Topology optimization using artificial intelligence

L'optimisation topologique en utilisant l'intelligence artificielle

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ABSTRACT. An analysis of topology optimization employing deep learning, namely Generative Adversarial Networks (GANs), and topology optimization utilizing the Solid Isotropic Material with Penalization (SIMP) method is presented in this research. We describe the theoretical foundations of GANs and the SIMP technique. A cantilever beam with predetermined boundary conditions was the topic of a static study to show the practical efficacy of these methods. The structural performance parameters, such as maximal directional displacement, maximal Von Mises stress, and deformation energy. The findings show that deep learning-based topology optimization, as demonstrated by TopologyGAN, provides considerable benefits in terms of improved design correctness and computing performance.

RÉSUMÉ. Cet article présente une analyse de l'optimisation topologique utilisant l'apprentissage profond, à savoir les réseaux adversariaux génératifs (GAN), et l'optimisation topologique utilisant la méthode SIMP (Solid Isotropic Material with Penalization). Nous décrivons les fondements théoriques des GAN et de la technique SIMP. Une poutre en porte-à-faux avec des conditions limites prédéterminées a fait l'objet d'une étude statique pour montrer l'efficacité pratique de ces méthodes. Les paramètres de performance structurelle, tels que le déplacement directionnel maximal, la contrainte maximale de Von Mises et l'énergie de déformation. Les résultats montrent que l'optimisation topologique basée sur l'apprentissage profond, telle que démontrée par TopologyGAN, offre des avantages considérables en termes d'amélioration de l'exactitude de la conception et de la performance informatique.

KEYWORDS. additive manufacturing, topology optimization, artificial intelligence, machine learning.

MOTS-CLÉS. Fabrication additive, optimisation topologique, intelligence artificielle, apprentissage machine.

1. Introduction

Topology Optimization (TO) is a crucial methodology in structural design, encompassing two main categories: size optimization and shape optimization. Its primary goal is to optimize the spatial distribution of materials, significantly enhancing design flexibility and providing a systematic framework for achieving high-performance and innovative structures [ZHA 94]. Topology optimization is used in a wide range of applications, including automotive, aerospace, and biomedical fields. Among the case studies of topology optimization, notable examples include the works of [ELJ 23], [ANT 22] and [LKA 24].

Bendsoe and Kikuchi [BEN 88] presented the homogenization approach in 1988, the first topology optimization technique. This technique has undergone development and exploration in several ways. In the study by [OUC 23], the effect of topology optimization (TO) parameters on the strength of the optimized structure was compared using four different topology optimization methods. Another study by [ANT 23] discussed the bending behavior of topologically optimized ABS mesostructures that were 3D printed using the FDM process. This research provides valuable insights into the mechanical properties of optimized structures produced through additive manufacturing.

Some of the derived approaches are Density-based techniques like the Level Set Method (LSM), the Rational Approximation of Material Properties (RAMP), and the Solid Isotropic Material with Penalization (SIMP). Additionally, evolutionary techniques have shown to be successful strategies for topology optimization. These include Evolutionary Structural Optimization (ESO), Bidirectional Evolutionary Structural Optimization (BESO). Feature-Driven Optimization (FDO), Morphable Mobile Voids (MMV) and Morphable Mobile Components (MMC) [OUC 22].

The complex structures obtained through topology optimization are manufactured using additive manufacturing (AM). AM, sometimes referred to as 3D printing (3DP), is the process of creating parts layer by layer employing a variety of methods, including deposition, melting, and adhesion of various material states, such as powder, liquid, or filamentc [STA 12]. The detailed exploration of additive manufacturing technologies and their benefits is thoroughly addressed in the works of [LKA 22] and [ELJ 23]. These papers provide comprehensive insights into the various techniques employed in additive manufacturing, as well as the numerous advantages these technologies offer. Several papers published in recent years have emphasized the advantages of artificial intelligence (AI) in additive manufacturing. AI is utilized to improve the overall effectiveness and caliber of the AM process by optimizing process parameters, designing supports, and dealing with manufacturing constraints [LAD 21] .

Artificial intelligence (AI) is the study and development of tools that enable machines to sense their environment and use intelligence and learning to make decisions and achieve goals [JIN 20]. AI is a broad field that includes machine learning (ML), deep learning (DL), reinforcement learning (RL), generative models (GM), and data processing methods.

