Optimization of Injection Stretch Blow Molding: Part I – Defining Part Thickness Profile

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Optimization of Injection Blow Molding: Part I - Defining Part Thickness Profile

This paper suggests a methodology based on a neuroevolutionary approach to optimize the use of material in blow molding applications. This approach aims at determining the optimal thickness distribution for a certain blow molded product as a function of its geometry. Multiobjective search is performed by neuroevolution to reflect the conflicting nature of the design problem and to capture some possible trade-offs. During the search, each design alternative is evaluated through a finite element analysis. The coordinates of mesh elements are the inputs to an artificial neural network that is evolved and whose output determines the thickness for the corresponding location. The proposed approach is applied to the design of an industrial bottle. The results reveal validity and usefulness of the proposed technique, which were able to distribute the material along most critical regions to adequate mechanical properties. The approach is general and can be applied to products with different geometries.

1 Introduction

Blow molding is an important industrial process for manufacturing hollow plastic parts. The production of jars, bottles and similar containers are among its main applications. 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 usage. This requires a trade-off between the costs of production and quality criteria, since reduce the amount of material can deteriorate important product properties (Biglione et al., 2016).

When optimizing injection blow molding, the main issue to be addressed consists in defining the complete shape and thickness profile of the injected pre-form in order to get a final part with the desired properties (e.g., mechanical properties and weight). Therefore, the optimization of this process must take into account its main phases, as detailed in section 2.2 and in Figure 1.

Figure 1 The injection blow molding process: black arrows – direction of the processing; open arrows – direction for optimization process

Evolutionary algorithms (EAs) allow to overcome limitations associated with traditional optimization methods. EAs are stochastic search methods that typically process a population of solution. This allows to perform global search without gradient information. In (Huang and Huang, 2007), genetic algorithm (GA) was used to find the optimal thickness distribution for parison to produce a blow molded bottle with the required wall thickness distribution. The relationship between parison thickness distribution and the objective function (which implies to minimize the deviation from the target bottle distribution) was approximated by neural network.

Some early studies showed the ability of Artificial Neural Networks (ANNs) to describe a blow molding process with a high degree of precision. In (Diraddo and Garcia-Rejon, 1993), a neural network was used to predict the wall thickness distribution from the parison thickness distribution. In (Huang and Liao, 2002) the diameter and thickness swells of the parison in extrusion blow molding were predicted from given operation parameters. In (Huang and Lu, 2005) neural networks were used to model a parison extrusion process in extrusion blow molding based on experimental data.

This study presents a new methodology for injection blow molding optimization which combines several techniques into a neuroevolutional approach. ANNs are used to model wall thickness profile from a given mesh, multiobjective optimization and neuroevolutional algorithms are used to find optimal solutions in a search space and computer modelling are used to simulate the injection blow process. The presented approach can be used in any of the phases of the whole process and can also be applied to products with different geometries. However, this paper focuses on the final stage of the blowing process, which forms the final molded part. Thus, the present approach is applied to find the optimal wall thickness distribution of an industrial plastic bottle, *i.e.*, the solution which gives best trade-off between total material weight and suitable mechanical properties.

2 Injection Blow Molding

2.1 The Process

A schematic view of the injection blow molding process is presented in Figure 1, along with the individual optimization steps that will be explained in section 2.2. The process phases are identified by letters, following the sequence indicated by black arrows. They are:

A) **Injection**. This phase is performed at the injection machine, comprising a screw rotating inside a heated barrel at a certain speed. The aim is to melt the polymer at the ideal conditions considering the injection molding parameters. The molten polymer is injected into a heated preform cavity, which is clamped around a mandrel (the blowing rod) that forms the internal shape of the preform.

B) **Stretching pre-form**. Depending on the products to be molded, this phase can be absent and/or can take place simultaneously with the next phase. The aim is to stretch longitudinally the pre-form in order to maximize the quantity of material at the bottom of the part. At the same time, the polymeric material will be oriented. For that purpose, the plastic must be heated until a temperature allowing the stretch without deforming permanently the material (or break it). Thus, the geometry of the blowing rod must be optimized in order to facilitate the flow of the material.

C) **Blowing**. Air at certain pressure is introduced inside the heated pre-form in order to expand the material up to contact and acquire the internal shape of the mold. The aim is to produce a part with an optimized thickness profile taking into account the original pre-form thickness profile and the mold geometry, but at the same time maximizing the mechanical properties required and minimizing the material weight.

D) **Mold opening**. The mold is opened after cooling. The time required for cooling must be defined carefully as the part cannot deform during the opening. Thus, a critical situation of this process consists in obtain a part with uniform properties, both in the part surface and in its thickness.

E) **Blow-molded part**. In this phase the part continues to cooling during storage. The aim is to obtain a part with uniform properties (which also depends of the cooling rate). However, in this phase the cooling rate is less critical than in the three previous steps.

2.2 Global optimization

As described in section 2.1, the injection blow molding is a complex process, comprising different phases and involving several distinct topics. The major related concerns are setting the parameters for operating conditions in each stage and to define the best blowing-rod and mold geometries in order to obtain the best final part thickness profile and properties, while minimizing the quantity of material required in the process. A general optimization methodology is based on linking computational modeling and optimization procedures. The former performs numerical simulations describing the underling process and evaluates the performance of a particular design in terms of important process parameters. The latter generates potential solutions to the problem and is responsible for exploring the design space. These computational procedures require a trade-off between simple and complex models. Simple models often omit various important details and have disadvantage of possibly being unrealistic. Complex models attempt to include more details in order to be more realistic. However, they are more difficult to solve. Also, there are efficiency requirements dictated by limited computational resources.

The design optimization of injection blow molding can be performed by breaking down the entire process into several tasks (decomposition approach), as shown in Figure 1. This can be addressed by taking into consideration a customer specification for a blow molded container and applying procedures in an attempt to find the optimal settings for different phases of the blow molding process, *i.e.*, in the proposed methodology, the optimization starts at the end of the process. Figure 2 shows the framework proposed for injection blow molding optimization. There are four major steps composing the global optimization (see Figures 1 and 2).

Figure 2 The global optimization approach

To perform the process optimization, it must be clear, in each step, what the objectives to be accomplished and the decision variables to be optimized. In the proposed methodology (Figure 2) the results of a given step are the objectives of the subsequent step. Each step can be summarized as follows:

I) Optimization of the mechanical properties and final weight. The results in this phase are the thickness profile of the final part (which may result from the previous optimization step). The objectives are to maximize the mechanical properties and minimize the final weight. The decision variables are the thicknesses in the locations defined by the numerical mesh. It is also necessary to consider the non-isotropic nature of the mechanical properties of the part, as its different locations suffer different orientation and cooling rates. However, due to the high difficulty in dealing with this issue, in this study an isotropic condition will be considered.

II) Optimization of the final part thickness profile. The thickness profile used here was the one obtained in the previous optimization step. The results, *i.e.*, the decision variables, are the blowing conditions and the pre-form thickness profile after stretching (when stretching is applied).

III) Optimization of pre-form (after stretching) thickness profile. The decision variables are the stretching conditions and the injected pre-form thickness profile, to be used in the next step.

IV) Optimization of the pre-form thickness profile. The decisions variables are the injection conditions and the cavity geometry.

The relationship between the steps is indicated by open arrows in Figure 2. In any case, there is the possibility, when the optimization reaches a certain step, to go back to reformulate the results obtained in any other previous steps. This is indicated by grey arrows in Figure 2. For example, when doing step IV) is possible to go back to any other previous steps (which means restarts the optimization procedure proposed), but using other values for decision variables taking account the knowledge acquired about the system during previously optimization processes.

2.3 Proposed methodology

The main idea of the proposed methodology consists in treating a container's wall thickness as a function of its geometry, building an ANN that computes the wall thickness at any location based on the corresponding coordinates. It is important to point out a distinction between a traditional regression task that makes use of a data set with known target values of dependent variable and the proposed approach where such values are unavailable. The overall approach consists in finding the parameters for a neural network so that it produces the optimal wall thickness distribution for a blow molded container as a function of its geometry.

Figure 3 outlines the proposed neuroevolutionary approach. After reading necessary input parameters, the population of chromosomes encoding neural networks is randomly generated in the initialization procedure.

Figure 3 Neuroevolutionary algorithm

After completing initialization, for a predefined number of generations a steady-state variant of evolutionary process is performed. This means a single offspring is produced in each generation, with one generation consisting of selection, variation and replacement. 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.

