Optimization of Plastic Injection Molding Process by Combination of Artificial Neural Network and Genetic Algorithm

Mohammad Saleh Meiabadi[a,*], Abbas Vafaeesefat[b], Fatemeh Sharifi[c]

[a]Instructor, Industrial Engineering department, Islamic Azad University, Malayer Branch, , Malayer, Iran
[b]AssociateProfessor,Mechanical Engineering Department, Imam Hussein University
[C]Instructor, Computer Engineering Department, Chamran University, Ahvaz, Iran

Received 25 April, 2012; Revised 15August, 2012; Accepted 18 November, 2012

Abstract

Injection molding is one of the most important and common plastic formation methods. Combination of modeling tools and optimization algorithms can be used in order to determine optimum process conditions for the injection molding of a special part. Because of the complication of the injection molding process and multiplicity of parameters and their interactive effects on one another, analytical modeling of the process is either impossible or difficult. Therefore Artificial Neural Network (ANN) is used for modeling the process. Process conditions data is needed for modeling the process by the neural network. After modeling step, the model is combined with the Genetic Algorithm (GA). Based on the injection molding goals that have been turned into fitness function, the optimized conditions are obtained.

Keywords: Optimization; Solution space; Control variable; Neural network; Genetic algorithm.

1. Introduction

Plastic injection molding is one of the well known manufacturing techniques that should be able to produce complex- shaped and large-sized products in short time at low cost. To avoid the high costs and time delays associated with problems discovered at the start of manufacturing, it is necessary to consider the combined effects of part geometry, material characteristics, mold design and processing conditions on the manufacturability of a part. The factors that affect the part manufacturability are shown in Fig. 1.

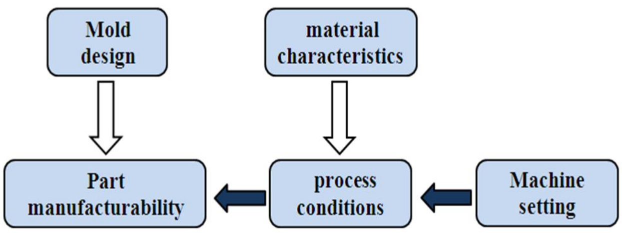

Fig. 1. Parameters influence on part manufacturability

Final optimal process parameter setting are recognized as one of the most important steps in injection molding for improving the quality of molded products. Since the quality of injection molded plastic parts are mostly influenced by process conditions, how to determine the optimum process parameters becomes the key to improving the part quality. Previously, production engineers used trial-and-error or Taguchi's parameter design method to determine optimal process parameters setting for plastic injection molding. Trial-and-error method is costly and time consuming. Besides, the optimum process parameters may not be achievable by this method. Chen *et al.*(2008, 2009) declared that application of conventional Taguchi parameter design method is unsuitable when one of the process parameter variables is continuous and it cannot help engineers obtain optimal results for process parameter settings. Hybrid system of artificial intelligence is a scientific approach for obtaining optimum process conditions in plastic injection molding. The following can be cited from previously researches that have used hybrid system of artificial intelligence for optimization injection molding process. Hamedi*etal*(2006)used a hybrid system of artificial intelligence to optimize the dimensional contradictions in the plastic injection process. Spina (2006) introduced evaluation of the Finite Element (FE) simulation results through the ANN system. They found artificial neural network system as an efficient method for the assessment of the influence of process parameter variation on part manufacturability, and possible adjustments to improve part quality.

