

Diffusion Models Beat GANs on Topology Optimization

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Abstract

Structural topology optimization, which aims to find the optimal physical structure that maximizes mechanical performance, is vital in engineering design applications in aerospace, mechanical, and civil engineering. Recently, generative adversarial networks (GANs) have emerged as a popular alternative to traditional iterative topology optimization methods. However, GANs can be challenging to train, have limited generalizability, and often neglect important performance objectives such as mechanical compliance and manufacturability. To address these issues, we propose a new architecture called TopoDiff that uses conditional diffusion models to perform performance-aware and manufacturability-aware topology optimization. Our method introduces a surrogate model-based guidance strategy that actively favors structures with low compliance and good manufacturability. Compared to a state-of-the-art conditional GAN, our approach reduces the average error on physical performance by a factor of eight and produces eleven times fewer infeasible samples. Our work demonstrates the potential of using diffusion models in topology optimization and suggests a general framework for solving engineering optimization problems using external performance with constraint-aware guidance. We provide access to our data, code, and trained models at the following link: <https://decode.mit.edu/projects/topodiff/>.

1 Introduction

Structural topology optimization (TO) of solid structures involves generating the optimal shape of a material by minimizing an objective function, for instance, mechanical compliance, within a given domain and under a given set of constraints (volume fraction, boundary conditions, and loads). TO is therefore becoming an essential design tool and is now included in most professional design software, such as Autodesk’s Fusion 360 and Solidworks. It is the driving force behind Autodesk’s generative design toolset, where designers input design goals into the software, along with parameters such as performance or spatial requirements, materials, manufacturing methods, and cost constraints. The software quickly generates design alternatives. Most methods to solve TO rely on gradient-based approaches, the most common method being the Solid Isotropic Material with Penalization method (Bendsøe and Kikuchi 1988; Rozvany, Zhou,

and Birker 1992). Despite their wide adoption, these traditional methods have two major pitfalls: their iterative nature makes them computationally expensive and they may generate non-optimal designs, for example, when penalization and filtering augmentations are used to avoid grayscale pixels in SIMP (Sigmund and Maute 2013).

Several deep learning methods have been developed in recent years to improve and speed up the TO process (Yu et al. 2018; Sharpe and Seepersad 2019; Nie et al. 2021; Behzadi and Ilieş 2021) by learning from large datasets of optimized structures. The latest and most promising results were obtained with deep generative models (DGMs) and notably with conditional generative adversarial networks (cGANs) trained for image synthesis, which take as input the boundary conditions and directly generate images of optimized structures. Although popular, most of these models optimize a loss function that does not align with the primary goals of topology optimization — getting high-performance and feasible structures. They often train for loss functions related to image reconstruction to achieve visual similarity and ignore modeling the physical performance of the generated structures. Most of them produce disconnected, floating material that seriously affects the manufacturability of the generated design. They also suffer from limited generalizability, especially for out-of-distribution boundary conditions.

We hypothesize that the absence of explicit methods to generate designs with low compliance and good manufacturability causes these issues. We further hypothesize that the reliance of the optimization objective on the sole cGAN prompts the model to only mimic pixel-wise the ground truth produced by traditional TO methods. As a result, two images with comparable pixel-wise similarity may still have significantly different performance values. The absence of explicit external guidance is even more problematic since the ground truth data is not guaranteed to be optimal, as explained above.

This paper introduces TopoDiff, a conditional diffusion-model-based method for TO. Dhariwal and Nichol (2021) have shown that diffusion models can outperform GANs for image generation, are easier to train, and are thus more readily adaptable to other tasks. We show that by introducing performance and constraints to diffusion models, they also outperform GANs on topology optimization problems. In addition, the sequential nature of diffusion models makes

them compatible with external guidance strategies that assist with performance and feasibility goals. By creating surrogate models to estimate performance, we thus introduce external guidance strategies to minimize mechanical compliance and improve manufacturability in diffusion models.

Our main contributions include proposing: (1) TopoDiff — a diffusion model based end-to-end Topology Optimization framework that achieves an eight-times reduction in average physical performance errors and an eleven-times reduction in infeasibility compared to a state-of-art conditional GAN, (2) a new guidance strategy for diffusion models to perform physical performance optimization with enhanced manufacturability constraint satisfaction, and (3) a generalized framework to solve inverse problems in engineering using diffusion models, when sample feasibility and performance are a high priority.

2 Background and Related Work

2.1 Topology Optimization

Structural Topology Optimization (TO) finds an optimal subset of material Ω_{opt} included in the full design domain Ω under a set of displacement boundary conditions and loads applied on the nodes of the domain and a volume fraction condition. A structure is optimal when it minimizes an objective function, such as mechanical compliance, subject to constraints. Fig. 1 summarizes the principle of TO.

