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Optimization of extrusion blow molding processes using soft computing and Taguchi's method

JYH-CHENG YU

Department of Mechanical and Automation Engineering, National Kaohsiung First University of Science and Technology, 2, Juoyue Rd., Nantz District, Kaohsiung 811, Taiwan, R.O.C.
E-mail:jcyu@ccms.nkfust.edu.tw

XIANG-XIAN CHEN and TSUNGG-REN HUNG

Department of Mechanical Engineering, National Taiwan University of Science and Technology No. 43, Keelung Rd., Sec. 4, Taipei 106, Taiwan, R.O.C.

FRANCIS THIBAULT

Industrial Materials Institute, Boucherville, Quebec, Canada

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The objective of this study is to present a new numerical strategy using soft computing techniques to determine the optimal die gap programming of extrusion blow molding processes. In this study, the design objective is to target a uniform part thickness after parison inflation by manipulating the parison die gap openings over time. To model the whole process, that is the parison extrusion, the mould clamping and the parison inflation, commercial finite element software (BlowSim) from the National Research Council of Canada (NRC) is used. However, the use of such software is time-consuming and one important issue in a design environment is to minimize the number of simulations to get the optimal operating conditions. To do so, we proposed a new strategy called FUNTGA (FUzzy Neural-Taguchi network with Genetic Algorithm) that establishes a back propagation network using a Taguchi's experimental array to predict the relationship between design variables and responses. Genetic algorithm is then applied to search for the optimum design of die gap parison programming. As the number of training samples is greatly reduced due to the use of orthogonal arrays, the prediction accuracy of the neural network model is closely related to the distance between sampling points and the evolved designs. The Extrapolation Distance concept is proposed and introduced to genetic algorithm using fuzzy rules to modify the fitness function and thus improving search efficiency. The comparison of the results with commercial optimization software from NRC demonstrates the effectiveness of the proposed approach.

Keywords: Blow Molding, Multidisciplinary Design Optimization, Neural Network, Genetic Algorithm, Fuzzy, Soft Computing

1. Introduction

Extrusion blow molding is a very efficient low cost manufacturing process for complex hollow parts [1]. This process can be divided into several steps. First, the parison extrusion produces a molten thermoplastic tube coming out from the die. By moving a mandrel

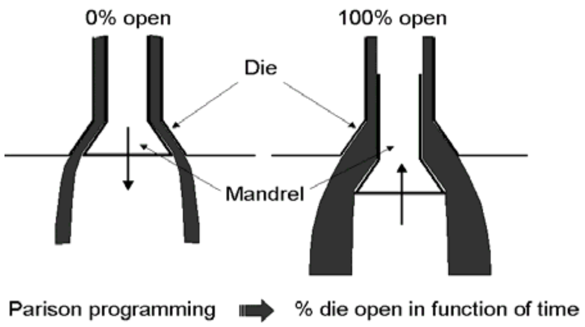

Fig. 1 The parison thickness control using the die gap programming (VWDS).

in and out from the die (Fig. 1), this allows to control the parison thickness over time. Once extrusion is finished, the parison is clamped and high-pressure air is blown into it to get the final part. Obviously, the inflated part thickness is strongly influenced by the parison thickness. Excessive resin usage results in material waste and increases cycle time, while an inadequate part thickness distribution can affect seriously the quality of the mechanical performance in service.

From an industrial point of view, the parison thickness is regulated using a Vertical Wall Distribution System (VWDS) that is the control of die gap openings variation. As illustrated for the bottle case (Fig.2), seven discrete die gap openings designated as design variables are used to control the parison thickness over time ($P(t_0)$, $P(t_1)$, $P(t_2)$, $P(t_3)$, $P(t_4)$, $P(t_5)$, and $P(t_6)$). The main objective of this study is to manipulate those design variables in order to target a uniform inflated part thickness distribution. To reach this goal, process engineers often use trial-and-error experimental tests based on the next heuristic rule, that is, a larger blow up ratio requires a greater parison thickness.

Different strategies have been used to model the whole process that is the parison extrusion, clamping, inflation and cooling. Lee et al. [2] 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. Diraddo et al. [3] established a neural network to predict the distribution of parison thickness and applied Newton-Raphson method to obtain the final blow molded part specifications [4]. However, the investigation of the relationship between design variables and the wall thickness distribution of blown parts requires expensive experiments and time-consuming simulations. To reduce the number of experiments and simulations, an efficient numerical strategy of data analysis is essential.

