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PERFORMANCE OPTIMIZATION OF EXTRUSION BLOW MOLDED PARTS USING FUZZY NEURAL-TAGUCHI METHOD AND GENETIC ALGORITHM

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ABSTRACT

This paper presents a soft computing strategy to determine the optimal die gap parison programming of extrusion blow molding process. The design objective is to minimize part weight subject to stress constraints. The finite-element software, BlowSim, is used to simulate the parison extrusion and the blow molding processes. However, the simulations are time consuming, and minimizing the number of simulation becomes an important issue. The proposed strategy, Fuzzy Neural-Taguchi and Genetic Algorithm (FUNTGA), first establishes a back propagation network using Taguchi's experimental array to predict the relationship between design variables and response. Genetic algorithm is then applied to search for the optimum design of 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 Reliability Distance is proposed and introduced to genetic algorithm using fuzzy rules to modify the fitness function and thus improve search efficiency. This study uses ANSYS to find the stress distribution of blown parts under loads. 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 process can be divided into several parts. First, the parison extrusion produces a molten thermoplastic tube coming out from the die. Once extrusion is finished, the parison is clamped and high-pressure air is blown into it to get the final part. To control the parison thickness over time, there is a mandrel that can move in and out to the die (Fig. 1). Obviously, the parison thickness controls the thickness of the inflated part. To satisfy the part mechanical performance, an adequate part thickness profile has to be determined. The aim is then to find the optimal die gap programming that will minimize the part weight and satisfy the part mechanical performance as well.

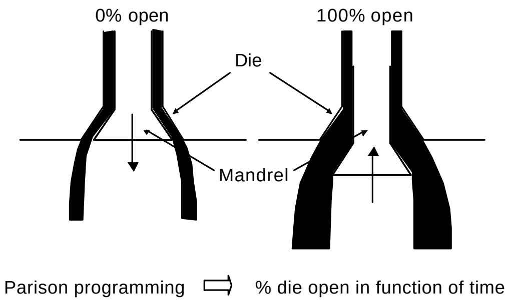

Fig. 1 The control of the parison thickness using the parison programming.

The programming points are specified by the extrusion time and the die gap opening of the 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 $P(t_6)$. These design variables will be manipulated to satisfy the mechanical part performance under service. For this case, the bottle part will be subjected to two different types of loading, that is a top load displacement and an internal pressurization to ensure the mechanical performance. The design objective is then to obtain a wall thickness distribution of minimal weight by manipulating the die gap programming subject to a Von Mises stress distribution that does not exceed the allowable level.

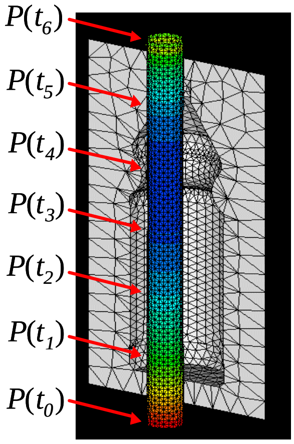

Fig. 2 Programming points of parison extrusion.

Extrusion blow molding involves complex processes such as parison extrusion, clamping, blow up, and cooling. 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. 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]**. 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 strategy of data analysis is essential.

In this study, we apply an optimization strategy based on Taguchi's method **[5]** and soft computing techniques **[6]** to the optimization of parison programming to obtain the thickness distribution of minimum weight. The finite element software, BlowSim, is used to simulate the parison extrusion and the blow molding processes. From a part thickness distribution obtained from BlowSim, ANSYS software is used to make the structural analysis for the two types of loading specified. The proposed strategy establishes a local neural network based on Taguchi's orthogonal array experiments and assumes the fuzzy inference to genetic algorithm to search for the optimal operating conditions.

2. OPTIMIZATION STRATEGY

Taguchi's method has proven its efficiency and simplicity in parameter design. The proposed optimization strategy, FUzzy Neural-Taguchi with Genetic Algorithm (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 optimum search 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.

