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Development of a MDO Methodology for Automotive Interior Blow Moulded Parts

Francis Thibault and Patricia Debergue
Industrial Materials Institute (IMI), Boucherville, Canada
Mike Milliste
Lear Corporation, Maple Plant, Concord, Ontario, Canada
Weiming Shen
Integrated Manufacturing Technologies Institute (IMTI), London, Canada
Hamada H. Ghenniwa
University of Western Ontario, London, Ontario, Canada
Yeh-Liang Hsu and Tzu-Chi Liu
Mechanical Engineering Department, Yuan Ze University, Taiwan
Jyh-Cheng Yu and Tsung-Ren Hung
Mechanical Engineering Department, National Taiwan University of Science and Technology (NTUST)

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ABSTRACT

The aim of this paper is to present the optimization algorithms and results obtained in the joint IMI-IMTI-Taiwan project for the development of design optimization methodologies that employ NRC blow moulding process simulation tools. The proposed optimization strategies consist of the manipulation of the die gap programming points and the mould temperature in order to optimize the part thickness distribution and to minimize the part warpage by using gradient-based and soft computing techniques. These strategies have been validated on simple blow moulded bottle part and on a complex planar shaped carpet part (filler panel) made by Lear Corporation. Finally, a strategy is proposed to integrate simulation technologies as well as optimization tools developed in this project on a Web-based design software environment (WebBlow).

Key words: blow moulding, automotive, optimization, gradient-based, fuzzy logic, neural networks, Taguchi's design experiments, Web-based software environment.

1. INTRODUCTION

Blow moulding is the most popular and efficient process for manufacturing commodity hollow plastic parts such as bottles, containers, toys, etc. More recently, this forming process has been applied to the manufacture of complex automotive parts such as fuel tanks, seat backs, air ducts, windshield washer and cooling reservoirs. One such value-added part is a planar part used in sport utility vehicles with carpet adhered of one of the sides (**Figure 1**). The quality of these complex hollow parts is governed by several parameters such as:

- Material properties,
- Operating conditions,
- Tooling parameters associated with the mould and the die design,
- Mechanical performance of the final part.

Blow moulded part designers in today's global environment are under increasing pressure to reduce part development time to a minimum, yet ensuring the maximum part quality and minimum manufacturing costs. In almost all industrial sectors, simulation technologies have proven to be a powerful tool for achieving a small-scale attainment of this goal. The use of optimization-based design allows the designers to treat complex design criteria via simulation and is expected to increase dramatically.

The main requirements of blow moulded automotive components usually combine part weight, thickness distribution, part dimension, shape and mechanical performance. These design variables can be controlled by manipulating the mould shape and operating conditions in order to minimize part weight and part deflection (warpage) subjected to mechanical performance.

In order to address industrial concerns about design tools for blow moulding, an international research initiative has been established between two institutes of the National Research Council of Canada (NRC) and two Universities in Taiwan as listed below:

- <u>From NRC</u>: the Industrial Materials Institute (IMI) and the Industrial Manufacturing Technology Institute (IMTI);
- <u>From Taiwan</u>: the Yuan Ze University and the National Taiwan University of Science and Technology (NTUST).

The team members provide complementary expertise that will make the research collaboration meaningful and mutually beneficial (**Figure 2**).

The goal of this project is to evaluate a multi-disciplinary design optimization (MDO) software environment, in particular different optimization approaches, for the design of automotive interior blow moulded parts. The methodology employs NRC's blow moulding simulation tools. In order to focus our team, Lear Corporation (Maple plant, Ontario, Canada), one of the largest Canadian manufacturers of automotive blow moulded interior parts, has been invited to participate in the project. The proposed MDO software environment will integrate process simulation tools, performance simulation tools into an optimization procedure in order to minimize the part weight and part deflection (warpage) subjected to mechanical constraints in service.

In this paper, we will describe the optimization methodologies developed based on different approaches such as gradient-based optimization and soft computing techniques. A summary of the numerical optimization algorithms and results will be presented for simple case study (validation purpose) and on a complex planar shaped carpet part (**Figure 1**) of Lear Corporation. Finally, a Web-based strategy will be presented for the integration of the simulation technology and the optimization tools developed in this project.

2. PROCESS SIMULATION

Before going into the core of this project, we would like to give a brief overview of the blow moulding process and the available simulation technology developed at IMI to model the whole process.

<u>Process Description</u>

The blow moulding process is a forming process, consisting of three phases: parison extrusion, part inflation and part solidification. The extrusion phase involves the extrusion of a polymer melt through an annular die to form a hollow cylindrical parison with a non-uniform material distribution and consequently non-uniform parison thickness along its length. Once the parison is extruded to the desired length, it is inflated to take the shape of an enclosing mould. The part then solidifies as a consequence of the heat transfer to the cooling mould. The parison thickness distribution is modified significantly by the inflation and the solidification stages to yield the final part thickness distribution.

Blow moulded parts often require a strict control of the thickness distribution and final weight. A good practice for achieving this goal is to manipulate the die gap profile of the extruder. The die gap can be adjusted as a function of time in order to obtain the desired thickness profile along the extruded parison **(Figure 3)**. Manipulation of the die gap programming points can lead to an optimal part thickness distribution.