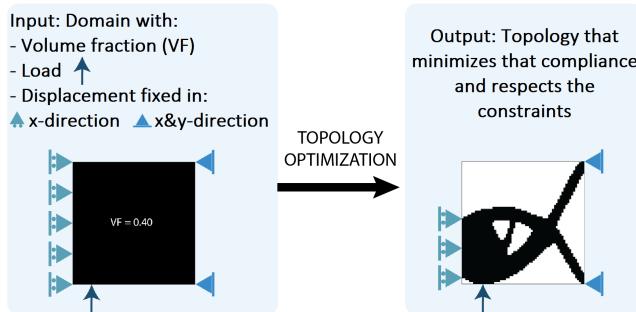


Figure 1: Topology Optimization aims to find the optimal structure that minimizes objectives such as compliance for a given set of load, boundary conditions, and volume fraction.

Traditional TO methods rely on Finite Elements Analysis (FEA) using gradient-based (Bendsøe and Kikuchi 1988) or gradient-free methods (Ahmed, Bhattacharya, and Deb 2013). One popular gradient-based method is the Solid Isotropic Material with Penalization (SIMP) method (Rozvany, Zhou, and Birker 1992). SIMP associates every element of the mesh with a *continuous* density to perform gradient-based methods (Sigmund 2001). However, because intermediary densities make no physical sense, SIMP uses a penalization factor to encourage binary densities. This penalization strategy (with $p > 1$) is efficient but introduces non-convexity in the objective function, as stated by Sigmund and Maute (2013). As a result, SIMP is likely to converge towards local optima. Other techniques to encourage binary densities include filters, but they also introduce non-convexity.

2.2 Deep Learning for Topology Optimization

Traditional TO methods are often slow due to the iterative FEA steps they include (Amir and Sigmund 2011). Many deep learning methods (Regenwetter, Nobari, and Ahmed 2022; Guo et al. 2018; Lin et al. 2018; Sosnovik and Osledets 2019) have recently been developed to improve the speed and quality of topology generation or address issues such as non-convexity.

Our work falls under a group of deep learning approaches that propose an end-to-end topology optimization framework from constraints to optimal topology (Oh et al. 2019; Sharpe and Seepersad 2019; Chandrasekhar and Suresh 2021; Parrott, Abueidda, and James 2022). Several representative works are reviewed below. Yu et al. (2018) suggest an iteration-free method that predicts a low-resolution solution using a CNN encoder-decoder, which is then refined by passing it through a GAN to increase the resolution. Similar to Rawat and Shen (2019), Li et al. (2019) use two GANs to solve the topology optimization problem and predict the refined structure at high resolution. Sharpe and Seepersad (2019) introduce conditional GANs to generate a compact latent representation of structures resulting from topology optimization. Nie et al. (2021) improve on this work by training their TopologyGAN on a more diverse set of conditions and using physical fields as input to represent loads and boundary conditions. In parallel, Wang et al. (2021) develop a U-Net to perform topology optimization for improved generalization. However, these promising models demonstrate limited generalization ability, particularly for boundary conditions outside the training distribution, and are prone to the problem of disconnected material. To address this issue, Behzadi and Ilieş (2021) propose a conditional GAN architecture that includes a topological measure of connectivity in its loss function, resulting in improved generalizability and connectivity. However, their work sets the volume fraction to a constant value, which limits the scope of the problem.

It is worth noting that the methods discussed so far do not explicitly incorporate a process to minimize compliance, which is the primary objective of TO. Instead, the minimization of compliance is expected to occur indirectly through neural network training, which can be difficult to control. Therefore, to ensure that predicted structural performance is considered during the optimization process, we propose explicit guidance methods in diffusion models that prioritize low-compliance and feasible structures.

2.3 Diffusion Models

Diffusion models are a new type of deep generative models (DGMs) introduced by Sohl-Dickstein et al. (2015). They have received much attention recently because Dhariwal and Nichol (2021) showed that diffusion models outperform GANs for image synthesis. Diffusion models are increasingly being applied to various fields: image generation (Nichol and Dhariwal 2021), segmentation (Amit et al. 2021), image editing (Meng et al. 2021), text-to-image (Nichol et al. 2022; Kim and Ye 2021), etc.

