Proceedings of the Conference on Computational Engineering and Science JSCES
Vol. 29, Jun. 2024

Magnetic shield design with data-driven topology design

Wu Renfei [1)] and Katsuya Nomura [2)] and Shintaro Yamasaki [3)]

[1)] Graduate school of Information, Production and Systems, Waseda University (Postal Address: 2-7 Hibikino, Wakamatsu, Kitakyushu, Fukuoka 808-0135, E-mail: leifwu@akane.waseda.jp)
[2)] Ph.D, Assistant Professor, School of Engineering, Kwansei Gakuin University (Postal Address: 1 Gakuen uegahara, Sanda, Hyogo 669-1330, E-mail: katsuya.nomura@kwansei.ac.jp)
[3)] Ph.D, Professor, Graduate School of Information, Production and Systems, Waseda University (Postal Address: 2-7 Hibikino, Wakamatsu, Kitakyushu, Fukuoka 808-0135, E-mail: s_yamasaki@waseda.jp)

This paper presents the integration of data-driven topology optimization into the design of magnetic shield structures utilizing ferromagnetic materials with significant non-linearity of permeability. Unlike traditional sensitivity-based methods, our approach effectively handles optimization problems characterized by high non-linearity by employing a data-driven framework. Superior material distributions are generated through solving a min-max optimization problem. Our results show clear trends of improvements in magnetic shielding performances, indicating the efficacy of our proposed method in addressing complex optimization challenges.

Key Words : *Data-driven topology design, Magnetic shield structures, Min-max optimization*

1. INTRODUCTION

With the past decades in the general optimization field, structural optimization is an acknowledged tool to find a global optimal or local optimal solution of structure considering some constraints. There are three aspects of structural optimization problems, that is size, shape, and topology optimization. The task of size optimization is to find optimal size parameters with a given prior of the design model and state variables. [1] Compared with size optimization, shape optimization enhances flexibility by handling the design model as the design variable. In comparison to size and shape optimization, topology optimization focuses on calculating the ideal distribution of materials in a design space to maximize or minimize the objective function and ensure the constraints are met. It has been widely utilized during the past decades in the engineering design field as it is efficient to handle complex design problems.

However, there is an inherent drawback in topology optimization as sensitivity-based mathematical programming is utilized. That makes undertaking strongly nonlinear topology problems challenging in topology optimization. Specifically, topology optimization encounters difficulties in determining the material distribution when the properties of the material exhibit non-linear characteristics. For example, the permeability of soft iron varies with magnetic field intensity, which makes the generation of a rational magnetic shielding layer structure by topology optimization laborious and computationally intensive. Thus, alternative methodologies have been proposed.

Yamasaki et al. proposed the framework of data-driven topology design [2], one of the sensitivity-free and multi-objective structural design methodologies. The deep generative model is employed for extracting features from existing elite material distribution and generating superior material distributions. Also, Rie Isshiki et al. proposed a methodology of topology optimization to combine the density method and CNN and deployed it for magnetic shield layer design. [3] In their work, CNN is employed as a filter to diminish the needlessly complicated structures and minimize the magnetic energy in the target domain. On the other hand, minimizing the magnetic energy does not make sure the magnetic flux density in the target domain is lower than the upper bound globally for the protection of medical equipment and therapeutic equipment. A sensitivity-based topology optimization experiences difficulties in minimizing the objective function of the maximum value of magnetic flux density. Considering this, we propose to exploit the data-driven topology optimization methodology to generate a structure for the magnetic shielding layer mitigating the maximum magnetic flux density in the target domain.

In the following, the details of the proposed method are described in section 2 and its effectiveness is verified using numerical examples in section 3. Finally, conclusions are summarized in section 4.