<u>Process Modelling</u>

The blow moulding process simulation consists of the modelling of the successive process stages in order to predict the final part quality as a function of the operating conditions, the mould geometry and the material properties. We used the commercial software (BlowSim) developed at NRC to model the process phases:

- Parison formation
- Clamping and inflation
- Part cooling and shrinkage
- Part mechanical performance

The process modelling is based on a large displacement finite element formulation [1]. The parison deformation is modelled using a multi-layer membrane element type and a non-isothermal visco-elastic material model. The mechanical performance is modelled with then use of using BlowSim or ANSYS software with the predicted thickness distribution, and the appropriate applied load.

3. PERFORMANCE OPTIMIZATION

When designing a part, it is very important to take into consideration its mechanical performance in service. A common practice for achieving this goal is to minimize the part weight subject to machine operating limits and part mechanical performance constraints such as top load, internal pressure resistance, part deflection, etc. In this project, we develop a performance optimization methodology, based on gradient and soft computing techniques to find the optimal part thickness distribution that satisfies the mechanical constraint subjected to bound part thickness limits. No more details will be given in this paper concerning the performance optimization algorithms. The interested reader is referred to the next references [11,12,13] for further information on this particular topic.

4. PROCESS OPTIMIZATION

The part thickness is predicted using three consecutive calculation steps (**Figure 4**). In the first step, a finite element mesh of the parison is created, while the second step consists in the non-linear finite element analysis of the forming phases. In the third analysis step, a uniform shrinkage factor is applied in the thickness direction. The local parison thickness is included as a mesh property $T_{a,k}$. Consequently, the part thickness distribution can be expressed by the product of three separated transfer functions as follows (5):

$$\underline{T_{p,i}} = F_s(\underline{T_{b,j}}) \tag{12}$$

$$\underline{T_{b,j}} = F_b(\underline{T_{a,k}}) \tag{13}$$

$$\underline{T_{a,k}} = F_a(\underline{\Theta_l}) \tag{14}$$

where Θ_l is the vector of the programming points and vectors $T_{a,k}$, $T_{b,j}$ and $T_{p,i}$ are the thickness distributions of the finite elements before (parison thickness), after forming (inflated parison thickness) and after shrinkage (part thickness).

The main objective of this process optimization is to manipulate the die gap programming (**Figure 3**) (die gap opening versus time) in order to target a uniform part thickness distribution or a non-uniform part thickness distribution obtained from the performance optimization. Sometime, the die geometry has to be manipulated as well to achieve this goal. However, for the sack of clarity, this issue will not be treated herein.

4.1 GRADIENT-BASED ALGORITHM

The commercial process optimization methodology (BlowOp), previously developed at NRC, uses a sequential linear gradient-based algorithm to determine the optimal die gap opening profile of the extruder that minimizes the variance of the part thickness distribution from a set point. The approach is evaluated on two applications in this work. Simulations of the consecutive process phases are used to predict the final part thickness distribution $T_{p,i}$ from a given set of operating conditions.

The proposed gradient-based algorithm for minimizing the part thickness variance around the target part thickness (T_{target}) uses an updated gap opening $\Theta_l^{\,q+1}$ given by the following equation:

$$\underline{\Theta_l}^{q+1} = \underline{\Theta_l}^{q} + \alpha\left[\nabla F_s^{\,q} \nabla F_b^{\,q} \nabla F_a^{\,q}\right]^{-1}\left(T_{target} - \underline{T_{p,i}}^{q}\right) \tag{15}$$

where $\nabla F_s^{\,q}$, $\nabla F_b^{\,q}$ and $\nabla F_a^{\,q}$ are the gradient matrices obtained from Equations 12-14 and α is the user-defined gain of the system. An appropriate choice for the gain has a major influence in the system convergence because of the strongly non-linear nature of such forming processes.

The gradients of the transfer function for the shrinkage analysis is given by:

$$\begin{aligned} \nabla F_{s,ij}^{\,q} &= S_T \quad , \quad i = j \\ \nabla F_{s,ij}^{\,q} &= 0 \quad , \quad i \neq j \end{aligned} \tag{16}$$

where S_T is the thickness shrinkage factor.

The transfer function F_b is difficult to determine since it results from a non-linear finite element analysis. In order to propose an explicit expression for its gradient matrix ∇F_b, the final thickness of each finite element is assumed to be only dependent on its initial thickness. This assumption neglects the coupled deformation pattern dependence on the initial parison thickness profile. Consequently, even though it provides a simple solution for an optimization algorithm, its use requires special care. The deformation gradient associated with the finite element analysis can then be expressed by:

$$\begin{aligned} \nabla F_{b,kj}^{q} &= \frac{T_{b,j}^{\;q}}{T_{a,k}^{\;q}} \quad , \quad k = j \\ \nabla F_{b,kj}^{q} &= 0 \quad , \quad k \neq j \end{aligned} \tag{17}$$

4.2 SOFT COMPUTING TECHNIQUES

4.2.1 FUZZY LOGIC

Gradient-based numerical optimization algorithms treat the optimization problem as pure mathematical problems. Valuable engineering knowledge is not utilized in the optimization process. Moreover, in engineering optimization problems, it is hard to make an exact mathematical optimization model. The idea of the fuzzy optimization algorithm is that, instead of using purely numerical information to get the new design point in the next iteration, engineering knowledge and human supervision process can be modeled in the optimization algorithm using fuzzy rules.

