

TOPOLOGICAL OPTIMIZATION USING NEURONAL ALGORITHM

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ABSTRACT

Topological optimization is a type of structural optimization that provides conceptual design for lighter structures. The aim of this method is to maximize system performance for a given set of loads, boundary conditions, and constraints. This method is based on element analysis finished assembly. The design of a lightweight robot is a key point since the weight of the robot is directly proportional to the load capacity of the robot and its motor power. The structural design is iterated in a loop until function convergence achieves the objectives and the satisfying constraints.

KEYWORDS: topology optimization, robot, neuronal algorithm

1. Introduction

Nowadays 3D printing technology allows the manufacturing of complex volumes, imitating structures from nature [1, 2]. Topology optimization is a process in which the shape of a part is optimized based on specific design specifications, limited conditions, and loads, while the design remains structurally intact [4-6]. A practical approach to topology optimization is an analysis of finite elements to evaluate the performance of a shape, such as using an equivalent of von Mises stresses to determine the stresses on a shape. The next step, based on the analysis of the finite elements, is to execute or optimize the topology, to minimize the mass, and maximize the performance according to imposed conditions [7-12]. Topology optimization is very useful because it can build complex 2D or 3D shapes in a design space. However, it can give rise to problematic issues in the stage of manufacturing, such as the difficulties of manufacturing certain complex shapes which can be manufactured only using 3D printing technology. In 3D printing technology removing structural supports is an important issue. The resulting geometry for a typical topology optimization algorithm must be modified to match the capabilities of the manufacturing process [13, 14]. Additive manufacturing can be used to fabricate very complex geometries with a relatively small additional cost [15, 16]. Additive manufacturing is the most preferred process of manufacturing for shapes that have been designed through topology optimization. Topology optimization of a part for fabrication might produce

an organic shape that is inspired by nature. However, solutions offered by some commercial topology optimization software must be post-processed so that the limited object fits the manufacturing process without unnecessary stress concentrations [17-21]. An important aspect of topology optimization is the selection of the mesh size. A fine mesh will provide a design more detailed but takes longer to run due to finite element analysis. A coarse mesh may not have the most optimal shape. Therefore, the mesh size should be selected with attention to balance these two aspects. The knowledge of 3D modeling is essential to the design process. The starting geometry (design space) for the topology optimization step influences the solutions that are determined. Selecting a design space that is too small can eliminate some of the possible solutions. However, the larger the design space, the better the computational cost of the topology optimization step is higher. For assembly, it is necessary to take into consideration how the system will be assembled (i.e. is it a simple feasible project). For loads and material properties, it is necessary to consider how large a selected load will be supported by the material. In addition, since the system will be 3D printed, it must be taken into account the part shrinkage. Topological optimization algorithm requires important computational resources. One way might be to use neural network algorithms to diminish computing time.

In this research, we aim to propose a neuronal algorithm in order to complete a proof-of-concept. Obviously, commercially available software is ready to solve the topological approach. Our proposed proof-of-concept approach shows the importance and

reliability of neural networks the topological optimization tasks.

2. Experimental procedure

The motor support was simulated as a whole, with loads given in the simulation for the weight-only transport box (Figure 1). The loads on each component were automatically calculated by the program for simulating static loads – Inventor Nastran. Network discretization, as it is shown in Figure 1 is dense enough to correlate a similar calculation with the real situation. In Figure 2 the part has been discretized with a much finer mean size to observe the time difference necessary for processing. Both cases brought the convergence of the calculation and similar results. The time of processing between the two cases was 30 minutes on a computer with about 10,000 points in PC Benchmark. Now that the part is set up, an FEA can be run to see how loads affect the shape, for example, to determine von Mises stresses. The simulation problem considers the loading in the 3D modeled assembly of the robot components of some static and dynamic loads. The static loads refer to a load of 5 Kg and the load is considered to act uniformly in the storage space for food transport, insecticide, and disinfectant substances. Generally, less material will increase the stress. However, if there are no stress concentrators in the design region and the maximum stress is within

the safety factor, from the structural point of view, the part is feasible. If the stress exceeds the allowable stresses, the part must be modified until the stresses are within the acceptable range. The topology optimization results can be found below.

The neural network should learn from the training phase for 40 cases on different values of loading. The material considered in the simulation was PLA.

The procedural is considering several steps: 1. Firstly, 40 models with holes in the model at different dimensions are built manually and tested in Inventor Nastran for static loading. 2. The data for training is used to train the network. The input layer is consisting of 40 neurons representing the dimensions of the holes in the part and location. The output layer consists of 20 neurons representing the deformations in 20 points on the part. 3. resulted from each simulation. The testing data is represented by 10 scenarios with different loading forces. We used the Pytorch library to develop the neural network in the Spyder development environment. The network architecture considered 30 hidden layers. In order to test the result, Inventor Nastran was used and the performance factor is considered the mass reduction. The predictions outputted by the neural network show a 20% precision compared with the simulations in Inventor Nastran. Taking into account that few testing training data were used, the prediction might improve in case of using many testing.