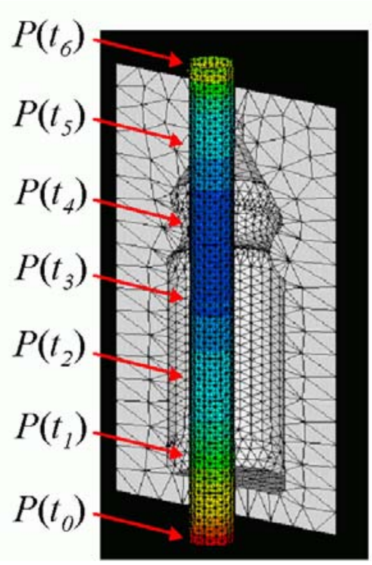

Fig. 2 Programming points of parison extrusion.

This study applies the optimization strategy based on Taguchi's experimental designs [5] and soft computing techniques [6] to manipulate the die gap openings over time in order to obtain a uniform part thickness distribution. The proposed strategy establishes a local neural network based on the orthogonal array experiments and assumes a fuzzy inference for the genetic search algorithm to find the optimal operating condition.

2. Optimization Strategy

The proposed optimization strategy, FUzzy Neural-Taguchi with Genetic Algorithm (FUNTGA), uses Taguchi's experimental designs for the training of a neural network model. The trained network becomes the function generator of the design fitness in the Genetic Algorithm (GA). The optimum search using GA enhances the possibility for a better design than the conventional ANalysis Of Means (ANOM). A fuzzy inference of the engineering knowledge is introduced to enhance the GA searching efficiency. The optimization flowchart strategy is illustrated in Fig. 3.

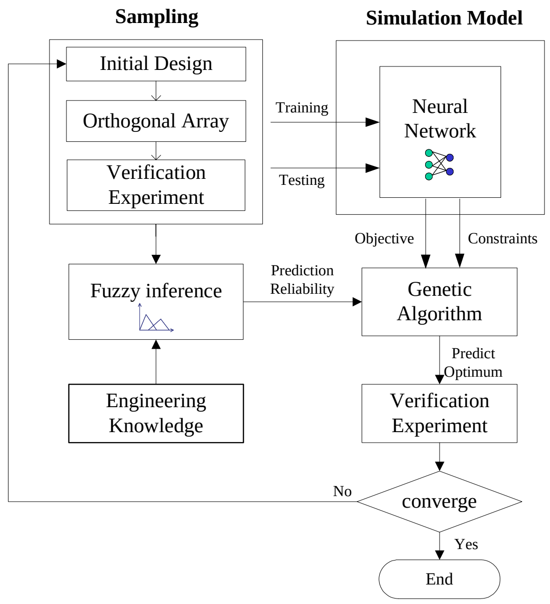

Fig. 3 The optimization flowchart of FUNTGA method.

2.1. Taguchi's Method

Taguchi's method has proven its efficiency and simplicity in parameter design. Based from statistical factorial experiments, Taguchi's method features orthogonal arrays and analysis of mean to analyze the effects of design variables. Each variable is assumed to have a finite number of levels (set points), such as two or three levels, within the investigating range. The orthogonal array is a type of fractional factorial experiments. The application of orthogonal arrays reduces the number of experiments, which is particularly effective for design optimization involving expensive experiments or time-consuming simulations. For instance, instead of 27 experiments for three-level full factorial experiments, the L9 orthogonal array selects only nine treatments as shown in Fig. 4. An ANOM study of experimental results reveals the design variable sensitivities that are used to determine the optimal level of each parameter. Although Taguchi's method does not guarantee a global optimum, it allows converging to a quasi-optimum that is good enough for engineering practices.

Taguchi's approach uses ANOM of fractional factorial experiments to predict the optimal design of the full factorial experiments. However, the prediction of the optimum is sensitive to the selection of factorial levels and interaction effects. Also, the restriction of parameter values to factorial levels eliminates the possibility of having 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 non-linear 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 and testing samples. Learning samples are used to determine the weighting matrices, W_{ij} and W_{jo}, among neurons, while testing samples are utilized to determine the accuracy and the generality of the network.