The idea behind diffusion models is to train a neural network to reverse a noising process that maps the data distribu-

tion to a white noise distribution. The forward noising process, which is fixed, consists of progressively adding noise to the samples following the Markov chain:

$$q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{\alpha_t}x_{t-1}, (1 - \alpha_t)I) \quad (1)$$

where $(\alpha_t)_{t=1}^T$ is a variance schedule. To reverse this noising process, we approximate the true posterior with the parametric Gaussian process:

$$p_\theta(x_{t-1}|x_t) = \mathcal{N}(\mu_\theta(x_t), \Sigma_\theta(x_t)). \quad (2)$$

We then generate new data by sampling an image from $\mathcal{N}(0, I)$ and gradually denoising it using Eq. 2.

Training a diffusion model, therefore, involves training two neural networks, $\mu_\theta(x_t)$ and $\Sigma_\theta(x_t)$, to predict the mean and the variance of the denoising process respectively. Let us note that Ho, Jain, and Abbeel (2020) showed that $\Sigma_\theta(x_t)$ might be fixed to a constant instead of being learned.

2.4 Guidance Methods in Diffusion Models

In many machine learning applications, a model is expected to generate samples conditioned on some input conditions. For example, popular text-to-image models such as DALL-E are conditioned on text input. Researchers have developed a few guidance methods to perform conditional image generation, such as including class labels when the model tries to generate an image corresponding to a given class.

Including conditioning information inside the denoising networks A method to condition a diffusion model consists in adding the conditioning information (for example, a class label) as an extra input to the denoising networks μ_θ and Σ_θ . In practice, the conditioning information can be added as an extra channel to the input image. Similarly, Dhariwal and Nichol (2021) suggest adding conditioning information into an adaptive group normalization layer in every residual block.

Classifier guidance Additional methods have been developed to guide the denoising process using classifier output. In line with Sohl-Dickstein et al. (2015) and Song et al. (2020), who have used external classifiers to guide the denoising process, Dhariwal and Nichol (2021) introduce *classifier guidance* to perform class-conditional image generation. In *classifier guidance*, a separate classifier is trained on noisy data (with different levels of noise) to predict the probability $p_\phi(y|x_t)$ that an image x_t at noise level t corresponds to the class y . Let $p_\theta(x_t|x_{t+1})$ be an unconditional reverse noising process. Classifier guidance consists of sampling from:

$$p_{\theta,\phi}(x_t|x_{t+1}, y) = Z p_\theta(x_t|x_{t+1}) p_\phi(y|x_t) \quad (3)$$

instead of $p_\theta(x_t|x_{t+1})$, where Z denotes a normalizing constant. Under reasonable assumptions, Dhariwal and Nichol (2021) show that sampling from $p_{\theta,\phi}(x_t|x_{t+1}, y)$ is equivalent to perturbing the mean with the gradient of the probability predicted by the classifier. Specifically, the perturbed mean is:

$$\hat{\mu}_\theta(x_t) = \mu_\theta(x_t) + s \Sigma_\theta(x_t) \nabla_{x_t} \log p_\phi(y|x_t) \quad (4)$$

where s is a scale hyperparameter that needs to be tuned. A variant called classifier-free guidance is proposed by Ho and Salimans (2021). This technique is theoretically close to classifier guidance but does not require training a separate classifier on noisy data.

However, none of these methods provide guidance for both continuous values (such as performance obtained from regression models) and discrete values (such as class labels obtained from classification models), which is important for TO to achieve feasible, high-performing samples. To overcome these issues, we propose a regressor and classifier guidance strategy that penalizes low-compliance and infeasible structures at every step.

3 Method

3.1 Architecture and General Pipeline

TopoDiff's diffusion architecture consists of a UNet (Ronneberger, Fischer, and Brox 2015)-based denoiser at every step with attention layers. We add conditioning to this architecture by including information on constraints and boundary conditions as additional channels to the input image given to the denoiser, as shown in Figure 2. The UNet model uses these extra channels as additional information to denoise the first channel of the input in a way that respects the constraints and is optimal for the given boundary conditions. Similarly to TopologyGAN, we use physical fields, namely strain energy density and von Mises stress, to represent constraints and boundary conditions. The physical fields are computed using a finite element method (Guarín-Zapata and Gómez 2020) and help avoid the sparsity problem caused by raw constraints and boundary condition matrices. The final input to our conditional diffusion model has four channels representing the volume fraction, the strain energy density, the von Mises stress, and the loads applied to the domain's boundary.

3.2 Minimizing Compliance

Most deep learning models used for TO rely on minimizing the pixel-wise error between the output topology and the ground truth obtained with traditional methods. For instance, the reference model TopologyGAN (Nie et al. 2021) attempts to mimic the ground truth topology and is encouraged to do so by the L2 loss function of its generator. GANs for TO are often evaluated using mean absolute error (MAE) between the ground truth topology and the topology predicted by their model. However, we hypothesize that setting the minimization of a pixel-wise error as an objective does not properly address the aim of TO: generate manufacturable structures that minimize mechanical compliance. We pose this hypothesis for two main reasons:

1. The topology used as ground truth may be sub-optimal due to penalization factor and filters (Sec. 2.1);
2. A small pixel-wise error is compatible with a large compliance error if the material is missing at critical places.

