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Optimization of Extrusion Blow Molding Using Soft Computing and Taguchi Method

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Abstract

This paper presents a soft computing strategy to determine the optimum die openings of parison programming of extrusion blow molding process. The design objective is to obtain a uniform thickness of blown parts. The proposed strategy, Fuzzy Neural-Taguchi, first establishes a back propagation network using Taguchi's experimental array to predict the relationship between design variables and response. Engineering knowledge is thus applied to genetic algorithm using fuzzy rules to improve search efficiency. This study uses the finite element simulation software, BlowSim, to simulate the thickness distribution of blown parts. The comparison of results demonstrates the effectiveness of the proposed strategy.

1. Introduction

Extrusion blow molding is a low cost manufacturing process for complex hollow parts [1]. The parison extrusion produces a melten thermoplastic tube from melten resin. The part molds then clamp both ends of the parison and high-pressure air is blown into the cavity to inflate the hollow part. The displacement of the mandrel controls the gap between the mandrel and the die, which determines the parison thickness (Fig. 1). The thickness of parison controls the thickness of inflated parts. Excessive resin usage results in material waste and increased cycle times. An inadequate thickness results in decreased mechanical strength. Parison programming controls the die openings of programming point to obtain the desired distribution of part thickness.

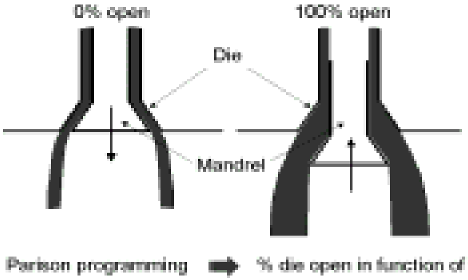

Fig. 1 The control of the parison thickness using the parison programming

The programming points are specified by the extrusion time of parison. As the example part shown in Fig. 2, we identify the die gap openings at 7 discrete extrusion times as the design variables: $P(t_0)$, $P(t_1)$, $P(t_2)$, $P(t_3)$, $P(t_4)$, $P(t_5)$, and $P(t_6)$. The design objective in this study is to obtain an inflated part of uniform wall thickness. Often process engineers manipulate the parison programming on a trial and error basis. Larger expansion area requires heavier wall thickness of parison.

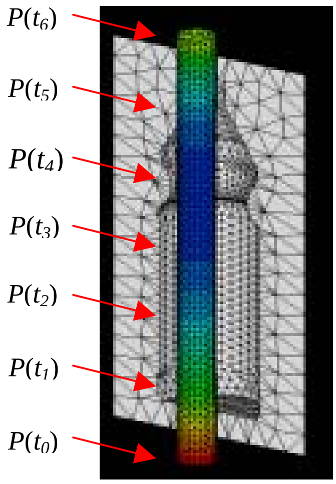

Fig. 2 Programming points of parison extrusion

Extrusion blow molding involves complicated processes including parison extrusion, clamping, blow up, and cooling. The investigation of the relationship between design variables and the wall thickness distribution of blown parts requires expensive experiments and time-consuming simulations. Diraddo et al. [2] established a neural network to predict the distribution of parison thickness and applied Newton-Raphson method to obtain the final blow molded part specifications [3]. Lee et al. [4] used a finite element model of thin film to simulate blow-molding processes, and applied the feasible direction method to minimize the parison volume at the constraints of part thickness.

This study applies an optimization strategy based on Taguchi's method [5] and soft computing [6] to the optimization of parison programming to obtain a uniform thickness distribution of final parts. The proposed strategy establishes a local neural network based on Taguchi's orthogonal array experiments and adopts the fuzzy inference to genetic algorithm to search for the optimum.

2. Optimization Strategy

Taguchi's method has proven its efficiency and simplicity in parameter design. The proposed optimization strategy, Fuzzy Neural-Taguchi (FUNTGA), applies Taguchi's experimental design to the training and testing of a neural network model. The trained network becomes the function generator of the design fitness in the Genetic Algorithm. The search for optimum using GA enhances the possibility for a better design than the conventional analysis of means (ANOM). A fuzzy inference of engineering knowledge is introduced to enhance the searching efficiency of GA. The flowchart of the optimization strategy is illustrated in Fig. 3.