Training samples are essential to the prediction quality of network models. This study employs Taguchi's experimental designs to select training samples to reduce the number of experiments and to maintain a good sample representation [7]. The steepest gradient method is assumed to train the weighting matrices. The verification experiment of the optimal design from the ANOM study will serve as

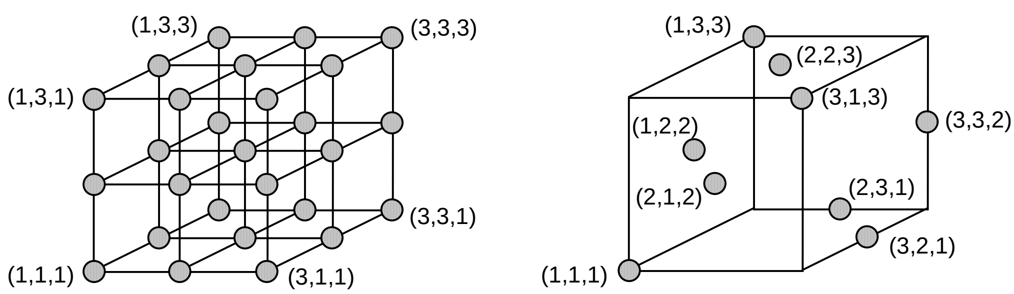

Fig. 4 Full factorial and fractional factorial experiments for three variables.

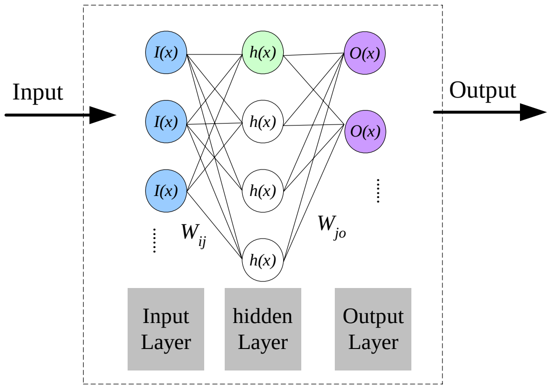

Fig. 5 Back-Propagation network.

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 parameter combinations in the investigating range. Genetic Algorithm is then applied to search for the optimal design variables. Because better prediction accuracy will exist around sampling points, our approach introduces a fuzzy inference to guide the search domain of GA to avoid the modeling error due to lack of samples. If the verification result of the predicted optimum is not satisfactory, the design will be served as additional training data for the network. The iteration process stops when the predicted optimum obtained from GA and the network converges.

2.3.1. Normalization of design parameters

To facilitate the distance calculation into the design space, the set point values of continuous variables x_k are normalized using the following scheme:

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

where $\min(x_k)$ and $\max(x_k)$ represent the minimum and the maximum values of the variable x_k in the learning samples. Therefore the normalized factorial values of an equally spaced three-level continuous variable, x_k, will become $(z_{k1}, z_{k2}, z_{k3}) = (-1, 0, 1)$. For discrete variables, the factorial values are equally assigned between -1 and +1.

2.3.2. The Extrapolation Distance

The Factorial Distance r_{ij} between the predictive designs, D_i, and the sample data S_j are defined as the mean Euclidean distance:

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

where n represents the number of variables.

Since the predictions around the learning samples of the trained network will have higher accuracy, this study defines the Extrapolation Distance (*ED*) of a predictive design as the minimum Factorial Distance between the prediction and the learning samples.

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

Also, the distance of an extrapolating design is assumed positive and the distance of an interpolating design is assumed negative. A design is termed extrapolating if any variable, x_k, of the design is outside the $\min(x_k)$ and $\max(x_k)$ range of the network learning samples. Otherwise, the design is termed interpolating. For instance, the Extrapolation Distance of D_1 in Fig. 6 is negative and the Extrapolation Distance of D_2 is positive. Later on *ED* will serve as a rough index of the network prediction accuracy.

2.3.3. The fuzzy rules of prediction accuracy

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 the network training samples as compared with conventional random sampling. Based on the heuristics of neural networks, the accuracy of the predicted design decreases if the design is away from the learning samples. Also, the prediction reliability of extrapolating designs is often much worse than the interpolating designs. This study applies the Extrapolation Distance (*ED*) concept and proposes the following fuzzy rules for the Prediction Reliability (*PR*) of the network.