Our conditional diffusion model is prone to the same problem without additional guidance. To solve that issue, we introduce a new type of guidance called *regressor guidance*.

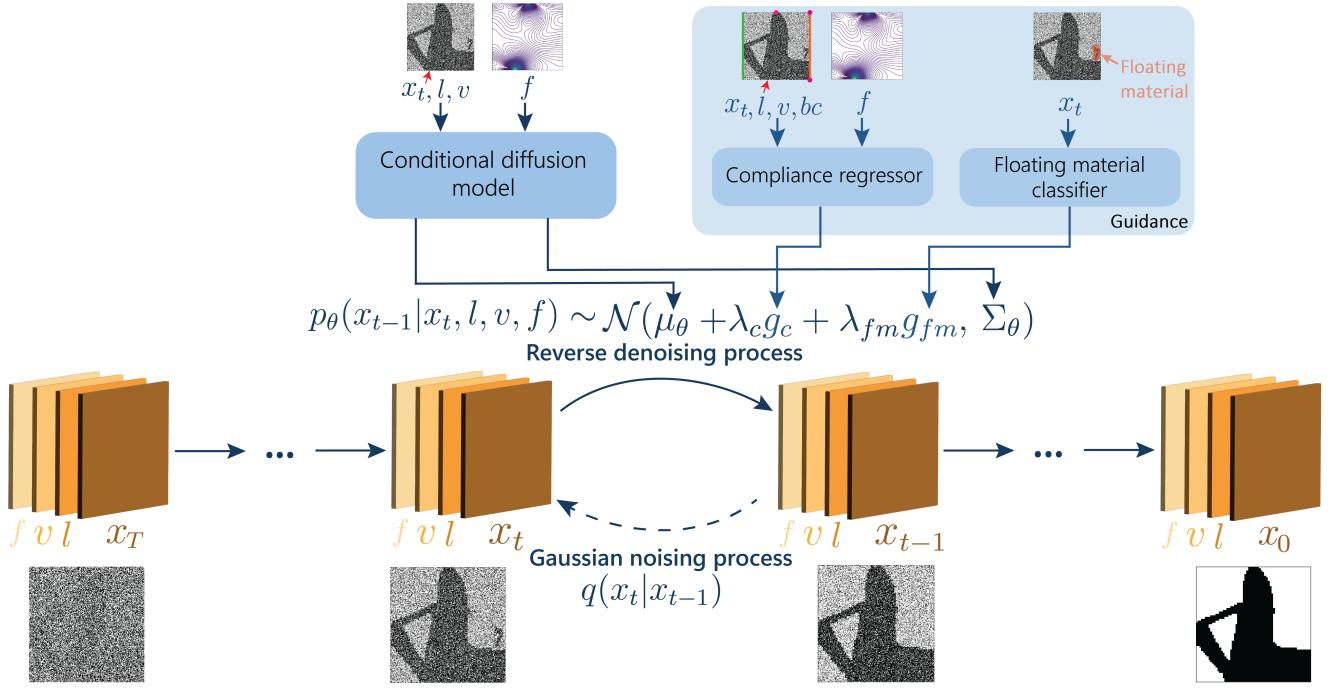


Figure 2: TopoDiff: Proposed constrained guided conditional diffusion model architecture for TO. $(x_t)_{t=0, \dots, T}$ is the gradually denoised topology; g_c and g_{fm} are the guidance gradients; l is the load applied, represented with an arrow on the topology; v is the volume fraction; f are the physical fields, and bc are the boundary conditions, represented with color lines and dots.

Consider a conditional diffusion model as presented in Sec. 3.1: $p_\theta(x_t|x_{t+1}, v, f, l)$, where v is the *volume fraction*, f are the physical fields (strain energy density and von Mises stress), and l are the loads applied. *Regressor guidance* consists in sampling each transition according to:

$$p_{\theta, \phi}(x_t|x_{t+1}, v, f, l, bc) = Z p_\theta(x_t|x_{t+1}, v, f, l) e^{-c_\phi(x_t, v, f, l, bc)} \quad (5)$$

where c_ϕ is a surrogate neural network predicting the compliance of the topology under given constraints, bc are the boundary conditions applied, and Z is a normalizing constant. It is worth noting that c_ϕ must be able to predict compliance on noisy images of structures. To perform this task, we use the encoder of a UNet architecture modified for regression values.