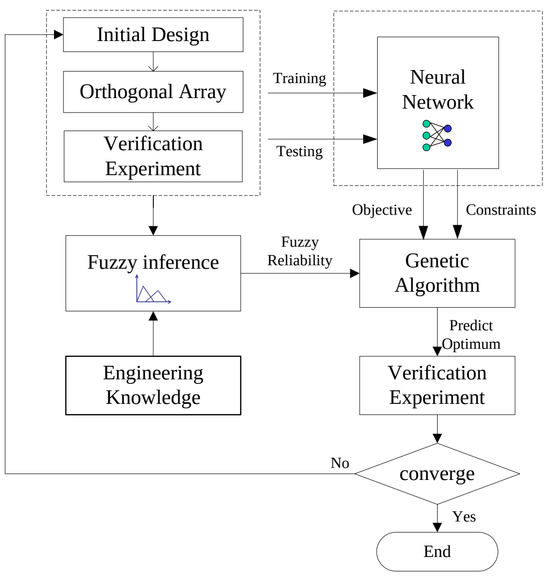

Fig. 3 The flowchart of Fuzzy Neural-Taguchi

2.1. Taguchi's Method

Inspired by statistical factorial experiments, Taguchi's method features orthogonal arrays and analysis of mean (ANOM) to analyze the effects of design variables. Each variable is assumed to have finite levels (set points), such as two or three levels, within the investigating range. The orthogonal array is a kind of fractional factorial experiments. The application of orthogonal arrays reduces the number of experiments, which is particular effective for design optimization involving expensive experiments or time-consuming simulations. For instance, instead of 27 experiments for three 3-level full factorial experiments, the L9 orthogonal array selects only nine treatments. ANOM study of the experiments reveals effects of design variables that are used to determine the optimal level of each parameter. Taguchi's result is not optimal; however, iterations of Taguchi's method can provide a near optimal design.

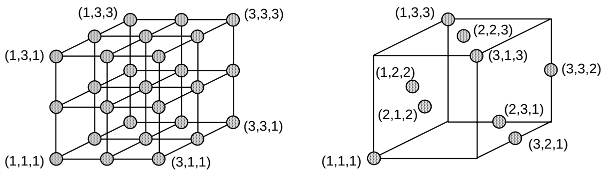

Fig. 4 Full factorial and fractional factorial experiments for three variables

Taguchi's approach utilizes ANOM of fractional factorial experiments to predict the optimal design of the full factorial experiments. However, the predictive optimal is sensitive to the selection of factorial levels and interaction effects. Also, the restriction of parameter values to factorial levels eliminates possible better designs between preset levels.

2.2. Neural-Taguchi network

Neural network technologies are effective in process control. The network is used to establish a simulation model for a complex nonlinear system. Fig. 5 represents a back-propagation network that consists of an input layer, a hidden layer, and an output layer. The back propagation network is a type of supervised learning networks. Sampling data are divided into learning samples and testing samples. Learning samples are used to determine the weighting matrices, W_{ij} and W_{jo}, among neurons. Testing samples are used to determine the accuracy and the generality of network.

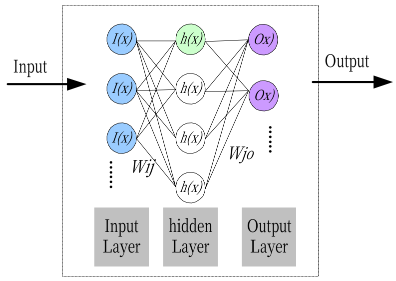

Fig. 5 Back-Propagation network

Training samples are essential to prediction quality of network models. This study employs Taguchi's experimental design to select training samples to reduce the number of experiments and to maintain the representivity of samples [7] [9]. The steepest gradient method is adopted to train the weighting matrices. The verification experiment of the optimal design from the ANOM study will serve as a testing sample. The trained network can accurately predict the responses for the parameter designs between factorial levels. Significant interactions often introduce complexity to experimental design and lead to erroneous prediction of optimal factorial levels. The network model can resolve interaction effects among variables. These features enable the network to explore a better design as compared with Taguchi's additive model.

