Suitable Die Shaping for a Rectangular Shape Bottle by Application of FEM and AI Technique

N. Ploysook, R. Rugsaj, C. Suvanjumrat

Abstract—The characteristic requirement for producing rectangular shape bottles was a uniform thickness of the plastic bottle wall. Die shaping was a good technique which controlled the wall thickness of bottles. An advance technology which was the finite element method (FEM) for blowing parison to be a rectangular shape bottle was conducted to reduce waste plastic from a trial and error method of a die shaping and parison control method. The artificial intelligent (AI) comprised of artificial neural network and genetic algorithm was selected to optimize the die gap shape from the FEM results. The application of AI technique could optimize the suitable die gap shape for the parison blow molding which did not depend on the parison control method to produce rectangular bottles with the uniform wall. Particularly, this application can be used with cheap blow molding machines without a parison controller therefore it will reduce cost of production in the bottle blow molding process.

Keywords—AI, bottle, die shaping, FEM.

I. INTRODUCTION

THICKNESS of bottles which produced by the extrusion blow molding process was major controlled with parison controller [1], [2]. Parison programming could adjust parison wall thickness by moving the mandrel up or down during extrusion. Thickness of parison could increase or reduce along the bottle height which was depended on the blow-up ratio between the diameter of the finished bottle and the diameter of parison. Therefore, parison programming was proper to used for bottles which had an axis-symmetry shape.

Nowadays finite element method (FEM) was conducted to simulate the blow molding process of plastic bottles [3]–[5]. The simulation was performed to determine parison thickness which was proper to blow bottles with uniform thickness. It was the advance method to reduce the waste plastic from a trial and error method for setting the parison controller. However simulation of the plastic bottle blow molding was not simple to determine parison thickness rapidly. It consumed many time to find out the suitable thickness of parison.

Some research aimed to apply optimizing techniques for the relative function between the parison and the finished bottle wall thickness. The objective was to search for an appropriate

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bottle thickness with minimum weight under the mechanical performance constraint which required for bottle testing [6]. Traditional optimization schemes such as the gradient based method might not be suitable for solving complex behavior with high degree of nonlinearity which was found in the extrusion blow molding process.

The artificial intelligent (AI) technique comprised of artificial neural network (ANN) and genetic algorithm (GA) which was appropriate to applied in the FEM of the bottle blow molding process. The ANN was used to build the relative function between the initial parison thickness and thickness distribution along the bottle height. The GA had advantage ability over other optimization techniques and then it was used to search for the better solution near optimum of the current solution without trapping in local optimum [7]–[9]. The ANN and GA was couple of AI techniques for determining a suitable parison thickness however limited only an axis-symmetric shape of bottles because of the complexity to define the input and output of the ANN function.

The rectangular shape preferred to design for lubricant oil bottles. These bottles could not have a uniform wall by setting parison with the parison programming method arising from the difference of the blow-up ratio around the bottle wall. The die shaping was an only one method to adjust thickness around the parison diameter. Initial method to adjust a die gap for a suitable thickness of parison to obtain the uniform wall thickness of rectangular shape bottles was the trial and error method. Therefore, the waste plastic and time could not avoid for the bottle blow molding process.

This research aimed and challenged to apply AI techniques which were ANN and GA to optimize the die gap shape for the parison blow molding process and the uniform thickness of a rectangular bottle. The FEM was performed to create the input and output data under the validation of finite element results with experiments. This application can be improved for another rectangular shape bottles and is useful for the cheaper blow molding machines which not have without the parison controller.