* Corresponding author Email: saleh.meiabadi@gmail.com

Kurtaran*et al*.(2005) determined the best injection molding process conditions for a bus ceiling lamp using FE software MoldFlow and ANN. Genetic optimization reduced the maximum warpage of the initial model by 46.5% .
Changyu*etal*(2007) expressed that the combination of artificial neural network and genetic algorithm gives satisfactory results to improve the quality index of the volumetric shrinkage variation in the part. Ozcelik*etal*(2006) confirmed that the use of artificial neural network and genetic algorithm is an efficient optimization methodology in minimizing warpage of thin shell plastic parts manufactured by injection molding.
Chavanatnusorn(2009) presented a systematic approach to determine the optimal processing conditions by optimizing the quality of plastic injection-molded parts and their process cycle time. Two plastic parts were used as study cases, a rectangular lid and a roof tile. Six process parameters in injection molding including material type, melt temperature, injection speed, packing pressure, packing time and cooling time, were optimized by using Computer-Aided Engineering (CAE) software, the Design of Experiments (DOE) technique, the ANN model, and the GA method.
In most researches the purpose was minimizing injection defects like shrinkage and warpage but the purpose of this research is obtaining process parameters ensure accurate part weight, less process cycle time and injection pressure. In this study the most important control variables affecting specified injection goals are recognized by statistical design of experiments feature of MoldFlow software. The combination of the full factorial and random approach is used to create the solution space, since both are advantageous. Optimum structure of neural network is determined by Nerosolution software. Plastic injection molding process is modeled by neural network and then the fitness function optimized by Genetic algorithm. Finally efficiency of optimization method is confirmed by experimental fabrication. The material type is SABIC PP 512MN10. Material properties are reported in Table 1.

Table 1
Material properties

Density	905kg/m^3
Melt Flow Rate: at 230 °C and 2.16 kg	37g/10min
Tensile test: tensile stress at yield(ISO 527)	26N/mm^2
Heat distortion temperature: at 0.45 MPa(ISO 75/B)	89 °C

2. Optimization Steps

Optimization steps is a systematic approach to determine the optimum process conditions in plastic injection molding using CAE, DOE, ANN, and GA. CAE software was used to simulate the manufacturing process and DOE involves in determining the significant control variables in the injection molding process. Using ANN model with GA is a promising natural computation technique for optimization because ANN has become a practical method for predictive capability to very complex non-linear systems. GA can be used to find the optimum value of the process parameters. The proposed method should be used when multi-response quality characteristics is needed. Fig. 2 shows the optimization steps in the proposed method.

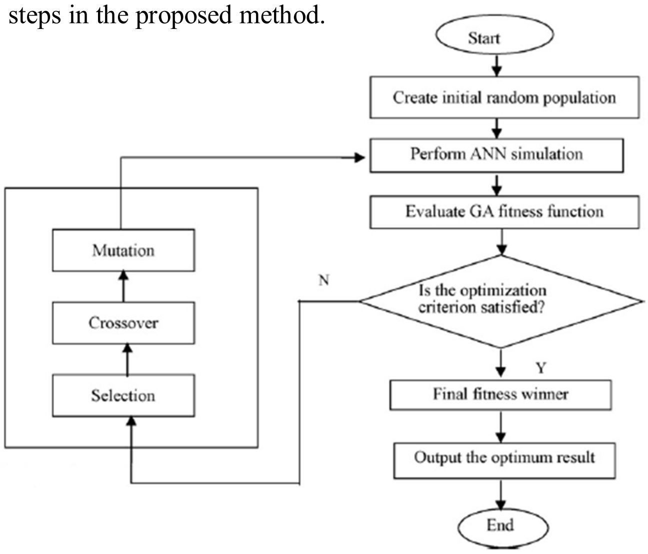

Fig. 2. Flow chart of combining ANN/GA

2.1. Choose Injection Goals

One of the main goals in injection molding is the improvement of quality of molded parts besides the reduction of process cycle time. The purpose of this research is to obtain process parameters ensuring accurate part weight, less process cycle time and injection pressure. Chen *et al.* (2008) are among the researchers which showed that product weight is a critical quality characteristic and a good indication of the stability of the manufacturing process in plastic injection molding. Part weight is closely associated with the other quality criteria such as surface quality, mechanical properties and dimensional specifications. Economically, process cycle time should be short without negative effects on the quality. Another criterion is the injection pressure that forces more material into the injection mold. The hydraulic pressure limit is set high enough to allow the machine to maintain the set injection speed. A sharper and more changing pressure curve causes more fluctuations in produced parts weight.

2.2. Simulation of Part and Runner System in MoldFlow

Computer-aided engineering software is used to simulate practical experiments for the cost and time saving. Moldflow Plastics Insight(MPI) is one of the commercial CAE softwares for plastic injection molding process. MoldFlow software represents the most comprehensive suite of definitive tools for simulating, analyzing, optimizing, and validating plastics part and mold designs. The CAD model of the product was initially imported and converted into a FE mesh but runner system is modeled in MoldFlow. Due to low thickness of the part, two-dimensional surface (fusion) element is selected. The simulation results of the injection process are used into modeling injection process by neural network. But results of the software should be confirmed with experimental validation. Also the most important control variables affecting injection goals are recognized by statistical design of experiments features of MoldFlow. Fig. 3 shows the part and the runner system in MoldFlow.