2.3. The search for the optimum of the Neural-Taguchi network

The trained Neural-Taguchi network can predict responses for the parameter combinations in the investigating range. Generic Algorithm is thus applied to search for the optimum. If the verification result of the predicted optimum is not satisfactory, the design will be used as an initial design and another set of orthogonal array experiments will be conducted. The results will be served as additional testing data for the network. The iteration process stops when the predicted optimum obtained from GA and the network converges.

The Neural-Taguchi network replaces Taguchi's additive model to predict design outputs. The search for the optimum in the investigating range using GA will explore the possibility of better designs other than factorial points. However, the application of orthogonal arrays significantly reduces the number of training samples as compared with conventional random sampling. Owing to that better prediction accuracy will exist around sampling points, our approach introduces a fuzzy inference to steer the search direction of GA.

2.3.1. Normalization of design parameters

To facilitate the calculation of the distance among designs, the values of the set points of continuous variable x_k are normalized to z_k using the following transformation,

$$z_{kl} = \frac{\left(x_{kl} - \frac{(\max(x_k) + \min(x_k))}{2}\right)}{\left(\frac{(\max(x_k) - \min(x_k))}{2}\right)} \qquad (1)$$

where $\max(x_k)$ represents the maximum and $\min(x_k)$ represents the minimum values of the factorial variable x_k. Thus the normalized factorial values of an equal spaced three-level continuous variable, x_1, will become $(z_{11}, z_{12}, z_{13}) = (-1, 0, 1)$. For discrete variables, the factorial values are equally assigned between -1 and +1.

2.3.2. The Reliability Distance

The factorial distances between predictive designs, D_i, and the sample data S_j are defined as follows,

$$r_{ij} = \left[\frac{1}{n}\sum_{k=1}^{n}\left(D_{ik} - S_{jk}\right)^2\right]^{0.5} \qquad (2)$$

where n represents the number of variables.

Because that the predictions around the sampling points of the trained network will have higher accuracy, this study defines the Reliability Distance of a predictive design as the minimum factorial distance between the prediction and sampling data.

$$RD_i = \min(r_{ij}) \qquad (3)$$

Smaller RD results in higher prediction accuracy. Also, the distance of an interpolating design is assumed negative and the distance of an extrapolating design is assumed positive. For instance, the Reliability Distance of D_1 in Fig. 6 is negative and the Reliability Distance of D_2 is positive.

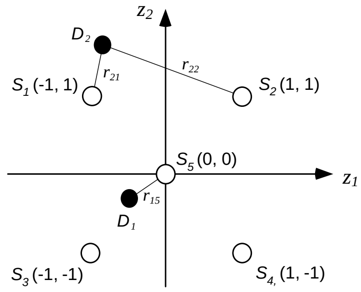

Fig. 6 The factorial distances of predicted designs

2.3.3. The fuzzy rules of prediction accuracy

The Reliability Distance of a predictive design determines the prediction accuracy of the design. The reliability of the predicted design decreases when the absolute value of *RD* increases. Also, the reliability of extrapolating designs is often much worse than the interpolating designs. Based on the above characteristics of neural network, this study propose the fuzzy rules of the design reliability as follows,

R1: If *RD* is PB then prediction reliability is Bad
R2: If *RD* is PM then prediction reliability is Poor
R3: If *RD* is PS then prediction reliability is Fair
R4: If *RD* is ZE then prediction reliability is Excellent
R5: If *RD* is NS then prediction reliability is Excellent
R6: If *RD* is NM then prediction reliability is Good
R7: If *RD* is NB then prediction reliability is Fair

Seven levels are defined to describe the condition variables: PB(Positive Big), PM(Positive Medium), PS(Positive Small), ZE(Zero), NS(Negative Small), Negative Medium (NM), and NB(Negative Big). Five levels are defined to describe the assessment results: Excellent, Good, Fair, Poor, and Bad. Standard membership functions shown in Fig. 7 and Fig. 8 are used.