Variation is applied to parents using evolutionary operators in order to produce offspring. This is an important design issue as it plays a crucial role in the exploration of the search space. Therefore, different continuous variation operators are investigated in the 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 neuroevolutionary algorithm is designed to deal with multiple objectives, replacement must ensure the population convergence and diversity. These two requirements are known as somewhat conflicting in nature and are essential for a proper exploration of the objective space. The adopted replacement strategy is based on the concept of the Pareto dominance to provide convergence and the *hypervolume* measure (Zitzler and Thiele, 1998) to ensure diversity. Such replacement strategy is popular in the field of evolutionary multiobjective optimization and proved to be effective in various studies (Beume et al., 2007). The Pareto Front of a certain population is a set of nondominated solutions, being chosen as optimal, if no objective can be improved without degrading other objective function values.

Each time a new individual is generated it is sent for evaluation, which involves the computation of the thickness for each element of the mesh. This is graphically illustrated in Figure 4, where the coordinates of each mesh element are fed into the neural network to compute the corresponding thickness. The resulting finite element model is submitted to perform the computer simulation, whose subsequent output is read to extract the mass and strain. In practice, each ANN represents an entire bottle, *i.e.*, the thickness of all the x, y and z coordinates.

Figure 4 Thickness calculation

As multiple objectives are considered, in the end of evolutionary process a set of Pareto optimal neural networks is expected. The obtained solutions will suggest the design of a container providing different trade-offs between the mass and mechanical properties.

3 Results and discussion

3.1 Case study

The geometry model of the particular industrial bottle addressed in this study is shown in Figure 5. The aim is to produce as new bottle able to support high pressures. Simultaneously, the symmetrical geometry allows to check the validity of the model. The bottle has a diameter of 45 mm and a height of 182 mm. The material used for production is plastic with the mass density of 1.15 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 0.0027. The minimum and maximum allowable values of wall thickness are 1 and 3 mm, respectively.

Figure 5 Geometry model of the bottle (dimensions in millimeters)

It is important to point out that the neural network is not aware of the geometry of the final product since receives as input just a single coordinate. In order to obtain uniform thickness distributions along the wall of final product a third objective was considered besides mass and strain. Figure 6 shows the bottle mesh with vertical lines highlighted. To obtain a uniform distribution throughout the wall, these lines should have at the end of the optimization the same thickness distribution as much as possible. Thus, the objectives considered in the experiments were to minimize: i) the total mass of final product (f_1), ii) the maximum strain obtained (f_2) and iii) the maximum difference between thickness distributions of each vertical line in the mesh (f_3). The difference between two vertical lines is calculated using the root-mean-square error index (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y_i} - y_i)^2}$$

where $\hat{y_i}$ 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 with all the others, being f_3 the maximum calculated RMSE, that is to be minimized.

Figure 6 Bottle mesh with vertical lines which are desirable to have same thickness distribution

Computational experiments were carried out to investigate the effectiveness of different search operators under the proposed framework. This feature greatly affects the overall problem-solving capability, hence, deserves a particular attention. The results were compared using the *hypervolume*.

Numerical simulations estimating the responses of particular designs were carried out by finite element analysis software ANSYS Workbench[1]. A finite element model with a mesh of 4674 elements was defined. Due to time necessary to evaluate each solution a small population size of 50 potential solutions was used and the process finish when 5000 evaluations were made. Neuroevolutionary algorithm developed for optimizing a wall thickness distribution was

[1]Version 18.1

investigated with two state-of-the-art variation operators for continuous optimization, namely real-coded genetic algorithm (GA) and differential evolution (DE). Both operators were adopted with the polynomial mutation (PM) (Deb, 2001) that is applied with the mutation probability of $p_m = 1/n$ (where $\boldsymbol{n}$ - is the chromosome length) and the distribution index of $\eta_m = 20$.

3.2 Study of different variants

Figure 7 displays the evolution of the *hypervolume* for the two different variation operators. There is a clear separation between the two performance curves. The best result in terms of the *hypervolume* is obtained by GA. This operator acts on chromosomes in a gene-wise manner, which means each gene is treated separately. GA recombines individual genes of two parents using the SBX crossover method. Since correlations between the different genes are not exploited, such mechanism produces a disruptive effect on the coupling between the network parameters encoded into the chromosome. On the other hand, DE explores the search space using differences between genomes of distinct population members. DE operator produces an offspring by perturbing a particular individual with a scaled difference of randomly selected population members.

Figure 7 Evolution of hypervolume for different variation operators (the higher the better)

Better *hypervolume* values are related to a better performance in practical terms. This can be understood when comparing the results of GA and DE variants, whose Pareto front approximations are shown in Figure 8. Solutions forming both approximations lie quite close to each other in terms of f_1 and f_2. However, GA variant gives a significant difference in terms of f_3, where the maximum error (RMSE) was 0.0094 while for DE was 0.0660. Thus, the obtained results stress the importance of a proper search strategy for solving the problem. From this analysis it is clear the importance of the studied operators in the performance of the optimization algorithm. GA operator was chosen for the remaining of the calculations.

Figure 8 Pareto optimal solutions obtained by neuroevolution with different variation operators

3.3 Optimization results

Figure 9 shows the obtained Pareto optimal solutions for the initial Population (randomly generated) and for the 100th generation in terms of mass and strain minimization (the third objective was not represented). At first glance, it seems that the initial population presents optimal solutions requiring none or minimal optimization, once many solutions of 100th generation presents the same (or very close) values for mass and strain when compared with the initial population. However, an analysis of Figure 10, which shows all objectives of both populations, it can be clearly seen that the optimization process had a significant impact on the RMSE values, which means that the solutions of the final population have better uniform thickness distributions. This can be better observed in Figures Figure 11 and Figure 12.

Figure 11a) shows the Pareto optimal solutions for initial population with five solutions highlighted on the graph, where each of them provides different trade-offs between mass and strain.

Figure 9 Pareto optimal solutions for mass (f_1) and strain (f_2) for the initial population and at 100th generation

Figure 10 Pareto optimal solutions obtained for the initial population and at 100th generation

For instance, solution S2 gives a certain thickness distribution which leads to a final product with 21g and maximum strain of 0.0028 whereas for solution S5 the maximum strain is 0.0003 but with 83g of mass. Figure 11b) shows the thickness distribution (at all vertical lines, from bottleneck towards the bottom of the bottle) for the selected solutions. Finally, Figure 11c) makes a small zoom at the same point and with roughly same scale for each solution of Figure 11b). Can be seen that all solutions do not have uniform distributions (the lines are not overlapped), which means that the optimization was not complete.

Figure 11 Pareto optimal solutions for initial Population

Figure 12 Pareto optimal solutions for 100th generation

Figure 12 shows the same, but now for the final population. For instance, solution S2 has a total mass of 9.2g and maximum strain of 0.0105 whereas solution S5 has a maximum strain of 0.0003 but with nearly 80g of mass. Figure 12b) shows the thickness distributions for the selected solutions and Figure 12c) makes the same zoom (at same position and scale) as the Figure 11c). It can be seen that all solutions have uniform thickness distributions (lines are much closer each other, or even overlapped), which was expected once the values for RMSE are significant smaller when compared with initial population.

The selected solutions from Figure 12a) represents different trade-offs between mass and the maximum strain. Considering the conflict nature of the objectives, the best relationship is usually located at the knee of the curve, which it might be represented by solutions S2 and S3. The thickness distribution of each selected solution are represented in Figure13a), 13b), 13c), 13d) and 13e). Table 1 shows the corresponding objective function values.

Table 1 Optimal solutions selected from Pareto front

Solution	Mass (g)	Maximum strain
S1	3.0	0.0590
S2	9.2	0.0105
S3	15.3	0.0047
S4	52.1	0.0007
S5	79.8	0.0003

Figure 13 Thickness distribution of solution S1 to S5

There are some important observations that can be made. There is a bottle of the Pareto optimal region where the material usage can be significantly reduced from the maxim value of 79.8g (solution S5) to approximately 3.0g (solution S1). This can be the most interesting bottle 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 cannot be satisfied. The quality of solution and its relevance is greatly affected by the design parameters. The advantage of multiobjective optimization lies in the ability to obtain a wide range of available design alternatives and based on the acquired knowledge about the problem to make a decision regarding the implementation of a particular design. These results illustrate the importance of proper tools to support product development.

Analyzing the values at Table 1, the best trade-off between mass and maximum strain is given by solution S3 (which is in the knee region of the Pareto front), where the total mass is 15.3g and maximum strain is 0.0047. **Error! Reference source not found.**3c show that S3 has also a better uniform thickness distribution along the wall of the bottle. Thus, it can be considered the optimal thickness distribution, *i.e.*, which gives the best relationship between material usage and mechanical properties.