One can easily prove that under simple assumptions, adding *regressor guidance* amounts to shifting the mean predicted by the diffusion model by $-\Sigma \nabla_{x_t} c_\phi(x_t, v, f, l, bc)$ where Σ is the variance of the Gaussian distribution representing $p_\theta(x_t|x_{t+1}, v, f, l)$. This method thus modifies the distribution according to that which we sample at each step by penalizing structures with high compliance. The resulting algorithm is Alg. 1.

3.3 Avoiding Floating Material

Disconnected pixels in predicted structures are a serious problem because this phenomenon leads to floating material and affects the predicted topology's manufacturability. This problem is generally ignored in deep learning models

Algorithm 1 Regressor guidance for TO, given a conditional diffusion model $(\mu_\theta(x_t|x_{t+1}, v, f, l), \Sigma_\theta(x_t|x_{t+1}, v, f, l))$ and a regressor $c_\phi(x_t, v, f, l, bc)$.

Require: $v, l, bc \triangleright$ Volume, loads and boundary conditions
Require: $f \triangleright$ Physical fields
Require: $\lambda_c \triangleright$ Regressor gradient scale

$$x_T \leftarrow \text{sample from } \mathcal{N}(0, I)$$

for t from T to 1 **do**

$$\mu, \Sigma \leftarrow \mu_\theta(x_t|x_{t+1}, v, f, l), \Sigma_\theta(x_t|x_{t+1}, v, f, l)$$

$$x_{t-1} \leftarrow \text{sample from } \mathcal{N}(\mu - \lambda_c \Sigma \nabla_{x_t} c_\phi(x_t, v, f, l, bc)|_{x_t=\mu}, \Sigma)$$

return x_0

for TO and is notably not considered by the pixel-wise error because a small pixel-wise error is compatible with the presence of floating material.

Similar to what has been exposed in Sec. 3.2, we further modify the sampling distribution at each step by penalizing structures that contain floating material. To do so, we train a classifier p_γ that returns the probability that the topology does *not* contain floating material. We then use this classifier to perform *classifier guidance*, as introduced in Sec. 2.4. Eventually, this amounts to shifting the mean predicted by the diffusion model by $+\Sigma \nabla_{x_t} \log p_\gamma(x_t)$.

3.4 Combining Guidance Strategies

Our model ultimately consists of one conditional diffusion model $p_\theta(x_t|x_{t+1}, v, f, l)$ and two surrogate models used

for guidance when sampling: $c_\phi(x_t, v, f, l, bc)$ for compliance and $p_\gamma(x_t)$ for floating material. One challenge is to find a way to combine these two guidance strategies. To combine them, we sample at every step according to:

$$p_{\theta, \phi, \gamma}(x_t | x_{t+1}, v, f, l, bc) = Z p_\theta(x_t | x_{t+1}, v, f, l) e^{-c_\phi(x_t, v, f, l, bc)} p_\gamma(x_t). \quad (6)$$

This amounts to shifting the mean predicted by the diffusion model by:

$$- \lambda_c \sum \nabla_{x_t} c_\phi(x_t, v, f, l, bc) + \lambda_{fm} \sum \nabla_{x_t} \log p_\gamma(x_t) \quad (7)$$

where λ_c and λ_{fm} are gradient scale hyperparameters.

However, as is, this approach has two pitfalls: 1. The gradients are always computed at the same point μ (the mean predicted by the diffusion model), even though this mean is shifted by the previous guidance strategy; and 2. The gradients are computed at every denoising step, even if we might want to favor one guidance over the other at a given denoising step. We modify the point at which the second gradient is computed to address these issues by considering the shift induced by the previous gradient. In addition, we determine a maximum level of noise (MLN) beyond which the *classifier/regressor guidance* should not be included for every classifier and regressor. We then introduce *classifier/regressor guidance* only if the image is denoised enough to have a noise level below the MLN of the given classifier or regressor.

The final guidance algorithm resulting from the combination of these guidance strategies is Alg. 2. Fig. 2 also summarizes the overall architecture.

Algorithm 2 Guidance strategy for TO using Conditional Diffusion Model.

