary equipment. The second sub-aim focuses on optimization of process parameters in the operating process, to reduce energy consumption. Whereas in the first sub-aim, adoption of new-generation or rebuilt machines with advanced energy-saving devices is very expensive, a much lower cost is required in the optimization-based second aim which only requires experimental or simulated data. In this sub-aim, a mathematical model among process parameters and an energy model are established, based on supplied data.

Energy-saving via process parameter optimization has attracted much research attention. By using analytical method or artificial neural network (ANN), the interrelationship between process parameters and energy consumption was established [4, 5]. However, among these studies, product quality was lacking.

To reduce energy-consumption and carbon emissions, while increasing product quality in the injection molding process of plastic car fender, this paper proposes a multi-objective optimization framework that addresses multiple considerations in the process. The paper focuses on optimiz-

*Corresponding author. Tel.: +82-52-259-2294, Fax.: +82-52-259-1680
E-mail address: phosk@ulsan.ac.kr

doi:10.7315/JCDE.2014.025



(a) (b)

(c)

Figure 1. The prototyping mold and plastic car fender: (a) movable die, (b) stationary die, (c) molded part.

ing process parameters which can be changed during the molding process. The remainder of the paper is organized as follows. Section 2 introduces a framework to approach and solve multi-objective optimization problem. Section 3 presents numerical experiments and descriptive data analysis. Section 4 describes optimization results. Section 5 gives conclusions and goes over possible future work.

2. Optimization framework

2.1 Optimization problem

The prototyping mold and plastic car-fender product are shown in Figure 1. The part's dimension were 650 mm × 1160 mm × 235 mm, and the thickness was fixed at 2.8 mm. In the injection molding process of car fender, energy is consumed by plasticization, heating, molten-plastic injection, clamping forces, auxiliary device-operation, and mold movements / part-ejection. Through previous studies [6], manufacturing data and the interviews with company experts, an investigation indicated that the greatest amount of energy was consumed in plasticization, where the energy-consumption rate was 48%. Barrel heating expenditure was 19%. Clamp-force use rate was 12%. Injection force consumption-rate was 11%. Only small amounts of energy (4% per each process) were used by linear movements to open and close molds, and retract barrels for cooling. The share total energy consumption is shown in Figure 2.

According to the analysis of energy consumption, except

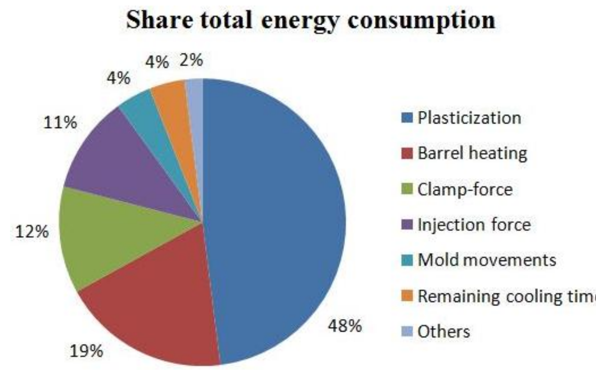


Figure 2. Share total energy consumption.

the plasticization and heating process, clamping force can be considered as the great influence factor for energy saving. In this paper, we focus on the minimizing clamping force which gives rise to clamping energy based on the optimization of process parameters. Additionally, due to thin-shell characteristic, the warpage values that should be minimized to improve molded product quality are employed as the optimization criteria. To save the time and costs, the simulation-based optimization is employed instead of expensive physical experiments. Because the simulation values correlated sufficiently with the experimental values [7], a FE-based model is developed to obtain desired criteria. The commercial software, namely Autodesk Molflow Insight 2012 that can guarantee reliable results is used to simulate the molding process.

During the simulation, the maximum value of injection pressure has been set as the fixed value according to real manufacturing conditions. Based on the molding process conditions and previous studies [2-5], five critical parameters are considered as control factors: mold temperature (T_M), melt temperature (T_{ME}), packing time (P_t), packing pressure (P_P), and cooling time (t_c). Multiple-objective optimization functions can be described in the below equation:

$$\begin{cases} Minimizing\ F(T_M,\ T_{ME},\ P_t,\ P_P,\ t_c) \\ Minimizing\ W(T_M,\ T_{ME},\ P_t,\ P_P,\ t_c) \end{cases}$$

$$\begin{cases} T_{M\min} \le T_M \le T_{M\max} \\ T_{ME\min} \le T_{ME} \le T_{ME\max} \\ P_{t\min} \le P_t \le P_{t\max} \\ P_{P\min} \le P_P \le P_{P\max} \\ t_{c\min} \le t_c \le t_{c\max} \end{cases} \tag{1}$$

where F denotes the clamping force, W presents the warpage.