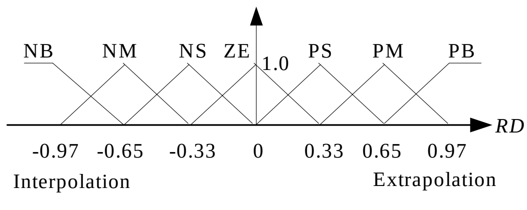

Fig. 7 Membership functions of condition variables

Fig. 8 Membership functions of assessment variables

3. Optimization of blow molding parameters

This study applies the proposed optimization strategy to the parameter design of extrusion blow moldings. The example part is a HDPE bottle. The design objective is to obtain a uniform wall thickness of 2*mm*. BlowSim is applied to obtain the distribution of the wall thickness of blow-molded parts. BlowSim is a finite element software package designed to simulate parison meshing, blow molding, and thermoforming processes [8]. This software has been developing at the Industrial Materials Institute (IMI) of National Research Council (NRC), Canada. The application procedure is described in this section, and the results are compared with Taguchi's method and heuristic control to show the effective of our approach.

3.1. Taguchi's parameter design

3.1.1. Experimental Design

As stated in Fig. 2, the die gap openings at 7 discrete extrusion times are selected as the control factors: $P^i(t_0)$, $P^i(t_1)$, $P^i(t_2)$, $P^i(t_3)$, $P^i(t_4)$, $P^i(t_5)$, and $P^i(t_6)$. The design optimization manipulates the die openings at the programming points to obtain uniform thickness of final inflated parts.

Because large errors are expected for extrapolation of the neural network, the selection of the factorial range should cover the optimum design to increase prediction accuracy. The required parison thickness mainly depends on the inflation ratio although the parison might expand annularly and longitudinally. The inflation ratio is defined as the ratio between the parison diameter and the inflated part diameter. We assume that the parison thickness is determined by the die gap opening despite the complexity of parison extrusion. The cross section areas of the parison and the final part will be then approximately equal, which provides the initial design of die opening. The relationship between parison thickness and inflated part thickness are approximately as follows,

$$\pi \cdot d_f \cdot t_f = \pi(d_p t_p - t_p{}^2) \tag{4}$$

d_p : outside diameter of parison (mm)

d_f : final part diameter(mm)

t_f : final part thickness(mm)

The L18 orthogonal array is selected as the experimental design that is stated in Table 1. The openings at each programming are assumed three levels with the initial design at the middle. The range between the upper and the lower levels is the design space. The ranges are tentatively set to be 30% for the middle and 10% for both ends of the programming points. The basic idea is to cover the optimum design in the parameter ranges.

3.1.2. Objective Function

A quality blow molding part requires on-target and uniformly distributed wall thickness. The proposed objective function is defined as the average quality loss due to the deviation of thickness,

$$Avg\_loss = \frac{\sum_{i=1}^{n}(t_i - T)^2}{n} \tag{5}$$

where t_i stands for the thickness of node *i*; *T* stands for the target thickness; *n* stands for the number of nodes of the simulation model. The calculation of thickness distribution should exclude flash portions.

Any deviation from the target thickness will cause quality loss. The average quality loss can be divided into two parts: the deviation of the mean from the target thickness and the variation of the thickness around mean.

$$\frac{\sum_{i=1}^{n}(t_i - T)^2}{n} = (\bar{t} - T)^2 + \frac{\sum_{i=1}^{n}(t_i - \bar{t})^2}{n} = (\bar{t} - T)^2 + \frac{(n-1)s^2}{n} \tag{6}$$

where $\bar{t}$ is the mean thickness and s^2 is the sampling variance. The design optimization seeks to minimize the variation of thickness and the difference between the target and the mean thickness. The BlowSim simulation responses of the initial design and the L18 experiments are stated in Table 1.

