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Abstract	Injection blow molding process is widely used in the industry to produce plastic parts. One of the main challenges in optimizing this process is to find the best manufacturing thickness profiles which provides the desirable mechanical properties to the final part with minimal material usage. This paper proposes a methodology based on a neuroevolutionary approach to optimize this process. This approach focuses on finding the optimal thickness distribution for a given blow molded product as a function of its geometry. Neural networks are used to represent thickness distributions and an evolutionary multiobjective optimization algorithm is applied to evolve neural networks in order to find the best solutions, i.e., to obtain the best trade-off between material usage and mechanical properties. Each solution is evaluated through finite element analysis simulation considering the design of an industrial bottle. The results showed that the proposed technique was able to find good solutions where the material was distributed along the most critical regions to maintain adequate mechanical properties. This approach is general and can also be applied to different geometries.

Keywords (separated by '-')	Blow molding - MOEA - Neuroevolutionary

Neuroevolutionary Multiobjective Methodology for the Optimization of the Injection Blow Molding Process

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Abstract. Injection blow molding process is widely used in the industry to produce plastic parts. One of the main challenges in optimizing this process is to find the best manufacturing thickness profiles which provides the desirable mechanical properties to the final part with minimal material usage. This paper proposes a methodology based on a neuroevolutionary approach to optimize this process. This approach focuses on finding the optimal thickness distribution for a given blow molded product as a function of its geometry. Neural networks are used to represent thickness distributions and an evolutionary multiobjective optimization algorithm is applied to evolve neural networks in order to find the best solutions, i.e., to obtain the best trade-off between material usage and mechanical properties. Each solution is evaluated through finite element analysis simulation considering the design of an industrial bottle. The results showed that the proposed technique was able to find good solutions where the material was distributed along the most critical regions to maintain adequate mechanical properties. This approach is general and can also be applied to different geometries. AQ1

Keywords: Blow molding · MOEA · Neuroevolutionary

1 Introduction

One of the most important processes to manufacture plastic parts in industry is the injection blow molding process, which is widely used in the production of several kinds of container products, such as bottles, jars and containers to hold different types of liquids (laundry detergents, oil, water, among others). In general, this process comprises the injection of molten material (to form a preform, also called parison) into a mold which is inflated with gas (usually air). The pressure imposed by the gas pushes the melted material towards the mold, leading the plastic material to acquire the shape of the mold. After cooling, the plastic is pulled out, producing the final part.

The total costs of blow molded products are heavily influenced by the amount of material used in manufacturing and therefore can be reduced by minimizing material usage. However, several mechanical properties are also dependent on this feature.

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Thus, this requires a trade-off between production costs and quality criteria, once the reduction of material can affect important properties of the final product [1].

A common approach to optimize blow molding process is reducing the material empirically, but good results will rely on expert experience. In this context, numerical models can help to reduce the number of empirical trials or even eliminate real productions needs by using simulations during the optimization process. Several numerical approaches, such as Finite Element Methods (FEMs), neural networks, gradient-based and stochastic search techniques have been used in blow molding design [1–4]. The major challenge to optimize this process is to find the best geometry and thickness profile of injected preform in order to obtain the final part with all desirable mechanical and weight properties satisfied.

Artificial Neural Networks (ANNs) has been used in several studies to describe blow molding process with high accuracy. In [2] the authors use a neural network to predict wall thickness distribution of a container from the parison (preform) thickness distribution. In [5] the preform diameter and thickness swells were predicted by an ANN from operation parameters. In [3] the authors use ANNs to model a parison extrusion process based on experimental data.

Besides ANNs, genetic algorithms and other kind of optimization techniques have been used as well. In [6] the authors use a genetic algorithm to find the optimal thickness distribution for a preform in order to produce a blow molded bottle with desired wall thickness distribution. In [7] ANNs and particle swarm optimization are used to modeling nonlinear relationships between power lamp settings and output temperature in infrared ovens used to heat PET (Polyethylene terephthalate) preforms during injection blow molding process.