II. THE BLOW MOLDING EXPERIMENTS FOR RECTANGULAR SHAPE BOTTLES

Rectangular shape bottles used for containing lubricant oil are produced by using a blow modeling machine, Sinco model 5000DC, as shown in Fig. 1. Parisons were extruded thought die which were adjusted die gap shape and had an outer diameter of 52.0 mm for blowing rectangular shape bottles.
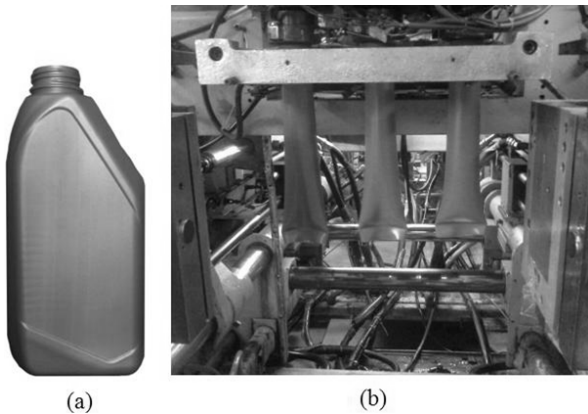
Fig. 1 (a) A HDPE lubricant oil bottle and (b) Parison extrusion by blow molding machine with the adjusting die
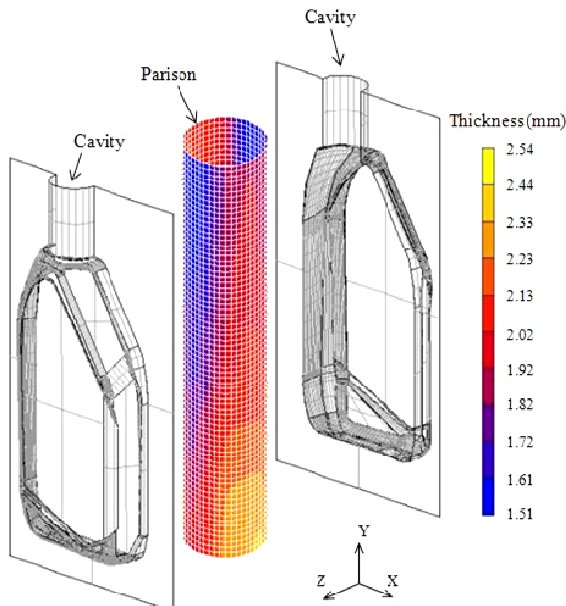

Fig. 2 CAD model of a lubricant oil bottle

Fig. 3 The finite element model preparing for the blow molding simulation of a lubricant oil bottle

Parison thickness, temperature and blowing pressure were measured for input data of the finite element (FE) model. The bottle thickness obtained from measuring wall of bottles using a vernier caliper with an accuracy of ±0.01 mm, Mitutoyo model absolute 150 mm, and would use to compare and validate with the finite element result.

III. THE FEM FOR AN EXTRUSION BLOW MOLDING OF A RECTANGULAR SHAPE BOTTLE

The lubricant oil bottle which had a capacity of 1 liter was modeled by the computer aided design (CAD) software, SolidWorks version 2011, for using to be cavity of the simulated model (Fig. 2). The parison is modeled by shell elements which has thickness around a diameter according to the experimental thickness as shown in Fig. 3. Thickness of parison could indicate by color contour. The thickest and thinnest parison wall was signified by yellow and blue, respectively. The surface model of mold cavity was defined as rigid body and assigned contact boundary conditions. Two boundary conditions assigned on the FE model 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. Parison behaviors which were cool and solidify were almost instant after parison connected to the cavity.

The viscoelastic material model was used to describe the large deformable behavior of polymer at high temperature. Properties of high density polyethylene (HDPE) polymer at a temperature of 150 °C were modeled by using the generalized Maxwell constitutive equation in the form of shear relaxation spectrum [10] as follows

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

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

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

where a_T is a time-temperature shift factor at temperature T (°C), C_1 and C_2 is the WLF constant, and T_{ref} is a 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.

The blow molding of a lubricant oil bottle was analyzed and performed using the FE software – MSC.Marc version 2010. The pressure of 2 MPa was defined into parison model. The blowing step of the blow molding process finished in time of 0.5 sec and used time to analyze about 10 min by a personal computer with a processor specification of Core 2 Duo 2.4 GHz. FE results are illustrated the parison blowing to be the lubricant oil bottle which has a rectangular shape in Fig. 4. Parison thickness distribution was depicted by a color contour. The thickest and thinnest bottle wall was signified by yellow

and blue, respectively.

The thickness around bottles at 50% of bottle height was compared to determine an error of the FEM. The comparison between the average wall thickness of bottles and FE results is shown by graphs in Fig. 5. An average error of FE obtained 31.37% when compared with experimental results.
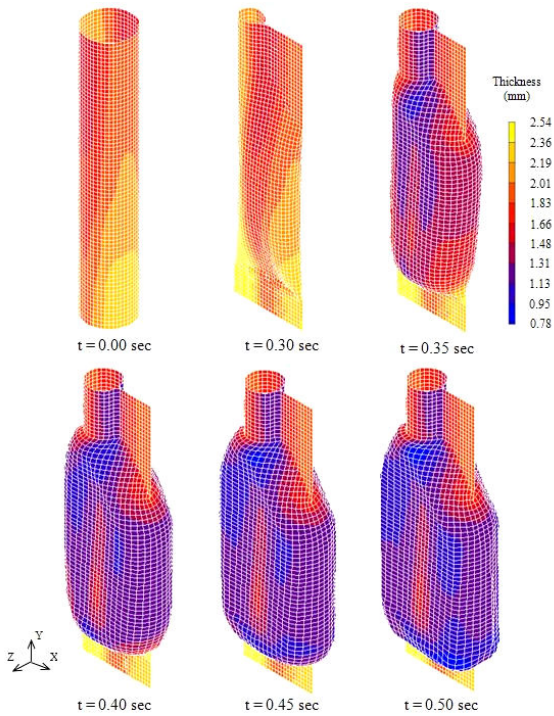