4 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 approach aims at determining the optimal distribution of material as a function of the product geometry. This function is approximated by neural network. The structure and parameters of the network are determined by neuroevolution. The search is performed by naturally addressing multiple objectives, such as reducing material usage and minimizing the resultant degradation of mechanical properties. This leads to a set of Pareto optimal networks which represents different trade-offs between objectives. This allows to obtain valuable information in terms of available design alternatives and enables *a posteriori* decision making.

The application of the proposed approach 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 internal pressure. Different variants of neuroevolutionary algorithm were investigated. The obtained results indicate the importance of using proper search strategies and the ability of neuroevolutionary approach to optimize a thickness distribution for given conditions. Another major benefit of the proposed approach is its versatility, as its applicability is not dependent of the product geometry.

As a future work, the proposed methodology will be applied to other phases of injection blow molding process, such as optimize the preform and operating conditions to obtain the final molded part with desired features.

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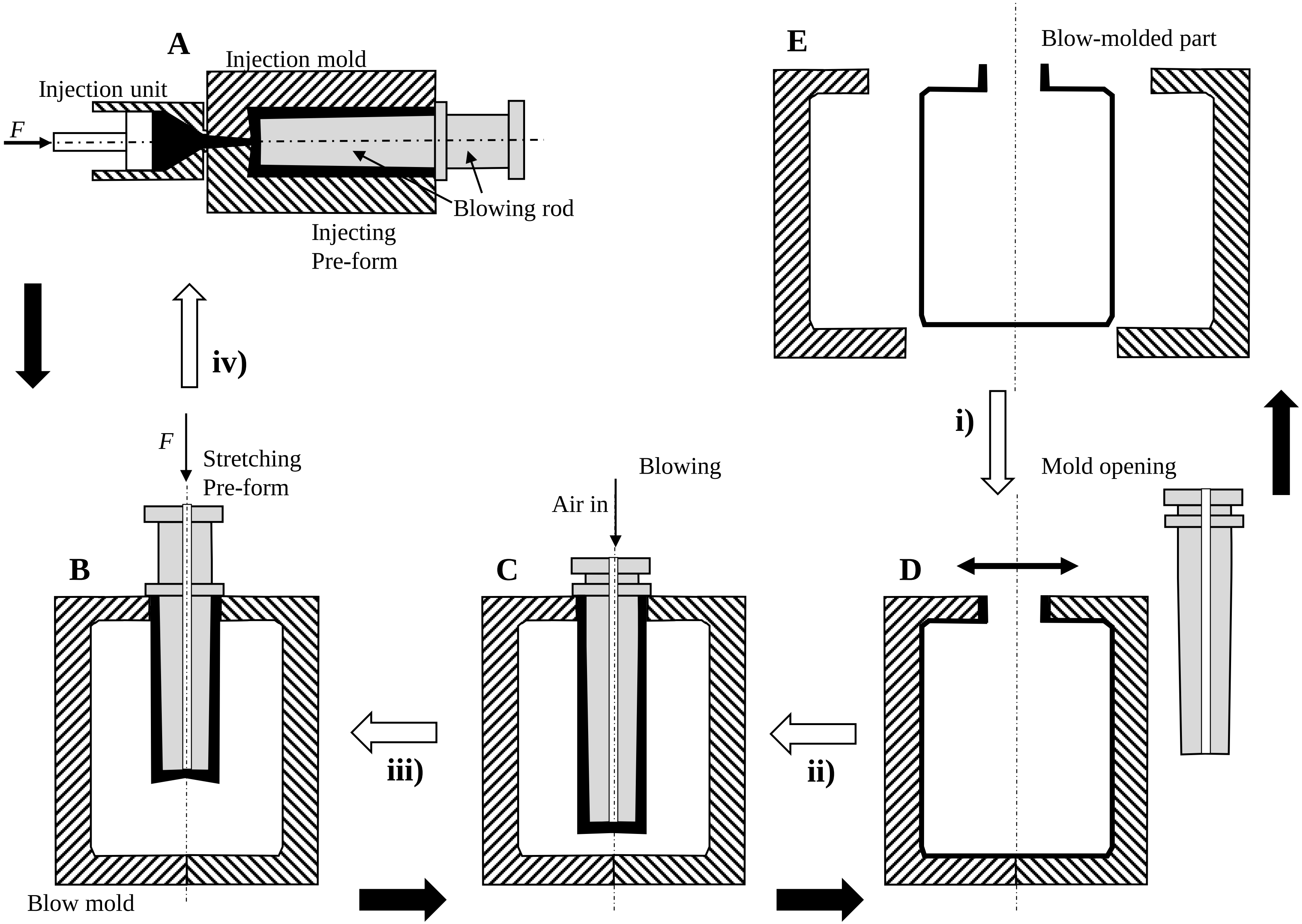
Figure 1



A
Injection mold
Injection unit
F
Blowing rod
Injecting
Pre-form
E
Blow-molded part
iv)
i)
F
Stretching
Pre-form
Blowing
Mold opening
Air in
B
C
D
iii)
ii)
Blow mold