This study proposes a new methodology for injection blow molding optimization which merges several methods into a neuroevolutionary approach. Wall thicknesses distributions are modeled through ANNs, the injection blow molding process are simulated using Finite Element Models (FEM) and evolutionary multiobjective optimization algorithms are applied to find optimal solutions, i.e., thickness distributions which gives the best trade-off between the total amount of used material and suitable mechanical properties. Although this approach can be applied to all stages of injection blow molding process, this study focuses on the final stage, aiming at finding the thickness profile of the final part which satisfies required mechanical properties. The methodology is applied to an industrial bottle model.

2 Injection Blow Molding Optimization

2.1 Process Overview

In general, the injection blow molding process can be summarized into five phases which are illustrated in Fig. 1. These phases are (P1) Injection, (P2) Stretching, (P3) Blowing, (P4) Mold opening and (P5) Blow molded part, respectively.

The process starts in P1, where the polymer should be melted at right conditions considering injection molding parameters. This phase is performed at the injection machine which has a heated barrel with a rotating screw that helps to mix molten

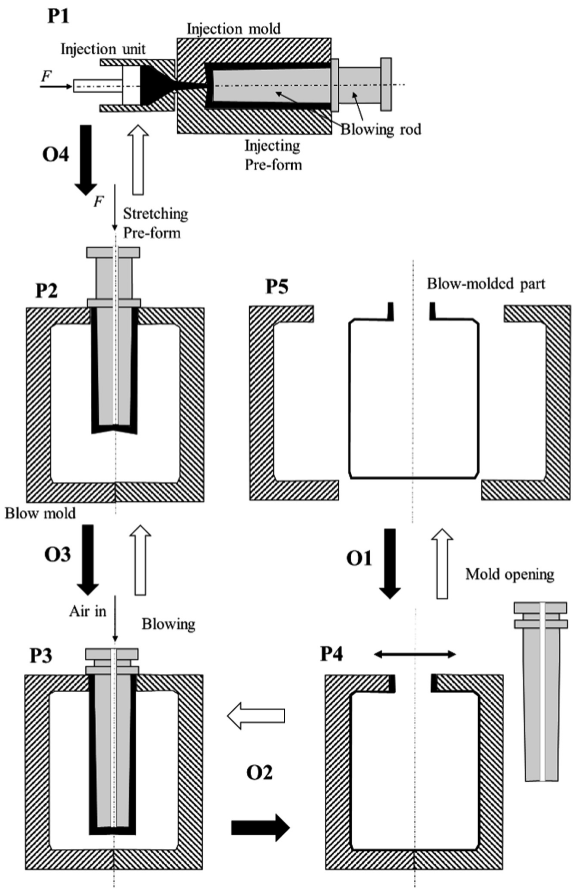

Fig. 1. Injection blow molding process overview.

material, distribute heat and drive material forward. The molten material is injected into a heated cavity to form the preform and then is clamped around a blowing rod.

The next phase (P2) comprises stretching the preform. This phase might be unnecessary for certain products or even be executed simultaneously with phase P3. Stretching the preform allow the maximization of the amount of material at the bottom of final part. Temperature should be controlled to avoid deformation or damage to the material during stretching. The geometry of blowing rod should be optimized to facilitate material flow.

Phase P3 comprises the injection of air (at a certain pressure and velocity) inside the preform resulting from the previous phase, pushing the material towards the mold and leading it to match its internal shape. The preform thickness profile and the mold geometry will determine the thickness profile and hence mechanical properties of the final part. Thus, optimization process should find thickness profiles which lead to less material utilization at the same time that required mechanical properties are accomplished.

Phase P4 starts right after the blowing phase and comprises the wait for material cool down at a safe temperature, where the plastic are rigid enough to not break or deform when pulled out from mold. The thickness profile is also important for this phase since cooling time will be different across parts with irregular geometries. After cooling time, the mold is opened and the plastic part is pulled out.

Phase P5 is the last step of the process, when the final part keeps cooling and is ready for storage. Controlling cooling rate is important to obtain uniform properties in the final part.

2.2 Global Optimization

In this study, the optimization of injection blow molding process will be divided into four major steps that can be optimized separately, as show in Fig. 2.