A new trend is the merging of AI and topology optimization especially DL based on deep neural network (DNN). Three views can be used to generalize DNN-based approaches to TO: regression model-based and generative model-based approaches for learning data; direct design, sub-procedure substitution, post-processing, and reparameterization for DNN in TO; and the properties of the solved TO problem (stiffness problem, stress constraint problem, and nonlinear problem) [RUS 16]. Research on improving current topology optimization methods with machine learning and deep learning primarily aims at seven major goals: reducing the dimensionality of the design space, improving optimizers, facilitating generative design (design exploration), accelerating iterations, enabling non-iterative optimization, developing meta-models, and improving post-processing [SOS 19]. The numerous applications of ML approaches for improving TO can be categorized from several angles, including the form of input data, the ML loss function, the incorporation of physical information, and the various uses of learning algorithms [SHI 23].

In this paper, we present the formulation of the SIMP method and generative adversarial networks in Section 2. Additionally, we conduct a static analysis in section 3 to compare topology optimization using the SIMP method with that using deep learning. Finally, we discuss the static analysis results.

2. Material and methods

One of the most powerful algorithms in deep learning-based topology optimization is TopologyGAN, which is founded on conditional generative adversarial networks (cGANs). Instead of directly mapping boundary conditions to the resulting optimal forms, this algorithm utilizes information obtained from various physical fields computed on the original domain with the prescribed boundary conditions. This approach enables the network to learn more precise mappings [NIE 21].

Finite element analysis and the SIMP approach are integrated into the TopologyGAN network design, which is shown in Figure 1. The generator uses the ground truth (GT) output produced by the SIMP method to translate the initial physical fields f to the estimated optimum topology and volume fraction. The generator uses U-SE-ResNet, a downsampling–upsampling structure that combines a U-Net with the SE-ResNet module. PatchGAN is used by the discriminator, which is conditioned on more data. It picks up the ability to tell authentic structures from fakes.

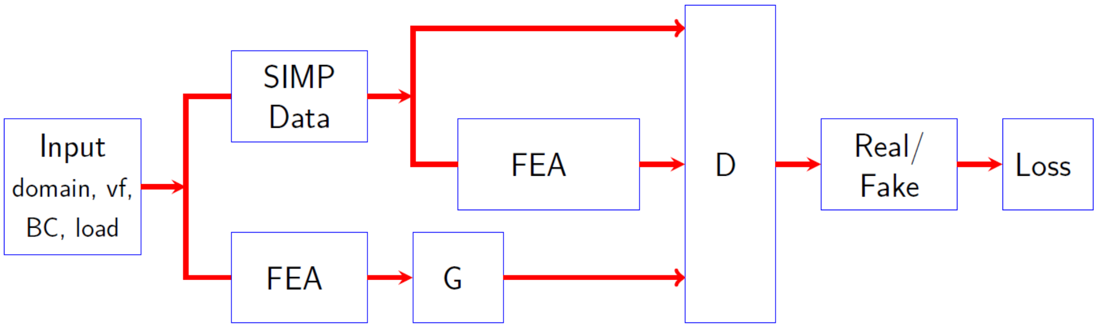

Figure 2. *Network Architecture of TopologyGAN*

The formulation of the SIMP method to optimize compliance is presented in Equation 1. Where Cy is the compliance, N is the total number of elements, K is the stiffness matrix, ue is the elemental displacement vector, ke is the elemental stiffness matrix, and y is the domain design. U and F are the displacement and force vectors.

$$\min_{y} Cy = U^T K U = \sum_{e=1}^{N} y_e^p u_e^T k_e u_e$$
$$s.t.$$
$$: \frac{Vy}{V_0} = VF$$
$$: KU = F$$
$$: 0 \leq y_e \leq 1$$

[1]

The GAN formulation [GOO 14] is used to calculate the loss functions of discriminator and the generator L_D^{GAN} and L_G^{GAN}. This formulation is described in equation 2.

$$\mathcal{L}_{G,D}^{cGAN} = \mathrm{E}_{(x,y)\backsim pdata(x,y)} [\log D(x,y)] + \mathrm{E}_{x\backsim pdata(x),z\backsim pz(z)} [\log(1 - D(x, G(x,z)))]$$
$$\mathcal{L}_{G,D}^{cGAN} = \mathrm{E}_{x,y,z}[\|y - G(x,z)\|_1]$$
$$G^* = \arg\min\max \mathcal{L}_{G,D}^{cGAN} + \lambda\mathcal{L}_{L1}(G)$$

[2]

where $G^*$is the optimized design, G is random noise z sampled from a distribution $p_z(z)$, G the generator and D the discriminator, y_r is the real sample, y_g the fake sample. To demonstrate the effectiveness of the topology optimization with AI, we conducted a static analysis on the cantilever beam showen in figure 2. The structure, measuring 120x60 mm, is fixed at point A and supports forces $Fx = 0.5\ N$ and $Fy = 0.87\ N$. With an element size of 1 mm, this results in a total of 7200 elements. The topology optimization parameters include a volume fraction vf=0.4 and a penalization factor p=3.