Figure 2

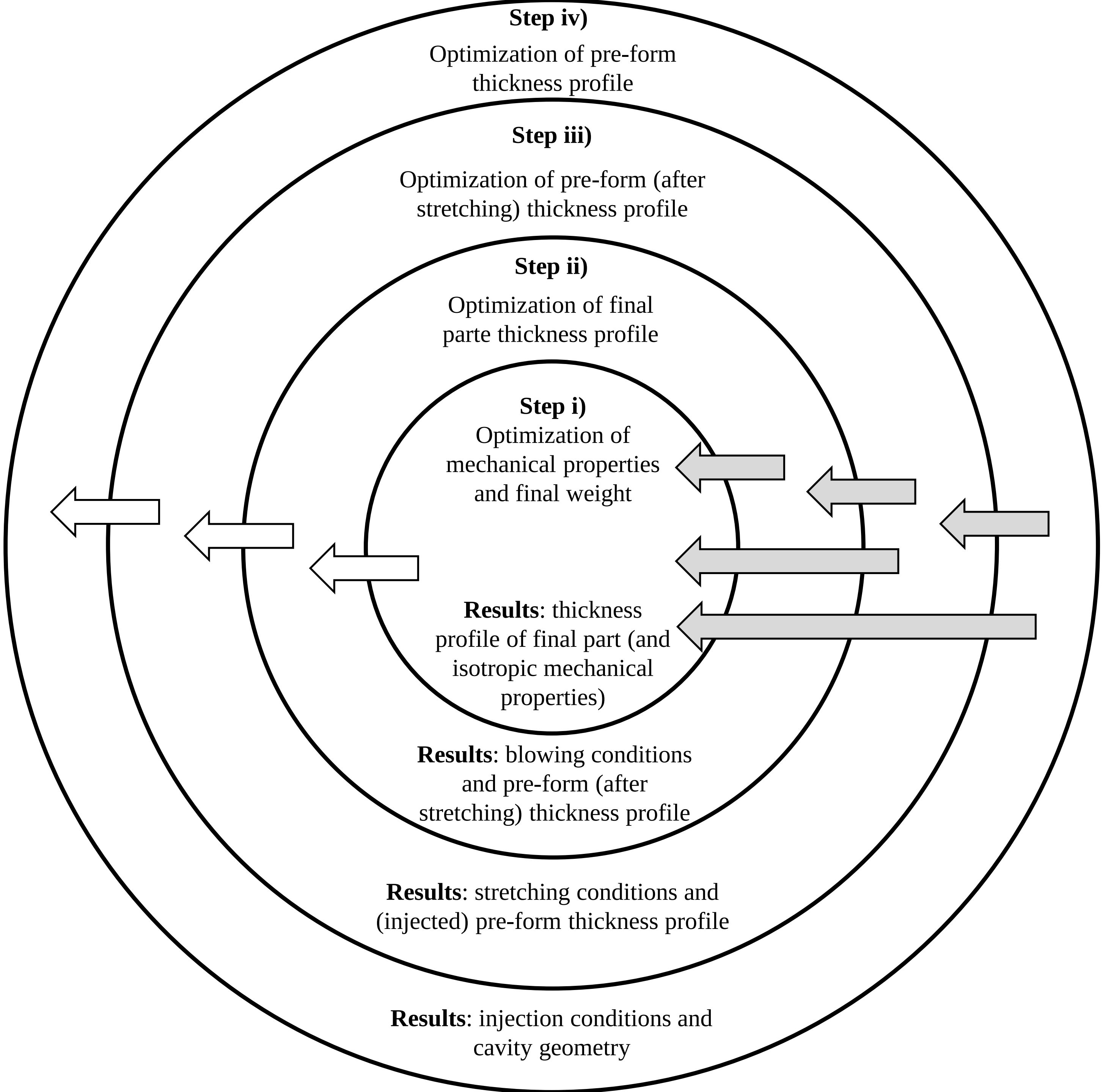
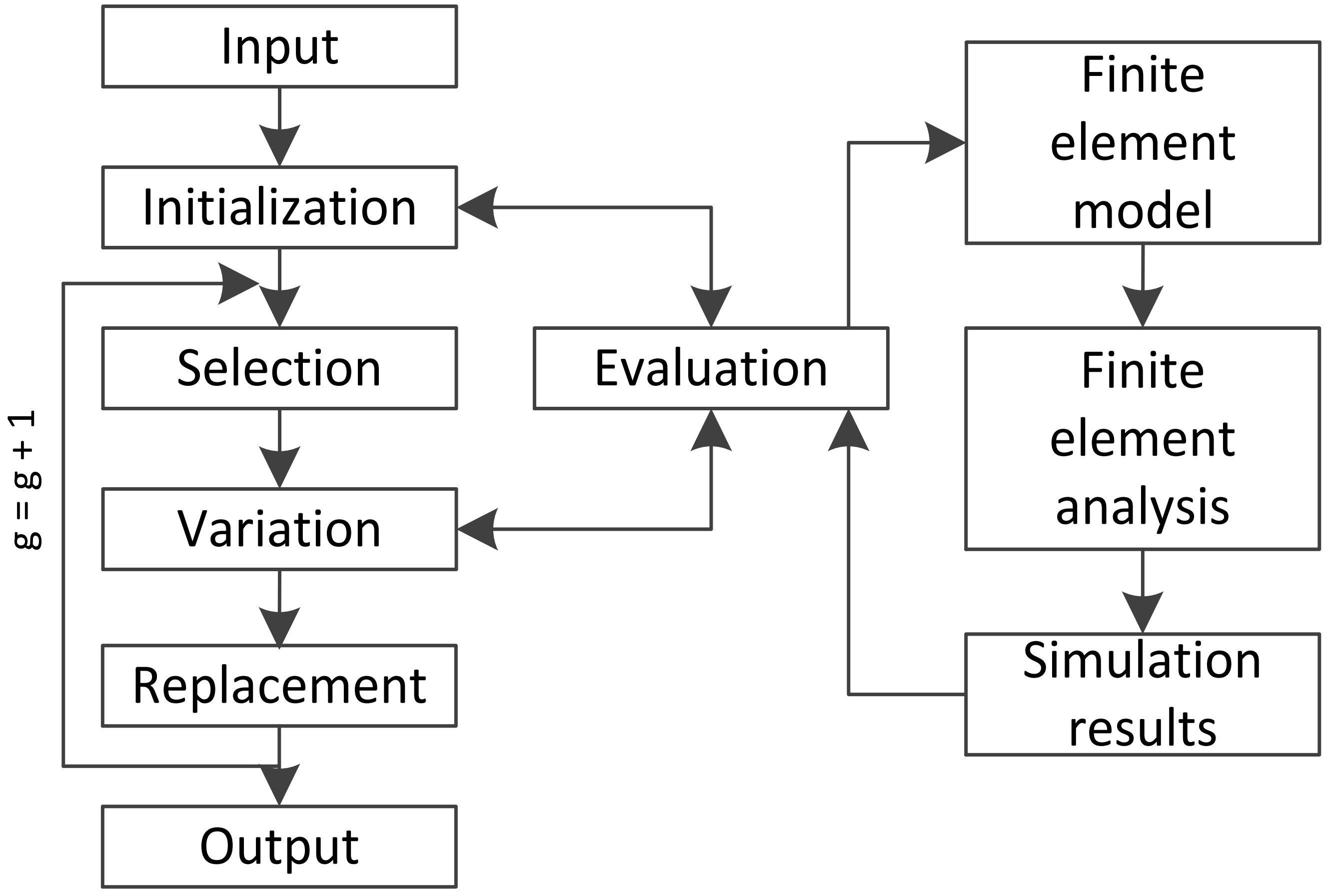
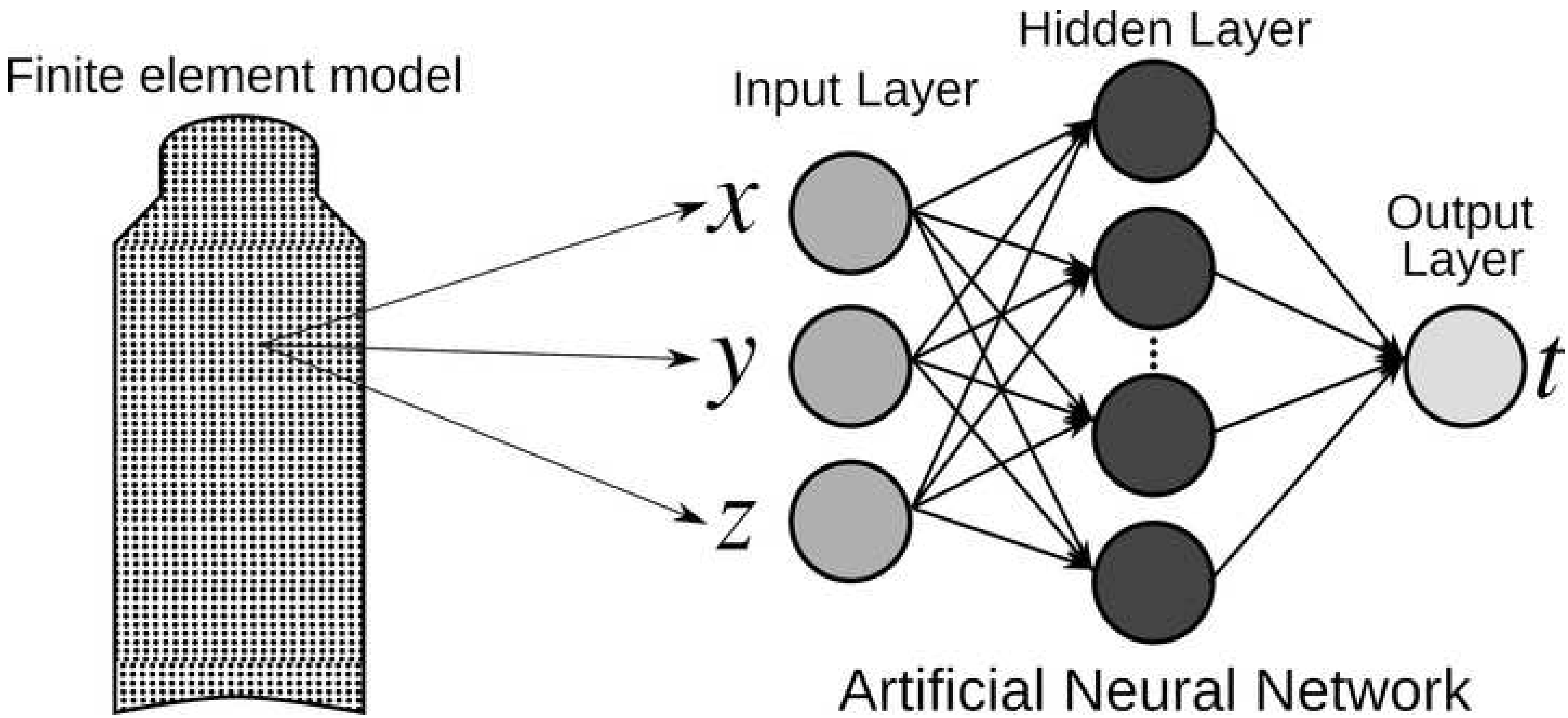

Step iv)
Optimization of pre-form thickness profile
Step iii)
Optimization of pre-form (after stretching) thickness profile
Step ii)
Optimization of final parte thickness profile
Step i)
Optimization of mechanical properties and final weight
Results: thickness profile of final part (and isotropic mechanical properties)
Results: blowing conditions and pre-form (after stretching) thickness profile
Results: stretching conditions and (injected) pre-form thickness profile
Results: injection conditions and cavity geometry

Figure 3



Input
Initialization
Selection
Variation
Replacement
Output
g = g + 1
Evaluation
Finite element model
Finite element analysis
Simulation results