Table 1. L18 orthogonal array

$L_{18}(2^1 3^7)$	A $P(t_0)$	B $P(t_1)$	C $P(t_2)$	D $P(t_3)$	E $P(t_4)$	F $P(t_5)$	G $P(t_6)$	Objective
1	0	45	60	60	48	0	0	0.69
2	0	60	75	75	63	5	5	0.62
3	0	75	90	90	78	10	10	0.63
4	5	45	60	75	63	10	10	0.93
5	5	60	75	90	78	0	0	0.93
6	5	75	90	60	48	5	5	0.72
7	10	45	75	60	78	5	10	0.82
8	10	60	90	75	48	10	0	0.79
9	10	75	60	90	63	0	5	0.69
10	0	45	90	90	63	5	0	1.14
11	0	60	60	60	78	10	5	0.53
12	0	75	75	75	48	0	10	0.62
13	5	45	75	90	48	10	5	1.07
14	5	60	90	60	63	0	10	0.67
15	5	75	60	75	78	5	0	0.49
16	10	45	90	75	78	0	5	1.01
17	10	60	60	90	48	5	10	0.82
18	10	75	75	60	63	10	0	0.55
Initial	0	60	60	60	48	5	0	0.52
Taguchi's Optimum	0	75	60	60	78	10	10	0.49

3.1.3. Parameter design

Taguchi's method applies the analysis of means (ANOM) to estimate factor effects. Fig. 9 depicts the effects of each die openings on the design objective. An additive model based on ANOM can be formulated. The additive model estimates the optimum treatment combination is $A_1B_3C_1D_1E_3F_3G_3$. The BlowSim simulation result of the optimum (Table 1) demonstrates that Taguchi's method does provide a better design than the initial and all the L18 experiments. However, the

BlowSim simulation of the optimum shows no significant improvement over the initial design that might be due to possible interactions among variables and strong system nonlinearity.

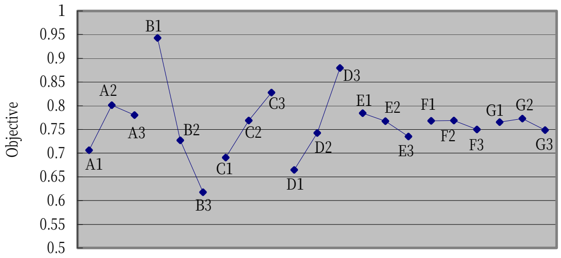

Fig. 9 Effect plot of control variables

3.2. Design Optimization using BlowOP

BlowOp is an optimization module of BlowSim, which uses engineering heuristics to adjust the die openings of the programming points of parison extrusion. The heuristics are as follows,

1. If the thickness of a programming point is larger than the target thickness, then increase the corresponding die gap opening.
2. If the thickness of a programming point is smaller than the target thickness, then reduce corresponding die gap opening.

The iteration procedure is determined by the following equation:

$$A_{i+1} = A_i - \alpha_u \alpha_p (T_i - T) \quad (7)$$

where A_i and A_{i+1} are the parison thickness of each programming point at iterations i and i+1. The die opening determines the parison thickness. T_i is the part thickness at iteration i, and T is the target thickness of the final part. α_u is the user-defined proportional gain and α_p is the inflation gain defined by $\alpha_p = A_i/T_i$.

The die opening is set at 75% at all time in the first iteration. Given the proportional gain α_u of 0.3, BlowOp converges in 12 iterations. The objective and the die openings of the optimum obtained by BlowOp are stated in Table 2.

Table 2 BlowOp's Optimum

	$P(t_0)$	$P(t_1)$	$P(t_2)$	$P(t_3)$	$P(t_4)$	$P(t_5)$	$P(t_6)$	*Objective*
BlowOp	0.0	83.1	81.4	84.3	80.3	0.0	0.0	0.38

3.3. Design optimization using Fuzzy Neural-Taguchi

3.3.1. Establishment of neural network

The L18 orthogonal experiments are used as training samples for the Back Propagation Network of the extrusion blow molding. The initial design and Taguchi's optimum design are used as testing samples for the trained network. This study applies the Multilayer Function Link Network to enhance learning capability. Logarithm and exponential neurons are added to the input and output layers of BPN to improve the network's sensitivity to small and large values. There are 18 neurons in the first hidden layer and 13 neurons in the second hidden layer. The initial learning rate is set at 0.95 and the initial momentum term is set at 0.5. The RMS error reduces to 0.055 after 10000 epochs.