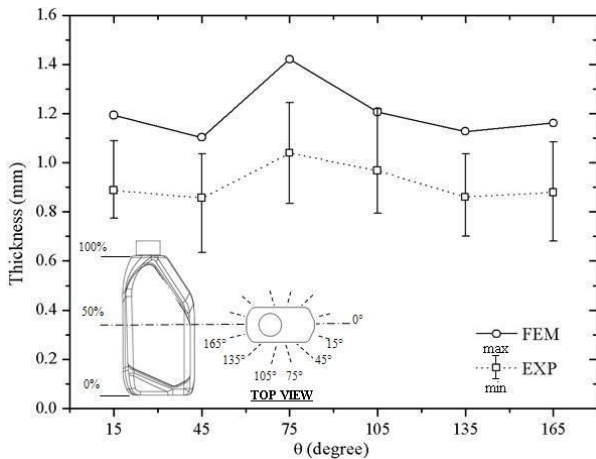Fig. 4 Sequence images of finite element results for the blow molding of a lubricant oil bottle

Fig. 5 The relative graphs between wall thicknesses and angles around bottles at 50% of bottle height

IV. DESIGN OF EXPERIMENT AND DATA PREPARING FOR ANN

An initial parison thickness and a finished bottle thickness was designed to be the set of input and output data for training ANN of the extrusion blow molding process. The thickness bottle of 1.16 mm was required which was determined from the FE result of top load test with the weight of 25 kg and the maximum bottle weight lower than 80 g. The cross section at the 50% of the bottle height was divided equality to be 12 zones around the diameter as shown in Fig. 6. Half portion of the parison and bottle cross section was needed to be collected only for the input and output variables due to a symmetrical shape. The value of initial parison thickness at each zone was assigned to be 6 input variables for ANN training which consisted of t_1, t_2, t_3, t_4, t_5 and t_6. In the same manner, the output data from 6 zones around cross section of bottles in the same side as parison was collected and assigned to be output variables which comprised of b_1(min, max), b_2(min, max), b_3(min, max), b_4(min, max), b_5(min, max) and b_6(min, max) for supervised learning of ANN.

The average parison thickness around cross section could be calculated by using theoretical blow-up ratio as shown in (3) [11] and used to be an initial parison thickness of finite element analysis (FEA).

$$t_{avg} = \frac{P_1}{\pi D} t_d \qquad (3)$$

where P_b is perimeter of the bottle at the middle height, D is parison diameter (52 mm) and t_b is the objective of bottle thickness (1.16 mm). The FEA was then performed and results of the finished bottle thickness results in each horizontal zone was collected and used to determine input variables of the ANN using (4),

$$t_i = \frac{t_{avg}}{b_{fem,i}} t_d \qquad (4)$$

where t_i is an initial parison thickness at each zone. 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 (3) and (4) produced the number of data sets in the array concluded as the following (5),

$$n^2(i-1) = 54 \qquad (5)$$

where n is level ($n = 3$) and i is zone of parison ($i = 6$).

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.

V. ARTIFICIAL NEURAL NETWORK MODEL

This research used multilayer feed forward neural network and Levenberg-Marquardt back propagation algorithm to train the network. The architecture of neural network was designed by 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 of complexity might affect to the amount of time spent during training of the network or in data memorial results instead learning [12].
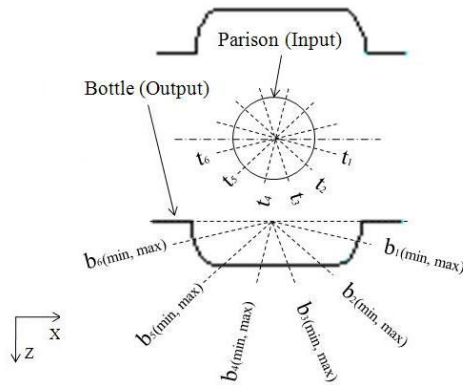

Fig. 6 The input and output data diagram selecting from the FE results

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 data such as the initial parison thickness in each zone may conclude as

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

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. 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.

VI. GENETIC ALGORITHM

The objective for optimizing the die gap was the parison blow molding to produce bottles with the minimum uniform thickness of 1.16 mm. In this case, the training network was used to build the fitness function for optimization of the die gap shape with GA. The fitness function used in this research based on the minimization of sum of the residual square approach. The finalized fitness function can define by

$$f(t) = \sum_i (t_i - t_d)^2 \quad (7)$$

The 40 population sizes were set. The upper and lower bound within the same range as ANN normalization was applied. The optimum searching by GA which converged after there was no further improvement or change in value lower than predetermination of the fitness tolerance in each

generation. The optimum of the symmetrical die gap in each zone which obtains from GA optimization is summarized in Table I.

