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

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

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

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

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

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

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

73 Problem Formulation

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

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

Fig. 1 Geometry model of the bottle



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

90 Neuroevolutionary Thickness Optimization

91 This section describes the proposed methodology to design blow molded containers
92 with an optimized wall thickness distribution. The main idea consists in treating the
93 wall thickness as a function of container's geometry. The realization of this ideal
94 relies on capabilities of neural networks. Neural networks are used to convert the
95 coordinates along the wall into the thickness values. This can also be viewed as
96 a regression model. Though, it is important to point out the distinction between a
97 traditional regression that makes use of data points with known input and target
98 variables and the proposed methodology where only input variables are available.
99 In turn, this hinders the application of traditional gradient-based methods to learn
100 the parameters of the neural network. To overcome this issue, neuroevolution is
101 used. Neuroevolution refers to the use of evolutionary algorithms to evolve neural
102 networks. It provides the potential to evolve both the topology and parameters of
103 neural networks. The outline of the proposed neuroevolution is given by Algorithm
104 1.

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

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

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

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

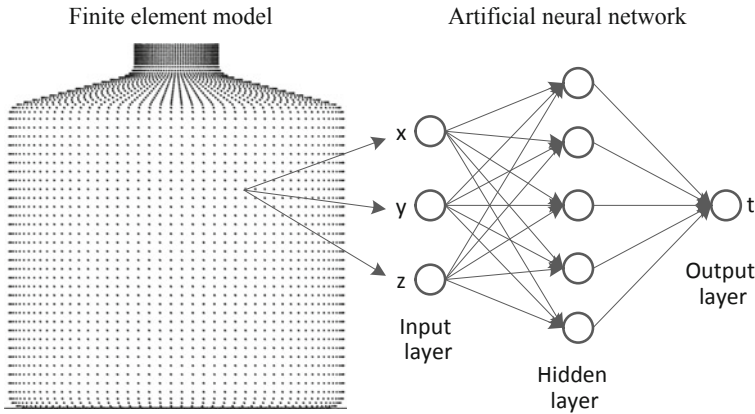


Fig. 2 Thickness calculation

Algorithm 1 Neuroevolution

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

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

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

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

148 Computational Experiments

149 *Experimental Setup*

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

158 The numerical simulations based on finite element analysis were carried out by
 159 Abaqus 6.13-4 provided in a network licensing format. A high computational time
 160 required for each simulation and a limited number of analysis jobs allowed to be run
 161 simultaneously on a network restricted considerably optimization runs. Thus, five
 162 independent runs were performed by each neuroevolutionary variant. The population
 163 size of 50 was used and the number of available evaluations was 100. The other
 164 parameter settings are shown in Table 1. The results were quantitatively assessed
 165 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	$\tau_0 = 1/\sqrt{2n}, \tau_1 = 1/\sqrt{2\sqrt{n}}, \sigma_0 = \sqrt{1/(3n)}$
DE	$CR = 1, F = 0.5$
CMA	$d = 1 + n/2, p_{succ}^{target} = 1/(5 + \sqrt{1/2}),$ $c_p = p_{succ}^{target} / (2 + p_{succ}^{target}), c_c = 2/(n + 2),$ $c_{cov} = 2/(n^2 + 6), p_{thresh} = 0.44$

166 **Results**

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

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

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

191 Visualization of the obtained Pareto optimal solutions leads to several important
 192 observations. In particular, there is a part of the Pareto optimal region where the
 193 material usage can be significantly reduced from the maxim value of 2.032 kg to
 194 approximately 0.2 kg with relatively a small degradation in mechanical properties.
 195 This can be the most interesting part from a practical perspective. However, a further
 196 reduction in the material results in a significant degradation of mechanical properties.
 197 Although such solutions are appealing from an economic point of view, they may be
 198 unacceptable as important quality criteria can be not met. Thus, these results further
 199 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

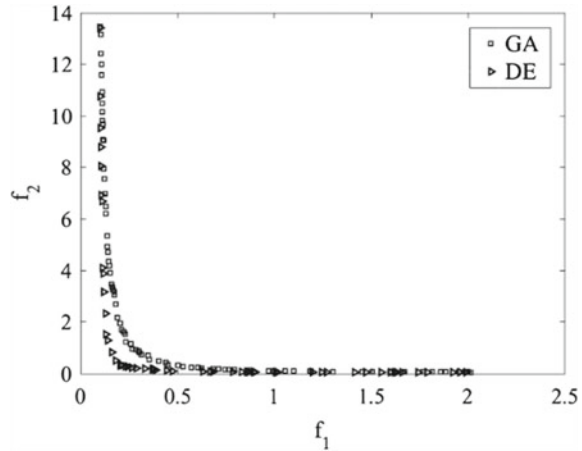
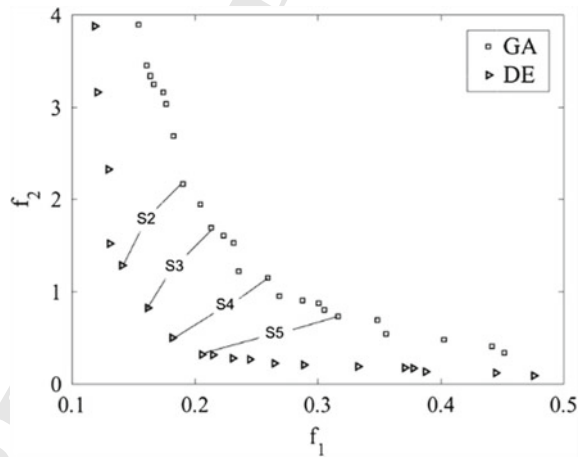


