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Abstract

In industry, there is a growing interest to optimize the use of raw material in blow molded products. Commonly, the material in blow molded containers is optimized by dividing the container into different sections and minimizing the wall thickness of each section. The definition of discrete sections is limited by the shape of the container and can lead to suboptimal solutions. This study suggests determining the optimal thickness distribution for blow molded containers as a function of geometry. The proposed methodology relies on the use of neural networks and finite element analysis. Neural networks are stochastically evolved considering multiple objectives related to the optimization of material usage, such as cost and quality. Numerical simulations based on finite element analysis are used to evaluate the performance of the container with a thickness profile determined by feeding the coordinates of mesh elements in finite element model into the neural network. The proposed methodology was applied to the design of industrial bottle. The obtained results suggested the validity and usefulness of this methodology by revealing its ability to identify the most critical regions for the application of material.

Keywords (separated by '-')

Blow molding - Neural networks - Multiobjective optimization - Neuroevolution

Evolving Neural Networks to Optimize Material Usage in Blow Molded Containers

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Abstract In industry, there is a growing interest to optimize the use of raw material in blow molded products. Commonly, the material in blow molded containers is optimized by dividing the container into different sections and minimizing the wall thickness of each section. The definition of discrete sections is limited by the shape of the container and can lead to suboptimal solutions. This study suggests determining the optimal thickness distribution for blow molded containers as a function of geometry. The proposed methodology relies on the use of neural networks and finite element analysis. Neural networks are stochastically evolved considering multiple objectives related to the optimization of material usage, such as cost and quality. Numerical simulations based on finite element analysis are used to evaluate the performance of the container with a thickness profile determined by feeding the coordinates of mesh elements in finite element model into the neural network. The proposed methodology was applied to the design of industrial bottle. The obtained results suggested the validity and usefulness of this methodology by revealing its ability to identify the most critical regions for the application of material.

Introduction

Blow molding is an important industrial processes for manufacturing hollow plastic parts. The production of jars, bottles and similar containers are among its main applications. Such products are widely used all over the world to contain liquids from

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drinks for human consumption to cosmetics and oil. In blow molding, a molten material is placed into a mold and inflated with gas whose pressure pushes the material out to match the mold. The costs of raw materials compose a significant share of the total costs of blow molded products. Thus, reducing costs and increasing competitiveness for manufacturing companies can be effectively achieved by minimizing the material use. This requires a trade-off between the costs of production and quality criteria, as reducing the amount of material can deteriorate important product properties.

The conventional trial-and-error approach is tedious and inefficient to optimize product development. It can lead to a significant waste of time and energy whereas the results are highly dependent on expert experience. Computer Aided Engineering (CAE) has become increasingly popular to support engineering tasks. Computer simulations and optimization can help to reduce the number of empirical trials, thus saving time and money. Numerical approaches such as Finite Element Methods (FEMs) and optimization techniques are promising and have a long history of use in blow molding design.

When optimizing blow molding, two major problems can be identified. The one is to determine a wall thickness distribution of the final container. The other is concerned with finding a shape of the preform and setting appropriate process parameters to produce a container with a desired thickness distribution. Optimization of thickness distribution is typically addressed by dividing the preform or container into distinct sections and optimizing the thickness of each section. In Laroche et al. (1999), the optimal preform thickness distribution was sought that yields a given uniform part thickness. In Gauvin et al. (2003), two approaches were presented, with the optimization aiming at finding a thickness distribution that minimizes the weight and satisfies mechanical constraints.

The other problem arising in blow molding is concerned with a process optimization aiming at finding the optimal operating conditions that minimize the weight and respect the thickness distribution found by the performance optimization. In Thibault et al. (2007), an approach to optimize the stretch blow molding process was presented, aiming at establishing the optimal preform geometry (thickness and shape) and optimal operating conditions to produce a container with a target thickness distribution. In the above studies, optimization was performed by gradient-based search methods. These methods have good theoretical properties and fast convergence. However, gradient-based methods are essentially local search techniques and their performance highly depends on the initial point.

Evolutionary algorithms (EAs) allow to overcome limitations associated with traditional optimization methods. EAs attempt to perform global search without using gradient information. In Huang and Huang (2007), genetic algorithm (GA) was used to find the optimal thickness distribution for preform. In Yang et al. (2014), particle swarm optimization was used to adjust parameters of a neural network in order to fit experimentally collected data and to obtain the appropriate lamp settings. The preform geometry was optimized in Biglione et al. (2016) to obtain a target wall thickness distribution. In Hopmann et al. (2015), this also included the optimization of process parameters.