2.2 Optimization strategy

In this section, a multi-objective optimization framework is presented to obtain optimal process parameters. Figure 3 describes two stages of the multi-objective optimization procedure of the proposed approach. A systematic methodology based on response surface methodology (RSM) is adopted to establish a relationship between process parameters and the performance of objective functions. The RSM relates to re-

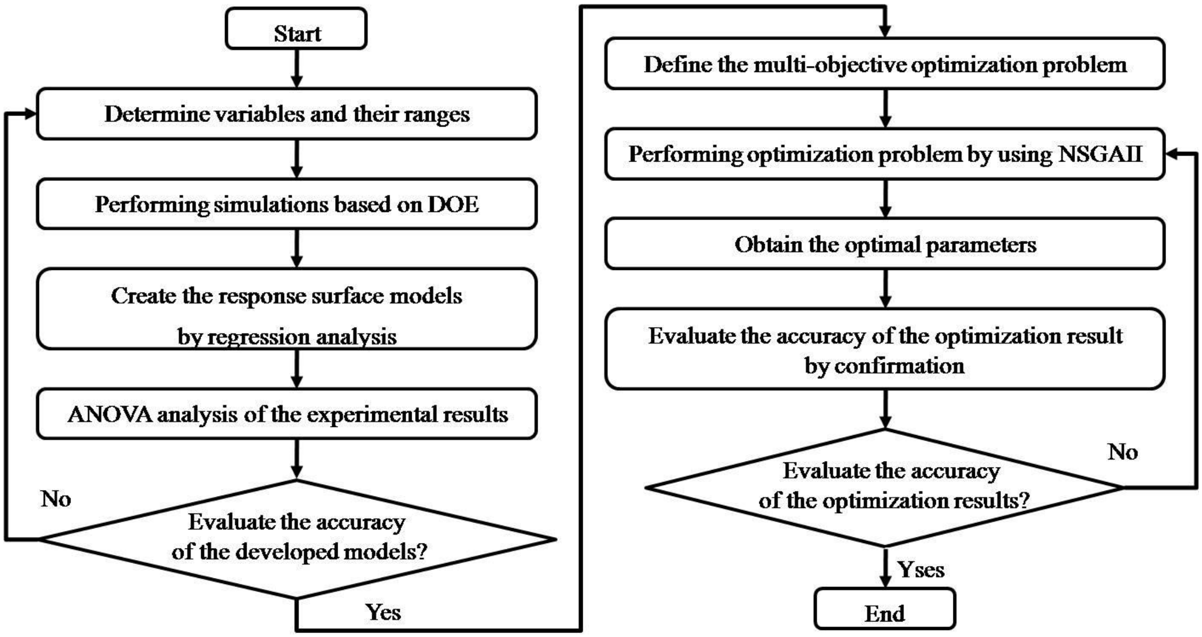


Figure 3. Multi-objective optimization framework.

gression analysis and numerical-experiment statistical design, towards constructing the global optimization. RSM is a well-known method with higher accuracy and better ease-of use than other popular meta-models, such as radial basis function and kriging model. The second-order RSM model is suitable for modeling the moderate non-linear behavior with few design variables. These factors make the RSM model an appropriate method.

The general form of the approximate RSM function expressing the relation among process parameters and the responses is as follows:

$$f_k = \beta_0 + \sum_{i=1}^{5} \beta_i x_i + \sum_{i=1}^{5} \beta_{ii} x_i^2 + \sum_{i=1}^{4} \sum_{j=i+1}^{5} \beta_{ii} x_i x_j + \varepsilon \quad (2)$$

Where β_0, β_i, β_{ii} and β_{ij} are called regression coefficients; ε is an approximate error; x_1 to x_5 denote T_M, T_{ME}, P_t, P_p, and t_c, respectively; f_k denotes the responses including clamping force and warpage value. The accuracy approximate model which expresses the relation between inputs and responses is often assessed by the coefficient of determination or R-squared analysis.

Prior to the optimization process, relationships between process parameters and objective functions should be created. Thus, DOE or space sampling techniques are employed to establish experiments-matrix design. After acquisition of numerical data, an approximation process is carried out in order to establish a mathematical model. Based on the simulation data, analysis of variance (ANOVA) is conducted to validate not only the effect of process parameters on the desirability but also the significance of response variables. The optimization process was resolved based on explicit equations in regression that were obtained through the previous approximation.

To solve the optimization problem, the non-sort dominated genetic algorithm II (NSGA II) [8] is employed in solving trade-offs among objective functions. The NSGA II is a multi-objective, exploratory technique that is well-suited for highly non-linear design spaces.

The algorithm is adopted to search Pareto-optimal solutions in multi-objective optimization problems. Non-dominated sorting genetic algorithm II (NSGA II) is a multi-objective evolutionary algorithm that was developed by Deb. As compared to other optimization algorithms, such as neural network or PSO, this algorithm is reliable and cheaper. The schematic view of NSGA-II on a flow chart is shown in Figure 4.

The procedure of NSGA II can be roughly described according to the following steps:

(Step 1) Identify NGSA II parameters including population size, crossover and mutation probability, termination criteria, and design variable ranges.
(Step 2) Initialize population within boundary conditions.
(Step 3) Sorting population based on non-domination criteria.
(Step 4) Computation of crowding distance. Once the sorting is complete, the crowding distance is calculated for each individual. The individuals in the population are selected based on rank and crowding distance.
(Step 5) Employing genetic results with intermediate population.
(Step 6) Combining offspring population and current generation. Calculation of the individuals for the next generation based on the rank and crowding distance.
(Step 7) Go to step 3 and repeat until termination criteria are satisfied.