3.3.2. Fuzzy rules for engineering heuristics

The fuzzy rules for prediction accuracy can only reduce the prediction reliability of those designs far away from the sampling data, but do not provide positive suggestions for the directions of better designs. For this example case of blow molding, the engineering heuristics such as those used in BlowOp can be applied to adjust the penalty functions to improve the searching efficiency of GA.

If the average thickness of the section around a certain programming point is larger than the target thickness, the die opening of the programming should be reduced. Similarly, if the average thickness of the section around a certain programming point is smaller than the target thickness, the die opening of the programming should be increased. These engineering heuristics will provide the reliability for a given design generated from GA.

Five levels are defined to describe the condition variables: PB(Positive Big), PS(Positive Small), ZE(Zero), NS(Negative Small), and NB(Negative Big). Five levels are defined to describe the predictive actions of die opening: BI(Big Increase), SI(Small Increase), ZE(No adjustment), SD(Small Decrease), and BD(Big Decrease). Five levels are defined to describe the design reliability: Excellent, Good, Fair, Poor, and Bad. For instance,

If the average thickness is Positive Bigger than the target thickness ***and*** the die opening has a Big Increase
Then the reliability of this design is Bad.

The Complete fuzzy rules are illustrated in Table 3.

Table 3 Fuzzy rules between the current part thickness and the die opening of next iteration

Thickness / Opening	PB	PS	ZE	NS	NB
BI	Bad	Bad	Bad	Fair	Excellent
SI	Poor	Poor	Fair	Excellent	Good
ZE	Fair	Fair	Excellent	Fair	Fair
SD	Good	Excellent	Fair	Poor	Poor
BD	Excellent	Fair	Bad	Bad	Bad

3.3.3. Optimum search using GA

The fitness function is defined as the negation of the average loss of eq. (5). The trained network will then be used as the function generator for each chromosome combination. The crossover rate is 0.75, the mutation rate is 0.03, and the population size is 40 in this study.

The fuzzy rules for prediction accuracy and engineering heuristics are applied to GA to improve the searching efficiency. The optimum search using GA converges in 300 generations. The optimum chromosome is presented in Table 4.

Table 4 FUNTGA's optimum

	$P(t_0)$	$P(t_1)$	$P(t_2)$	$P(t_3)$	$P(t_4)$	$P(t_5)$	$P(t_6)$	Objective
FUNTGA's Optimum	0	74	67.6	70.1	74.2	0	0	0.36

3.4. Comparison of results

Figure 10 compares the profiles of optimal die openings of parison programming and Table 5 compares the thickness distributions of the optimum obtained from BlowOp, Taguchi's method, and the Fuzzy Neural-Taguchi strategy. Taguchi's optimum provides a design with the mean thickness to target but a larger thickness deviation. BlowOp is quite effective and converges in 12 iterations. BlowOp's result has a much smaller objective function value than Taguchi's optimum. However, FUNTGA outperforms BlowOp at the cost of more simulations. Although the proposed strategy spend consumes total 21 design simulations to locate the optimum, the FUNTGA's optimum exhibits a mean thickness closer to the target and a smaller deviation than the BlowOp's optimum. In fact, BlowOp's result will not show any improvement even after the same number of iterations. Figure 11 presents the variations of thickness distributions using BlowSim that appears that FUNTGA's optimum has a more uniform thickness distribution.