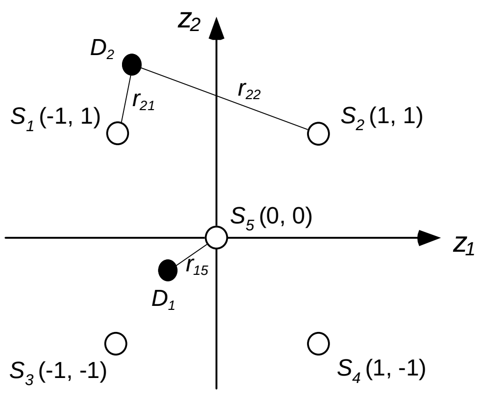

Fig. 6 The factorial distances of predicted designs.

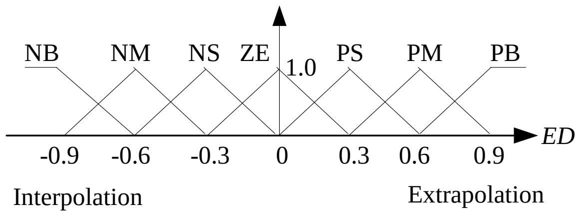

Fig. 7 The membership functions of the conditioned variables.

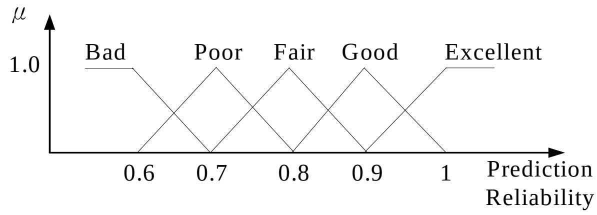

Fig. 8 The membership functions of the assessment variables.

R1: If the Extrapolating Distance (*ED*) is *PB* then the Prediction Reliability (*PR*) is Bad
R2: If *ED* is *PM* then *PR* is Poor
R3: If *ED* is *PS* then *PR* is Fair
R4: If *ED* is *ZE* then *PR* is Excellent
R5: If *ED* is *NS* then *PR* is Excellent
R6: If *ED* is *NM* then *PR* is Good
R7: If *ED* is *NB* then *PR* is Fair

Seven levels are defined to describe the conditioned variables: *PB* (Positive Big), *PM* (Positive Medium), *PS* (Positive Small), *ZE* (Zero), *NS* (Negative Small), *NM* (Negative Medium), and *NB* (Negative Big). Because of the normalization of design parameters, the *ED* of interpolating designs will be between 0 and –2. Five levels are defined to describe the assessment results of *PR*: Excellent, Good, Fair, Poor, and Bad. *PR* is assumed as a number between 0 and 1. Standard membership functions are shown in Fig. 7 and Fig. 8. The definition of the membership function will be case-dependent and empirical. The rule-of-thumb is that if the study case is highly nonlinear, the Prediction Reliability should be further reduced for designs with large *ED.* Otherwise, the Prediction Reliability could be increased to search a larger area. The fuzzy Prediction Reliability then modifies the fitness function of GA estimated by the Neural-Taguchi network. The modification restrains the GA search from the domains away from the learning samples where large prediction errors often occur.

3. Optimization of blow molding parameters

In this research, the design objective was to target a uniform part thickness of 2 *mm* after parison inflation for an HDPE bottle case. To predict the part thickness distribution, we used a finite element analysis software (BlowSim) [8] developed by the National Research Council of Canada (NRC). This software can be used to model the extrusion blow molding, the stretch-blow molding and thermoforming processes [9][10]. Since this software used a gradient-based technique to target a uniform part thickness, which will allow us to compare this optimization technique to the one proposed in this paper.

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 design variables: $P^i(t_0)$, $P^i(t_1)$, $P^i(t_2)$, $P^i(t_3)$, $P^i(t_4)$, $P^i(t_5)$, and $P^i(t_6)$. The optimization algorithm will then manipulate these variables to obtain a uniform inflated part thickness.

Since large errors are expected when extrapolating with the neural network method, the selection of the factorial experiments will likely cover the optimum design and by the fact increase the prediction accuracy. The targeted parison thickness mainly depends on the blow up ratio although the parison might inflate in

Table 1. L18 orthogonal array experiments.