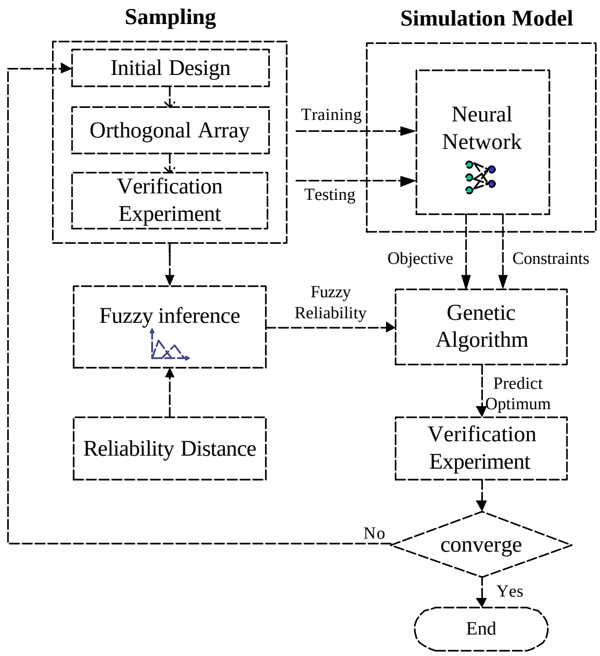

Fig. 3 The Optimization flowchart of FUNTGA.

2.1. Taguchi's Method

Inspired from 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 type 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 experiment results reveals the effects of design parameters that are used to determine the optimal level of each parameter. Knowing that Taguchi's result is not a global optimum, however iterations of Taguchi's method can provide a solution near to the optimum design.

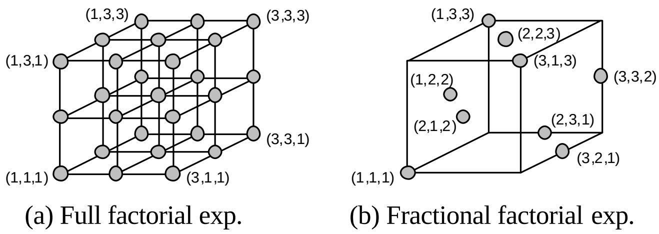

Fig. 4 Full factorial and fractional factorial experiments for three variables

Taguchi's approach utilizes ANOM of fractional factorial experiments to predict the optimal design of the full factorial experiments. However, the prediction of the optimal design is sensitive to the selection of factorial levels and interaction effects. Also, the restriction of parameter values to factorial levels reduces 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 set up 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 and testing samples. Learning samples are used to determine the weighting matrices, W_{ij} and W_{jo}, among neurons and testing samples to determine the accuracy and the generality of the network.

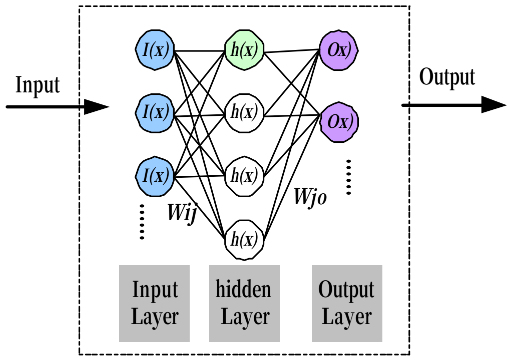

Fig. 5 Back-Propagation network.

Training samples are essential to the 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 a good sample representation **[7] [9]**. 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 a testing sample. The trained network can accurately predict 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

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

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

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

where n represents the number of variables.

Since predictions around the sampling points of the trained network will have higher accuracy, we proposed to use the

Reliability Distance of a predictive design as the minimum factorial distance between the prediction and sampling data.

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

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.

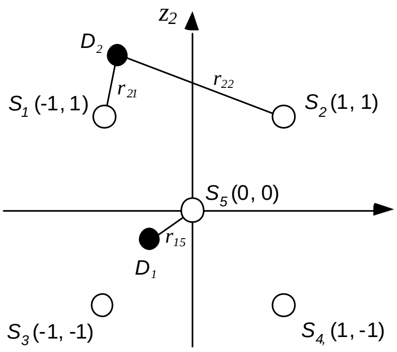

Fig. 6 The factorial distances of predicted designs.

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, we propose to use 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 associated with these statements are illustrated in Fig. 7 and Fig. 8.