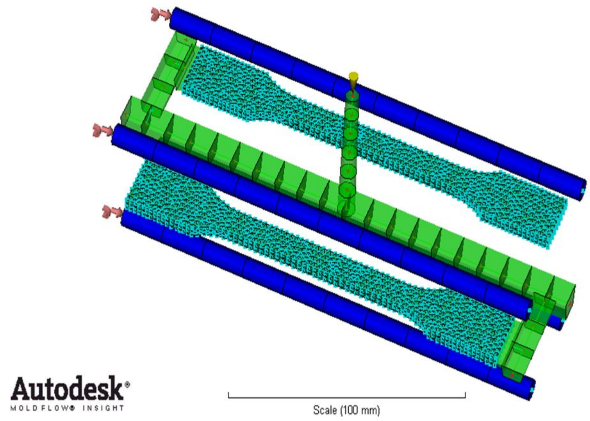

Fig.3. Part and runner system modeled and meshed in MoldFlow

2.3. Determine Main Process Parameters

In this step , the most important process parameters affecting the injection goals are determined.This greatly increase the efficiency of optimization method. Persentage impacte of considered parameters on injection goals can be determined by statistical design of experiment feature of MoldFlow. Table 2 shows the percentage impact of parameters on part weight, process cycle time and maximum injection pressure. Melt temperature, packing time, packing pressure and mold wall temperature are considered as the main process parameters.

Table 2
Percentage impact of considered parameters

Rank	Process parameter	percentage
1	Melt temperature	70.85
2	Packing time	20.13
3	Packing pressure	6.45
4	Mold wall temperature	2.29
5	Injection time	0.28

2.4. Define Solution Space

The most important parameters affecting the injection goals are considered as control variables and the selected criteria for injection goals considered as response variables. Response variables data are obtained by control variables test. Sets of the control variables are called solution space. Solution space is defined in two approaches. In the first approach, a regular solution space equal to that obtained with a 3^n Full Factorial technique was defined. In this way, the influence of each process parameter on selected responses can be evaluated. The parameter ranges are reported in Table 3. The second approach considered an initial solution set in which control variables were randomly distributed. The advantage of this approach is the definition of a solution space in which regions leading to unfeasible solutions were avoided. The solution space is consisted of 81 sets created by permuting the minimum, middle and maximum levels of the process parameters, plus 16 sets randomly generated.

Table 3
Process parameter ranges

Process parameter	Max	Mid	Min
Melt temperature (C)	215	225	235
Mold wall temperature (C)	20	35	50
Packing time (s)	10	25	40
Packing pressure (MPa)	10	25	40

Injection speed was set to 20 mm/s and net cooling time equal to 15 s in MoldFlow process setting. The net cooling time is the time after the pressure phase and before the part is ejected from the mold. The relationship between control variables and response variables are identified by several tests performed by MoldFlow.

2.5. Modeling Plastic Injection Molding Process by Neural Network

The complex relationships between control variables and response variables could not be determined by any analytic model. Bharti*et al* (2010)declared that neural networks have been shown to be an effective technique for modeling complex nonlinear processes. They are useful for functional prediction and system modeling where the processes are not understood or are highly complex. Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function (Matlab help). The neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements. Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. The artificial neural network used in this study is a Feed Forward network consisting of one input, two hidden and one output layers. Hidden layers have ten neurons, whereas input and output layers have four and three neurons, respectively. The neuron number of the input layer of neural network is determined by the number of control variables and the neuron number of the output layer is determined by the number of the response variables. The transfer function between the input layer and the hidden layer is ‘Tansig’, while the transfer function between the hidden layer and the output layer is ‘Purelin’. The learning rule was based on the Levenberg-Marquardt algorithm while the performance function was the Mean Square Error (MSE) minimization of the network errors on the training set.

The samples of control variables and response variables are then assigned as input–output data to train and test the neural network. The dataset used in this study consist of 97 sets, which is divided to 75%, 15% and 15% used for training, testing and cross validation respectively. The neural network architecture is shown in Fig. 4.