TABLE I
THE OPTIMUM DIE GAP SHAPE IN EACH ZONES OBTAINING FROM GA

t_1 (mm)	t_2 (mm)	t_3 (mm)	t_4 (mm)	t_5 (mm)	t_6 (mm)
1.9682	2.0094	1.6143	1.5523	2.2181	2.2772

VII. RESULTS AND DISCUSSION

The optimum die gap shape obtained from AI application would be validated by using to be an initial parison thickness of FEM. Simulation of the extrusion blow molding process was performed using a new optimized initial thickness. The thickness distribution of the finished bottle from parison with the non-die gap shaping and AI applied die gap shaping is depicted by the color contour as shown in Fig. 7. The FE result showed the thickness distribution on bottle surface at 50% of bottle height area which used AI application for setting parison thickness was uniform with the thickness about 1.16 mm. The simulated thicknesses at each angle around a centre of bottle cross section at 50% of bottle height are compared with the objective thickness of bottle by graphs as shown in Fig. 8. The AI application for the uniform thickness by optimizing die gab shape was in a good agreement with objective when proved with FEM. Thickness of bottle at position 75 degree was more than another area when the FEM used parison thickness from die without adjusting die gap shape. The trial die gap shape by die maker also has the finished bottle thickness was closed to the objective however lost many time for achieving the appropriate die gap shape. The bottle blow molding with AI technique for parison thickness obtained an average error of the finished bottle wall thickness from the thickness of objective about 5.62%.
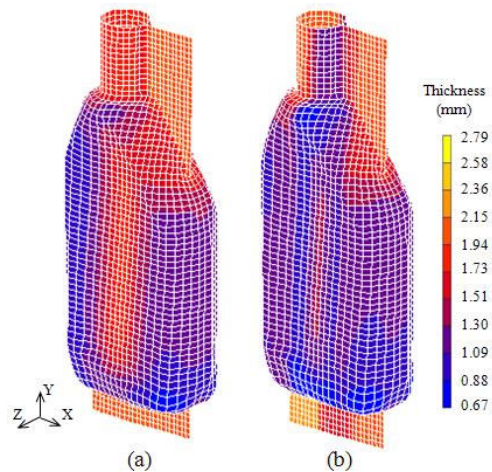

Fig. 7 Thickness distribution of final bottle by (a) non-die shaping and (b) AI applied die shaping
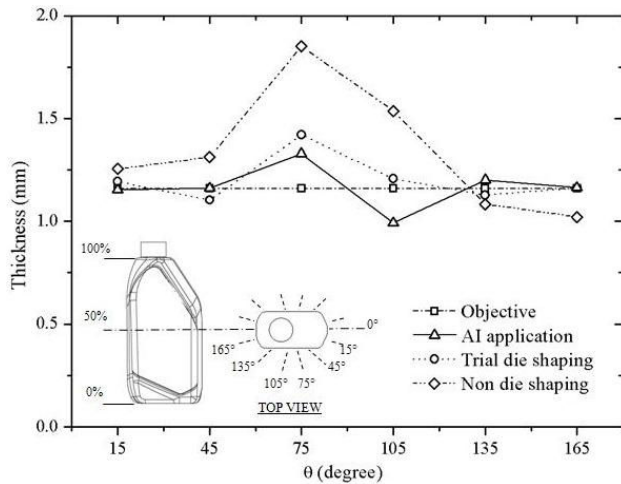
Fig. 8 The relative graphs between wall thicknesses and angles around bottles at 50% of bottle height for comparison parison inputs

VIII. CONCLUSION

Optimization of the die shape was performed for adjusting the die gap. Functions from AI application which was the combination of ANN and GA had been used to determine the suitable die gap shape for producing rectangular shape bottles with the uniform thickness. Input and output data obtained from the FE results which validated with experiment results was used for the ANN model. The objective was controlled by GA. The die gap shape which received from the AI technique was conducted to set as the initial parison thickness of FE model for simulating the blow molding process. Simulated results were compared with the objective. The comparison between bottle thickness and objective shown the optimized thickness was a good agreement with the objective thickness. This optimization technique with GA combined into the thickness relationship function could be applied to find the required die gap shape in the extrusion blow molding process to produce bottles which had a desire uniform thickness under the mechanical constraint. This method could be applied to complex shape bottles and reduce the need of trial and error method which supported to reduce the plastic waste, time and cost of production lines. Particularly, this method can use with the cheaper blow molding machine which not has the parison controller.

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