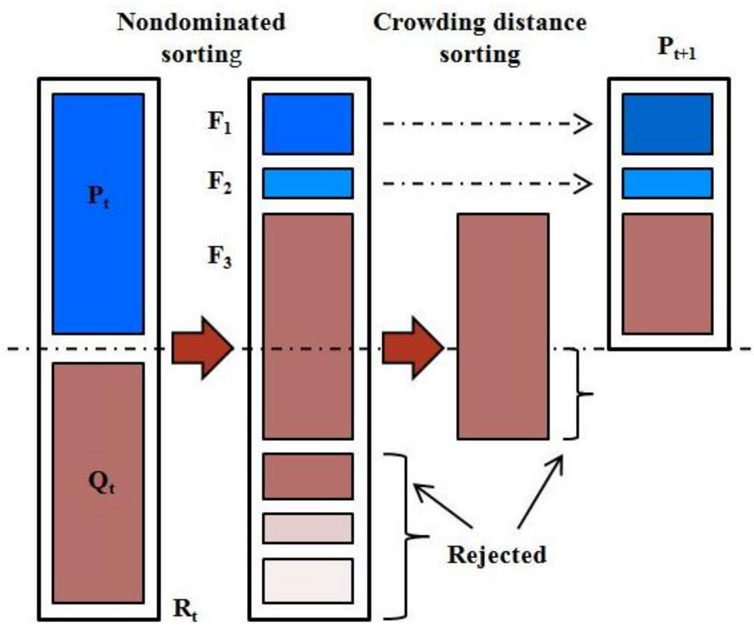


Figure 4. Schematic of the NSGA-II procedure [6].

Table 1. Material properties of GTX810.

Melt density (g/m3)	1.2465
Solid density (g/m3)	1.3493
Eject temperature (℃)	231
Maximum shear stress (MPa)	0.45
Maximum shear rate (1/s)	50000
Thermal conductivity (W/m℃)	0.23
Elasticity module (MPa)	3869.81
Poisson ratio	0.4232

Many researchers have demonstrated that NSGA II is an efficient technique for solving complex optimization problems [9-11]. In NSGA II, each objective is treated separately, and a Pareto front is constructed through selection of feasible, non-dominated designs. Pareto plots allow the designer to reach compensable solutions according to customized requirements. Ultimately, numerical experiments test the reliability of the optimal parameters and the proposed methods.

3. Numerical experiment results

3.1 FE model

To develop green products [12], non-steel substitution materials such as aluminum, composite, and plastic have been used. While thermoplastics have lower mechanical strength and dimensional stability than steel, they offer huge potential, due to both a lower density and a higher possibility for functional integration. Car fender is made of short fiber-reinforced plastic, Noryl GTX810. Material-properties of this material, as obtained from MoldFlow data, are given in Table 1. In order to reduce the mold-making cost and improve cooling-performance and applicability, a cooling channel using an array of baffles is adopted in the plastic injection molding process (Figure 5).

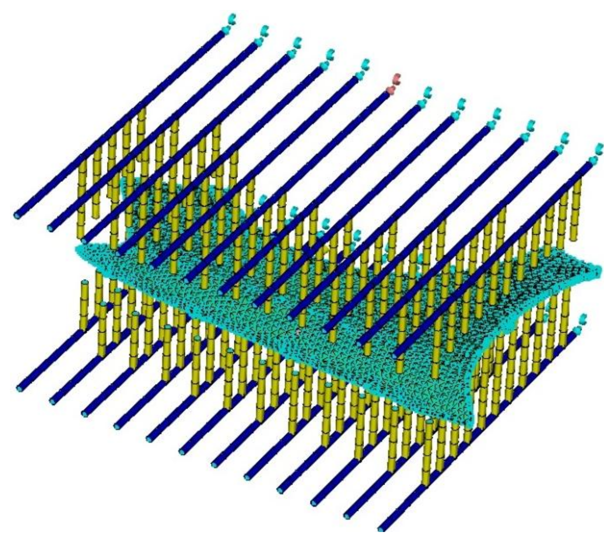


Figure 5. Simulation model in MoldFlow environment.

3.2 The combination between CAE-Integration tools

In order to reduce time and cost, a framework that combines MoldFlow with integrated tool, namely I-Sight is presented in Figure 6. The combination of process parameters based on DOE techniques, the number of simulations, reading as well as storing data, and optimization of response values are carried out by integration tools.