A common feature that limits the applicability of the discussed approaches is that a container being optimized is divided into a number of sections, assuming a uniform thickness within each section. A proper division can be not straightforward as it greatly depends on the geometry of container. Poor results can be obtained if sections are inadequately defined. Also, such approach can lead to discontinuities in junctions between sections.

The specific contributions of this paper are the application of a regression model to find the optimal thickness distribution as a function of the container's geometry and solving the problem using multiobjective neuroevolutionary algorithm.

Problem Formulation

This study aims at developing a methodology for the optimization of material usage in blow molded containers, which is also a major concern for industry due to the influence of the costs of raw materials on the total production costs. The particular industrial bottle whose design is herein addressed has a diameter of 395 mm and a height of 625 mm. The material is plastic with the mass density of 1.15×10^{-9} g/cm^3 and Poisson's ration of 0.4. The bottle is set to experience a blowing pressure. The ratio between the pressure and Young's modulus is 0.0014. The minimum and maximum allowable values of wall thickness are 0.1 and 2 mm, respectively. Figure 1 shows the geometry model of the bottle used in this study.

The problem consists in determining the optimal wall thickness distribution. This problem involves several criteria that must be considered, such as the cost of utilized

Fig. 1 Geometry model of the bottle

material and the product quality. In order to capture possible trade-offs between these criteria, the problem is posed as a multiobjective optimization problem. The mass of the container and the stress are two objectives (f_1 and f_2) to be minimized. These objectives are estimated by computer simulations performed by Abaqus, the finite element analysis software.

Neuroevolutionary Thickness Optimization

This section describes the proposed methodology to design blow molded containers with an optimized wall thickness distribution. The main idea consists in treating the wall thickness as a function of container's geometry. The realization of this ideal relies on capabilities of neural networks. Neural networks are used to convert the coordinates along the wall into the thickness values. This can also be viewed as a regression model. Though, it is important to point out the distinction between a traditional regression that makes use of data points with known input and target variables and the proposed methodology where only input variables are available. In turn, this hinders the application of traditional gradient-based methods to learn the parameters of' the neural network. To overcome this issue, neuroevolution is used. Neuroevolution refers to the use of evolutionary algorithms to evolve neural networks. It provides the potential to evolve both the topology and parameters of neural networks. The outline of the proposed neuroevolution is given by Algorithm 1.

First, a population of neural networks is randomly generated in the initialization procedure. Each individual in the population is represented by two chromosomes. The first is defined by a binary string that determines the network topology by indicating which neurons are used in the hidden layer. The second is given by a real-valued string that encodes all weights and biases in the neural network.

Each time a new individual is generated it is sent for evaluation. The evaluation procedure comprises decoding the individual's genotype into the neural network, calculating the thickness profile of the bottle and computing the objective values reflecting its performance.

Figure 2 graphically illustrates the idea behind the calculation of the thickness profile. The coordinates of each mesh element in finite element model are fed into the neural network. The output is the thickness at the corresponding location. Processing this way all the mesh elements gives a thickness profile of the bottle. The resulting finite element model with the calculated thickness profile is submitted to perform computer simulation, whose subsequent output is read to extract the values of the mass and stress.

The population of neural networks is evolved for a predefined number of generations using a steady-state variant of evolutionary process (lines 2–6 in Algorithm 1). This means a single offspring is produced in each generation. Selection aims at selecting parents for producing offspring. This study uses a simple uniform selection where each population member has an equal chance to be selected.

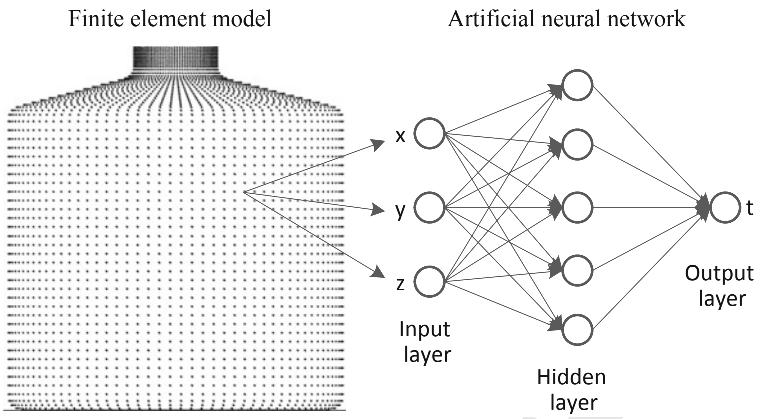

Fig. 2 Thickness calculation

Algorithm 1 Neuroevolution	
1:	initialization()
2:	**repeat**
3:	selection()
4:	variation()
5:	replacement()
6:	**until** the stopping criterion is met

