The 2021 World Congress on
Advances in Structural Engineering and Mechanics (ASEM21)
GECE, Seoul, Korea, August 23-26, 2021

Machine Learning-based Topology Optimization: A Review

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ABSTRACT

Topology Optimization determines the optimal material layout within a given design space under certain constraints on load and boundaries. Since topology optimization was introduced, various optimization methodologies have been studied. However, these conventional topology optimization methods are time consuming and requires large computing cost. Recently, a lot of research applied various machine learning techniques to topology optimization to effectively optimize initial design by improving optimization algorithms and reducing computational costs. These studies utilized various types of machine learning methods as an approach to topology optimization for various purposes. The goal of this research is to review previous studies of machine learning-based topology optimization based on the methods and purpose of applying machine learning.

1. INTRODUCTION

Topology optimization is a method for determining optimal material distribution within a given design space under certain constraints on load and boundaries. This allows the optimal distribution of materials with desired properties to be determined, while meeting the design constraints of the structure. Topology optimization is meaningful in that, unlike conventional optimization approaches, it can be designed without initial design and parametrized design variables. Therefore, various topology optimization methodologies have been studied until now. However, while these conventional topology optimizations have the advantage of conceptual design, computational cost is large because they are mostly based on finite element and have many design variables and iterations to derive optimal solutions. To solve the shortcomings of these conventional topology optimization methodologies, recent studies on topology optimization have been

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actively conducted by applying machine learning techniques as an approach to optimize the initial topology quickly and effectively. Since machine learning-based topology optimization complement the problems of conventional topology optimization, which requires high computational cost caused by thousands of design iterations, many recent studies have been conducted to improve topology optimization algorithms and reduce computational costs by using machine learning. This paper reviews various machine learning-based topology optimization studies currently developed and seeks to analyze features of the studies, based on the purpose of applying machine learning to topology optimization, and the machine learning methodology used.

2. PURPOSE OF MACHINE LEARNING-BASED TOPOLOGY OPTIMIZATION

The objectives of machine learning-based topology optimization can be divided into five categories: acceleration of topology optimization process, non-iterative topology optimization, performance prediction through Finite Element Analysis (FEA) meta-modeling, generative design, and post-processing of topology optimization.

2.1 Acceleration of optimization

There are studies that apply machine learning methods to accelerate the topology optimization process. For acceleration purposes, like Sosnovik (2019), most of the studies predict the final optimized image using the density gradient between iterations, which is obtained by processing topology optimization until a certain number of iterations, instead of processing it all the way.

2.2 Non-iterative optimization

Non-iterative topology optimization studies derive optimal topologies instantly without any iterations, by inputting design conditions such as load and boundary conditions. However, non-iterative optimization may lead to optimization results with poor performance or low-resolution images than the iterative optimization. Therefore, these studies propose non-iterative optimization integrated with additional process to obtain good optimal topology. For example, Yu (2019) upscaled the low-resolution images generated by non-iterative optimization into high-resolution, Zhang (2019) uses FEA information as additional input for the process of non-iterative optimization, and some studies evaluated the performance of the generated topology from the non-iterative process.

2.3 FEA meta-modeling

To obtain a high-resolution optimal topology from the conventional mesh-based topology optimization, FEA is time-consuming. Therefore, there are studies that replace FEA by evaluating objective function or predicting sensitivity through machine learning to accelerate the optimization process. For example, Lee (2020) aims to accelerate optimization by replacing FEA and evaluating objective function with convolutional neural network. The image is inserted as input to predict compliance and volume fraction information, which allows it to proceed directly to Optimality Criteria methods without going through FEA.

2.4 Generative design

There are also studies that generate diverse topology optimized designs using machine learning. Most of the studies used variety of generative adversarial network (GAN) for generative design, like Oh (2019) that used boundary equilibrium GAN (BEGAN) to generate various wheels. As such, different types of GAN can create various topologies. This is also extended to 3D generative design problem, Yoo (2021). Other than that, there are studies that used reinforcement learning and autoencoder to generate topologies with good performance.

2.5 Post-processing

The purpose of the studies that post-process the generated optimal image using machine learning can be divided into two. The first is that the generated optimal topology often has an optimization result with gray scale and does not have a clear boundary. To address this, there are studies suggesting structural boundary processing methods using machine learning to clearly distinguish the boundaries of an optimized image. Secondly, compared to low-resolution images, obtaining high-resolution optimal topologies requires a large computational cost. If high resolution images can be predicted from low resolution structures, a large amount of computational costs can be reduced. For this purpose, studies like Napier (2020) upscales the generated optimal image into high-resolution.

3. MACHINE LEARNING METHODOLOGY

This section will analyze the types of machine learning applied to topology optimization. The machine learning methodology used in machine learning-based topology optimization can be divided into supervised learning, unsupervised learning, and reinforcement learning.

3.1 Supervised Learning

In supervised learning, convolution neural network (CNN) and deep neural network (DNN) are most commonly used. In addition, various methodologies such as support vector machine (SVM), support vector regression (SVR), and K-nearest neighbors (KNN) are also applied for some studies.

The method using CNN and DNN can be classified into two types: a method that predicts the performance of topology to evaluate or to replace the time-consuming FEA in the optimization process, and a method that predicts the optimal shape. SVM is mainly used for post-processing of optimized results like Chu (2016) and Strömberg (2020).

3.2 Unsupervised Learning

For unsupervised learning, studies that applied different types of GAN and autoencoder are representative, and K-means clustering and Deep Belief Network (DBN) are also used for some studies.

Due to the characteristics of being able to generate various shapes and relatively easy to insert performance information of the structures into the training process, different types of GAN are being used as the most diverse method in the field of unsupervised machine learning for topology optimization. First, GAN is used to generate diverse topology for a given design condition. Second, some generates optimal topology by inputting structural information as a condition value of conditional GAN. Lastly, some studies upscale the low-resolution image generated by GAN to get a high-resolution result.

3.3 Reinforcement Learning

Reinforcement learning is also used for topology optimization in few studies. The studies that uses reinforcement learning for topology optimization aims to generate diverse optimal topology effectively. These studies used methods such as Q-learning, ε-greedy policy, and Proximal Policy Optimization (PPO) to generate topologies. For instance, Jang (2020) proposed a generative design process based on reinforcement learning to maximize design diversity, and Sun (2020) generated various design options by simply varying few parameters.

4. CONCLUSIONS

To supplement the problems of existing topology optimization methodologies, there have been many recent studies on machine learning-based topology optimization, and various machine learning techniques have been applied to effectively derive optimized topologies. Each study utilized various types of machine learning methods, including supervised, unsupervised, and reinforcement learning, to apply to topology optimization for purposes such as acceleration, non-iterative, FEA meta-modeling, generative design, and post-processing. Through this, we looked at studies that speeds up the topology optimization process and reduces computational costs.

There are various studies in this field, but there are still many non-generalizable studies that cannot be applied to other design problems or new objective functions. Especially, there are many studies that have limitations on 3D expansion. Since 3D topology optimization requires high computational costs, it is important to reduce computational costs and accelerate the topology optimization process through machine learning methods. Therefore, we expect effective machine learning-based topology optimization studies that can be applied to 3D topology optimization to be conducted in the future.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grants funded by the Korean government [grant numbers 2017R1C1B2005266, 2018R1A5A7025409].

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