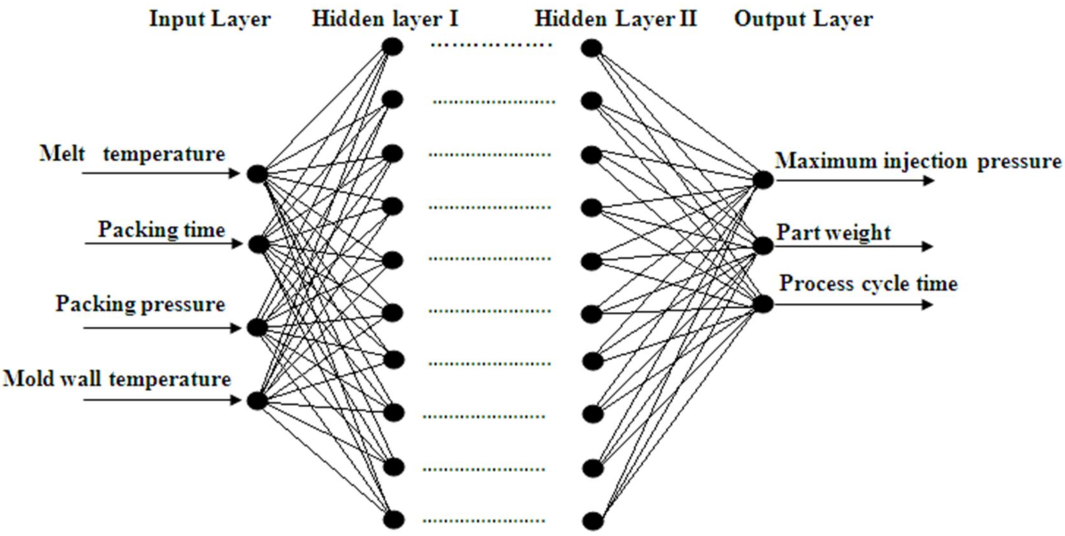

Fig. 4. AAN Architecture

The optimal neural network architecture is obtained by Nero solution software. Based on the results of Neuro solution software the best structure of the network is obtained by ten neurons for each hidden layer.

2.6. Define Fitness Function

The trained neural network is capable of predicting maximum injection pressure, process cycle time and part weight while control variables is applied to the ANN. Suitability of control variables are determined when the outputs of the neural network(response variables) are applied to the fitness function. When process parameters (control variables) satisfy injection goals, fitness function will produce a smaller number. Fitness function is defined as follows:

$$f(y_1, y_2, y_3) = \frac{y_1}{18.3092} + \frac{[Abs(y_2 - 17.1713)]}{2} + \frac{y_3}{55}$$

y_1: Maximum injection pressure
y_2: Desired weight of the part
y_3: Process cycle time
The maximum injection pressure is 18.3092 (Mpa) in response variables data.
The desirable part weight is 17.713(g). Maximum difference between desirable part weight and worst weight in response variables data is 2.274(g) and the maximum process cycle time is 55(s).

2.7. Finding Optimum Process Parameters by Genetic Algorithm

Optimum values of the main process parameters are efficiently obtained by genetic algorithm. Accurate part weight and less process cycle time and injection pressure can be achieved by setting optimum process conditions. The genetic algorithm is a method for solving optimization problems that is based on natural selection and a process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution (Matlab help). To solve the above optimization problem GA is coupled with the neural network. It should be mentioned the direct link between the simulation software and GA required a long time before optimum process parameters were identified. An initial population is generated at random, and the fitness function based on the neural network model is used to calculate the fitness for all initial individuals. Then, selection, crossover and mutation are used to reproduce a new generation. The process is repeated until the maximum generation number or population convergence occurs. Based on the above algorithm, the optimization program for the injection molding process has been developed using MATLAB. In this study the population size is 20 and value of Elite count is considered 2. The number of individuals with the best fitness values in the current generation who are guaranteed to survive to the next generation are called Elite children. The value of crossover fraction is 0.8. The Crossover fraction specifies the fraction of each population, other than elite children that are made up of crossover children. Figure 5 shows the best fitness achieved after 51 generations. Table 4 shows the optimized process parameters.