Require: $v, l, bc \triangleright$ Volume, loads and boundary conditions
Require: $f \triangleright$ Physical fields
Require: $\lambda_c, \lambda_{fm} \triangleright$ Regressor and classifier gradient scale
Require: $MLN_c, MLN_{fm} \triangleright$ Maximum levels of noise
 $x_T \leftarrow$ sample from $\mathcal{N}(0, I)$
for t from T to 1 **do**
 $\mu, \Sigma \leftarrow \mu_\theta(x_t | x_{t+1}, v, f, l), \Sigma_\theta(x_t | x_{t+1}, v, f, l)$
 if $t < MLN_{fm}$ **then**
 $\mu \leftarrow \mu + \lambda_{fm} \sum \nabla_{x_t} \log p_\gamma(x_t) |_{x_t=\mu}$
 if $t < MLN_c$ **then**
 $\mu \leftarrow \mu - \lambda_c \sum \nabla_{x_t} c_\phi(x_t, v, f, l, bc) |_{x_t=\mu}$
 $x_{t-1} \leftarrow$ sample from $\mathcal{N}(\mu, \Sigma)$
return x_0

Note that our framework can apply *regressor* and *classifier guidance* for various engineering constraints (e.g., volume, load position). However, in this study, the conditional diffusion model respects these constraints adequately, making additional guidance unnecessary.

4 Empirical Evaluation

We created three datasets to train the proposed models, which are made publicly available.

4.1 Dataset

The main dataset consists of 33000 64x64 2D images corresponding to optimal structures for diverse input conditions. Every data sample contains six channels:

1. The first channel is the black and white image representing the optimal topology;
2. The second channel is uniform and includes the prescribed volume fraction;
3. The third channel is the von Mises stress of the full domain under the given load constraints and boundary conditions, defined as $\sigma_{vm} = \sqrt{\sigma_{11}^2 - \sigma_{11}\sigma_{22} + \sigma_{22}^2 + 3\sigma_{12}^2}$;
4. The fourth channel is the strain energy density of the full domain under the given load and boundary conditions, defined as $W = \frac{1}{2}(\sigma_{11}\epsilon_{11} + \sigma_{22}\epsilon_{22} + 2\sigma_{12}\epsilon_{12})$;
5. The fifth channel represents the load constraints in the x-direction. Every node is given the value of the force applied in the x-direction on this load (0 if no force is applied on the load);
6. The sixth channel similarly represents the load constraints in the y-direction;

where $(\sigma_{11}, \sigma_{22}, \sigma_{12})$ and $(\epsilon_{11}, \epsilon_{22}, \epsilon_{12})$ are respectively the components of the stress and strain fields.

We randomly selected a combination of conditions (volume fraction, boundary conditions, loads) to generate every structure and then computed the optimal topology using the SIMP-based TO library ToPy (Hunter et al. 2017). We defined the possible conditions in a similar way to what was done in previous works, namely: 1. The volume fraction is chosen in the interval $[0.3, 0.5]$, with a step of 0.02; 2. The displacement boundary conditions are chosen among 42 scenarios for training and five additional scenarios only used for testing; 3. The loads are applied on unconstrained nodes randomly selected on the domain's boundary. The direction is selected in the interval $[0, \pi]$, with a step of $\frac{\pi}{6}$. The main dataset is divided into training, validation, and testing as follows:

1. The **training data** consist of 30,000 combinations of constraints containing 42 of the 47 boundary conditions;
2. The **validation data** consist of 200 new combinations of constraints containing the same 42 boundary conditions;
3. The **level 1 test data** consist of 1800 new combinations of constraints containing the same 42 boundary conditions;
4. The **level 2 test data** consist of 1000 new combinations of constraints containing five out-of-distribution boundary conditions.

In all test data, the combination of constraints is unseen. While *level 1* dataset contains boundary conditions that are also in the training data, we introduce more difficult conditions in *level 2* to rigorously compare the TopoDiff model's generalization ability with existing methods. In addition to the main dataset, two other datasets consisting of 12,000 and 30,000 non-optimal structures are used to train *regressor* and *classifier guidance* models.

4.2 Evaluation Metrics

Selecting the right evaluation metrics is critical for mechanical design generation because most metrics used in DGMs do not correspond to the physical objective one wants a design to achieve. In this work, contrary to most generative models applied to TO in previous works, we do not use pixel-wise error as a primary evaluation metric because it does not guarantee low compliance, which is the objective we are trying to achieve.

Hence, we define and use four evaluation metrics that reflect the compliance minimization objective, as well as the constraints that the generated structures have to respect:

1. Compliance error (CE) relative to the ground truth, defined as: $CE = (C(\hat{y}) - C(y))/C(y)$ where $C(y)$ and $C(\hat{y})$ are, respectively, the compliance of the SIMP-generated topology and the topology generated by our diffusion model. It should be noted that a negative compliance error means that our model returns a topology with lower compliance than the ground truth;
2. Volume fraction error (VFE) relative to the input volume fraction, defined as: $VFE = |VF(\hat{y}) - VF(y)|/VF(y)$ where $VF(y)$ and $VF(\hat{y})$ are, respectively, the prescribed volume fraction and the volume fraction of the topology generated by our diffusion model;
3. Load violation (LV), defined as a boolean that is 1 if there is no material at a place where a load is applied and 0 if there is always material where loads are applied;
4. Presence of floating material (FM), defined as a boolean that is 1 if the topology contains floating material and 0 otherwise.