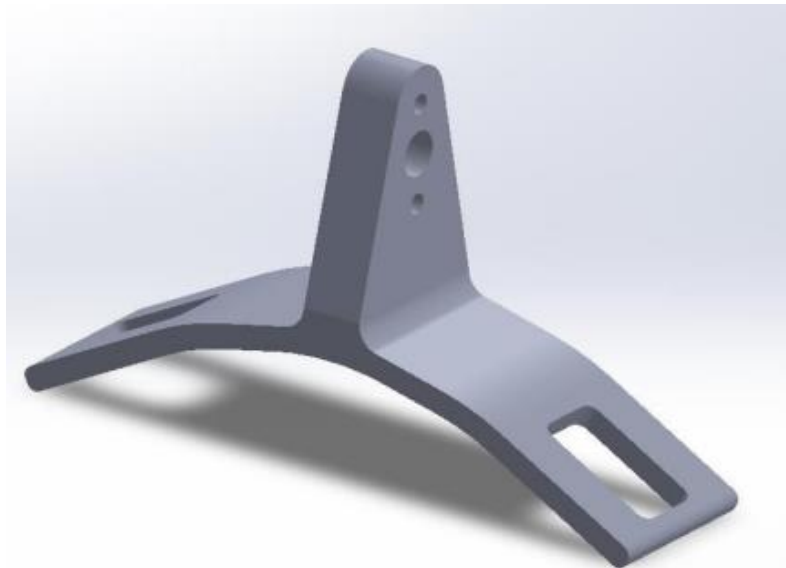


Fig. 1. Un-optimized part

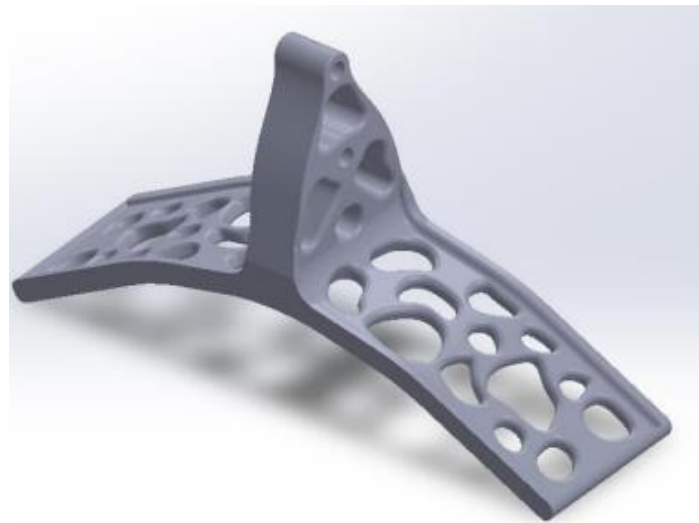


Fig. 2. Topologically optimised part

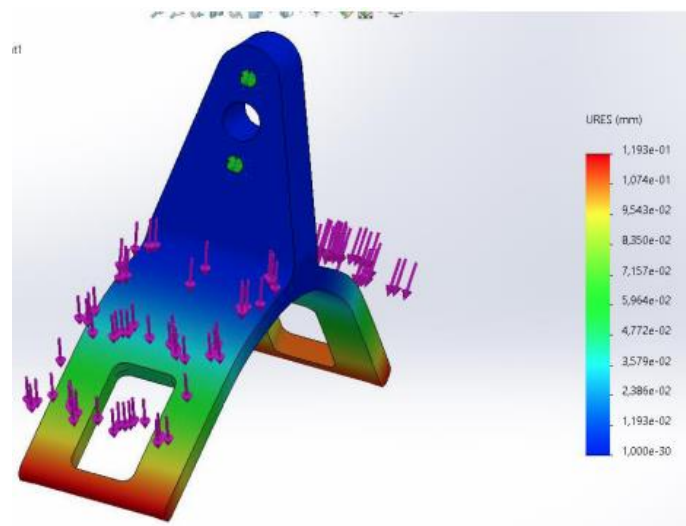


Fig. 3. Deformation distribution for the support part

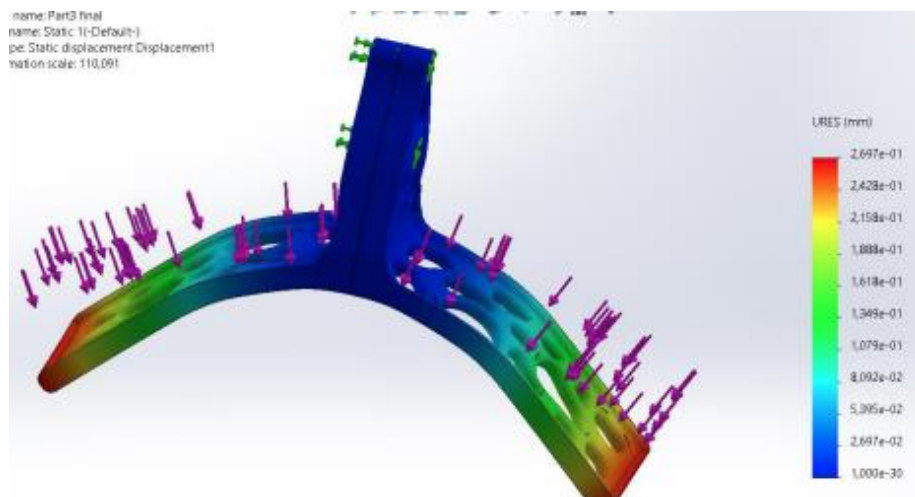


Fig. 4. Deformation of a topological optimized part

4. Conclusions

Topology optimization is a mathematical process that optimizes the appearance of a material based on specific design specifications, limited conditions, and loads while keeping the design structurally intact.

Topological optimization allows obtaining subassemblies that fulfil the conditions imposed but which require the use of a minimum amount of material.

3D modeling knowledge is required for the design process. The solutions that are determined are influenced by the starting geometry (design space) for the topology optimization step.

The deformation distribution shows that the part meets the conditions and can be considered for production.

Neural network algorithm provides promising results in topological optimization.

In this paper, the low precision of prediction outputted by the neural network is due to a small amount of training data.

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