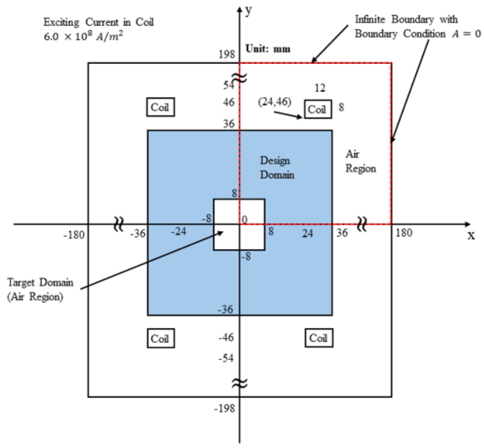

Fig. 1 Magnetic shield model

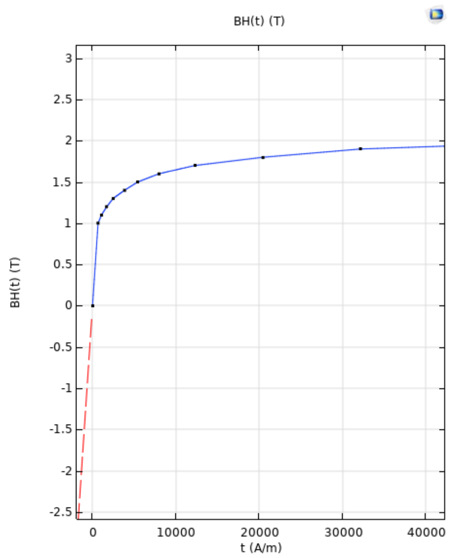

Fig. 2 BH curve of soft iron

2. Optimization Problem and Method

(1) Optimization Problem

In this paper, we cope with the minimization problem of the maximum magnetic flux density. The 2D magnetic shield model shown in Figure 1 is employed as an analysis model, in which the magnetic shield material is assumed to be soft iron. The magnetic shield model is symmetric across all four quadrants and the magnetization curve with magnetic saturation of soft iron is shown in Figure 2. Soft iron is commonly applied in the design of magnetic shielding layers owing to its high permeability.

In the scenario of the static magnetic fields, the magnetic lines of force tend to pass through the shielding layer with higher permeability, instead of accessing the protected domain. The relationship between permeability, magnetic field strength, and magnetic flux density is defined as:

$$\mu = \mu_r \mu_0 = \frac{B}{H} \tag{1}$$

μ_r is the relative permeability; μ_0 is the vacuum permeability defined as $4\pi \times 10^7$ A/m. B and H denote the magnetic flux density and the magnetic field strength.

Given the symmetry of the model, we generated new material distributions and with them, deployed the finite element analysis on the quarter area. In the finite element analysis, the quantity of materials and the maximum magnetic flux density in the target domain are evaluated. According to the guideline of ICNIRP [4], the maximum constraint of the magnetic flux density is $0.5mT$ taking the safety of medical equipment and therapeutic equipment into account. Different from conventional paper, our objective is to minimize the maximum magnetic flux density in the target domain. The maximum magnetic flux density optimization problem can be formulated as:

$$\begin{aligned} \underset{\rho}{\text{minimize}} \quad & f_0 = \max(B(\rho))\ in\ \Omega_T \\ & V_0 = \int_D \rho_e \, d\Omega, \\ \text{subject to} \quad & 0 \leq \rho_e \leq 1 \end{aligned} \tag{2}$$

where:

- B is calculated based on the generated material distribution ρ by Maxwell's equations,
- ρ collects all the design variables ρ_e,
- Ω_T, D denotes the target and design domain.

(2) Method

The max operator in the objective function introduced complications in the optimization because the maximum value of magnetic flux density could appear in any coordinates of the target domain. To alleviate the difficulty, the data-driven topology design using a deep generative model is employed to capture the feature from prevailing elite material distributions and then generate new material distributions. The overall data process flow of the framework is shown in Figure 3.