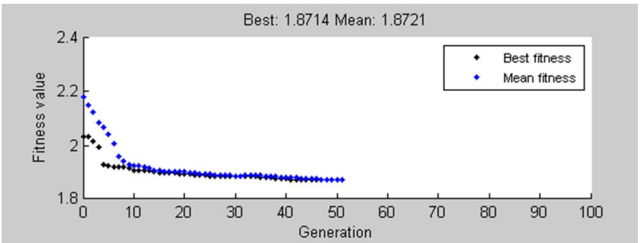

Fig. 5. Evolution of generations for injection molding process optimization

Table 4
Optimized process parameters

Packing pressure (MPa)	Packing time (s)	Melt temperature (C)	Mold wall temperature(C)
10	16/457	233/065	23/154

3. Experimental Test and Results Comparison

The optimized process parameters should be tested by experimental fabrication to evaluate efficiency of the proposed method. The experimental fabrication is performed by Krauss Maffei 150 C2 injection machine. The moveable half of mold is shown in Fig. 6.
Table 5 shows the comparison between results of the Moldflow simulation, neural network and experimental fabrication using optimal process parameters setting. The results of experimental fabrication were in good agreement with Moldflow and neural network results that reveal accuracy of Moldflow simulation and neural network. The part weight is close to desirable weight and the process cycle time is reduced from 35.5 to 32 second.

Fig. 6. Moveable half of mold

Table 5
Comparison between FE simulation, ANN r and experimental fabrication results

	Maximum injection pressure(MPa)	Part weight(g)	Process cycle time(s)
Moldflow simulation	10.8496	16.1513	32.0001
ANN pridiction	10.8225	16.0373	31.6015
Experimental fabrication	11	16.34	32.7

4. Conclusions

The purpose of this research was to obtain the process parameters that ensure the accurate part weight, less process cycle time, and injection pressure. The research results indicate that the proposed approach can effectively help engineers determine optimal process parameters setting and achieve competitive advantages of product quality and costs. The efficiency of the method depends on the selection of appropriate process parameters, process parameter ranges and accuracy of Moldflow simulations and neural network predictions.
In this study, the process parameters were determined within constraints of machine tools and mold steel. Thus, some parameters could not be considered as the parameters for optimizing the injection process. Because of the fixed mold constraint, the gate location and coolant point could not change their locations. For future study, the researcher should perform the experiments using this methodology before producing new products and its mold.

5. References

[1] Bharti, P.K. and Khan. , M. I. (2010). Recent methods for optimization of plastic injection molding process –a retrospective and literature review. International Journal of Engineering Science and Technology, 2(9), 4540-4554.

[2] Changyu, S., Lixia. , W. and Qian, L. (2007).Optimization of injection molding process parameters using combination of artificial neural network and genetic algorithm method. Journal of Materials Processing Technology, 183, 412–418.

[3] Chavanatnusorn. , P. (2009). Determination of the optimal processing conditions in plastic injection molding using computer-aided engineering, artificial neural network model, and genetic algorithm. M.sc thesis. kasetsart university.

[4] Chen, W.C., Fu, G.L., Tai, P.H. and Deng, W.J. (2009). Process parameter optimization for MIMO plastic injection molding via soft computing. Expert Systems with Applications, 36, 1114–1122.

[5] Chen, W.C., Wang, M.W., Fu, G.L. and Chen, C.T. (2008). Optimization of plastic injection molding process via taguchi's Parameter Design Method, BPNN, AND DFP. Proceeding of Seventh International Conference on Machine Learning and Cybernetics. Kunming. 12-15July, 3315-3321.

[6] Hamedi, M. and Bisepar, M. (2006). Application of a Hybrid of Artificial Intelligence for Optimization Part Dimensional Contradictions in Plastic Injection Process .14th Annual Mechanical Engineering Conference.

[7] Kurtaran, H., Ozcelik, B. and Erzulumla, T. (2005). Warpage optimization of a bus ceiling lamp base using neural network model and genetic algorithm. Journal Materials Processing Technology, 169, 314- 319.

[8] www.mathworks.com/help/matlab/

[9] Ozcelik, B., Erzulumla, T. (2006). Comparison of the warpage optimization in the plastic injection molding using ANOVA, neural network model genetic algorithm. Journal Materials Processing Technology, 171, 437- 445.

[10] Spina, R. (2006). Optimization of injection molded parts by using ANN-PSO approach. Journal of Achievement in Materials and Manufacturing Engineering, 15, 146-152.