$L_{18}(2^1 3^7)$	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	0.48
2	0	60	75	75	63	5	5	0.38
3	0	75	90	90	78	10	10	0.40
4	5	45	60	75	63	10	10	0.86
5	5	60	75	90	78	0	0	0.86
6	5	75	90	60	48	5	5	0.52
7	10	45	75	60	78	5	10	0.67
8	10	60	90	75	48	10	0	0.62
9	10	75	60	90	63	0	5	0.48
10	0	45	90	90	63	5	0	1.30
11	0	60	60	60	78	10	5	0.28
12	0	75	75	75	48	0	10	0.38
13	5	45	75	90	48	10	5	1.14
14	5	60	90	60	63	0	10	0.45
15	5	75	60	75	78	5	0	0.24
16	10	45	90	75	78	0	5	1.02
17	10	60	60	90	48	5	10	0.67
18	10	75	75	60	63	10	0	0.30
Initial	0	60	60	60	48	5	0	0.27
Taguchi's Optimum	0	75	60	60	78	10	10	0.24

radial and axial directions. The blow up ratio is defined as the ratio between the parison thickness at the end of extrusion over the inflated part thickness. We assume that the parison thickness is determined by the die gap opening despite the complexity of parison extrusion. The cross section area of the parison and the final part will be then approximately equal, which provides the initial design of die gap openings over time. The next relationship is used to link the parison thickness and the inflated part thickness as the following:

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

where d_p is outside diameter of parison (mm), t_p is parison thickness(mm), d_f is final part diameter(mm), and t_f is final part thickness(mm)

The L18 orthogonal array is selected as the experimental design (see Table 1). For each opening, we assume a three-level variation around the initial design located in the middle of the design space. The design variable ranges are assumed to be 30% for the middle and 10% for both ends of the programming points. The main idea is to cover the optimum design in the range to increase the prediction accuracy.

3.1.2. *The Objective Function*

The objective function is defined as the average quality loss due to its thickness deviation from the targeted value

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

where t_i corresponds to the i-th nodal thickness, T the targeted thickness, and n the number of nodes into the simulation model.

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

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

where $\bar{t}$ is the mean thickness and s^2 is the sampling variance. The optimization strategy seeks to minimize the thickness variation and the difference between the target and the mean thickness. The objective function values obtained for all L18 orthogonal experiments and the initial design are shown in Table 1.

3.1.3. Design Variable Sensitivities

Taguchi's method uses the analysis of means [5] to estimate design variable sensitivities. Fig. 9 represents the sensitivity for each die gap opening. For example, for the die gap opening $P(t_1)$ (design variable B), one can notice that an increase of die gap opening will decrease the design objective function and then improve the design. Based on the additive model of ANOM, the optimum design variable combination is $A_1B_3C_1D_1E_3F_3G_3$. This optimum is called the Taguchi's optimum. As stated in Table 1, Taguchi's method does provide a better design than the initial design and all other L18 experiments. However, the improvement is not significant due to possible interactions among design variables and strong system non-linearity.

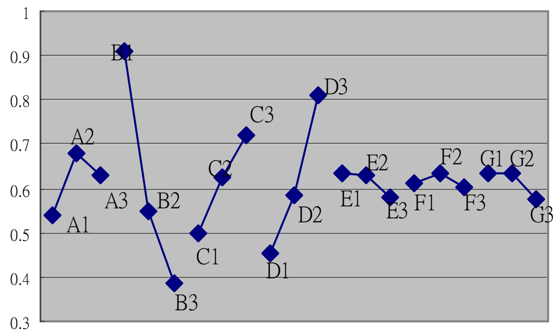

Fig. 9 Design variable sensitivities.

3.2. Design Optimization using BlowOp

BlowOp is a gradient-based optimization module developed by NRC to control the die gap openings over time (parison programming points) to target a uniform inflated part thickness. From a practical point of view, BlowOp uses the following heuristics rules:

(1). If the thickness of a programming point is larger than the targeted thickness, then increase the corresponding die gap opening.

(2). If the thickness of a programming point is smaller than the targeted thickness, then reduce corresponding die gap opening.