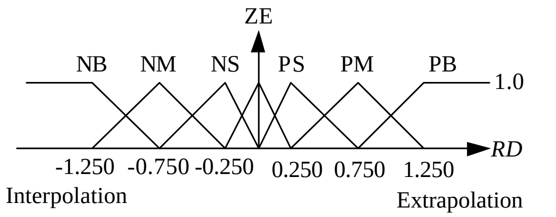

Fig. 7 Membership functions of condition variables.

Fig. 8 Membership functions of assessment variables.

3. OPTIMIZATION OF BLOW MOLDING PARAMETERS

This work uses the proposed optimization strategy to get the optimal parameter design of extrusion blow molding process for the High Density Polyethylene (HDPE) bottle case. Two types of loading will be investigated: an internal pressurization at 110 (psi) and a top displacement of 5 (mm) during 5 seconds as illustrated in Fig. 9. The maximum allowable stress, corresponding to the ultimate tensile strength of the material, is set to 33 MPa. For this material, the Young's modulus is 879 MPa and we assume that the thickness part shrinkage is 3%.

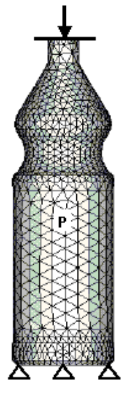

Fig. 9 The mechanical loading of the blown bottle: internal pressurization and top displacement.

3.1. Objective Function

The design objective is to minimize the part weight subject to stress constraints of the bottle under loadings. The reduction of an element thickness results in the increase of its stress level. Consequently, the design objective can be replaced by a minimization of the stress variance around the stress mean close to the stress constraint. The smaller variance of the stress distribution, the closer the mean can be moved to the allowable material strength, that leads to thinner elements, and thus minimal part weight. However, any element stress exceeding the allowable strength might result in part failure. In this work the constrained optimization is replaced by an unconstrained minimization of the variance of stress distribution around the allowable stress level using the external penalty method as illustrated in Fig. 10.

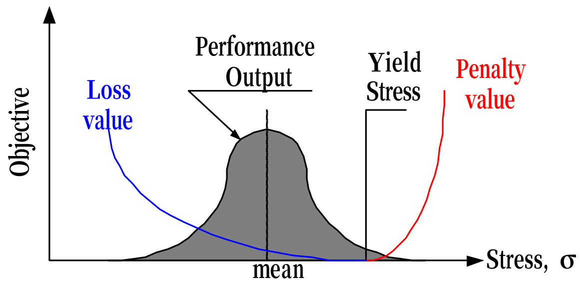

Fig. 10 Illustration of the design objective

The objective function (Eq. [4]) contains two portions: the quality loss due to variation of stress distribution and the penalty loss due to constraint violation

$$MOBJ = \frac{\sum_{i=1}^{n}(t_i - T)^2}{n} + \sum_{i=1}^{n} < t_i - T >^2 \qquad (4)$$

where t_i stands for the stress of node i, T for the allowable strength of material and n represents the total number of nodes of the simulation model.

The quality loss due to variation of stress distribution is estimated by the mean squared deviation of the element stress from the allowable stress level. The average quality loss can be divided into two parts: the deviation of the mean stress from the allowable strength and the variation of the stress around mean.

$$\frac{\sum_{i=1}^{n}(t_i - T)^2}{n} = (\bar{t} - T)^2 + \frac{\sum_{i=1}^{n}(t_i - \bar{t})^2}{n} = (\bar{t} - T)^2 + \frac{(n-1)s^2}{n} \qquad (5)$$

where $\bar{t}$ is the mean stress and s^2 is the sampling variance. Reducing the quality loss leads to a stress distribution of a smaller variance and a mean stress closer to the allowable strength.

The second portion of the modified objective function, the penalty loss, is estimated using a second order singularity function.

$$< t_i - T >^2 = \begin{cases} 0, \text{ if } t_i \le T \\ (t_i - T)^2, \text{ if } t_i > T \end{cases} \qquad (6)$$

This portion accounts for the penalty of elements violating the stress constraint.

The search for the design of minimum objective function will provide a thickness of minimum part weight while satisfying the stress requirement.