Figure 5 shows the fuzzy optimization process. The inputs to the fuzzy optimization engine are, $\mathbf{Y}^q$ (the vector of system target output at the q-th iteration), $\mathbf{y}^q$ (the vector of system process output at the q-th iteration), and $\Delta\mathbf{y}^q = \mathbf{y}^q - \mathbf{y}^{q-1}$. Analogous to a standard line-search algorithm, the output of the fuzzy logic optimization engine is $\Delta\mathbf{x}^q = \alpha^q \cdot \mathbf{s}^q$, in which equation $\mathbf{s}^q$ is the search direction in the design space and α^q is the distance that we wish to move in direction $\mathbf{s}^q$. Then we can get the values of the design variable values for the next iteration $\mathbf{x}^{q+1}=\mathbf{x}^q+\Delta\mathbf{x}^q$, and feed in the plant to complete the closed loop.

In the optimization process, the objective is to minimize the standard deviation between the system process output $\mathbf{y}$ and the system target output $\mathbf{Y}$ as expressed by

$$f = \left(\sum_{i=1}^{n}(y_i - Y_i)^2 \Big/ n-1\right)^{0.5} \tag{18}$$

where n is the total number of components in system output $\mathbf{y}$, and i is the number of system output.

In **Figure 5**, the task of the fuzzy logic optimization engine is to generate the search direction $\mathbf{s}^q$ and step length α^q using fuzzy rules. A fuzzy system is characterized by a collection of linguistic statements based on expert knowledge. The linguistic statements are usually in the form of IF-THEN rules. For example, in the blow molding process optimization, we describe the engineering heuristics as follows:

(1) If the thickness of a certain node is lager than the target thickness, then reduce the respective opening rate.
(2) If the thickness of a certain node is smaller than the target thickness, then increase the respective opening rate.

These engineering heuristics indicate that the thickness of a certain node is a monotonic increasing function with respect to the corresponding gap opening rate. We can make our fuzzy rules according these engineering heuristics:

IF thickness is PB THEN gap opening is NB,
IF thickness is PS THEN gap opening is NS,
IF thickness is ZE THEN gap opening is ZE,
IF thickness is NS THEN gap opening is PS,
IF thickness is NB THEN gap opening is PB.

Quantization table is a key for the fuzzy optimization engine. Table 1 is the quantization table for the 5 rules described above.

Table 1. Quantized Variables.

Boundaries of fuzzy input, y_i	Quantized Level
$Y_i + (y_{i,\max} - Y_i)$	2
$Y_i + [(y_{i,\max} - Y_i)]/Q_{is}$	1
Y_i	0
$Y_i - [(Y_i - y_{i,\min})]/Q_{is}$	-1
$Y_i - (Y_i - y_{i,\min})$	-2
Boundaries of fuzzy reasoning, Δx_i	**Quantized Level**
$(x_{j.\max} - x_j)\cdot f_o$	2
$[(x_{j.\max} - x_j)\cdot f_o]/Q_{os}$	1
0	0
$[(x_j - x_{j,\min})\cdot f]/Q_{os}$	-1
$(x_j - x_{j,\min})\cdot f_o$	-2

Y_i : target value of system (target thickness in the blow moulding example),

$y_{i,\max}$: maximum initial value of system output y_i (maximum thickness in the initial design),

$y_{i,\min}$: minimum initial value of system output y_i (minimum thickness in the initial design),

$x_{j,\max}$: maximum initial value of system input x_j (maximum gap opening),

$x_{j,\min}$: minimum initial value of system input x_j (minimum gap opening),

Q_{is} : quantization input scale that define the linearity of quantized level with respect to the fuzzy input,

Q_{os} : quantization output scale that define the linearity of quantized level with respect to the fuzzy output,

f_o : fuzzy reasoning value that defines the maximum distance we wish to move in one iteration.

4.2.2 Fuzzy Neural-Taguchi with Genetic Algorithm (FUNTGA)

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 [9]. 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 engineering knowledge is introduced to enhance the searching efficiency of GA. The flowchart of the optimization strategy is illustrated in **Figure 6**.

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 [9]. The application of orthogonal arrays reduces the number of experiments, which is particular effective for design optimization involving expensive experiments or time-consuming simulations. ANOM study of experiment results reveals the effects of design parameters that are used to determine the optimal level of each parameter. 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.

Neural-Taguchi Network (NTN)

Our neural network uses a back-propagation network (BPN) that consists of an input layer, a hidden layer and an output layer. Sampling data are divided into learning and testing samples. Learning samples are used to determine the weighting matrices among neurons and testing samples 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 design to select training samples to reduce the number of experiments and to maintain a good sample representation [10]. The verification experiment of the optimal design from the ANOM study will serve as a testing sample. Significant interactions often introduce complexity to experimental design and lead to erroneous prediction of optimal factorial levels using ANOM. 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.

Optimum Search of the Neural-Taguchi Network Using GA

The trained Neural-Taguchi network predicts 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.

The Reliability Distance

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 where z_k =-1 and z_k =1 represent the maximum and the minimum values of the factorial variable x_k.

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

$$r_{ij} = \left[\frac{1}{n} \sum_{k=1}^{n} \left(D_{ik} - S_{jk} \right)^2 \right]^{0.5} \qquad (10)$$

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* (*RD*) of a predictive design as the minimum factorial distance between the prediction and sampling data.

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 **Figure 7** is negative and the *Reliability Distance* of D_2 is positive.

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 **Figures 8 and 9**.