Fig. 4 Nondominated solutions near the knee points



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

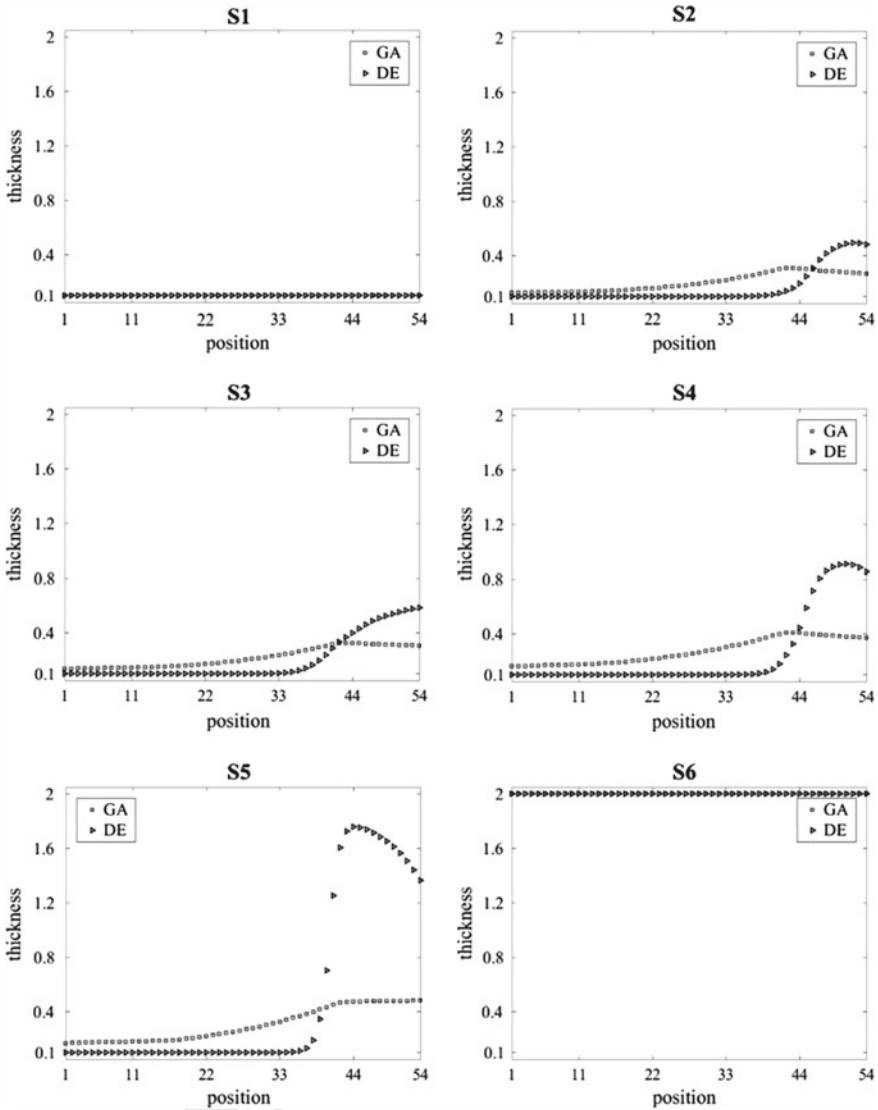


Fig. 5 Thickness distribution from top to bottom of the bottle

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

216 Conclusions

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

228 The application of the proposed methodology is demonstrated in a case study
 229 addressing the design of industrial bottle. Finite element analysis software was
 230 employed to simulate the response of the particular design to a static pressure. Differ-
 231 ent variants of neuroevolutionary algorithm were investigated. The obtained results
 232 indicate the importance of using proper search strategies and the ability of neuroevo-
 233 lution to optimize the thickness distribution under given conditions. Generality is a
 234 major advantage of the proposed methodology, as its applicability is independent of
 235 the bottle geometry.

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

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