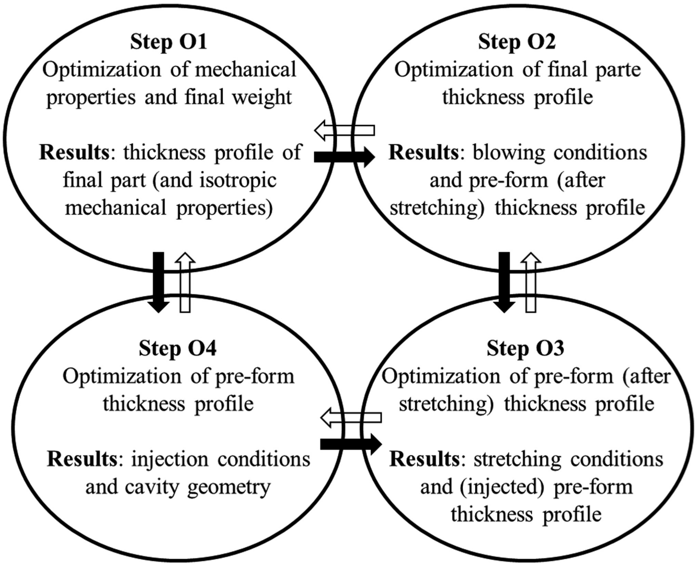

Fig. 2. Global optimization steps for injection blow molding.

The optimization process can be started by taking into account a costumer specification for a blow molded product, i.e., which properties should be accomplished by the final part. Then, the proposed optimization methods should be applied to each phase of the blow molding process in order to find the best settings that will produce the desirable final part at the end of the process. It should be clear in each optimization which objectives to be accomplished and variables to be optimized.

This study proposes four major steps to compose the global optimization process of injection blow molding (Fig. 2). In this methodology, the bests results of a given step will be the objectives of the next (starting by the end of manufacturing process). Each step can be summarized as follows:

- (O1) Optimize the mechanical properties and weight of the final part. This step aims at find the optimal thickness profile of the final part which gives the best trade-off between mechanical properties and the total weight. Decision variables are the wall thickness profile of the final part, which is composed by the thickness values for each point of the mesh that represents the final part.
- (O2) Optimize the final part thickness profile. This step aims at find the best preform geometry which gives the optimal final part thickness profiles that was obtained in the previous step. Decision variable are the blowing conditions and the preform thickness profile (after stretching, when applicable).
- (O3) Optimize the preform thickness profile after stretching. This step should be done when stretching is applicable. Decision variables are stretching conditions and the preform thickness profile. The optimization process is analogous as the previous step, but this step aims at find the best solutions which produces the optimal preform thickness profile obtained in step (O2).
- (O4) Optimize the preform thickness profile (before stretching). Decision variables are injection conditions and cavity geometry. This step aims at find the best solutions which produces the optimal preform thickness profile (before stretching) obtained in previous step.

It is important to point out that the optimization algorithms and procedures used in each step are exactly the same except by decision variables and results considered in each of them. Since the results of a given step is used by the next one, the optimization should follow the chain during its execution, but at any time it is possible to go back to previous steps to reformulate the results. In this case, further steps should be executed again to update the results. The optimization workflow is indicated by white arrows in Fig. 2.

2.3 Proposed Methodology

Injection blow molding simulations are done through finite element methods hence all parts are modeled in 3D meshes where each mesh point is supposed to have a certain thickness value. One of the main issues concerning the optimization is how to handle the different sizes and geometries of each mesh. For instance, a simple bottle mesh can be composed by thousands of points (to have good accuracy). Furthermore, considering each point as a decision variable will lead to a huge search space for optimization algorithms.

The proposed methodology follows the described global optimization to optimize injection blow molding process. To reduce the search space and handle different kinds of models (and meshes), thickness profiles are treated as a function of the container's geometry and neural networks are used to compute the wall thickness at any location of the mesh based on the respective coordinates. It is important to point out that no supervised training method are used, the parameters for the networks are determined by the evolutionary multiobjective optimization process. As a result of optimizations, there will be a neural network which gives the optimal thickness profile of the corresponding optimization phase, that might be the profile of final part or the parison thickness profile, for example.