Evolutionary operators are applied to parents in order to produce offspring in the variation procedure. Variation plays a crucial role in the exploration of the search space. Multichromosomal representation used in this study allows the application of operators that proved effective in the exploration of binary and continuous search spaces. Herein, a simple bit-flip mutation is performed on the binary string. A particular attention is given to a continuous variation operator, as most of the genome is represented by a real-valued chromosome encoding all weights and biases, which are central to the expressiveness of the neural network. Different continuous variation operators are investigated in the experimental study.

Replacement aims at forming a population of the next generation relying on the concept of the survival of the fittest from natural evolution. As the proposed neuroevolution is designed to deal with multiple objectives, replacement must ensure the convergence and diversity of population. These two requirements are known to be somewhat conflicting in nature. The adopted replacement strategy relies on the concept of the Pareto dominance to provide convergence and the hypervolume measure to ensure diversity. First, the population is sorted using the nondominated sorting procedure to find individuals in the last nondominated front. Then among the found individuals the one with the least volume of exclusively dominated objective space is removed (Beumea et al. 2007).

The result of the above described process is expected to be a set of neural networks, where each neural network gives the design of the container providing a specific trade-off between its mass and mechanical properties.

Computational Experiments

Experimental Setup

Neuroevolutionary algorithm developed for optimizing a wall thickness distribution was investigated with different variation operators, taking advantage of multichromosomal representation. For real-coded genetic algorithm (GA) operator, simulated binary crossover (SBX) and polynomial mutation (PM) were used. Evolution strategy (ES) operator was used with a non-isotropic mutation. Differential evolution (DE) operator with *rand/1/bin* variant and PM was employed. Covariance matrix adaptation (CMA) operator was used with a step size adaptation rule relying on a population-based notion of success.

The numerical simulations based on finite element analysis were carried out by Abaqus 6.13-4 provided in a network licensing format. A high computational time required for each simulation and a limited number of analysis jobs allowed to be run simultaneously on a network restricted considerably optimization runs. Thus, five independent runs were performed by each neuroevolutionary variant. The population size of 50 was used and the number of available evaluations was 100. The other parameter settings are shown in Table 1. The results were quantitatively assessed using the hypervolume measure (Zitzler and Thiele 1998).

Table 1 Parameter settings (n—is a chromosome length)

Operator	Parameters
SBX	$p_c = 1,\ \eta_c = 20$
PM	$p_m = 1/n,\ \eta_m = 20$
ES	$\tau_0 = 1/\sqrt{2n},\ \tau_1 = 1/\sqrt{2\sqrt{n}},\ \boldsymbol{\sigma}_0 = \sqrt{1/(3n)}$
DE	$CR = 1,\ F = 0.5$
CMA	$d = 1 + n/2,\ p_{succ}^{target} = 1/\left(5 + \sqrt{1/2}\right),$ $c_p = p_{succ}^{target}/\left(2 + p_{succ}^{target}\right),\ c_c = 2/(n+2),$ $c_{cov} = 2/\left(n^2 + 6\right),\ p_{thresh} = 0.44$

Results

Table 2 shows the final results of statistical runs with respect to the hypervolume. The last row of the table refers to the hypervolume for all nondominated solutions obtained by combining results of the five runs. The results indicate that GA is the worst performing operator. It can be because crossover treat genes independently when producing offspring. This causes a disruptive effect on the linkage between genes. Although ES does not explicitly accounts for relations between genes, its slightly better performance can be explained by the self-adaption mechanism that learns mutation strength for each gene. Both DE and CMA mechanisms allow for the adaptation to fitness landscape. CMA works better for extreme runs, whereas DE gives the best median value and the hypervolume for the approximation set composed by the results of all runs. This can be because CMA has a larger number of parameters that require proper settings.