Profit from the advantage of extracting features from elite data, the proposed framework can manipulate the optimization of the objective function with the max operator. The framework set out to generate hand-crafted material distributions in the design domain. Then the performance of those initial data is evaluated and only those data entities appraised as the high-rank data or to say, elite data will be preserved. In this problem, the quantity of material and the maximum magnetic flux density in the target domain are assessed. If the convergence criterion is satisfied, the framework terminates and outputs the elite data as the final result.

In the absence of termination, the data will be used to train a neural network. In light of the simplicity and robustness, the architecture of VAE [5] is implemented, which is one of the emblematic deep generative models up to this point. The architecture of VAE is shown in Figure 4. Through the training, a latent space is created and new data will be generated by sampling the latent space. Those newly generated data will be inversely transmuted complying with the design domain and evaluated for performance by the finite element analysis. Those data with superior performance will be merged into the dataset to train the neural network and generate new data. This process renders it feasible to capture the feature from the elite data and generate new data based on the feature as a replacement for updating the data by sensitivity information. Via the iteration of the aforementioned process, we set out to generate material distributions for the magnetic shield to curtail the maximum magnetic flux density in the target domain with constraints on the quantity of materials.

3. EXPERIMENTS

Inspired by the ferromagnetic tube shields proposed in [6], the parabola structure is generated manually as an initial dataset including one-layer and two-layer structures as shown in Figure 5. The length of each layer is randomly generated from $1.5mm$ to $3.5mm$.

After 50 iterations of implementing the algorithm aforementioned, the material distribution dataset exhibiting richer features compared to the origin data is generated as output. The material distribution within the dataset demonstrated clear trends of variation as shown in Figure 6.

The improvement of the performances of the elite solutions through the iteration is shown in Figure 7.

4. CONCLUSION

In this paper, we have effectively integrated data-driven topology optimization into the design process of magnetic shield structures, taking account of the significant non-linearity of permeability. We have achieved superior material distribu-