The proposed neuroevolutionary approach is illustrated in Fig. 3. It begins by reading input parameters and generating the initial population randomly. Each population is composed by a set of individuals, each of them representing a neural network that models a wall thickness distribution. The information of ANNs (weights and biases) is encoded in a chromosome of real numbers. Thus, the size of each chromosome will be directly related with the topology of the network. Figure 4 illustrates the thickness calculation process. The coordinates of each point of a given mesh are fed into an ANN that will output the wall thickness value for each point, respectively. The network is composed of three layers where the number of neurons in the hidden layer can be fixed or vary during optimization. Due to computational resources and time constraints, in this study two fixed topologies were considered: 3-20-1 (20 neurons at the hidden layer) and 3-5-1 (5 neurons at the hidden layer). These topologies were previously determined by empirical experiments.

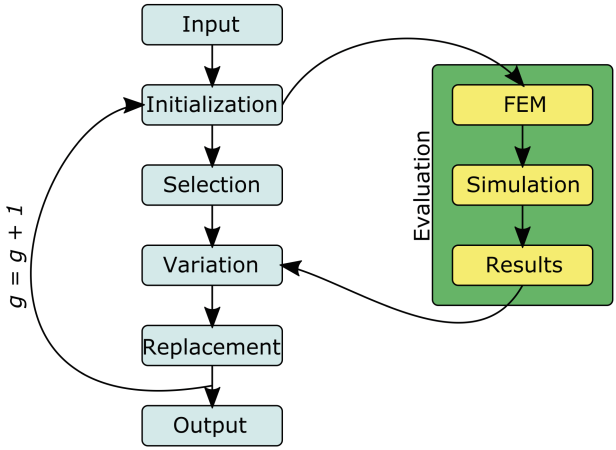

Fig. 3. Neuroevolutionary optimization workflow

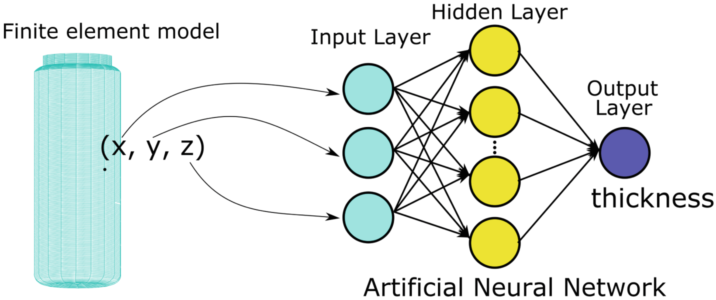

Fig. 4. Thickness calculation using neural network

When initialization is done, the algorithm performs a predefined numbers of generations of a steady-state variant of evolutionary process based on the SMS-EMOA multiobjective optimization algorithm [8]. A single offspring is produced in each generation. Selection is done by a uniform distribution (each member of the population has the same chance to be selected). Variation is performed by SBX-Crossover operator, which is adequate to work with real number representations and replacement strategy is based on Pareto front and *hypervolume* measure.

After being generated, each individual is evaluated by a procedure that comprises assembly the neural network from chromosome information and fed into the network the coordinates of each point of the finite element model. As a result of this step, the thickness of each point of the mesh will be provided, creating the thickness profile that will be considered in the simulation process.

At the end of optimization process there will be a set of optimal solutions, i.e., wall thickness profiles modeled by neural networks, each one giving different trade-off between the considered objectives.

3 Experiments and Results

3.1 Experimental Setup

The proposed methodology was applied to optimize injection blow molding of an industrial plastic bottle model. Figure 5a shows the geometry of the model, which is 45 mm in diameter and 182 mm height, composed by a plastic material with mass density of 1.15 g/cm^3 and Poisson's ration of 0.4. The ratio between the applied blowing pressure and Young's modulus is 0.0027.