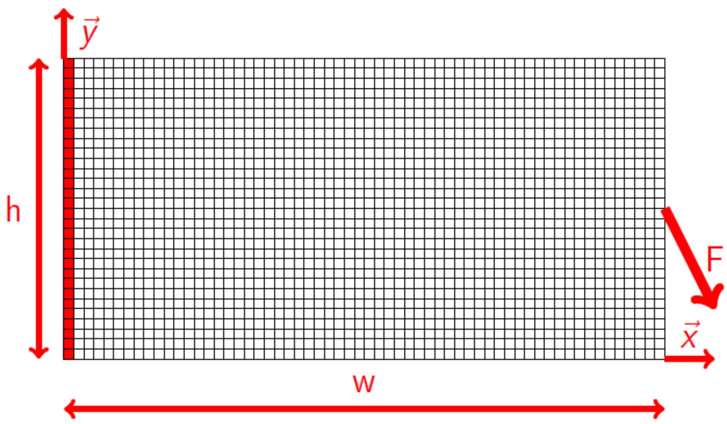

Figure 2. *Cantilever beam model*

3. Results and discussion

The optimal shape after 33 iterations is presented in Figure 3. The computation time for this result was 54 seconds using an ASUS computer Intel(R) Core(TM) i7-8565U CPU @ 1.80GHz 1.99 GHz RAM 16,0 Go. Table 1 presents the maximal Von Mises stress, the maximal directional displacement in the Y direction, and the deformation energy.

Design	Maximal Von Mises stress (MPa)	Maximal displacement in Y (10^{-5} mm)	Deformation energy (10^{-7} mJ)
Original	0.138	5.046	1.58
SIMP	0.297	9.09	5.17
TopologyGAN	0.809	51.097	41.79

Table 1. *Static analysis results*

The results of topology optimization using the SIMP method and TopologyGAN (Nie et al., 2021) are presented in Figure 3.

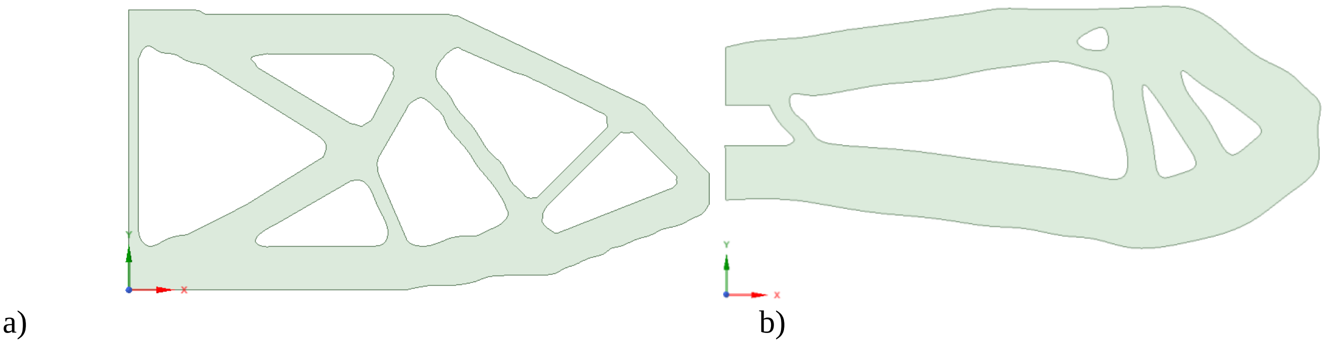

Figure 3. *Optimal model of cantilever beam, (a) SIMP result, (b) TopologyGAN result*

First the comparison of SIMP results with the original design, the structure's weight is reduced by 40%, but the maximal stress increases by 2.15 times, the maximal displacement by 1.8 times, and the deformation energy by 3.27 times.

Second the comparison of TopologyGAN results with the original design, the structure's weight is reduced by 46%, but the maximal stress increases by 5.86 times, the maximal displacement by 10.12 times, and the deformation energy 26.45 times.

Finally, the comparison of TopologyGAN results with the SIMP results, the maximal stress increases by 2.72 times, the maximal displacement by 5.62 times, and the deformation energy 8.08 times.

4. Conclusion

In this work, we evaluated the topology optimization performance of a deep learning-based methodology, namely TopologyGAN, with that of the conventional SIMP method. Our results show that the SIMP approach leads to increased peak stress, displacement, and deformation energy, even if it significantly reduces structural weight by 40%. On the other hand, TopologyGAN shows promise in yielding optimal designs with enhanced accuracy and computational economy. Using AI methods to enhance topology optimization frameworks offers a viable path toward creating structure designs that are both creative and high-performing. Subsequent research ought to concentrate on improving these AI-based techniques even more and investigating how they might be used to solve a wider variety of engineerings issus.

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