Once BlowSim has completed the simulations of the parison extrusion and the inflation, the blow up ratio is known for all parison nodes. Then, BlowOp updates the nodal parison thickness by using the following relationship,

$$A_i^{t+1} = A_i^t - \alpha_u \, BR_i^t \left(T_i^t - T\right) \tag{7}$$

where A_i^t and A_i^{t+1} are the nodal parison thickness at iterations t and $t+1$, T_i^t is the part thickness at iteration t, BR_i^t is the blow up ratio at iteration t defined by A_i^t / T_i^t, and T is the targeted part thickness. For its part, α_u represents the user-defined proportional gain. Once the nodal parison thickness has been updated, BlowOp evaluates the average part thickness ($\overline{T}$) at iteration t and $t+1$ associated with each programming point which allows to update the gap opening using the next expression

$$\Theta_j^{t+1} = \Theta_j^t + \frac{100}{\overline{G}_{\max} - \overline{G}_{\min}} \left(\overline{T}_j^{t+1} - \overline{T}_j^t\right) \tag{8}$$

where Θ_j^t and Θ_j^{t+1} are the gap openings of programming point j at iterations t and $t+1$ and $\overline{G}_{\min}$ and $\overline{G}_{\max}$ represent the minimum and the maximum average die gap openings.

For the HDPE bottle case studied, the initial die gap openings are set to 75% during the extrusion period for the first iteration. Assuming that the proportional gain α_u is equal to 0.3, BlowOp used 12 iterations to get convergence. The optimum die gap openings as well as the objective function value obtained by BlowOp are shown in Table 2.

Table 2. The optimization result obtained by BlowOp method.

	$P(t_0)$	$P(t_1)$	$P(t_2)$	$P(t_3)$	$P(t_4)$	$P(t_5)$	$P(t_6)$	*Objective*
BlowOp' Optimum	0.0	83.1	81.4	84.3	80.3	0.0	0.0	0.15

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

Opening	*Thickness*				
	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

Table 4. The optimization result obtained by FUNTGA approach.

	$P(t_0)$	$P(t_1)$	$P(t_2)$	$P(t_3)$	$P(t_4)$	$P(t_5)$	$P(t_6)$	*Objective*
FUNTGA's Optimum	0	74	67.6	70.1	74.2	0	0	0.13

3.3. Design optimization using FUNTGA

3.3.1. Establishment of neural network

The L18 orthogonal experiments were used as training samples for the back propagation network (BPN). The initial design and Taguchi's optimum design have also been used as for testing samples for the trained network. The BPN uses a multi-layer function link network to enhance learning capability. Logarithm and exponential neurons were added to the input and output layers to improve the network's sensitivity to small and large values. In more details, we used 18 neurons in the first hidden layer and 13 neurons in the second one. The initial learning rate was set to 0.95 and the initial momentum term set to 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 the HDPE bottle case studies, the engineering heuristics, as mentioned previously, used by BlowOp can be readily applied to adjust the penalty function to further improve the searching efficiency of GA.

If the average thickness of the parison section around a certain programming point is larger than the targeted thickness, the die gap opening of the related programming should be decreased. Similarly, if the average thickness of the parison section around a certain programming point is smaller than the targeted thickness, the die gap opening of the related programming should be increased. These engineering heuristics were used to adjust the reliability for a given design generated by the GA.

Five levels were defined to mimic and describe the condition variables: *PB* (Positive Big), *PS* (Positive Small), *ZE* (Zero), *NS* (Negative Small), and *NB* (Negative Big). We also used five levels to describe the predictive actions of each die gap opening: *BI* (Big Increase), *SI* (Small Increase), *ZE* (No adjustment), *SD* (Small Decrease), and *BD* (Big Decrease). Finally, the design reliability has been described by five levels as well: Excellent, Good, Fair, Poor, and Bad. For instance,

If the average thickness is Positive Bigger than the targeted thickness ***and*** the die gap opening has a Big Increase
Then the Prediction Reliability of this design is Bad.

The complete set of fuzzy rules is illustrated in Table 3.

3.3.3. Optimum search using GA

The trained network will then be used as the function generator for each chromosome combination. The fitness function used by GA in this case is the negation of the average loss modified by the Prediction Reliability as shown in Equ. (9). The fuzzy rules for the prediction accuracy and engineering heuristics are applied to GA to improve the searching efficiency. The crossover rate was set to 0.75, the mutation rate to 0.03, and the population size was 40 for the case studied. The optimum search using GA converged after 300 population generations. The optimum chromosome is illustrated in Table 4.

$$Fitness_{GA} = -\frac{Avg\_loss}{PR} \tag{9}$$

3.4. Comparison of results

Figure 10 compares the optimal die gap opening profiles obtained by different numerical strategies (BlowOp, Taguchi's method, and FUNTGA), and Table 5 compares the prediction quality in term of thickness distribution for each method. One can note that the Taguchi's optimum provides a design with the mean thickness very close to the targeted thickness but with a larger thickness deviation. For its part, 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 consumes a total of 21 design simulations to find the optimum, FUNTGA's optimum exhibits a mean thickness closer to the target and a smaller deviation than the BlowOp's optimum. BlowOp's result will not show further improvement even after the same number of iterations. Figure 11 illustrates the thickness variations along the part. It appears that FUNTGA's optimum has a more uniform thickness distribution as previously mentioned.