Figure 4



Finite element model
Input Layer
Hidden Layer
Output Layer
x
y
z
t
Artificial Neural Network

Figure 5

Click here to access/download;Figure;Figure5.jpg

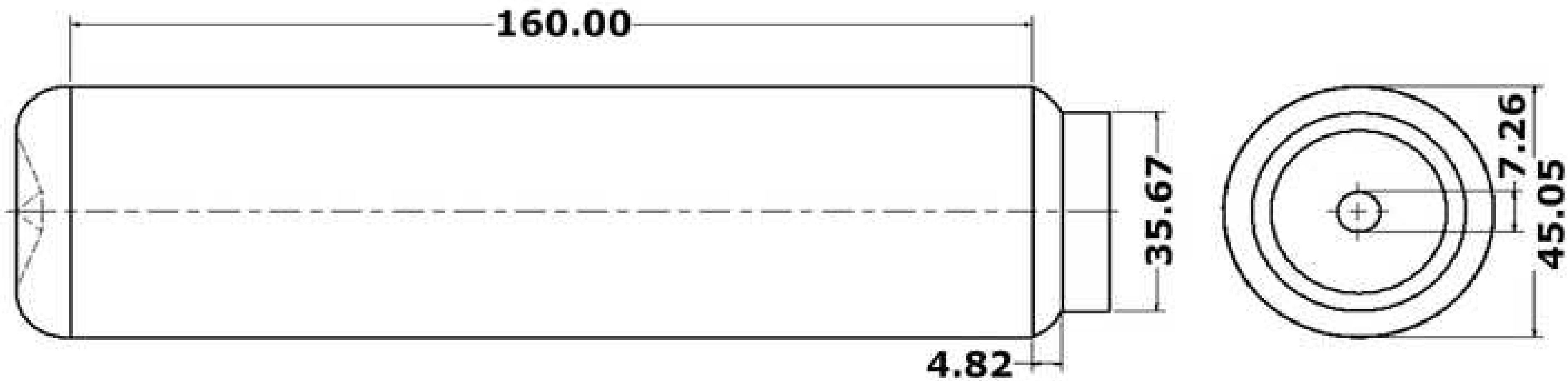


