CST015

Optimization of Parison Thickness for Extrusion Blow Molding of a Rectangular Shape Bottle Using FEM and AI Technique

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Abstract

A numerical optimization scheme based on finite element method (FEM) and combined artificial intelligence (AI) technique had been developed to determine an optimal parison thickness for blow molded bottles. The rectangular shape of a lube oil bottle preferred to be a challenge task for blow molding simulation. The objective was the uniform wall thickness under specification of a bottle weight. The finite element analysis (FEA) of the extrusion blow molding process was performed to predict thickness which was distributed from initial parison thickness to the final wall thickness of the bottle shape. The neural network (NN) model was then developed and trained from FEM results, in order to model the relationship between thickness of bottles and parisons. Finally, genetic algorithm (GA) method was used to search for distribution of the optimal parison thickness based on trained neural network. The result shown the accuracy of this technique, the error obtained by comparing results and targets was less than 10.75%.

***Keywords**: Optimization, Parison, Finite element method, Artificial intelligence, Blow molding.*

1. Introduction

The extrusion blow molding is process which used to produce hollow plastic parts such as bottles. Two steps consist of an extrusion of hollow plastic tube or parison into mold and an inflation of parison into cavity for shape of bottles are important for this process. Parison thickness can be distributed by controlling die gap to open as know as the parison programming. The trial and error method was often used to define the parison thickness. It is very difficult to receive the bottle wall thickness according to the requirement of the bottle design. Moreover if the bottle has complex shape, controlling of parison thickness is even more difficult to control. Therefore, the significant amount of wasteful plastic, cost and time were lost at the parison setting.

The computer aided engineering (CAE) method involved using finite element method (FEM) to simulate extrusion blow molding process and predict the final wall thickness of bottles had obtained to reduce the trial and error method for setting of the parison thickness [1]. The FEM has limitation because it cannot use to reverse the bottle thickness to the initial parison thickness.

Some works aimed to develop the relative function between parison and final part thickness by using the numerical model and optimize technique. The objective was to search for appropriate bottle thickness with minimum weight under the mechanical performance which required for bottle testing [2-3]. Nevertheless, the using of FEM was restricted only an axisymmetric shape of bottles and it was impossible to predict the parison thickness for bottles with the complex shape. Moreover traditional optimization scheme such as the gradient based method might not be suitable for solving the optimum thickness of the complexity and high degree of the nonlinearity characteristic which found in extrusion blow molding problems.

Artificial neural network (ANN) is a computational model that simulated a biological neural network, which is a system of interconnected artificial nodes or neural. The advantage of ANN lies in its ability to accurately simulate complex and nonlinear behavior. The using of ANN in previous works might be used to build the relative function between the initial parison thickness and the final thickness of bottle wall but it was limited to axisymmetric shape of bottles because the complexity in defining the input and output of the ANN function [4-6]. Moreover the ANN faced the same problem as FEM which could be used to simulate the ANN function but could not search for the optimum or appropriate parison thickness.

Genetic algorithm (GA) is an Artificial Intelligence (AI) method that can be used to search for optimal solution in wide variety of complex engineering problems. The concept of GA is based on natural selection principle where a population of candidate solutions (or individuals) in each iterations (or generations) is evolved toward better solutions by means of selection, cross over and mutation. GA has advantage over other optimization techniques due to its ability to search for better solution near optimum of the current generation without trapping in local optimum [7, 8].

This research developed a strategy for an optimization by FEM and the combined AI – ANN and GA. The ANN would use to build the relative function between the initial parison thickness and final bottle thickness from analysis results of extrusion blow molding process by FEM. The GA was used to search for an optimal parison thickness under the requirement for the bottle thickness or the bottle weight.

2. The FEM for an extrusion blow molding of a rectangular shape bottle

The surface model of rectangular shape bottle with capacity of 1 liter which used to create finite element model of mold cavity was modeled by CAD software as shown in Fig.1. The target of FEM was inflation of a 60 mm diameter of parison only, and then the parison was modeled by shell elements while the surface model of mold cavity was defined as rigid body for assigning contact conditions (Fig. 2).