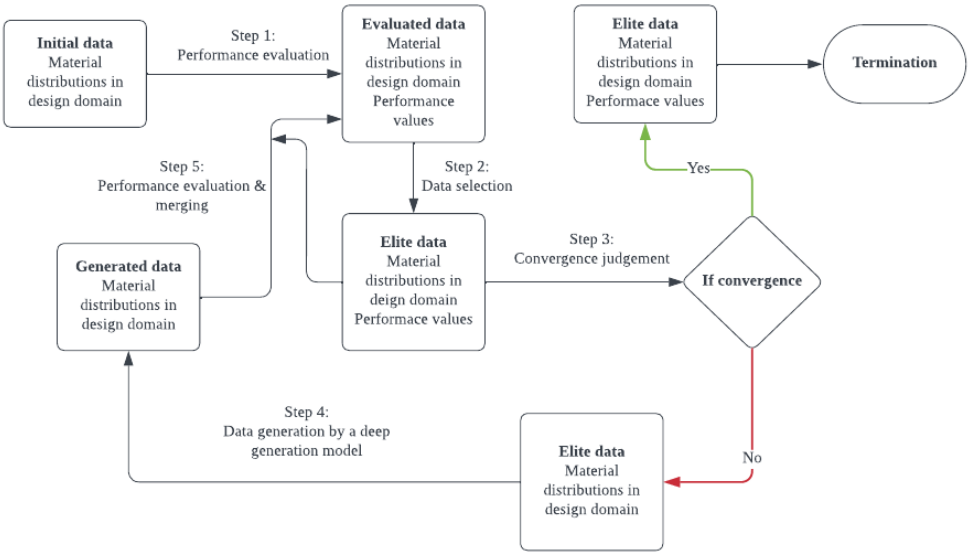

Fig. 3 the data flow of data-driven topology optimization

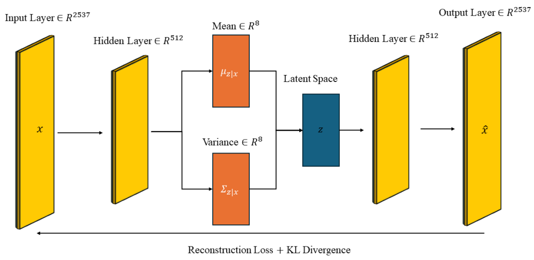

Fig. 4 the architecture of VAE

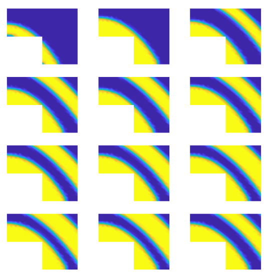

Fig. 5 samples in the initial dataset

tions with a data-driven approach to solve a min-max optimization problem. This approach contrasts with traditional sensitivity-based methods, which are often labor-intensive. Our experiments demonstrate the efficiency of data-driven topology optimization in handling optimization problems characterized by high non-linearity.

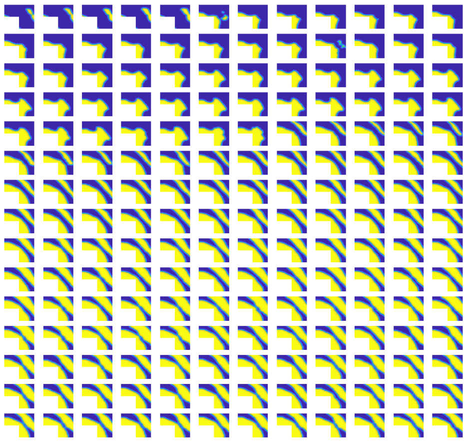

Fig. 6 180 samples in the final result

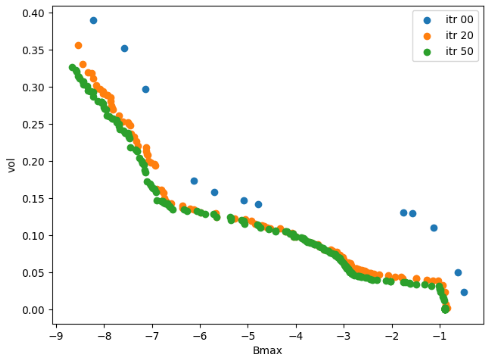

Fig. 7 Performances of elite solutions: iteration 0 (blue), iteration 20 (orange), and iteration 50 (green)

REFERENCES

[1] Martin Philip Bendsoe and Ole Sigmund. *Topology Optimization: Theory, Methods and Applications*. Springer, February 2004.

[2] Shintaro Yamasaki, Kentaro Yaji, and Kikuo Fujita. Data-driven topology design using a deep generative model. *Structural and Multidisciplinary Optimization*, 64, 09 2021.

[3] Rie Isshiki, Ryota Kawamata, Shinji Wakao, and Noboru Murata. Topology optimization in magnetic shield design by using density method in combination with cnn. *COMPEL - The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, 41(6):2109–2119, October 2022. Publisher Copyright: © 2022, Emerald Publishing Limited.

[4] G. Ziegelberger, P. Vecchia, M. Hietanen, Anders Ahlbom, L.E. Anderson, E. Breitbart, Frank de Gruijl, J.C. Lin, R. Matthes, A.P. Peralta, P. Söderberg, B.E. Stuck, A.J. Swerdlow, Masao Taki, R. Saunders, and Bernard Veyret. Guidelines on limits of exposure to static magnetic fields. *Health Physics*, 96:504–514, 04 2009.

[5] Diederik P Kingma and Max Welling. Auto-encoding variational bayes, 2022.

[6] Michela Fracasso, Fedor Gömöry, Mykola Solovyov, Roberto Gerbaldo, Gianluca Ghigo, Francesco Laviano, Andrea Napolitano, Daniele Torsello, and Laura Gozzelino. Modelling and performance analysis of mgb2 and hybrid magnetic shields. *Materials*, 15(2), 2022.