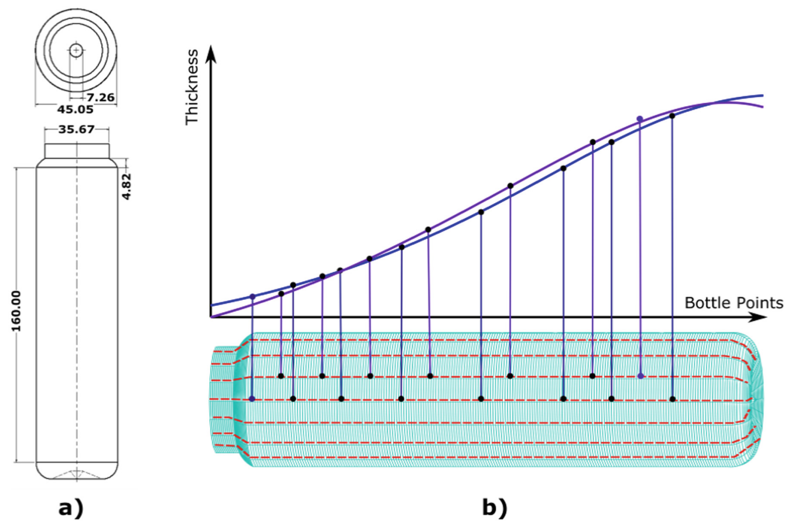

Fig. 5. Bottle model with wall thickness distribution illustrated (dimensions in millimeters)

The wall thickness distribution is composed by thickness values of each point of the mesh considering vertical lines from bottleneck to the bottom on the model. Figure 5b illustrates a thickness distribution plot for two vertical lines, but the points of all vertical lines should be plotted on the same graph, being possible to visualize how the thickness changes along the bottle. Note that for uniform distributions, lines will be overlapped.

Numerical simulations were carried out by finite element analysis software ANSYS Workbench version 18.1 to simulate an internal pressure applied to the final bottle. The objective of the optimization in this phase is to find optimal thickness distributions which provide the best relationships between the total mass and maximum strain supported by the bottle.

Since the ANNs are not aware of the geometry of the final product, non-uniform thickness distributions can be found by the optimization algorithm. However, for the model considered in this study, uniform distributions are desirable. Thus, an objective which takes into account the uniformness of thickness distributions was considered. Three objectives were chosen for the optimization: (i) the total mass of final product (f_1), (ii) the maximum strain suffered (f_2) and (iii) the maximum difference between each vertical line in the thickness distribution (f_3). The difference between two vertical lines is calculated using the root-mean-square error index (RMSE), given by Eq. (1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{y_\imath} - y_i)^2} \tag{1}$$

In Eq. (1) $\widehat{y_\imath}$ and y_i represents the thickness points of two different vertical lines and n are the total number of points in each distribution. All vertical lines are compared to each other and f_3 is the maximum calculated RMSE, that is to be minimized. The minimum and maximum allowable values of wall thickness were 0.1 and 3 mm, respectively.

Due to high simulation time to compute each solution, 50 individuals were considered as the population size and a total of 5000 evaluations were performed in each optimization, leading to a total of 100 generations. The two neural network topologies described were considered: 3-20-1 and 3-5-1. All neurons uses sigmoid as activation function.

3.2 Optimization Results

Figure 6 shows the evolution of *hypervolume* for each generation of both ANN topologies. All objective function values were normalized with the maximum and minimum values of the dataset, staying within the interval [0, 1]. The *hypervolume* was calculated with reference point (1.0, 1.0, 1.0). Once all objective functions are being minimized, higher *hypervolume* values means better optimization performance. Both topologies converge at generation 30 (approximately) and topology 3-20-1 presented better results than topology 3-5-1. Since the computational time for both optimizations is almost the same, as the computation time is proportional to the modelling time, the better topology can be used without significant loss of performance.

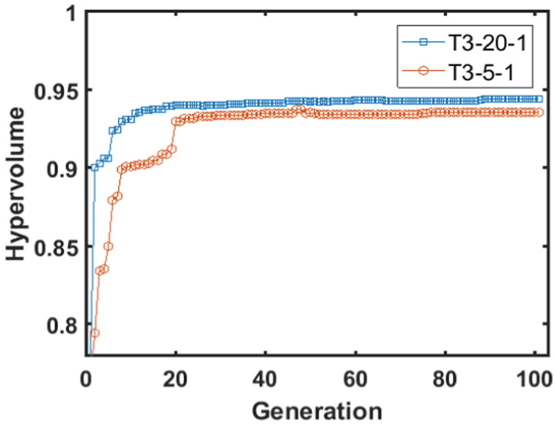

Fig. 6. Evolution of *hypervolume* for different ANN topologies

Figure 7 shows the Pareto front (for 100th generation) of both topologies. Topology 3-20-1 provides more different optimal solutions than topology 3-5-1, especially for the objectives f_1 (mass) and f_2 (maximum strain), where the Pareto front is much more distributed. Thus, the final results were selected from this front.