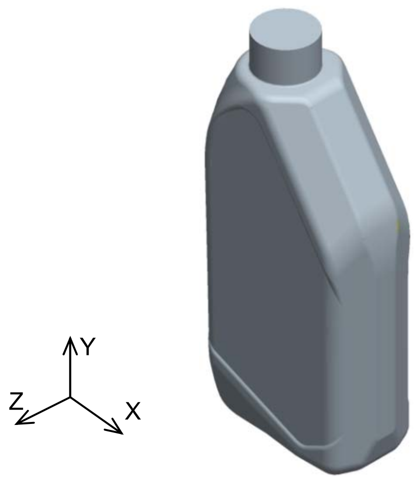

Fig. 1 Surface model of a rectangular shape bottle

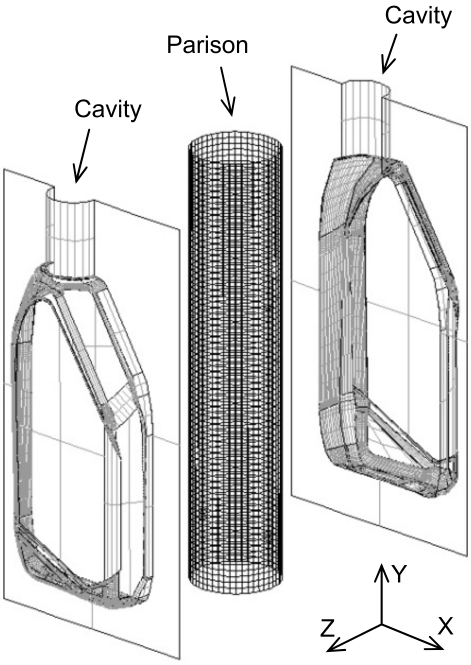

Fig. 2 Finite element model of the extrusion blow molding process

Two boundary conditions assigned on the FEM of a parison. First was the fix condition at top node of a parison in y direction (T_y = 0) and second was the pressure load on the inside face of parison elements. The contact condition between parison elements and mold cavity surfaces was defined as glued or further moving of node were not allowed after the mold collision or closing. The represented parison behaviors which were cool and solidify were almost instantly after parison connected to the cavity.

The viscoelastic material model was used to describe the large deformable behavior of polymer at high temperature. The property of HDPE polymer at temperature of 150 °C was modeled by using the generalized Maxwell constitutive equation in the form of shear relaxation spectrum [9] as follows

$$G(t) = G_0 - \sum_{i=1}^{n} G_i \left(1 - e^{-t/\tau_i}\right) \tag{1}$$

when $G(t)$ is shear relaxation modulus and τ is relaxation time. Time-temperature shift function was then used to express effect of temperature changing during the process by using William-Landrel-Ferry (WLF) equation as shown in Eq. (2),

$$\log a_T = \frac{-C_1\left(T - T_{ref}\right)}{C_2 + \left(T - T_{ref}\right)} \tag{2}$$

when a_T is time-temperature shift factor at temperature T (°C), C_1 and C_2 is WLF constant, and T_{ref} is reference temperature (°C). The parameters of WLF for HDPE used in this work are C_1 = 6.928, C_2 = 350 and T_{ref} = 150 °C [9].

3. Distributed thickness results on bottle wall using FEA

The finite element analysis (FEA) of extrusion blow molding process was performed with an initial parison thickness of 2 mm under pressure of 2 MPa. The result shown parison thickness which distributed to be the rectangular shape bottle and represented as spectrum as shown in Fig. 3. The blow molding of a bottle was analyzed and performed by using FE (Finite Element) software – MSC.Marc version 2010. According to the analysis, the blowing step of the blow molding process finished in time of 1.0 sec and used time to analyze about 5 min by a personal computer with a processor specification of Core 2 Duo 2.4 GHz.

4. Design of experiment and data preparation for ANN

The set of input and output data for training ANN of the extrusion blow molding process had