Since the hypervolume values presented in Table 2 differ slightly, it can misleadingly appear that the results obtained by different variants are quite similar. However, such seemingly small differences with respect to the hypervolume can be significant in practical terms. It can be understood when comparing the results of GA and DE variants, whose Pareto front approximations are shown in Fig. 3. Solutions forming both approximations lie sufficiently close to each other, being the most distant in the vicinity of the knee points.

However, the knee point region of the Pareto front is particularly interesting from an engineering perspective. When comparing the results with respect to the hypervolume DE variant gives an improvement of 1.71% relative to GA. Whereas in terms of the knee solutions the reduction by 32.34% of the material usage is achieved, which is significant for industry.

Visualization of the obtained Pareto optimal solutions leads to several important observations. In particular, there is a part of the Pareto optimal region where the material usage can be significantly reduced from the maxim value of 2.032 kg to approximately 0.2 kg with relatively a small degradation in mechanical properties. This can be the most interesting part from a practical perspective. However, a further reduction in the material results in a significant degradation of mechanical properties. Although such solutions are appealing from an economic point of view, they may be unacceptable as important quality criteria can be not met. Thus, these results further highlight the importance of proper tools to support product development.

Table 2 Results for statistical runs of different operators

Hypervolume	GA	ES	DE	CMA
Min.	0.9687	0.9713	0.9805	*0.9882*
Median	0.9701	0.9723	*0.9897*	0.9893
Max.	0.9746	0.975	0.9902	*0.9905*
Total	0.9749	0.976	*0.9918*	0.9916

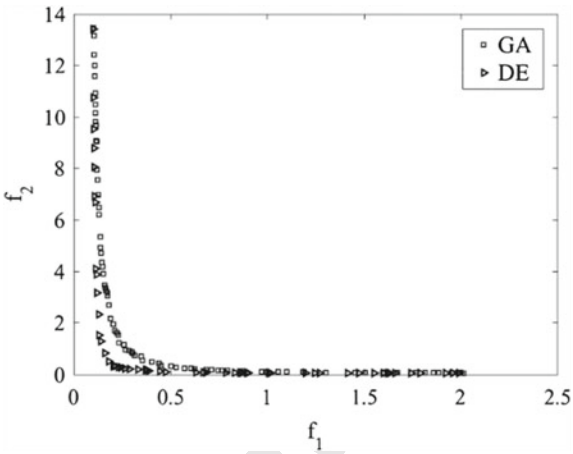

Fig. 3 Nondominated solutions

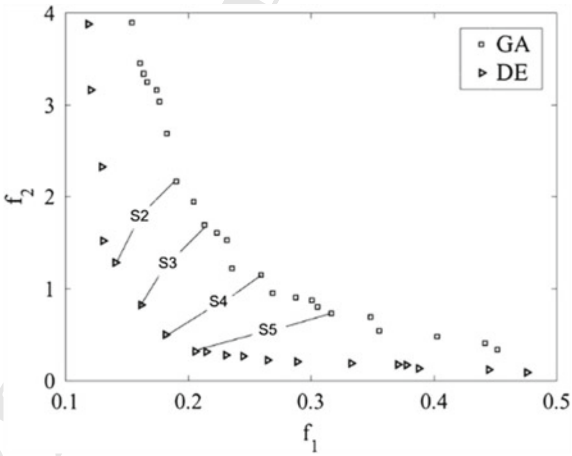

Fig. 4 Nondominated solutions near the knee points

Figure 4 shows the Pareto optimal solutions in the vicinity of the knee points. For both approximations, four different solutions are highlighted. For these solutions and solutions S1 and S6 that refer to the corners of the Pareto fronts, Fig. 5 depicts the wall thickness of bottle along the vertical axis from top to down. Corner solutions S1 and S6 represent extreme scenarios with minimum and maximum values of thickness along the entire bottle. On the other hand, solutions S2–S5 show intermediate scenarios representing different trade-offs between the use of material and mechanical properties. The difference can be observed between the thickness distributions of solutions given by GA and DE. The former offers larger values starting from the top. Whereas the latter yields values close to the minimum for the most positions and only increases thickness in the bottom of bottle. This way, neuroevolution identifies the most critical regions for applying material. It is also noteworthy that GA provides a valid design of the bottle. The comparison is for illustration purpose and to stress