4.3 SIMPLE CASE STUDY USING SOFT COMPUTING TECHNIQUES: BOTTLE

Fuzzy Logic Method

The fuzzy optimization algorithm is applied to the blow moulding of a simple bottle to evaluate its applicability. The design objective is to target a 2 mm final average part thickness. As shown in **Figure 10**, the fuzzy optimization algorithm terminates within 0.1% after 14 iterations. The objective function (part thickness standard deviation) decreases from 1.01 to 0.41, which means that the part thickness distribution has a better uniformity. One can notice that only 22 simulations are required. **Figure 11** shows the initial gap opening, which is set at 75% at all time, and the optimized gap opening. **Figure 12** compares the thickness distribution of the initial design and optimal design. For the optimal design, an average part thickness of 1.85 mm has been obtained, which is close to the thickness target.

FUNTGA Method

The FUNTGA optimization strategy is applied to the parison programming of the extrusion blow moulded bottle with a uniform wall thickness. The commercial simulation technology developed at NRC (BlowSim) has been used to predict the wall thickness distribution of blow moulded parts.

A quality blow moulding 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

$$Avg\_loss = \frac{\sum_{i=1}^{n}(t_i - T)^2}{n} \approx (\bar{t} - T)^2 + s^2 \tag{21}$$

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, $\bar{t}$ is the mean thickness, and s^2 is the sampling variance.

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. The design optimization seeks to minimize the variation of thickness and the difference between the target and the mean thickness.

Establishment of the Neural-Taguchi Network

The L18 orthogonal experiments are used as the training samples for the BPN of the extrusion blow moulding. This study assumes a constant cross section area of the parison and the final part, which provides the initial design of die opening (**Table 2**). The ranges are tentatively set to be 30% for the middle and 10% for both ends of the programming points. The initial design and Taguchi's optimum design are used as testing samples.

Optimum Search using GA

The fitness function is defined as the negation of the average loss of Eq. [21]. The trained network will then be used as the function generator for each chromosome combination. The fuzzy rules for prediction accuracy are applied to GA to improve the searching efficiency. The optimum chromosome is presented in **Table 2**.

Table 2. 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**
Initial Design	0	60	60	60	48	5	0	0.52
FUNTGA's Optimum	0	74	67.6	70.1	74.2	0	0	0.36

Table 3 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 FUNTGA used a total of 21 design simulations to locate the optimum, the optimum exhibits a mean thickness closer to the target and a smaller deviation than the BlowOp's results. **Figure 13** presents the variations of thickness distributions using BlowSim that appears that FUNTGA's optimum has a more uniform thickness distribution.

Table 3. Comparison of the analysis results.

	Mean Thickness	**Std.Dev. Thickness**
Initial	**1.66**	**0.40**
Taguchi's	**2.01**	**0.49**
BlowOp's	**1.93**	**0.38**
FUNTGA's	**1.94**	**0.35**

4.4 CASE STUDY USING GRADIENT-BASED TECHNIQUE: PLANAR CARPET PART

Before performing this process optimization, a series of experiments have been conducted at the Lear plant for validating the simulation technology for a complex part having a carpet on one of the sides. Several parts have been manufactured and cut to measure their part thickness distribution. These experimental results were compared with predicted values [2]. Good agreement has been obtained between experimental data and part thickness predictions. For a set of operating conditions, the simulation technology has proven to be an excellent tool for predicting the thickness of very complex shaped parts.

For this case study, only the gradient-based algorithm will be evaluated for minimizing part thickness variance by manipulating the die gap programming. The part thickness target has been set at 2 mm. The optimization results are illustrated on **Figures 14 & 15**. The part thickness distribution with the current programming profile is not uniform. The lower part has a smaller part thickness distribution when compared to the upper part. The statistical comparison between the actual and optimal die gap programming is indicated the following:

- Actual die gap programming: Avg=1.6 mm, σ=0.21 mm,
- Optimal die gap programming: Avg=1.99 mm, σ=0.17 mm.

With the proposed optimization methodology, we obtain an average part thickness closer to the target value and a better part thickness uniformity (lower part thickness standard deviation). This illustrates the ability of the optimization algorithm to get optimal operating conditions.

5. WARPAGE OPTIMIZATION

Warpage is a part distortion where the surfaces of the moulded part do not follow the intended shape of the design. Part warpage results from the relaxation of moulded-in residual stresses, which, in turn, is caused by differential shrinkage of material. If the shrinkage throughout the part is uniform, the moulding will not deform or warp, it simply becomes smaller. However, achieving low and uniform shrinkage is a complicated task due to the presence and interaction of many factors such as molecular orientations, mould cooling, part and mould designs, and process conditions.

The warpage problem is amplified with the presence of a part having a carpet on one of the sides (**Figure 1**). This carpet acts as an insulating material and yields a non-uniform part cooling. As a result, the part will warp significantly during the solidification (**Figure 16**). This is one of the major problems encountered by Lear Corporation Company and they refer to this phenomenon as the "*banana effect*".

To compensate for the non-uniform heat transfer coefficient on both sides of the part when cooling into the mould, the designer manipulates the mould temperatures. This is a typical optimization problem since one has to minimize the warpage phenomenon by manipulating the mould half temperatures as design variables.

Before addressing the minimization problem, one has to estimate the heat transfer coefficient on the carpet part side in order to predict correctly the heat transfer between the mould and the part (**Figure 17**). To obtain this overall heat transfer coefficient, a series of experiments were conducted at Lear Corporation to study the influence of several process parameters on the warpage characterization such as the cooling time, the mould temperature on the polymer side and the mould temperature on the carpet side [3].