Table 5. The comparison of the analysis results.

	Mean Thickness	*Std.Dev. Thickness*	*Avg. Loss*
Initial	1.66	0.40	0.27
Taguchi's	2.01	0.49	0.24
BlowOp's	1.93	0.38	0.15
FUNTGA's	1.94	0.35	0.13

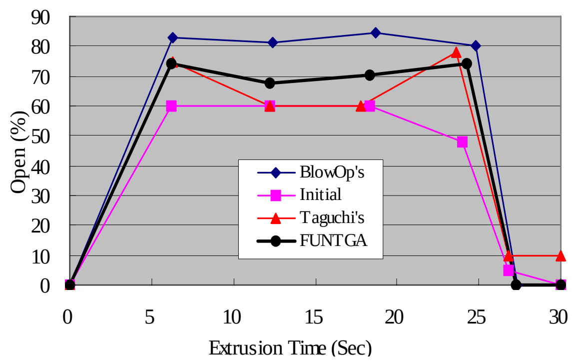

Fig. 10 The optimum designs using various methods.

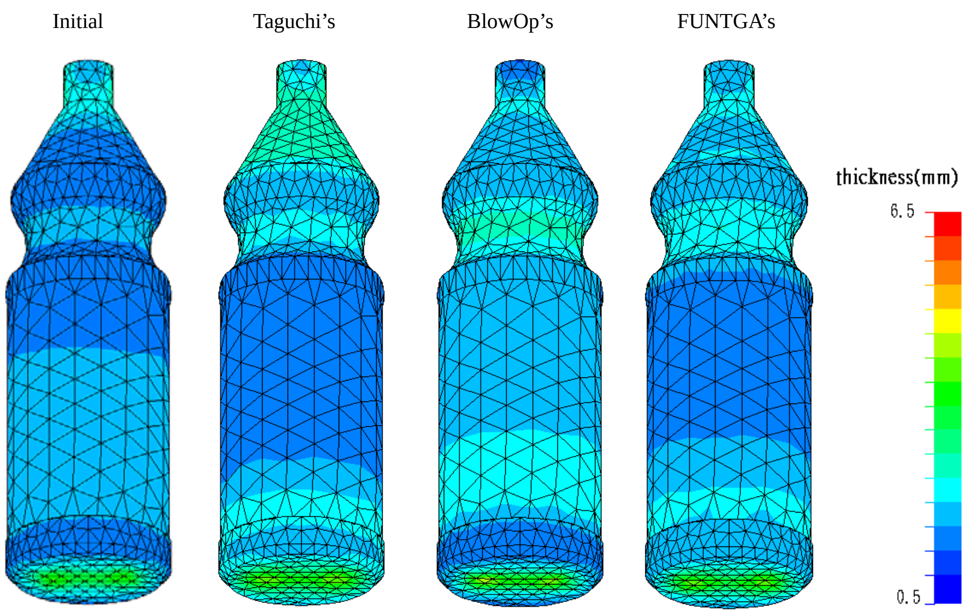

Fig. 11 The comparison of thickness distribution.

4. Conclusions

This study presents the application of soft computing technology to determine the optimum die gap programming of the extrusion blow molding process. A simple case study reveals that the Taguchi's method is cost effective to obtain an improved design in a few experiments. However, possible interactions among parameters and system non-linearity 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 comparison of results demonstrates the effectiveness of the proposed strategy. Extra iterations using FUNTGA's approach are possible if further improvement is desired. The previously derived optimum can be assumed as an initial design, and another orthogonal array of experiments can be conducted. The new experimental data will then be added to the training samples of the neural model to further improve the accuracy. Another advantage of FUNTGA over BlowOp optimization module is its flexibility to include other design variables such as materials, temperature control, and mold geometry in the future study.

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