High-scoring samples on these metrics should result in high-performance, manufacturable designs.

4.3 Choice of Hyperparameters

One of the most crucial hyperparameters is the gradient scales in our guidance strategies. These parameters quantify the relative importance of compliance minimization and floating material avoidance. As explained in Sec. 4.1, a validation dataset of 200 structures was used to perform hyperparameter tuning. We used a grid search method to decide the hyperparameters using compliance error and floating material presence as evaluation metrics. Topology generation and FEA were used to evaluate the results.

5 Results and Discussions

5.1 Evaluation of the Full Diffusion Model

To evaluate the performance, we use the two test sets described in Sec. 4.1, corresponding to two difficulty levels. We run every test nine times and then compute the results' average. We compare the performance of our model on all evaluation metrics (Sec. 4.2) to a state-of-art cGAN model, named TopologyGAN (Nie et al. 2021), which performs the same task as our model.

Fig. 3 shows examples of a few structures obtained with the SIMP method (ground truth), with TopologyGAN, and with TopoDiff for randomly selected constraints from *level*

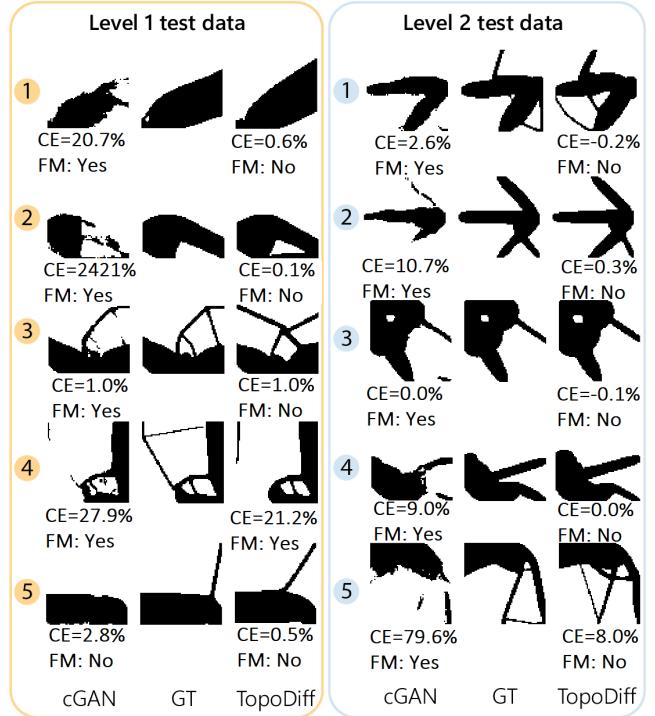


Figure 3: Comparison of generated structures on randomly selected samples from both test datasets. GT stands for ground truth, CE is the compliance error relative to the GT, and FM indicates the presence or not of floating material.

1 and *level 2* test sets. Qualitatively, we notice that TopologyGAN tries to mimic pixel-wise the topology obtained from SIMP but neglects both the compliance and the manufacturability of the generated structures, which almost all have some floating material and high compliance error. The ten structures generated by TopoDiff, on the other hand, may visually differ more from the SIMP results but have better physical properties than TopologyGAN. Only one of the TopoDiff-generated structures has floating material, and all ten outperform the TopologyGAN structures in terms of compliance error. To confirm these qualitative observations, Table 1 summarizes the performance of the structures obtained with all test sets. TopoDiff outperforms TopologyGAN on all the metrics.

On the *level 1* test set, TopoDiff notably reduces the average CE by a factor of eleven and the proportion of FM by more than a factor of eight. The proportion of non-manufacturable designs thus drops from 46.8% with cGAN to 5.5% with TopoDiff. It also significantly reduces the average VFE from 11.9% to 1.9%. On the *level 2* test set, TopoDiff demonstrates strong generalizability performance. It performs an eight-times reduction in the average CE, from 143.1% to 18.4%, and a four-times reduction in the median CE. Non-manufacturability drops from 67.9% to 6.2%, while the VFE is reduced by a factor of eight, from 14% to less than 2%. A paired one-tailed t-test confirms a reduction of the average CE and of the average VFE with a p-value