Figure 6

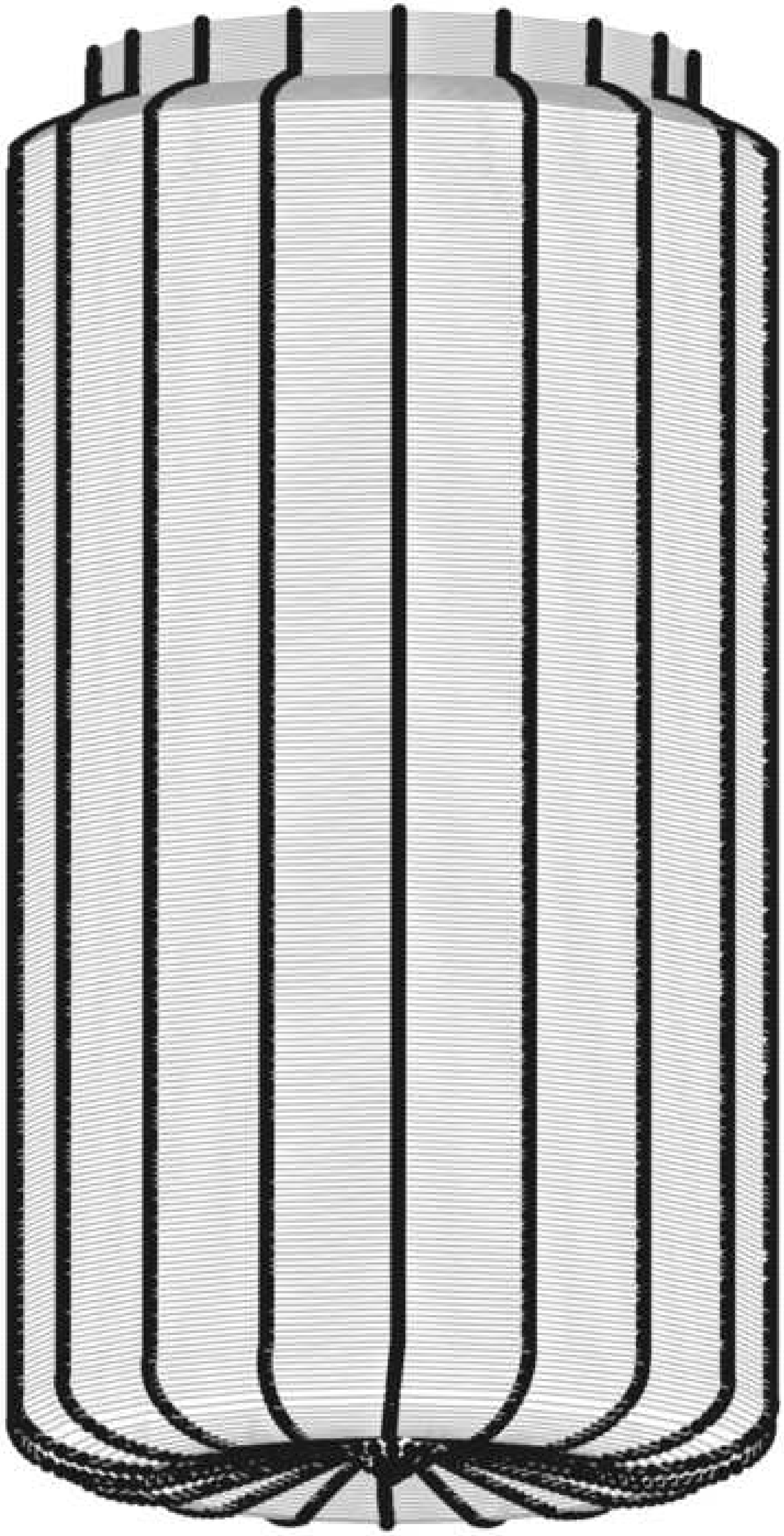


Figure 7

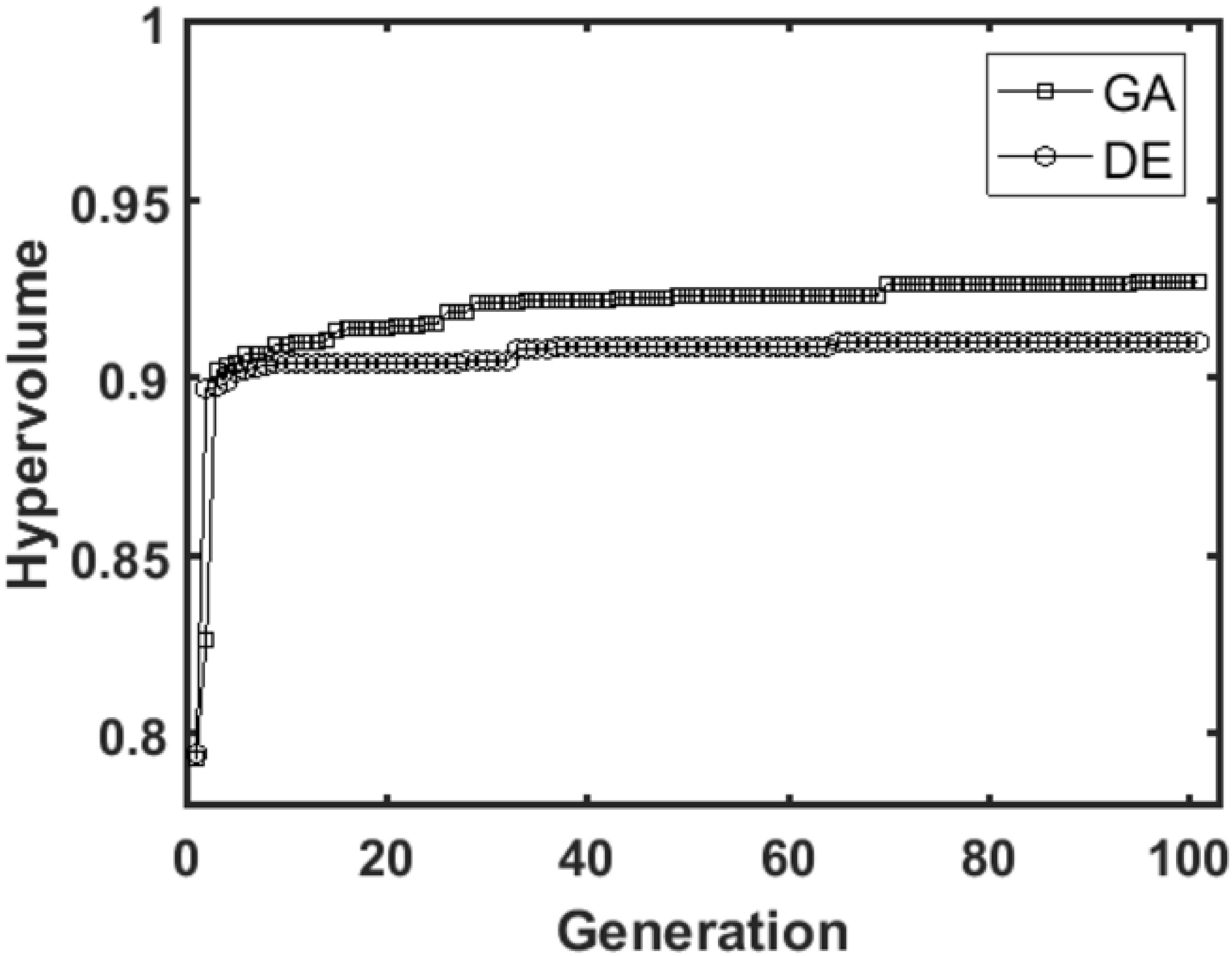


Figure 8

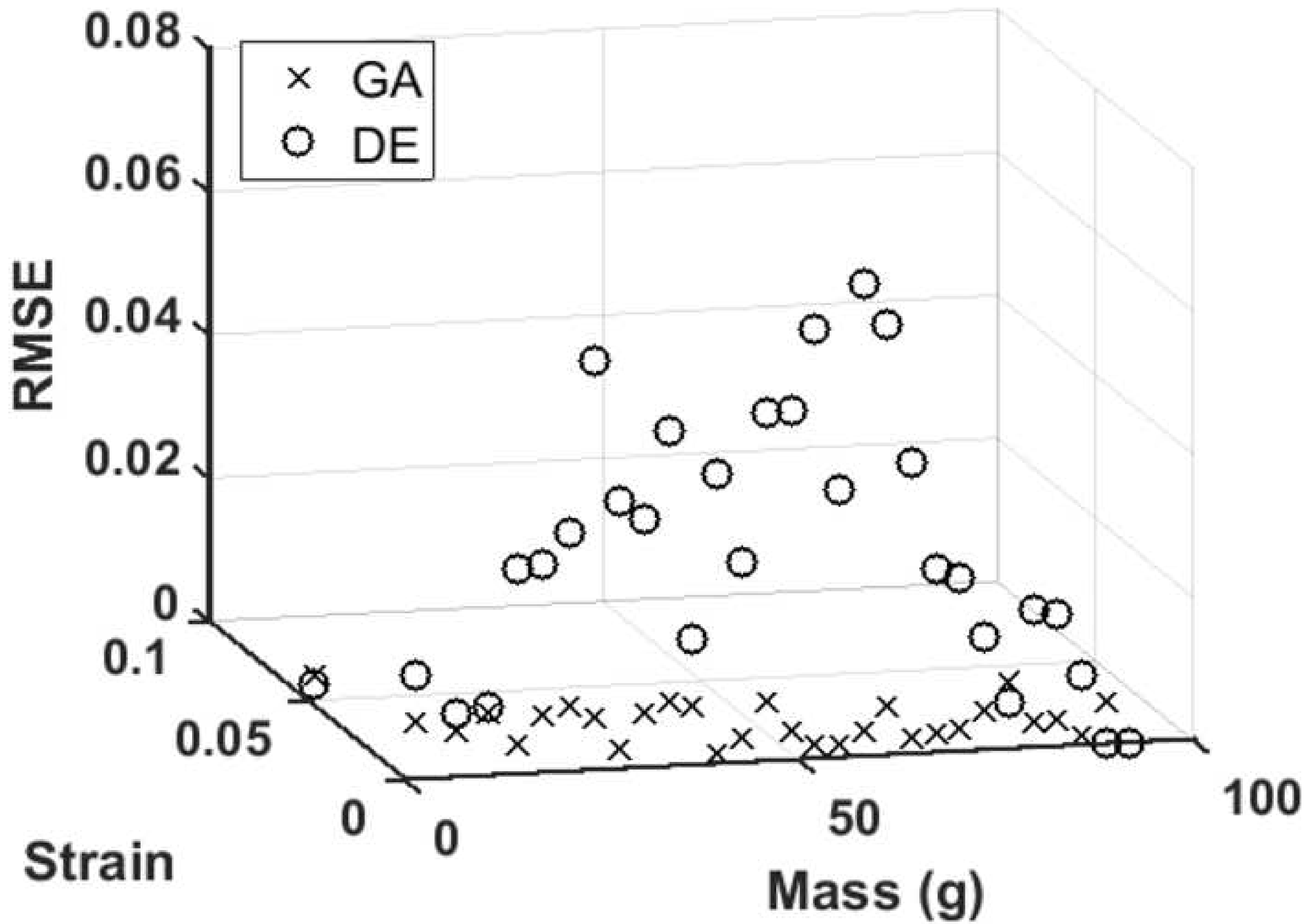
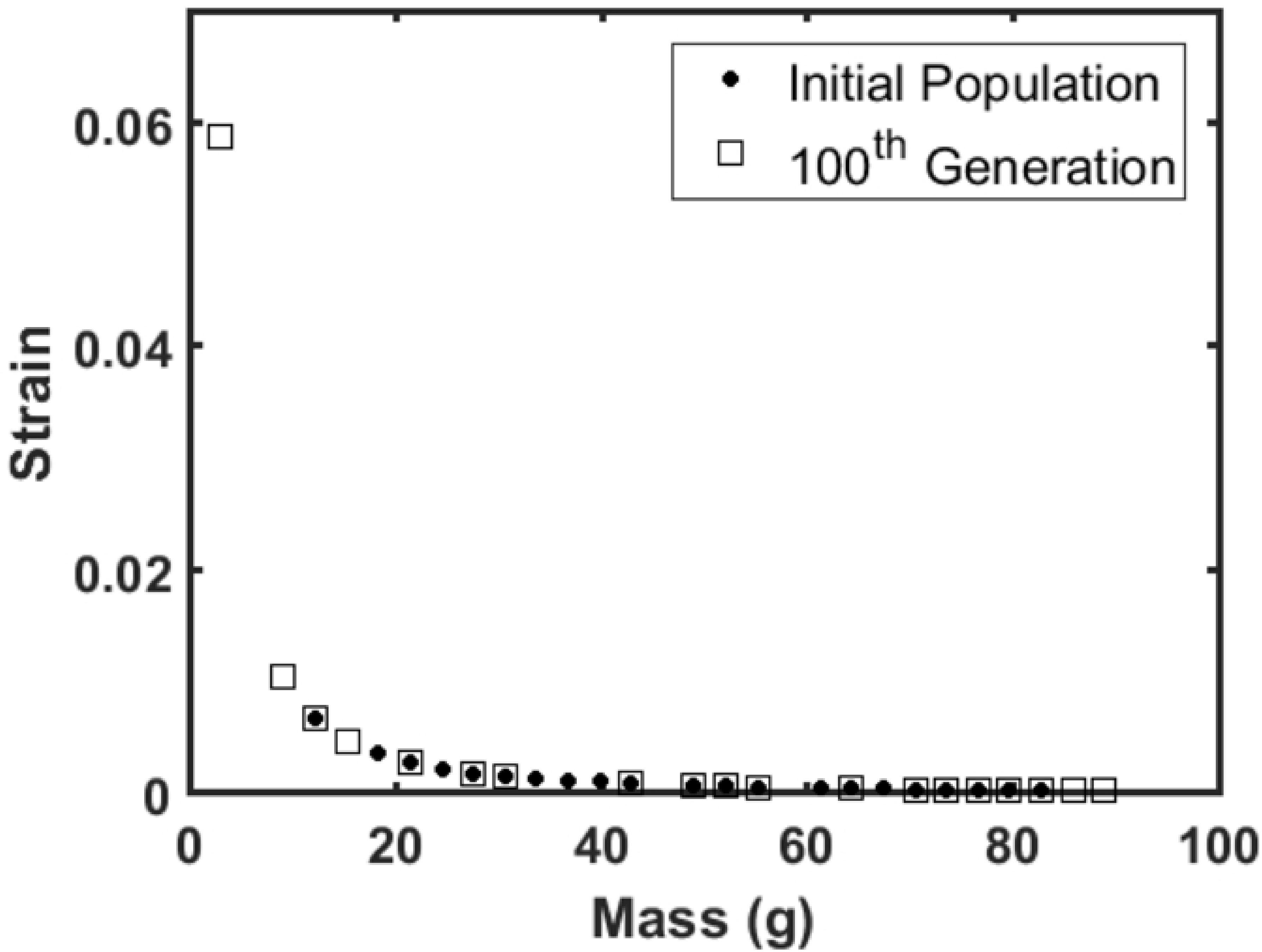