By using the NRC warpage simulation technology [4,5], we manipulated the heat transfer coefficient on the carpet side to match, for a particular experiment, the same level of experimental warpage. The overall heat transfer coefficient estimated is 606 W/m^2-°C.

We will now describe the optimization methodology for manipulating mould temperatures that minimize the part warpage. At this point, only a gradient-based optimization algorithm is evaluated. More details concerning the use of soft computing techniques to perform this optimization will be given at NRC-NSC Workshop on Advanced Manufacturing in London, Ontario, on Sept. 23-25, 2002.

5.1 GRADIENT-BASED METHOD

The second optimization solves for the minimization of the part deflection by manipulation of the two mould temperature settings, T_{m1} (carpet side) and T_{m2} (polymer side), assuming a constant cooling time. The objective function is expressed as the following

Minimize F = Max |Part Deflection| (22)
subjected to
$T_{m1,min} < T_{m1} < T_{m1,max}$ (mould temperature limits)
$T_{m2,min} < T_{m2} < T_{m2,max}$
$T_{cooling}$ = 86 sec (fix cooling time)

This problem is an unconstrained minimization problem. To perform this optimization, we employed optimization tools (DOT) from VanderPlaats [6]. DOT evaluates the mould temperature gradients ($\nabla F_{T_{m1}}, \nabla F_{T_{m2}}$) with a finite difference method. For each perturbation, the part deflection is evaluated from the model prediction and consequently the gradients are estimated in order to find an appropriate search direction as the following

$$T_{m_i}^{q+1} = T_{m_i}^{q} + \Delta T_{m_i}^{q} \qquad (23)$$

where T_m represents the mould temperature, i stands for the mould 1 and 2 and q for the optimization iteration.

This optimization method has been tested on the planar shape carpet part of Lear Corporation (**Figure 1**).

5.2 CASE STUDY: PLANAR CARPET PART

To perform the optimization, we started with the following initial design for the mould temperature (T_{m1}=25°C, T_{m2}=25°C). The mould temperature limits are defined as follows (10°C<T_{m1}<50°C, 10°C<T_{m2}<100°C). The results are shown in **Figure 18**. One can notice that after the first optimization iteration, the part deflection has decreased by a significant amount. At the end of the optimization process, the optimal mould temperatures obtained are T_{m1}=11.7°C and T_{m2}=54.1°C and the part deflection predicted is around 9 mm. This part deflection value is considered very small when compared to the part length (2 m). The optimal mould temperature values are close to the actual operating conditions of Lear, that is T_{m1}=14.5°C and T_{m2}=56.4°C. However, by using these actual operating conditions, Lear has observed some minor warpage problems (part deflection = 15 mm).

For this second optimization, the initial mould temperatures are (T_{m1}=50°C, T_{m2}=50°C). The same mould temperature limits are used for this optimization. The results are presented in **Figure 19**. The optimal mould temperatures obtained are T_{m1}=23.8°C and T_{m2}=67.1°C and the maximum part deflection predicted is 20 mm. As we can see, the optimal values obtained for the mould temperatures differ from the first optimization but the maximum part deflection changes slightly. The warpage prediction is not function of the absolute values of mould temperatures but rather of the differential mould temperature:

- First optimization : ΔT_m=54.1°C-11.7°C = **42.4°C-**
Second optimization : ΔT_m=67.1°C-23.8°C = **43.3°C-**
Operating conditions of Lear: ΔT_m=56.4°C-14.5°C = **41.9°C**

To minimize the warpage phenomenon, the differential mould temperature should be approximately 43°C. To avoid having multiple designs (solutions), a process constraint should be included into the optimization formulation problem, such as the average part temperature when the part is taking out of the mould should be lower that a prescribed value or lower that the heat deflection temperature (HDT).

6. DEVELOPMENT OF WEB-BASED DESIGN SOFTWARE

One of the primary objectives of this project is to build a distributed multidisciplinary design optimization (MDO) software environment (called WebBlow) for the design of blow moulded parts. The proposed methodology includes distributed system integration using intelligent agents and Internet/Web technologies. Web technology is becoming more and more popular to implement collaborative product design environments. Web-based approaches for the implementation of a blow moulded parts design system have several advantages:

- Software does not need to be installed on the client site, which in turn reduces design costs for user companies (particularly SMEs) by eliminating both software/hardware purchase and installation costs.
- Software upgrades need to be done only on the server site, which will save time and money for both the software supplier and user companies.
- Software suppliers will be able to protect their software from illegal duplications and distributions.

Although Web technology plays an important role in promoting and supporting sharing of information and design, it is not flexible enough for legacy systems integration as well as computing resource management. We propose an agent-oriented approach for Web-based collaborative design systems [7]. The proposed approach has a number of advantages:

- It provides greater flexibility for legacy systems integration through socket-based communication among local resource agents behind a Web server.
- It can enable real-time collaboration through communication among active Web servers which are implemented as autonomous intelligent agents communicating with each other actively. Such an implementation also provides a way to integrate various legacy systems separated by firewalls.
- It can improve the performance of development and design process, particularly in the cases of multiple projects and multiple users working at the same time.