3.2. Taguchi's parameter design

3.2.1. 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 gap openings of programming points to obtain a thickness distribution that will satisfy the mechanical performance.

The initial design adopts a uniform die gap opening of 75%. The L18 orthogonal array is selected as the experimental design (Table 1). For each opening, we assume a three levels variation around the initial design located in the middle of the design space. The range between upper and lower levels represents the design space. We assume 40% variation range. The objective function is converted to Taguchi's Signal-to-Noise ratio (*S/N_ratio*) to improve the prediction accuracy using ANOM's superposition model.

$$S/N\_ratio = -10 \times \log(MOBJ) \qquad (7)$$

Table 1. L18 orthogonal array

L_{18}	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 Function*	*S/N ratio*
1	55	55	55	55	55	55	55	456.5	-26.59
2	55	75	75	75	75	75	75	385.2	-25.86
3	55	95	95	95	95	95	95	508.8	-27.07
4	75	55	55	75	75	95	95	14188.3	-41.52
5	75	75	75	95	95	55	55	7164.1	-38.55
6	75	95	95	55	55	75	75	3036.2	-34.82
7	95	55	75	55	95	75	95	2957.2	-34.71
8	95	75	95	75	55	95	55	1388.3	-31.42
9	95	95	55	95	75	55	75	475.7	-26.77
10	55	55	95	95	75	75	55	32182.9	-45.08
11	55	75	55	55	95	95	75	2263.6	-33.55
12	55	95	75	75	55	55	95	930.4	-29.69
13	75	55	75	95	55	95	75	11021.9	-40.42
14	75	75	95	55	75	55	95	653.9	-28.16
15	75	95	55	75	95	75	55	723.8	-28.60
16	95	55	95	75	95	55	75	24137.5	-43.83
17	95	75	55	95	55	75	95	918.0	-29.63
18	95	95	75	55	75	95	55	2343.0	-33.70
Initial	75	75	75	75	75	75	75	368.8	-25.67
AOM	55	95	55	55	55	55	95	555.6	-27.45

3.2.2. Parameter design

Taguchi's method applies the analysis of means (ANOM) to estimate parameter sensitivities. Fig. 11 represents the factor effects for each die opening on the S/N ratio. A design with higher S/N ratio has a smaller value of the objective function. An additive model based on ANOM can be formulated:

$$S/N = m + A_i + B_j + C_k + D_l + E_m + F_{ni} + G_o \qquad (8)$$

The additive model estimates the optimum treatment combination to be $A_1B_3C_1D_1E_1F_1G_3$. The BlowSim simulation result of the optimum in Table 1 presents that Taguchi's method doesn't provide a better result than the initial design. The failure of Taguchi's approach might due to interactions among design variables and strong system non-linearity.

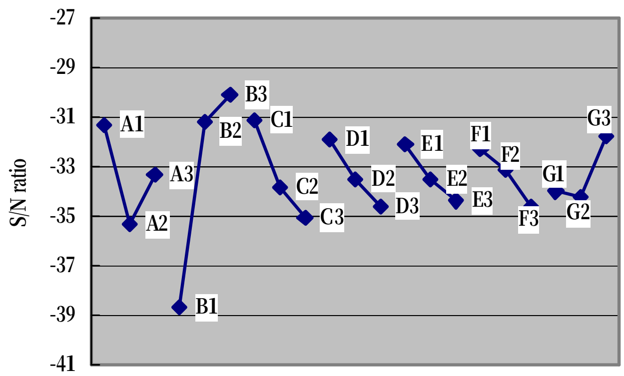

Fig. 11 Factor effects plot of control variables.

3.3. Design optimization using FUNTGA

3.3.1. Establishment of neural network

FUNTGA provides a more efficient and accurate optimum search using the same experimental data of Taguchi's experiments. The L18 orthogonal experiments are used as training samples for the Back Propagation Network (BPN) of the extrusion blow molding process. The initial design and Taguchi's optimum design are used as testing samples for the trained network. There are 14 neurons in the first hidden layer and 6 neurons in the second hidden layer. The initial learning rate is set to 1.4 and the initial momentum term is set to 0.5. The RMS error reduces to 0.055 after 16000 epochs.