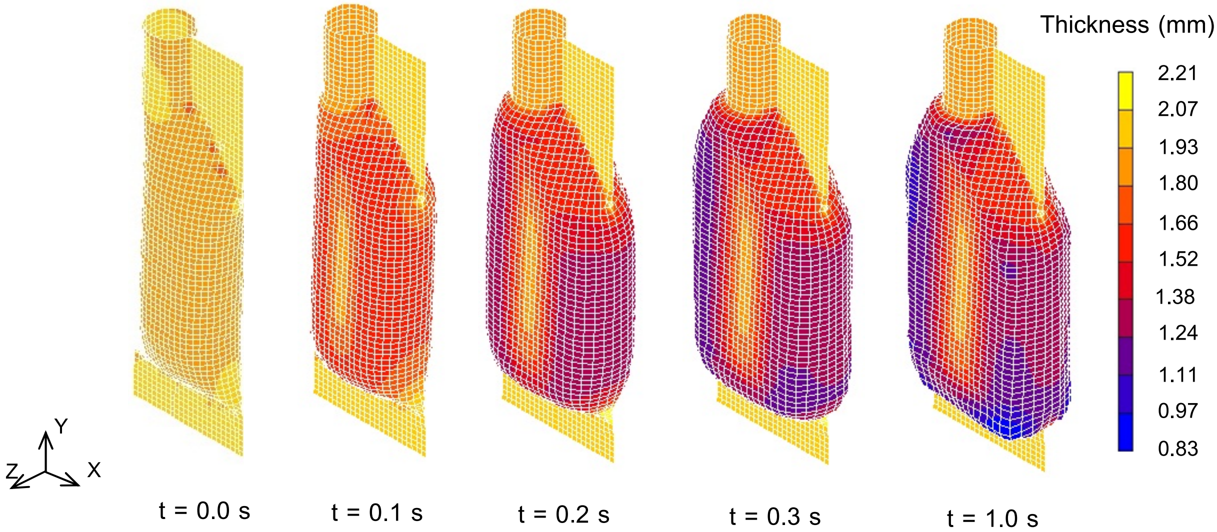

Fig. 3 Distribution of parison thickness in the blowing time of 0.0, 0.1, 0.2, 0.3 and 1.0 sec

been designed under the condition of product which was an initial parison thickness and a final part thickness, respectively. The required bottle thickness was 1.16 mm which was determined from the FE result of top load test with the weight of 25 kg while yielded the maximum bottle weight lower than 80 g. The initial parison thickness was divided into 5 zones along the height. The value of initial parison thickness at each zone was assigned to be 5 input variables for ANN training which consisted of t1, t2, t3, t4 and t5 (Fig. 4). In the same manner, output data was collected from final bottle thickness which was divided into 3 zones along bottle height i.e. neck, wall and shoulder of the bottle. The minimum and maximum thickness in each zones was then collected and assigned to be 6 output variables which comprised b1(min, max), b2(min, max) and b3(min, max), respectively for supervisor learning of ANN (Fig. 4).

The initial parison thickness of each zone could be calculated by using theoretical blow ratio and used to be set as input variables of the ANN

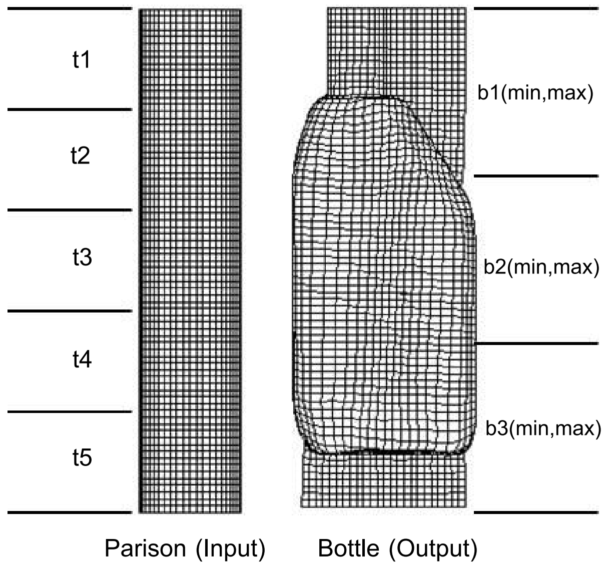

Fig. 4 Schematic diagram of the input and output data selecting from the FE thickness analysis

as shown in Eq. (3),

$$t_i = \frac{A_{bottle,i}}{\pi D h_i} t_{bottle,i} \qquad (3)$$

when i is zone of parison, D is parison diameter (60 mm), h_i is parison height in each zone and $t_{bottle,i}$ is a desirable bottle thickness (1.16 mm)

Each input variable was divided into 3 levels under bottle weight constraints. The relationship between the initial parison thickness in each zone and the bottle weight constraint is shown in Eq. (4),

$$M = \rho \sum_{i=1}^{n} \pi (Dt_i - t_i^2) h_i \le 80g \qquad (4)$$

The initial parison thickness in two connected zones was varied into three levels simultaneously while the other three zones remain fixed to the middle level value. The varying of the initial thickness was bring to the next two connected zones and this method repeated until every two connected zones had been completely varying to an array form of the initial thickness. Constraints from Eq. (3) and Eq. (4) produced the number of data sets in the array concluded as the following Eq.

$$n^2(i-1) = 36 \qquad (5)$$

when n is levels ($n = 3$) and i zones of parison ($i = 5$).

All input data would be added with a random number to prevent memorization of the data without learning of ANN. Each set of input data was used as the initial condition of FEA and the final thickness result would be collected to use as output data. The collected data would be stored in array to teach ANN in the next step.

5. Artificial Neural Network

This research used multilayer feed forward neural network and Levenberg-Marquardt back propagation algorithm which was used to train the network. The structure of Levenberg-Marquardt algorithm was not complex and could use to train the network in less time than other algorithms. The architecture of neural network was designed as two hidden layers where each hidden layer consisted of 20 and 10 neurons respectively. Practically neural networks often had 2 to 3 layers, while 4 or more layers network was not commonly using in practice arising from the increasing in complexity might affect the amount of time spent during training of the network or in data memorization results instead learning [10].