The procedure is based on a few steps. Simulation models are first designed in the MoldFlow environment with boundary conditions such as material properties, cooling channel properties, and process parameters. The analysis process is then performed sequentially with the variation of input para-

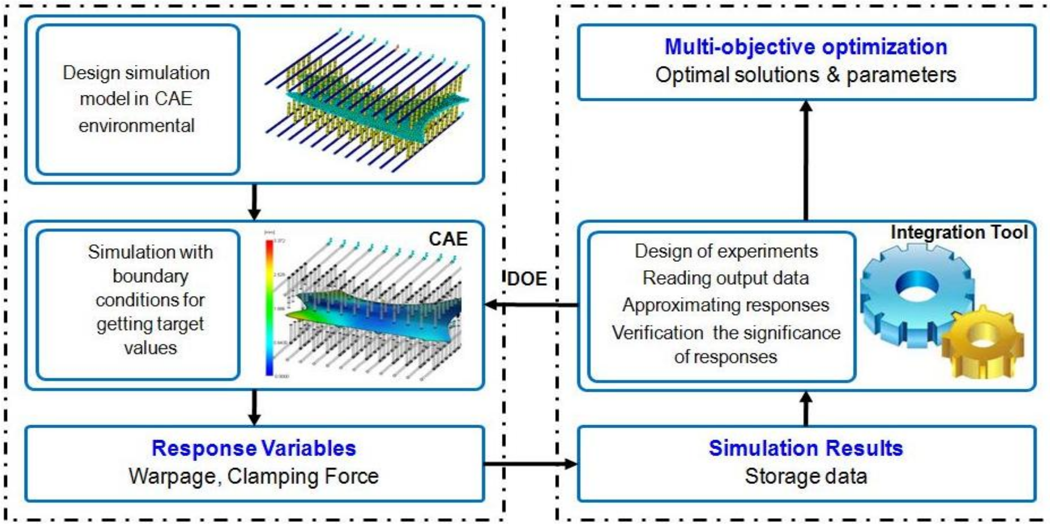


Figure 6. The integration between CAE-integrated tools.

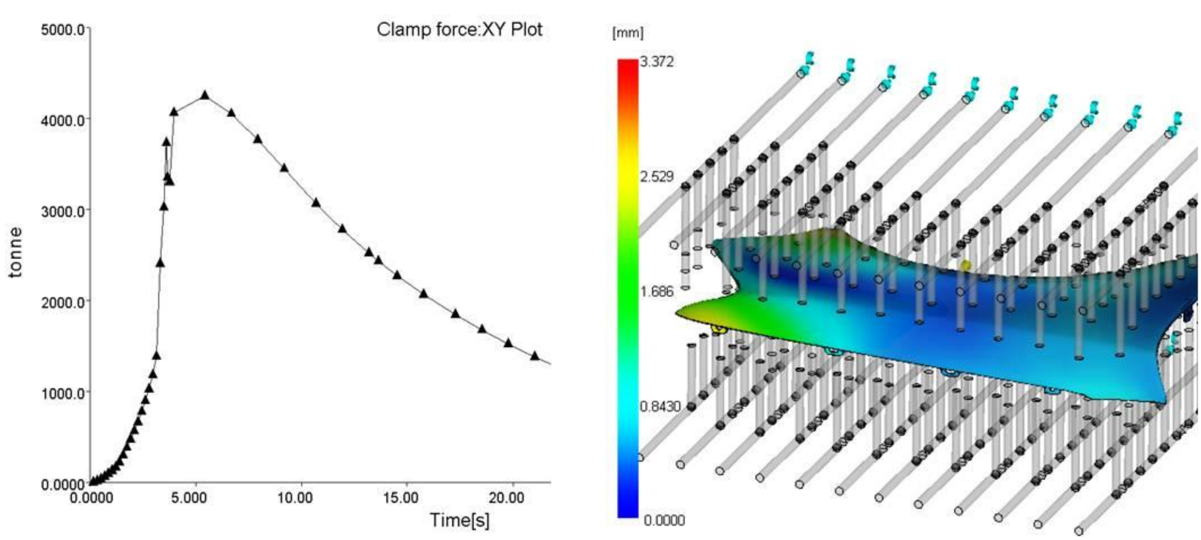
Table 2. Levels of process parameters.

Factor	Parameters	–1	0	+1
A	Mold temperature (℃)	60	80	100
B	Melt temperature (℃)	280	300	320
C	Packing time (s)	8	10	12
D	Packing pressure (% Injection pressure)	60	80	100
E	Cooling time (s)	10	15	20

meters to obtain response values. The responses are then calculated and stored in a text file. New loops for numerical experiments are completed until all necessary data, including clamping-force and warpage values, are obtained. Objective functions are then built up and significance is verified with the RSM methodology. The final step is for optimal solutions and optimal parameters to be obtained following NGSA II-based optimization searching. The intent is for the application programming interface (API) language to be applied and make all work automatically.

3.3 Simulation, approximation, and analysis

In this research, the experimental plans are generated using the stipulated conditions using the Box-Behnken experimental designs with 46 runs. Box-Behnken experimental method is one of the effective designs based on multi-dimensional sphere and all the design points lie on a same sphere with at least three or five runs at the center point [13]. During simulation, mold-temperature and melt-temperature ranges are determined, based on recommended values coming from MoldFlow. Packing pressure is set to be a fixed percentage of the maximum injection pressure during the packing process. Packing time and cooling time ranges are given from the molding process conditions. Parameters and their levels are



(a) (b)

Figure 7. The values of responses at the initial values: (a) clamping force diagram, (b) warpage value.