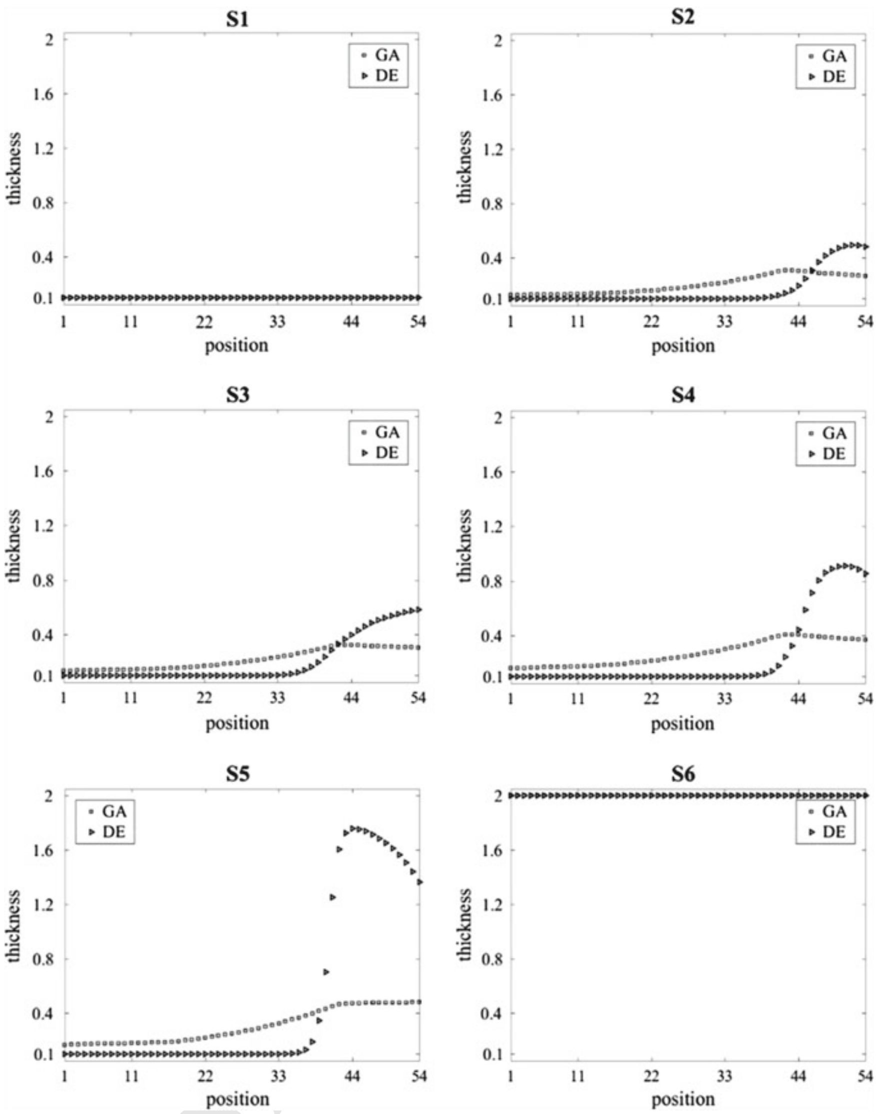

Fig. 5 Thickness distribution from top to bottom of the bottle

the importance of the neuroevolutionary design. Overall, these results demonstrate the ability of the proposed methodology to determine the material distribution for the bottle given its geometry, characteristics and design criteria to meet.

Conclusions

In blow molding industry, the product competitiveness can be effectively increased by reducing the costs of raw materials. This study suggested a methodology to optimize the material usage in blow molded products. This methodology aims at determining the optimal distribution of material as a function of the product geometry. Motivated by the universal approximation property, this function is approximated by neural network. The structure and parameters of the network are determined by neuroevolution. The search is performed addressing multiple objectives, minimizing the usage of material and the degradation of mechanical properties. This leads to a set of Pareto optimal networks representing different trade-offs between the objectives, which allows to obtain a valuable information about design alternatives and enables a posteriori decision making.

The application of the proposed methodology is demonstrated in a case study addressing the design of industrial bottle. Finite element analysis software was employed to simulate the response of the particular design to a static pressure. Different variants of neuroevolutionary algorithm were investigated. The obtained results indicate the importance of using proper search strategies and the ability of neuroevolution to optimize the thickness distribution under given conditions. Generality is a major advantage of the proposed methodology, as its applicability is independent of the bottle geometry.

In future, the developed methodology will be applied to optimize the preform and operating conditions.

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