4. Conclusions

This study presents how to apply soft computing technology to determine the optimum die openings of parison programming of extrusion blow molding. Taguchi's method is cost effective to obtain an improved design in a few experiments. However, possible interactions among parameters and system nonlinearity could complicate parameter design. Instead of using ANOM of Taguchi's experimental design, a back propagation network is established using Taguchi's experimental data. Engineering knowledge is applied to GA using fuzzy rules to search for the optimum. The proposed strategy works well with the bottle example. The comparison of results demonstrates the effectiveness of the proposed strategy. Another advantage over BlowSim's optimization module, BlowOp, is its flexibility to include other design variables such as materials, temperature control, and mold geometry.

5. Acknowledge

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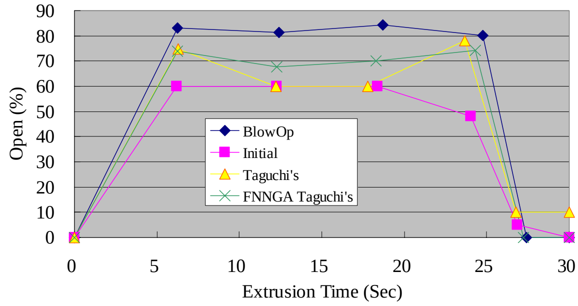

Fig. 10 Optimum designs using various methods

Table 5 Comparison of the analysis results

	Squared Root Avg. Loss	Mean Thickness	Std.Dev. Thickness
Initial	0.52	1.66	0.40
Taguchi's	0.49	2.01	0.49
BlowOp's	0.38	1.93	0.38
FUNTGA's	0.36	1.94	0.35

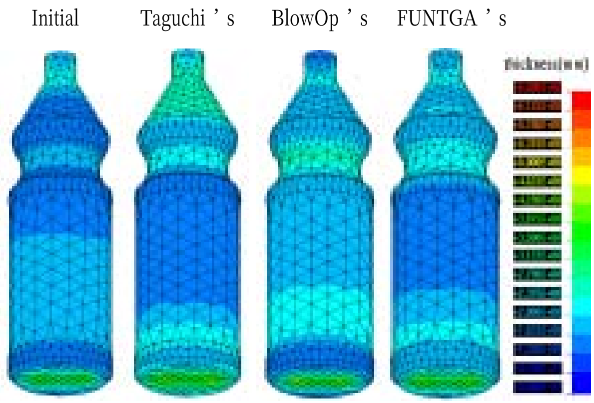

Fig. 11 Comparison of thickness distribution

6. Reference

[1]. D. Rosato and D. Rosato, "Blow Molding Handbook", Hanser Publisher, Munich, 1989.

[2]. R. W. Diraddo and A. Garcia-Rejon, "On-Line Prediction of Final Part Dimensions in Blow Molding: A Neural Network Computing Approach", Polymer Engineering and Science, MID-JUNE, v33, n11 (1993) 653-664,.

[3]. R. W. Diraddo and A. Garcia-Rejon, "Profile

Optimization for The Prediction of Initial Parison Dimensions From Final Blow Moulded Part Specifications”, Computers chem. Engng, v17 n8 (1993) 751-764.

[4]. D. K. Lee and S. K. Soh, "Prediction of Optimal Preform Thickness Distribution in Blow Molding", Polymer engineering and science, v36 n11 (1996).

[5]. G. Taguchi, “Performance Analysis Design.” Int. Journal of Production Research, 16 (1978) 521-530.

[6]. J. S. Jang, C. T. Sun and E. Mizutani, “Neuro-Fuzzy and Soft Computing: a computational approach to learning and machine intelligence”, Prentice-Hall, (1997).

[7]. C. T. Su, C. C. Chiu and H. H. C, “Parameter Design Optimization via Neural Network And Genetic Algorithm”, Int. Journal Of Industrial Engineering, 7(3) (2000) 224-231

[8]. BlowSim, 6.0, Industrial Materials Institute, National Research Council Canada 1999.

[9]. G. J. Wang, J. C. Tsai, P. C. Tseng and T. C. Chen, “Neural-Taguchi Method for Robust Design Analysis”, Journal of the Chinese Society of Mech. Eng., v19 n2 (1998) 223-230