Table 3. Coefficients of responses.

Term	Coefficients	Term	Coefficients
a_0	-76587.1735	b_0	201.1459
a_1	29.2760	b_1	0.3757
a_2	520.4209	b_2	-1.5619
a_3	463.9137	b_3	4.6255
a_4	24.8671	b_4	-0.2726
a_5	-7.3101	b_5	0.7469
a_6	-0.0037	b_6	-0.0013
a_7	-0.6048	b_7	0.00024
a_8	-0.00186	b_8	-0.00115
a_9	-0.3471	b_9	0.00187
a_{10}	-0.6795	b_{10}	-0.04225
a_{11}	-0.1498	b_{11}	0.00112
a_{12}	0.1847	b_{12}	-0.00456
a_{13}	-0.1808	b_{13}	-0.00895
a_{14}	0.3125	b_{14}	0.027
a_{15}	0.0923	b_{15}	0.00019
a_{16}	-0.1137	b_{16}	0.00057
a_{17}	-0.8541	b_{17}	0.00355
a_{18}	-9.9590	b_{18}	0.37272
a_{19}	0.7117	b_{19}	0.00048
a_{20}	-1.0496	b_{20}	0.0058

shown in the Table 2.

According to simulation results, regression response surface models for the two objective functions of evaluating clamping force and warpage are derived. Clamping force and warpage initial values are shown in the Figure 7.

Second-order polynomial regression is employed to establish non-linear relationships among design variables and responses. The responses are functions of mold temperature, melt temperature, packing time, packing pressure and cooling time, respectively. Approximate equations of two responses are presented as Eqs. (3) and (4), respectively. Table 3 describes values for coefficients of equations as determined by regression method.

$$\begin{aligned}\text{Clamping Force} &= a_0 + a_1A + a_2B + a_3C \\ &+a_4D + a_5E + a_6AB + a_7AC + a_8AD + a_9AE \\ &+a_{10}BC + a_{11}BD + a_{12}BC + a_{13}CD + a_{14}CE \\ &+a_{16}DE + a_{16}A^2 + a_{17}A^2 + a_{18}C^2 + a_{19}D^2 + a_{20}E^2 \end{aligned} \quad (3)$$

$$\begin{aligned}\text{Clamping Force} &= b_0 + b_1A + b_2B + b_3C \\ &+b_4D + b_5E + b_6AB + b_7AC + b_8AD + b_9AE \\ &+b_{10}BC + b_{11}BD + b_{12}BC + b_{13}CD + b_{14}CE \\ &+b_{16}DE + b_{16}A^2 + b_{17}A^2 + b_{18}C^2 + b_{19}D^2 + b_{20}E^2 \end{aligned} \quad (4)$$

Based on computational cost and time-of simulation, as compared with the MoldFlow, the developed predictive model is a much simpler and more efficient in predicting outputs with change-of-design variables. The adequacy of the developed models, including warpage and clamping force via ANOVA analysis with sums of squares (SQ), mean squares (MS), F-value (F), P-value (P) is shown in table 4 and table 5, respectively. The backward process eliminated the insignificant terms to adjust the quadratic models.

In the Table 4, the model "F-value" of 39.3 indicates that the model is considered to be statistically significant. "P-value" less than 0.05 indicate the model terms are significant. In this manner, all the single terms (A, B, C, D, E), interaction terms (AB, AD, BC, BD, BE) and quadratic terms (B^2, C^2) were found to be significant model terms. The other terms which P-value > 0.05 are not significant model terms which have little effect on the response variables in the design space.

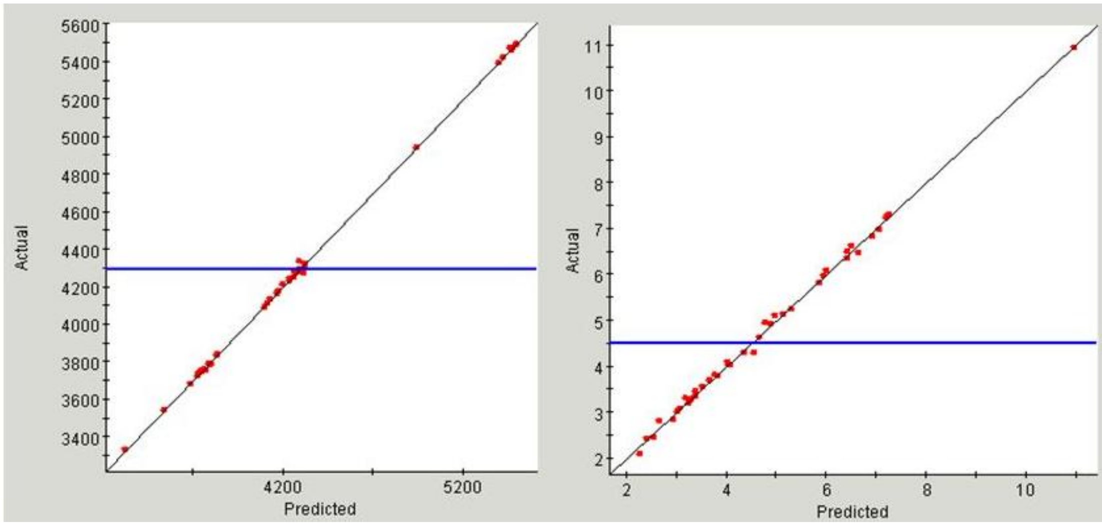
In the Table 5, the model "F-value" of 396.31 also implies that the response quadratic model is very significant. There is only a 0.01 chance that a "model F-value" this large could occur due to noise. Based on the identification that the factors with "P-value" bigger than 0.05 are insignificant terms, the

Table 4. ANOVA table for warpage.