3.3.2. Optimum search using GA

The fitness function is defined as the negation of the modified objective function of Eq. (4). The trained network will then be used as the function generator for each chromosome combination. The parameters of Genetic Algorithm used in this study are listed in Table 2. The fuzzy rules for prediction accuracy are applied to GA to improve the searching efficiency. The optimum chromosome is presented in Table 3.

Table 2 Genetic Algorithm parameters

Population size	Pool selection style	Scale style	Cross Over rate	Mutation rate	Max iteration
60	Parent and offspring	Linear scale	0.8	0.01	300

Table 3 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 Function*
FUNTGA's Optimum	50.7	85.6	74.9	83.5	76.0	58.5	70.6	327.2

3.4. Comparison of results

Figure 12 compares the profiles of optimal die gap openings of parison programming and Table 4 compares the stress distributions of the initial design and the optimal one obtained from Taguchi's method and FUNTGA strategy. Taguchi's ANOM approach is disturbed by parameter interactions and system non-linearity. Taguchi's optimum provides a mean stress closer to the allowable strength 33 MPa. However, the large variance of the stress distribution results in stronger violation of stress constraints than the initial design. FUNTGA's optimum exhibits a mean thickness close to the allowable and the smallest deviation in three designs, which leads to a design of smaller weight while satisfying the stress constraints. Figure 13 presents the stress distributions of three designs.

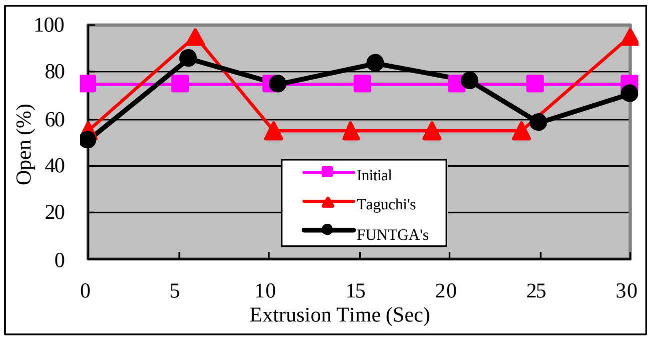

Fig. 12 The optimal designs from various methods.

Table 4 The comparison of various optima.

	Mean Stress	Std.Dev. Stress	Quality Loss	Penalty Loss	Objective Function
Initial	15.9	6.4	335.1	33.7	368. 8
Taguchi's	16.6	7.3	322.4	233.2	555.6
FUNTGA's	16.0	6.1	324.9	2.3	327.2

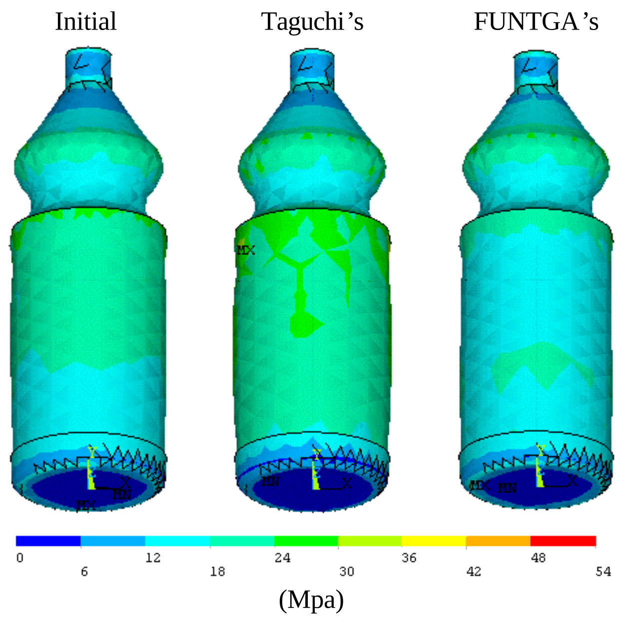

Fig. 13 The comparison of the stress distribution.

4. Conclusions

This study presents how to apply soft computing technology to determine the optimum die gap openings of parison programming of extrusion blow molding process. 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. Heuristic knowledge of prediction accuracy is applied to GA using fuzzy rules to steer the search direction. The proposed strategy works well with the bottle example. 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 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.

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