WebBlow system is composed of agents, Applets, Servlets and XML databases. Each of them has own responsibilities and they work together collaboratively. The agents are separated into two groups from physical location perspective. Some agents are located only within the optimization service provider organization site, and others may be anywhere in the world as long as the Internet access is available. The communication between agents over a firewall is through Applet/Servlet communication using HTTP protocol. On the other hand, the communication between agents within the firewall is through socket communication. The Graphic User Interface of WebBlow system is made up of 6 interfaces. **Figure 20** shows one example of the Web based user interfaces. More details of WebBlow will be presented at the NRC-NSC Workshop on Advanced Manufacturing in London, Ontario, on Sept. 23-25, 2002.

7. CONCLUSIONS

In this project, gradient-based and soft computing techniques have been presented to perform process optimization by manipulating the die gap programming points and mould’s temperature in order to optimize the part thickness distribution and to minimize the part warpage. The optimization tools performed well for the cases studied. Finally, the third year will be dedicated to validate these tools on industrial cases and to complete the integration of the simulation technology and the optimization tools on a Web-based software design environment.

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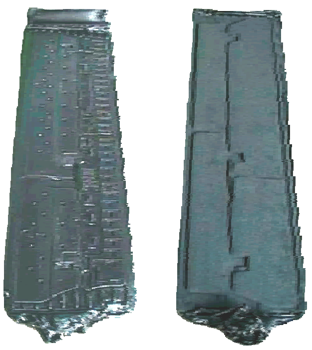

Polymer side **Carpet side**

Figure 1. Automotive filler-panel blow moulded part.

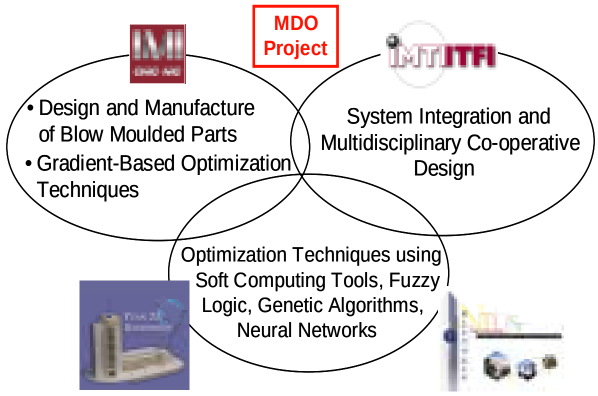

Figure 2. Description of research team expertise collaborating in the MDO project.

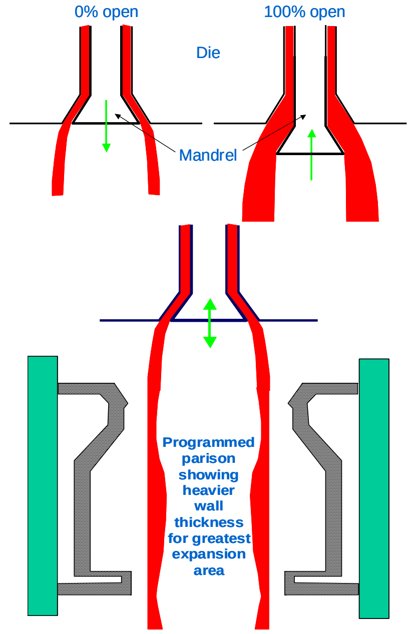

Figure 3. Description of parison programming.

$$T_a = F_a(\theta)$$
$$T_b = F_b(T_a)$$
$$T_p = F_s(T_b)$$

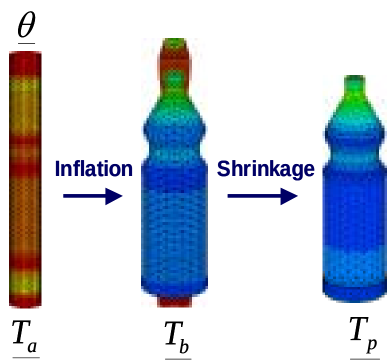

Figure 4. Prediction of part thickness through three consecutive steps: a) parison formation (θ = die gap programming), b) parison inflation and c) part shrinkage.

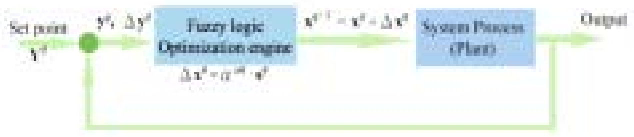

Figure 5. Structure of fuzzy optimization.

Figure 9. Membership functions of assessment variables.

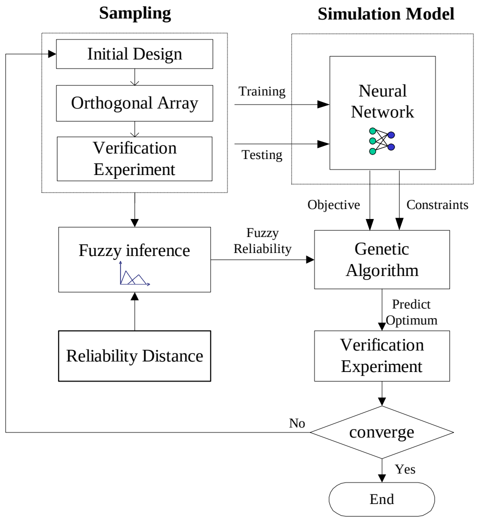

Figure 6. The Optimization flowchart of FUNTGA.