Input variables of the neural network would be normalized to the values between 0 and 1 for the appropriately using with logarithm of Sigmoid transfer function. The normalization equation used to modify value of input date such as the initial parison thickness in each zone may conclude as following Eq.

$$t_{i,norm} = \frac{(t_i - t_{i,\min})}{(t_{i,\max} - t_{i,\min})} \qquad (6)$$

The initial parison thickness and analyzed results of final bottle thickness in each zones was assigned as input and output data for training the neural network, respectively. Back propagation method was used to train the network with repeating the adjustable value of weight and bias until weight and bias was modified into the suitable value. The successfully training of ANN model could be used to build the thickness relationship function between the initial parison thickness and the final bottle thickness.

6. Optimization of parison thickness using Genetic Algorithm

The training network was used to build the fitness function for optimization of the bottle thickness using GA. The fitness function used in this research based on the minimization of sum of the residual square (least square summation) approach. The objective was the minimum thickness requirement equal to 1.16 which was obtained from results of top load test analysis using FEM. In addition, the ratio of maximum and minimum bottle thickness in each zone would be multiplied into the fitness function in order to ensure the uniform bottle thickness as much as possible. The finalized fitness function may define as following Eq.

$$f(t) = \sum_i \left(\frac{t_{i,\max}}{t_{i,\min}} \right) \left(t_{i,\min} - 1.16 \right)^2 \qquad (7)$$

The population size was set to be 40 and the upper and lower bound within the same range as ANN normalization range was applied. The optimum search using GA was performed and the optimization converged after there was no further improvement or change in value lower than predetermination of the fitness tolerance in each generation. The optimum of parison thickness in each zone obtained from optimization using GA and its associated final bottle thickness were represented in Table. 1 and Table. 2, respectively.

7. Validation of ANN and GA using FEA

The optimum thickness obtained from GA would be validated by using to be an initial

Table. 1 The optimum parison thickness in each zones obtaining from GA.

t1 (mm)	t2 (mm)	t3 (mm)	t4 (mm)	t5 (mm)
2.1942	2.1489	1.9905	2.1900	2.5568

Table. 2 The maximum and minimum final bottle thickness in each zone.

Zone	Minimum (mm)	Maximum (mm)
b1	1.1601	1.9967
b2	1.1604	2.1231
b3	1.1596	2.3242

parison thickness in FEA. The FEA of the extrusion blow molding process was performed using a new optimized initial thickness and the distribution of thickness was shown by the spectrum result in Fig. 5. The result shown the optimized bottle thickness from combination of FEM, ANN and GA had the thickness distribution nearly uniform under the desired minimum thickness. However some area of the bottle would be thick and might be impossible for obtaining the perfectly uniform thickness. Cause of this problem was the parison would only be the uniform radial thickness in the circular cross section of bottles. The bottle which had rectangular section in this case made the parison area that connected to the cavity first would be unavoidable thicker. The maximum and minimum bottle thickness between the FEA result and ANN combined with GA were compared. The result shown the optimized bottle thickness from combined ANN and GA was in a good agreement with simulated thickness distribution from FEA with an average error approximately 10.75%.

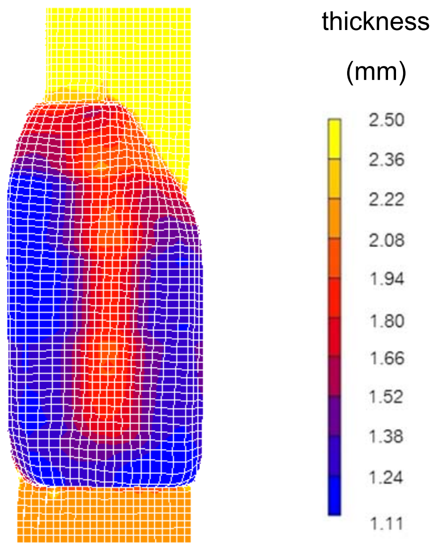

Fig. 5 Result of parison thickness distribution using optimum initial parison thickness from GA

8. Conclusion

The optimized parison thickness used the thickness relationship function from the combination of ANN and GA had been compared with FEA results to determine the accuracy. The comparison shown the optimized thickness was a good agreement with the FEA and obtained an average error of 10.75%. The optimization technique with GA combined into the thickness relationship function could be applied to find the required parison thickness in the extrusion blow molding process to produce bottles which had a desired thickness under the mechanical constraint. Particularly, this method could be applied to the complex shape bottle and reduce the need of trial and error method which helped to reduce the plastic waste, time and cost.

9. Acknowledgement

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10. References

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