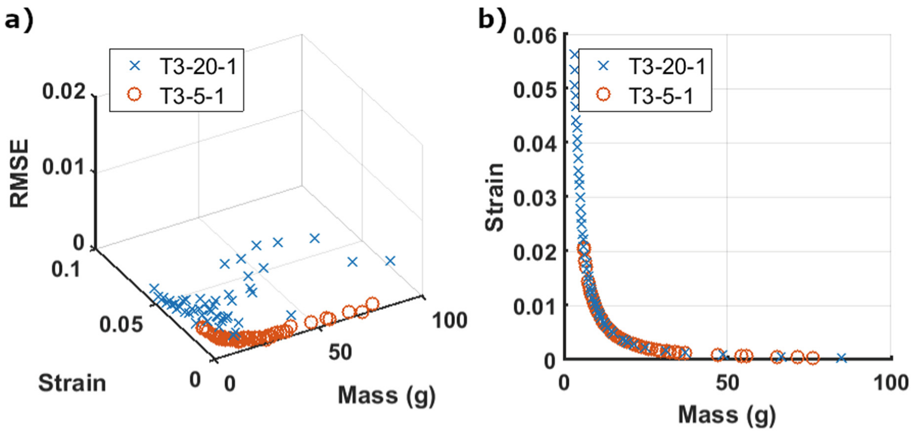

Fig. 7. Pareto front of each topology. In (a) all objectives are plotted whereas in (b) only objectives f_1 (mass) and f_2 (maximum strain) are shown

Figure 8a shows the evolution between the initial and last populations in the optimization process for topology 3-20-1. All objective functions were clearly minimized forming the Pareto front, which is shown in Fig. 8b (for f_1 and f_2).

The five selected solutions in Fig. 8b were selected along the Pareto front to obtain different trade-offs between the total mass of used material and the maximum strain supported by the bottle for the imposed pressure. For example, solution S2 gives a

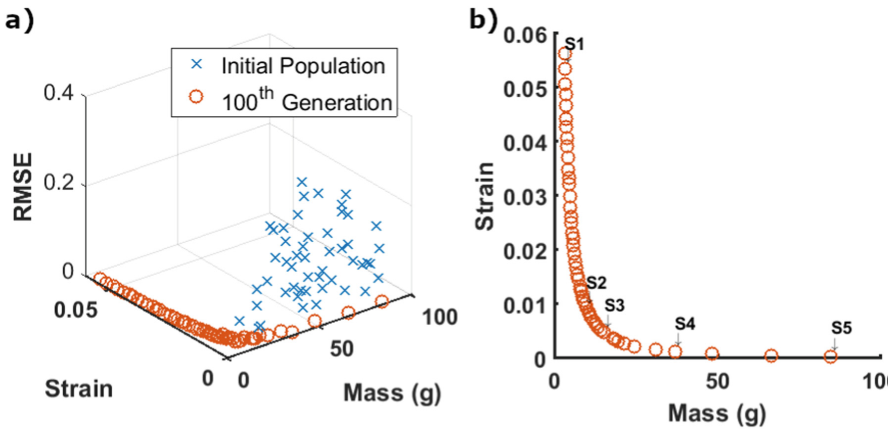

Fig. 8. (a) Initial and last population for topology 3-20-1. (b) Pareto front of last population where only objectives f_1 (mass) and f_2 (maximum strain) are shown. Five selected solutions are highlighted

certain thickness distribution for the final bottle which leads to a maximum strain of 9.4×10^{-3} with 9.8 g in weight. Considering the conflicting nature of the objectives, best relationships will be provided by solutions usually located at the knee of the curve. In this case, these solutions might be represented by S2 and S3. Table 1 contains the numerical values for all objectives of selected solutions.