Model	Level 1 test data			Level 2 test data		
	TopologyGAN	Unguided TopoDiff	TopoDiff	TopologyGAN	Unguided TopoDiff	TopoDiff
Average CE (%)	48.51 ± 16.38	4.10 ± 0.88	4.39 ± 0.94	143.08 ± 38.50	22.13 ± 8.52	18.40 ± 5.88
Median CE (%)	2.06	0.80	0.83	6.82	1.88	1.82
Prop. of CE>30% (%)	10.11	2.33	2.56	24.10	8.20	8.10
Average VFE (%)	11.87 ± 0.52	1.86 ± 0.03	1.85 ± 0.03	14.31 ± 0.75	1.81 ± 0.04	1.80 ± 0.04
Prop. of LV (%)	0.00	0.00	0.00	0.00	0.00	0.00
Prop. of FM (%)	46.78	6.64	5.54	67.90	7.53	6.21

Table 1: Comparison of performance between TopologyGAN and TopoDiff (guided and not guided) on the two level test sets. Values after \pm indicate the 95 % confidence interval around averages. The values in bold are the best ones for each level.

of $9 \cdot 10^{-12}$ and $5 \cdot 10^{-160}$ respectively. These results show the efficacy of diffusion models in learning to generate high-performing and manufacturable structures for a wide set of testing conditions.

5.2 Efficiency of Guidance Strategy

Surrogate models Guidance can only work if the regressors and classifiers can perform well on the challenging task of predicting compliance and floating material for noisy images. Table 2 shows the compliance regressor and floating material classifier performance according to the noise level. These results show that both surrogate models are reliable on low-noise structures, and as expected, their performance decreases with an increase in noise.

Noise level	0-25%	25-75%	75-100%	Global
Regressor R2 (%)	82.4	82.4	61.8	77.3
Classifier acc. (%)	98.8	76.8	54.6	76.8

Table 2: Performance (R2-score and accuracy) of both surrogate models on validation data with respect to noise level.

Ablation study We tested TopoDiff with and without guidance to evaluate its impact on performance (see Table 1). With *in-distribution* boundary conditions (*level 1*), our guidance strategy has no significant impact on average or median compliance error. A two-tailed paired t-test does not reject the null hypothesis ($p = 0.1$). This may happen because the diffusion model has implicitly learned to respect the boundary conditions and does not need explicit compliance guidance. In contrast, our guidance strategy significantly impacts the proportion of floating material, with decreases from 6.6% to 5.5%.

With *out-of-distribution* boundary conditions (*level 2*), the positive impact of our guidance strategy is evident. A paired one-tailed t-test confirms a reduction of the average CE with a p-value of 0.05. The average compliance error is reduced by 17% and the average proportion of floating material by 18%. As expected, guidance seems to have no effect on load respect and volume fraction error. More interestingly, guidance seems to have no significant effect on the median of the compliance error, which suggests that compliance *regressor guidance* primarily reduces the number of structures with very high compliance errors.

5.3 Limitations and Future Work

TopoDiff has demonstrated good performance and generalization to out-of-distribution boundary conditions, and its proposed guidance strategy is effective in minimizing compliance and satisfying constraints. However, there are still several challenges that need to be addressed. Diffusion models are slower than GANs, and TopoDiff takes 21.59 seconds to generate one topology, compared to TopologyGAN’s 0.06 seconds. However, recent research has shown promise in reducing the computation time of diffusion models, which could improve TO-based diffusion models (Ma et al. 2022). Other potential future research directions include applying TopoDiff to more complex TO problems, including 3D problems, and scaling it to higher resolutions and more boundary conditions. It is also crucial to reduce the dependency on mesh size and large training datasets. Our framework, which conditions a diffusion model with constraints, trains it on optimal data, and guides it with a regressor and classifiers, is a versatile method that can solve many design generation problems with performance objectives and constraints. Examples of such problems include airfoil (Heyrani, Chen, and Ahmed 2021) and bicycle design (Regenwetter, Curry, and Ahmed 2022). Finally, future work should also expand the TopoDiff framework to solve many inverse problems in engineering domains with multi-modal inputs.

6 Conclusion

Diffusion models have achieved remarkable success in modeling high-dimensional multi-modal distributions, particularly in generating high-fidelity images. In this paper, we propose TopoDiff, a conditional diffusion model for end-to-end topology optimization. Our method demonstrates that diffusion models can outperform GANs in engineering design applications. Additionally, we introduce an explicit guidance strategy to ensure performance maximization and avoidance of non-manufacturable designs. TopoDiff achieves an eight-times reduction in the average compliance error and produces 11-times fewer non-manufacturable designs compared to a state-of-the-art conditional GAN. It also achieves an eight-times reduction in volume fraction error and generalizes well to out-of-distribution boundary conditions. Our proposed approach can be applied to a broad range of physical optimization problems in engineering, where performance objectives and constraints, both continuous and discrete, are required to be considered.

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