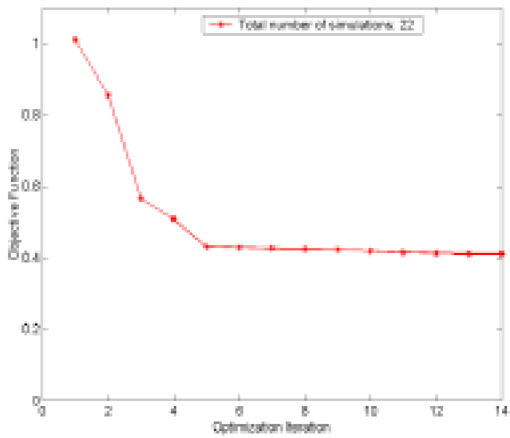

Figure 10. Iteration history of the fuzzy optimization algorithm on the bottle case.

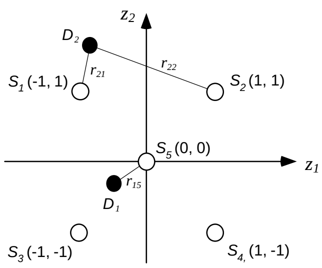

Figure 7. The factorial distances of predicted designs.

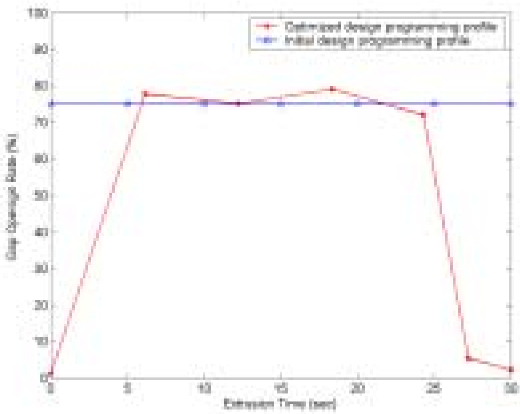

Figure 11. Comparison between optimized and initial programming profiles.

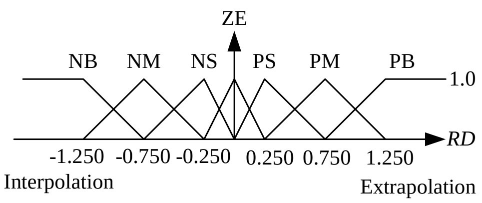

Figure 8. Membership functions of condition variables.

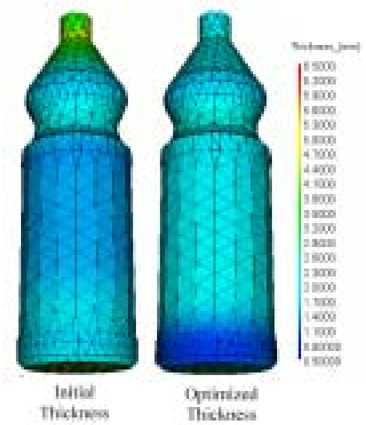

Figure 12. Comparison between optimized and initial thickness distribution.

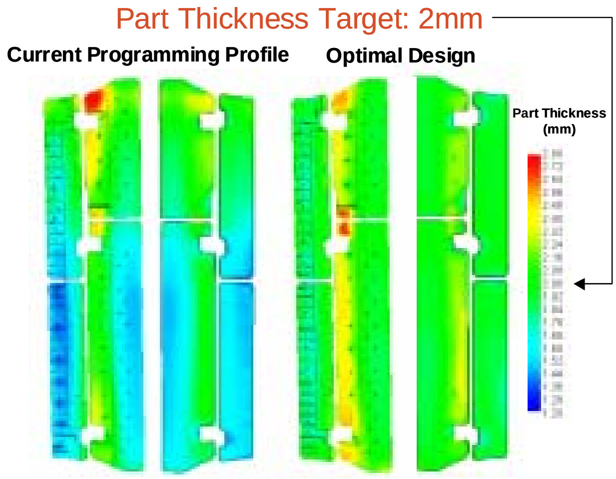

Figure 15. Part thickness distribution of the filler panel for a) the actual design and b) the optimal design.

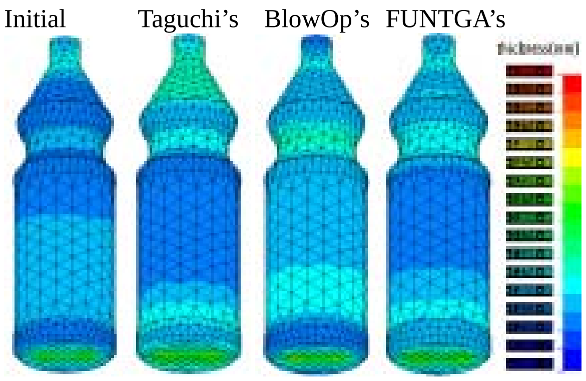

Figure 13. Comparison of thickness distribution.

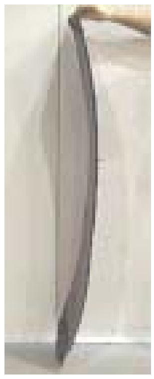

Figure 16. Example of part shape caused by a non-uniform cooling (warpage). This phenomenon is called banana effect at Lear Corporation.