Source	SQ	MS	F	P
Model	136.49	6.82	39.3	< 0.0001
A	0.72	0.72	4.13	0.05
B	26.38	26.38	151.95	< 0.0001
C	49.45	49.45	284.81	< 0.0001
D	9.08	9.08	52.27	< 0.0001
E	1.78	1.78	10.26	0.0037
AB	1.06	1.06	6.09	0.0208
AD	0.85	0.85	4.87	0.0367
BC	11.41	11.41	65.72	< 0.0001
BD	0.81	0.81	4.65	0.0409
BE	0.83	0.83	4.79	0.0382
B^2	17.59	17.59	101.32	< 0.0001
C^2	19.4	19.4	111.72	< 0.0001
Residual	1.25	0.17		
Total	137.74			

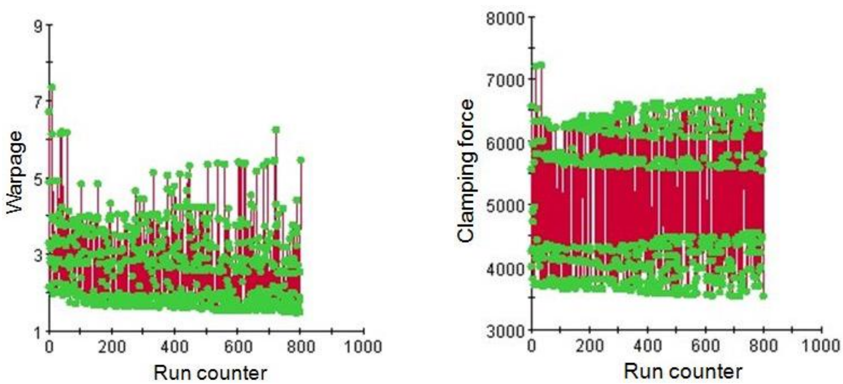
Table 5. ANOVA table for clamping force.

Source	SQ	MS	F	P
Model	1.497×10^7	7.486×10^5	396.31	< 0.0001
A	13292.36	13292.36	7.04	0.0137
B	4.449×10^5	4.449×10^5	235.53	< 0.0001
C	14975.6	14975.6	7.65	0.0115
D	1.211×10^7	1.211×10^7	6408.93	< 0.0001
BD	14360.43	14360.43	7.6	0.0107
A^2	18064.49	18064.49	9.56	0.0048
B^2	1.019×10^6	1.019×10^6	539.29	< 0.0001
C^2	13849.4	13849.4	7.33	0.012
D^2	7.072×10^5	7.072×10^5	374.43	< 0.0001
Residual	47219.81	1888.79		
Total	1.502×10^7			



(a) (b)

Figure 8. Predictive values and numerical values: (a) clamping force, (b) warpage.



(a) (b)

Figure 9. History plot of responses during optimization process using NSGAII: (a) history optimization of clamping force, (b) history optimization of warpage.

single terms of A, B, C and D, the interaction term of BD and the quadratic terms of A^2, B^2, C^2, D^2 are significant model terms for the clamping force.

Figure 8 presents a comparison among predicted and numerical experimental values for desirability. Predicted values were in agreement with the numerical data. R-squared clamping force and warpage were 0.99 and 0.99, respectively, indicating highly-accurate results for the regression models. The developed models could thus be applied in the optimization process. The optimization process will be described in the next step.

4. Optimization results

Process parameters such as mold temperature, melt temperature, packing time, packing pressure and cooling time have complex effects on objective functions. An objective for setting clamping force values was that equality constraint. In this study, warpage values acted as inequality constraints. Through practical conditions, acceptable warpage values were set as being smaller than the initial value. The optimization problem is described based on the following expressions:

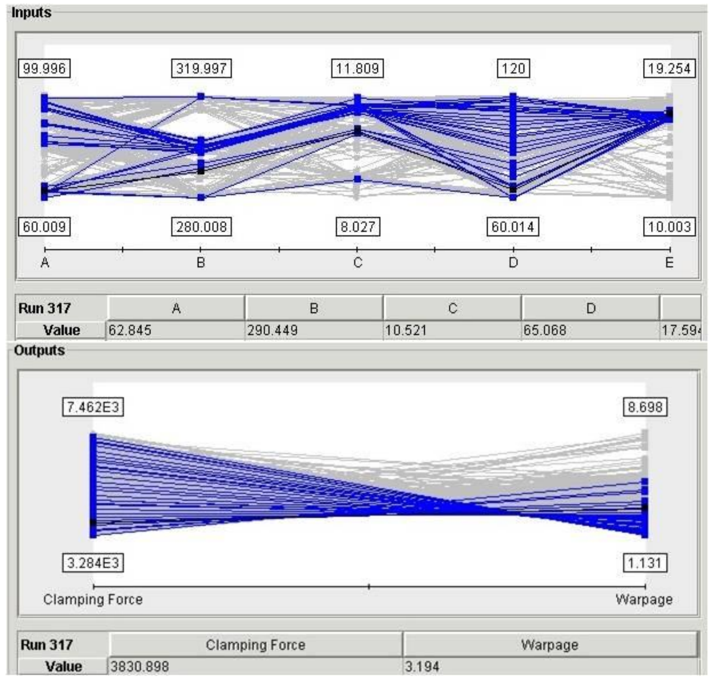
$$\text{Find } X = [T_M, T_{ME}, P_t, P_P, t_c]$$
$$\text{Minimize: } \lambda_1 f^n(F) + \lambda_2 f^n(W) \tag{5}$$

Subjected to constraints: $W \leq 3.372$ (mm)

Within ranges: $60 \leq T_M \leq 100$ (℃); $280 \leq T_{ME} \leq 320$ (℃); $8 \leq P_t \leq 12$ (s); $60 \leq P_P \leq 100$ (%); $10 \leq t_C \leq 20$ (s);

Where λ_1, λ_2 represent the weight of clamp force and warpage, respectively.

Specific NSGA II parameters were population size, number of generations, crossover probability, crossover distribution index, and mutation distribution index, with values of 30, 60, 0.9, 20, and 100, respectively. Due to the importance of energy consumption, clamping fforce and warpage weights were selected to be 2 and 1. Figure 9 describes the history of the NSGA II-based optimization process. Figure 10 shows engineering data-mining and Pareto plots employed to obtain optimal parameters and responses. The Pareto plots enable



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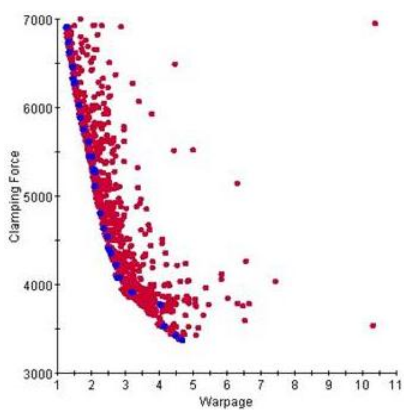

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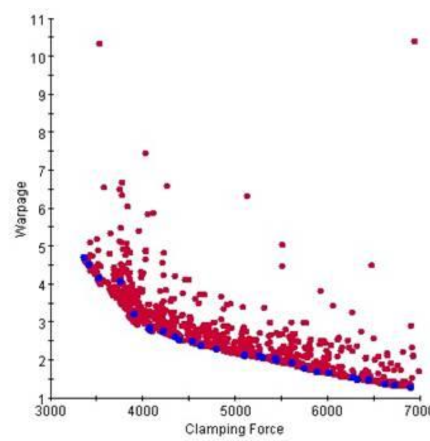


(c)

Figure 10. Engineering data mining and Pareto plot used to determine the optimum parameters: (a) engineering data mining of optimization process, (b) pareto plot between clamping force and warpage, (c) pareto plot between warpage and clamping force.

the designer to decide on optimal solutions.

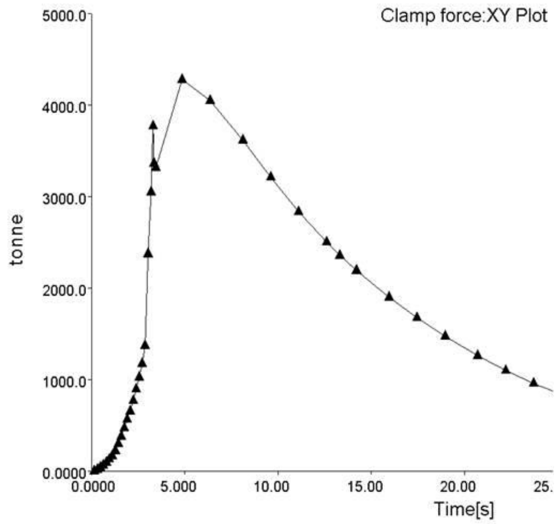
The optimized results are shown in Table 6. The results of this table describe how values of clamping force or energy consumption can be reduced. The decreasing percentage is approximately 12% in the value of clamping force, while warpage value also reduced, as compared to the initial value. The results prove that the proposed method can be applied in the injection molding process optimization, towards solving the trade-off between energy consumption and product quality.

Table 6. Saving energy compared to the initial value.