Figure 9



Initial Population
100th Generation
0.06
0.04
0.02
0
Strain
0
20
40
60
80
100
Mass (g)

Figure 10

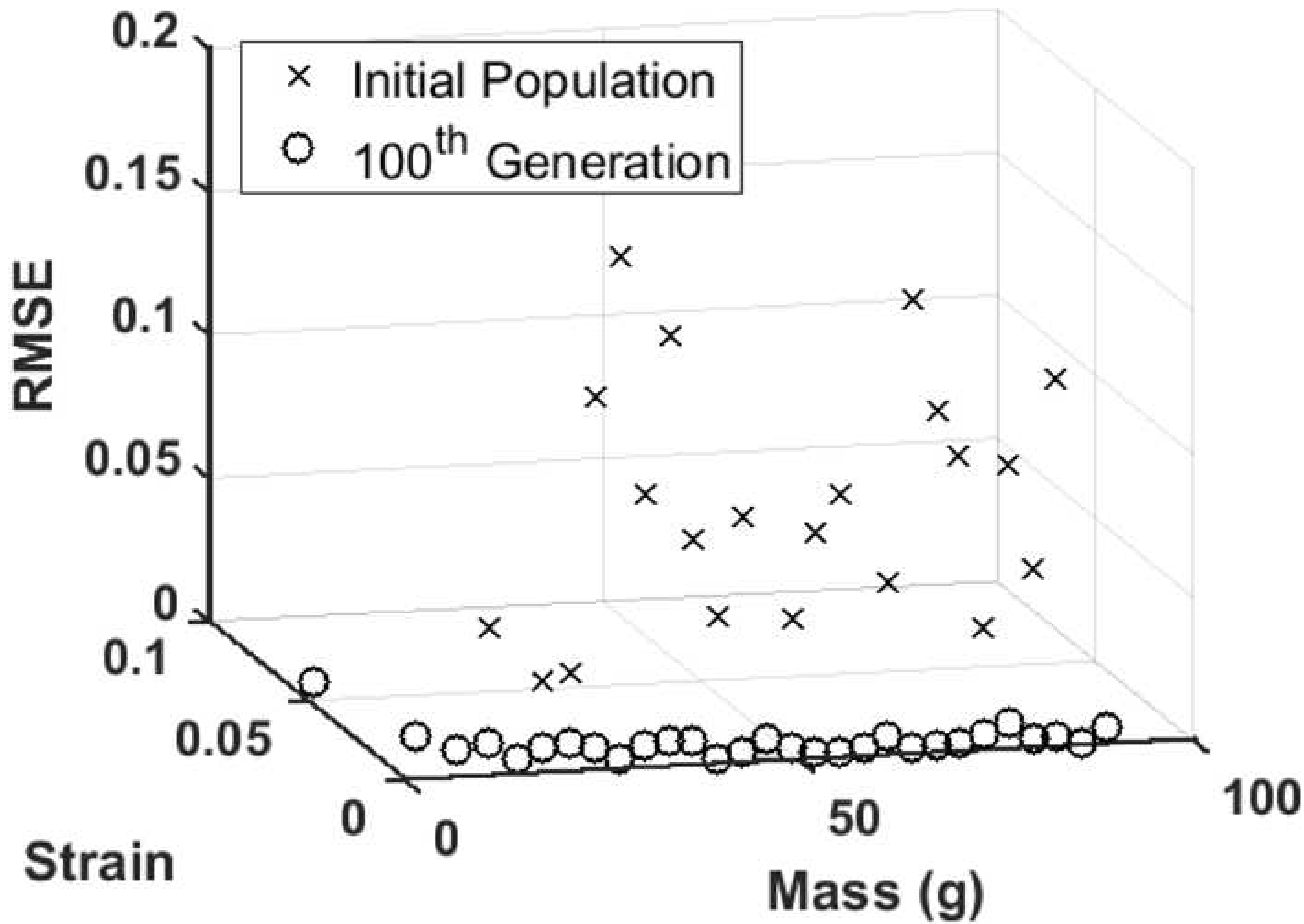

Initial Population
100th Generation
RMSE
0.2
0.15
0.1
0.05
0
0.1
0.05
0
Strain
0
50
100
Mass (g)