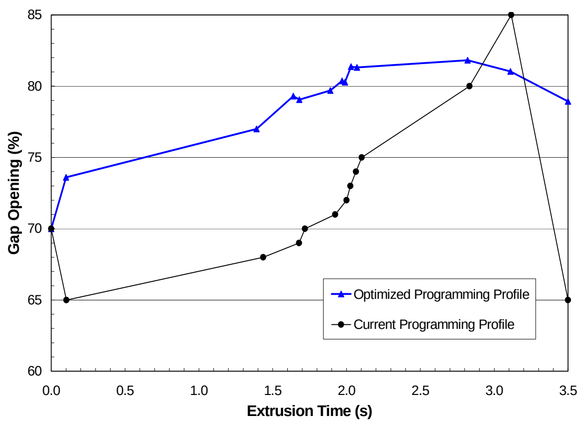

Figure 14. Comparison between optimized and current programming profiles

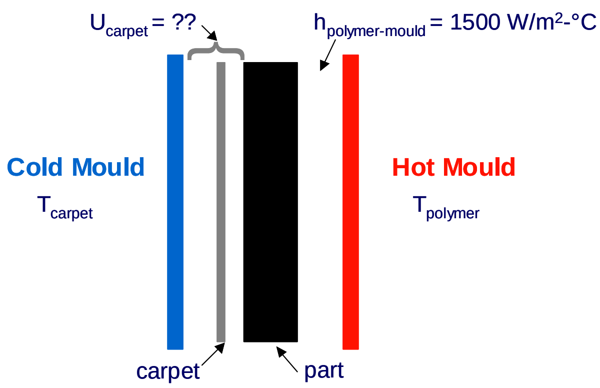

Figure 17. Illustration of the heat transfer coefficient between the part and the mould. U_{carpet} represents the overall heat transfer coefficient between the mould and the part on the carpet side.

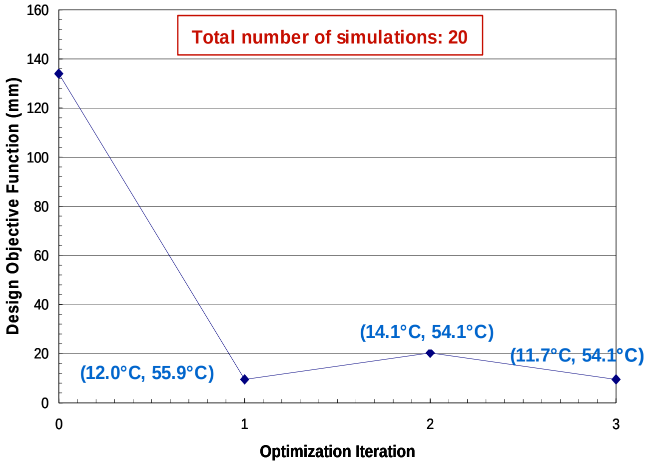

Figure 18. Evolution of mould temperatures and part deflection versus the optimization iteration (initial design: T_{m1}=25°C, T_{m2}=25°C).

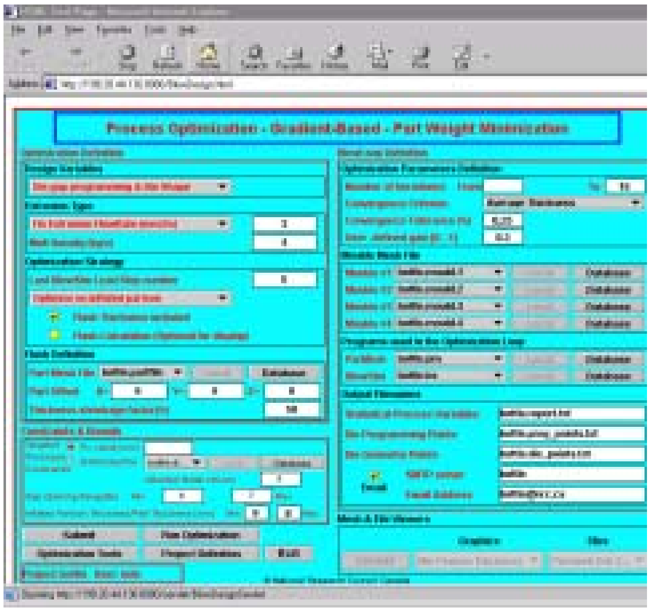

Figure 20. Sixth page of the Graphic User Interface.

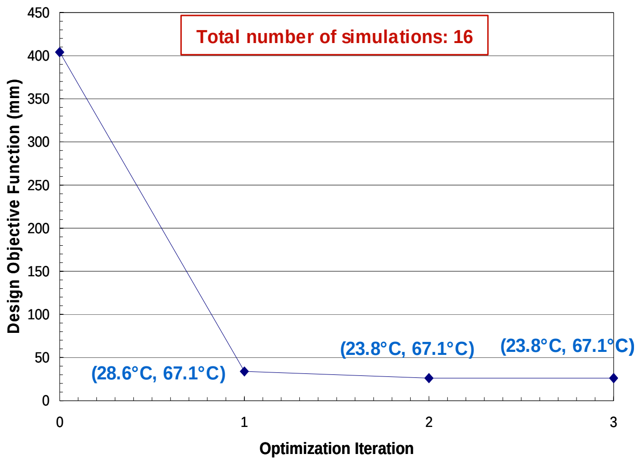

Figure 19. Evolution of mould temperatures and part deflection versus the optimization iteration (initial design: T_{m1}=50°C, T_{m2}=50°C).