Optimized parameters				
T_m (℃)	T_i (℃)	P_t (s)	P_P (%)	t_C (s)
62.845	290.45	10.52	65.07	17.6

Target values		Saving energy
F (Tonne)	W (mm)	%
3831	3.194	12

The optimized results are shown in Table 6. The results of this table describe how values of clamping force or energy consumption can be reduced. The decreasing percentage is approximately 12% in the value of clamping force, while warpage value also reduced, as compared to the initial value. The results prove that the proposed method can be applied in the injection molding process optimization, towards solving the trade-off between energy consumption and product quality.



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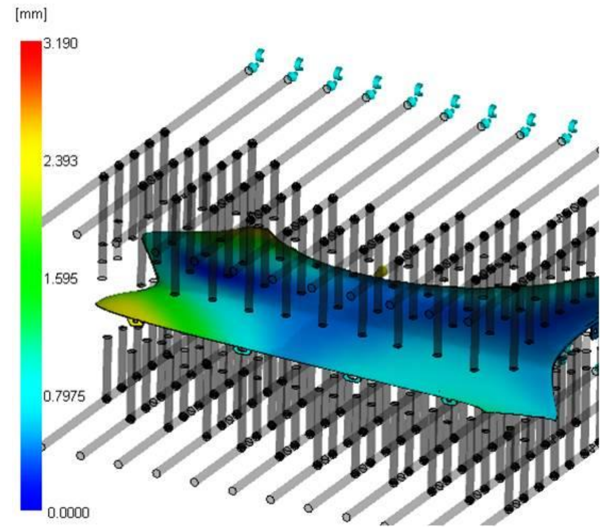

(b)

Figure 11. The responses at the optimal parameters: (a) clamping force diagram, (b) warpage value.

In order to check the accuracy of optimized result, error percentages for NSGA II and numerical experiments are compared. The comparative results are listed in the Table 7. Error percentages were very small. Deviation percentages for NSGA II and numerical experiments were 0.27%, and –0.13%, respectively. The numerical experimental values of the confirmation run are within the 95% prediction interval. These small errors demonstrate the optimization frpamework's efficiency and practical potential.

There is great potential for increasing energy efficiency in the injection molding process, due to high energy consumption and lack of optimization in sub-process. While energy-efficient electric and hybrid injection molding machines have been available for nearly 30 years, process parameter-based optimization is still the most effective solution, due to low cost and convenience. An examination of the energy flaow injection molding indicated that the reduction of heat losses of the drying system, barrel heating system, and optimization of the cooling system can contribute to the energy efficiency. To reduce heat losses [14], insulating devices can be employed on the barrel surface. Due to high barrel-surface temperature, there are considerable heat losses caused by radiation and convection. These devices are simple solutions, based on structure, low cost, and ease of manufacture and assembly. The worker's environment during manufacturing is improved, due to reduced radiation and lowered shop-floor temperature.

However, the influences of process parameters, the plasticizing process, the heating system, and cooling system on the energy consumption and the product's quality are complex. The effect of different variables of the objective function can be contradictory. For example, lower the melt temperature reduces the energy for heating and heat losses, but it increases the injection pressure that results in short shot or in the increase of the energy consumption for the hydraulic system. Lower the coolant temperature requires more energy for the chiller, but reduces the cooling time or cycle time that results in less energy per molding cycle. In addition, the quality of the molded part such as the variation of the part's weight, the shrinkage, the warpage, and residual stress are the non-linear functions of process parameters. Therefore, holistic optimization and a systemic approach to reduce the energy consumption on every issue where possible in a global sense, and from the process parameters are necessary to achieve multiple energy savings and to assure the product quality. Optimization of the whole process chains means a holistic optimization process, carried out based on optimized sub-processes, the interdependencies, and multi evaluation criteria. Instead of expensive physical experiment, simulation-based optimization can be adopted. The holistic approach can be conducted by using discrete-event simulation model, which is known mainly from the simulation of the process chains.

5. Conclusions

Engineers have conventionally used a trial-and-error process in the optimal process parameter determination. This conventional approach has some shortcomings which increase cost and lead to less-than-optimal values. In the current investigation, an injection molding process optimization of plastic car fender related to energy consumption and product quality is introduced. In the proposed approach, meta-model type-RSM and non-dominated sorting genetic algorithm II (NSGA II) are used, to obtain Pareto-optimal solutions. Relations among process parameters and response variables, including clamping force (relevant energy consumption) and warpage (relevant product quality), are expressed by explicit quadratic RSM equations. An evolutionary algorithm, namely the non-dominated sorting genetic algorithm II (NSGA II), was employed to obtain optimal parameters.

CAE-optimization tools were integrated, in order to reduce cost and time. Through optimal-solution derivation, it can be observed that energy consumption and product quality can be simultaneously optimized. At the same time, the proposed procedure can be applied to optimize complicated issues in the molding process. The approach is also an effective tool to assist engineers in finding optimal parameters while considering multiple responses.

Although the proposed approach can improve the energy efficiency and product quality in the injection molding process, this work still has some limitations and can be improved upon. First, the other criteria related to product quality, namely shrinkage can be considered in the optimization process. Second, optimization of sub-process such as heating process, plasticization process, or cooling system in terms of energy efficiency should be conducted. Based on those results, holistic optimization of injection molding process can be implemented to minimize energy consumption and resulting defects in future work.

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