Table 1. Optimal solutions selected from Pareto front

Solution	Mass (g)	Max. strain (x 10^{-3})	RMSE (x 10^{-3})
S1	3.2	56.3	0.9
S2	9.8	9.4	10.4
S3	15.2	4.8	11.3
S4	37.1	1.2	2.5
S5	84.8	0.3	5.9

Figure 9 shows the thickness distribution of each selected solution. All graphs except f) have the same absolute interval in y-axis (1 mm). Figure 9f contains all distributions on the same graph. Although each solution has a different value for RMSE, when considering absolute 1 mm interval (which is a high precision for an industrial blow molding process) there is no significant differences in distributions concerning the uniformity. However, each solution presents different thickness average levels, which can be seen in Fig. 9f. For instance, solution S5 has a mean thickness of 2.8 mm, giving lowest strain (0.3×10^{-3}) but with higher weight (84.8 g).

Looking at Table 1 values, solution S3 (15.2 g in total weight with maximum strain 4.8×10^{-3}) can be considered the general optimal solution, i.e., which gives the best trade-off between material utilization (mass) and the minimum strain suffered by the

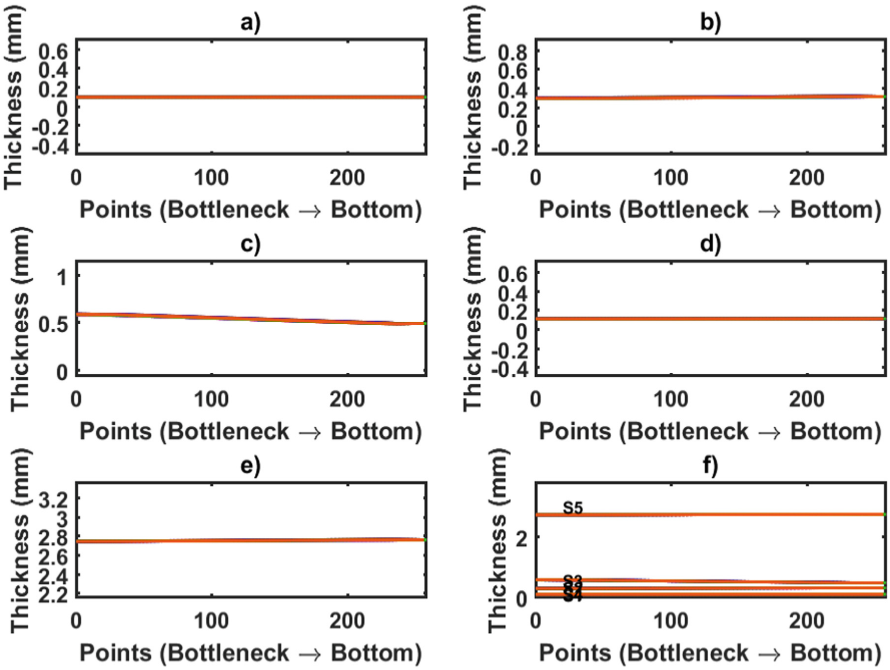

Fig. 9. Thickness distributions of selected solutions (a) S1, (b) S2, (c) S3, (d) S4 and (e) S5, respectively. (f) shows all distributions on the same graph

bottle. Thus, the thickness profile provided by S3 can be used in further optimizations of the global optimization process.

4 Conclusions

Optimization of injection blow molding is a great asset in industry since it can decrease production cost and improve manufacturing process. This paper proposes a new methodology based on a neuroevolutionary approach to optimize the injection blow molding process. Neural networks are used to model wall thickness distributions and evolutionary multiobjective optimization algorithms are applied to find optimal solutions, giving the best trade-offs between material utilization and mechanical properties. The methodology has been successfully applied to an industrial bottle model to find the best relationship between total mass and maximum strain when pressure is applied. As the result, a set of optimal thickness profiles has been found, providing less strain under pressure with less material utilization.

Optimization experiments provided by this study were applied to one phase of injection blow molding process. As a future work, the proposed methodology will be applied to other phases as well.

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