Figure 11

Click here to access/download;Figure;Figure11.jpg

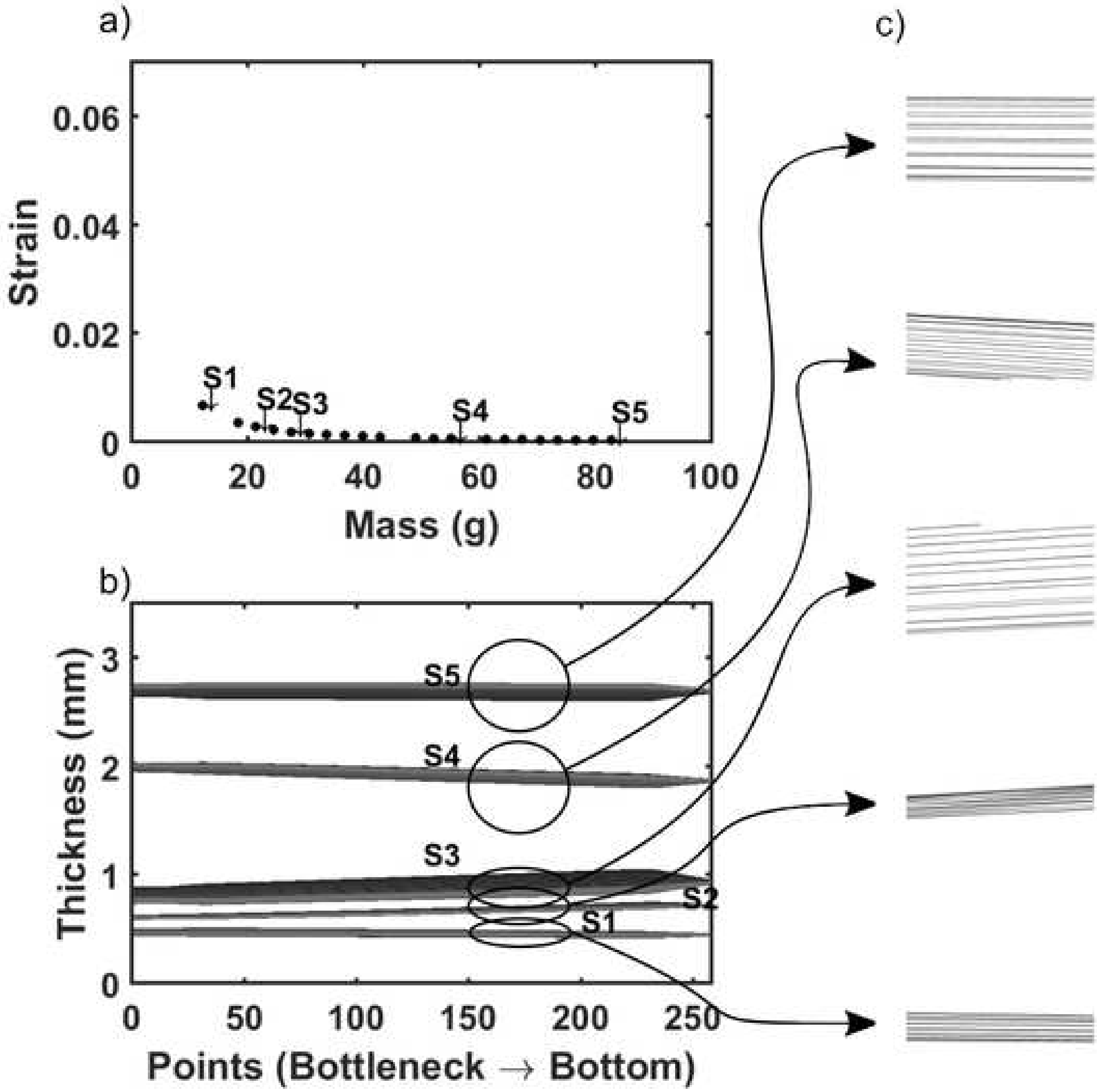


Figure 12

Click here to access/download;Figure;Figure12.jpg

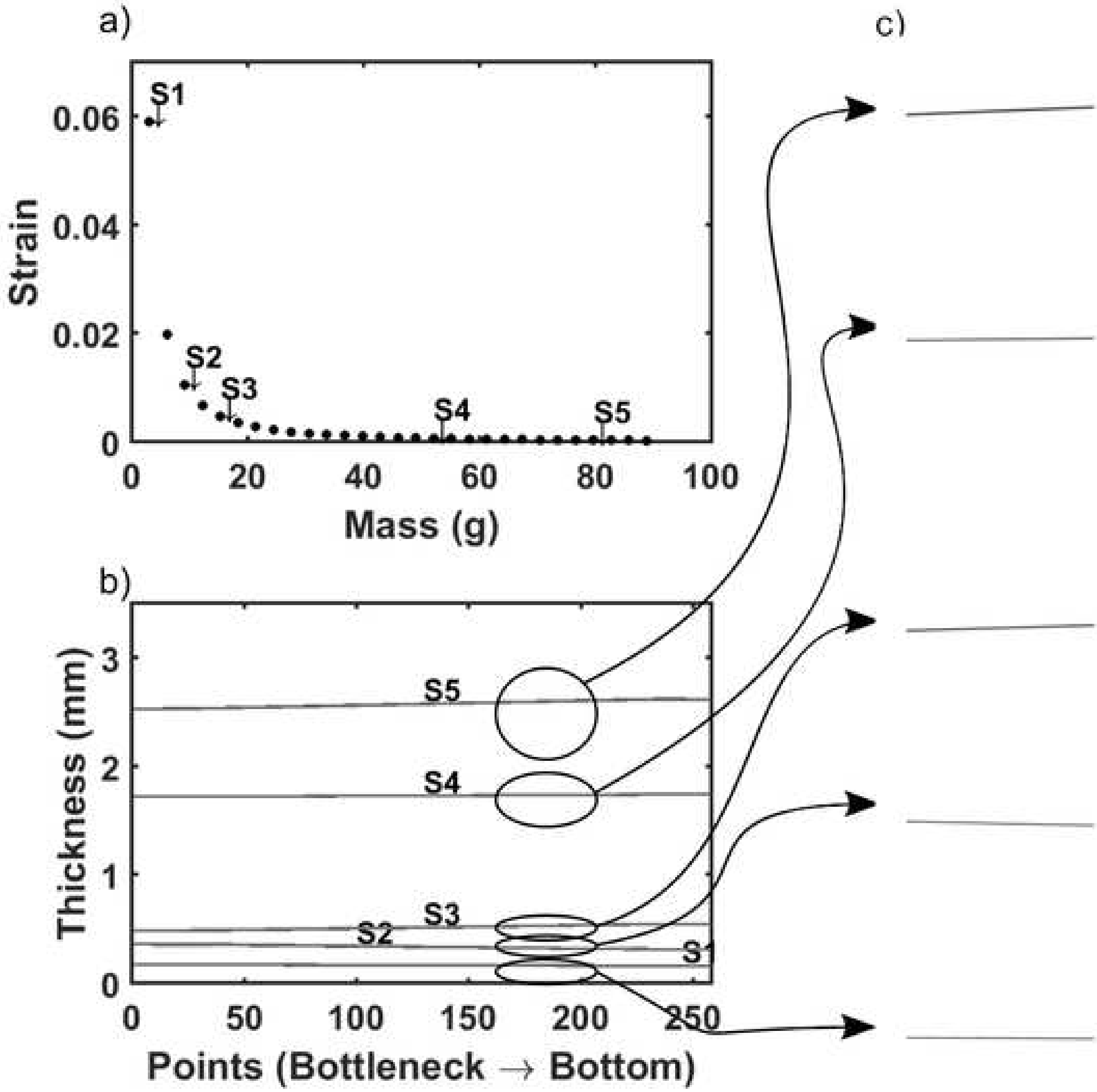
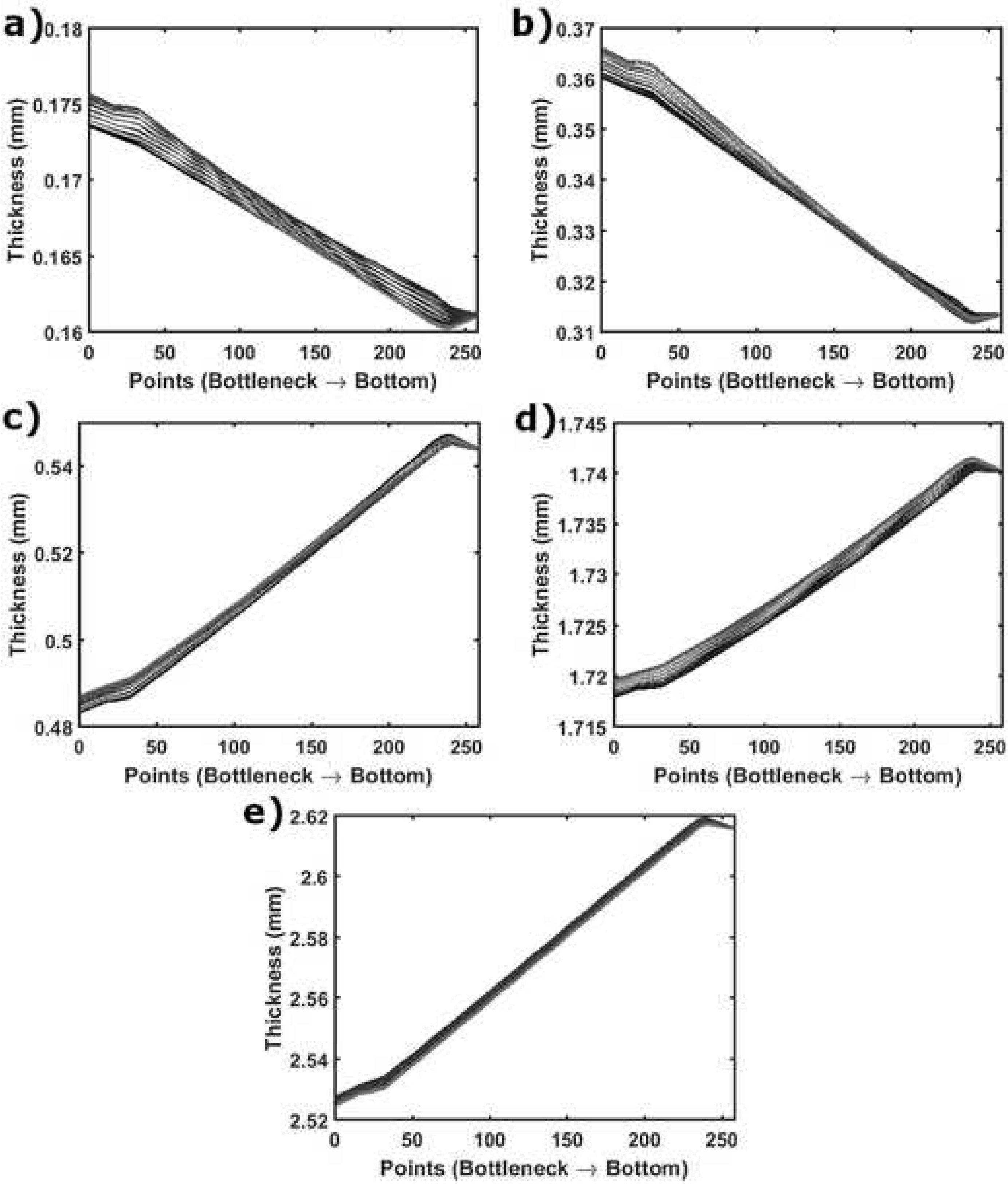


Figure 13


a)
0.18
0.175
0.17
0.165
0.16
Thickness (mm)
0 50 100 150 200 250
Points (Bottleneck → Bottom)
b)
0.37
0.36
0.35
0.34
0.33
0.32
0.31
Thickness (mm)
0 50 100 150 200 250
Points (Bottleneck → Bottom)
c)
0.54
0.52
0.5
0.48
Thickness (mm)
0 50 100 150 200 250
Points (Bottleneck → Bottom)
d)
1.745
1.74
1.735
1.73
1.725
1.72
1.715
Thickness (mm)
0 50 100 150 200 250
Points (Bottleneck → Bottom)
e)
2.62
2.6
2.58
2.56
2.54
2.52
Thickness (mm)
0 50 100 150 200 250
Points (Bottleneck → Bottom)