

Accelerating Surrogate Modeling for Electromagnetic Device with Active Learning

Yunyi Gong¹, Kenji Kawano¹, Yuki Sato², and Hajime Igarashi³

¹Kilby Labs, Texas Instruments Japan Ltd., Tokyo 108-0075, Japan, y-gong@ti.com

²Department of Electrical Engineering and Electronics, Aoyama Gakuin University, Kanagawa 252-5258, Japan, yuki-sato@aoyamagakuin.jp

³Graduate School of Science and Technology, Hokkaido University, Hokkaido 060-0814, Japan, igarashi@ssi.ist.hokudai.ac.jp

In this paper, active learning (AL) is introduced to accelerate the surrogate modeling for electromagnetic device, requiring fewer samples to achieve higher accuracy. A 3D inductor model with nonlinear magnetic material, described by 8 design parameters is used for the prediction of the inductances under 5 different current excitations, where random forest regressor (RFR) is employed as the surrogate model, trained via AL and random sampling (RS). The results indicate that the models trained by AL-selected samples outperform those trained by RS when data sets are limited. Meanwhile, AL demonstrates smoother learning curves, indicating enhanced robustness.

Index Terms—Inductors, Machine learning, Sampling methods, Active learning, Regression analysis, Surrogate model.

I. INTRODUCTION

IN electromagnetic (EM) device design, various design parameters are utilized to describe the device's structure, while several EM characteristics are necessary to evaluate the performance of each design. However, the required EM simulations using Finite Element Methods (FEM) for such design optimization can be time-consuming.

To accelerate design optimization, surrogate models are commonly used to represent the relationship between design parameters and electromagnetic (EM) characteristics, replacing finite element method (FEM) simulations. Once the surrogate model is well-trained, the time required to use it is typically much shorter than that needed for FEM, resulting in faster overall design optimization. Many studies have proposed various methods for generating surrogate models for FEM [1]-[3]. Regardless of the method employed, a sufficiently large training dataset is necessary to ensure the accuracy of the surrogate model. Thus, data preparation can become a significant challenge, particularly when the simulations of EM model demand extensive computational time, like large-scaled and non-linear model.

Recently, the application of active learning (AL) in machine learning has gained significant attention, as it can identify and select valuable samples to enhance model training, even with a small training dataset [4]-[6]. Consequently, AL is widely used in scenarios where collecting training data is challenging, such as time-consuming simulations and measurements [6].

In this study, we firstly introduce AL into generating surrogate model for simulation and optimization of EM devices. Focusing on a 3D inductor design problem with non-linear B-H curve considered, we treat the prediction of inductances from the inductor's design parameters as a regression problem. The training data for the regressor is selected using the AL algorithm. It is shown that the proposed method achieves higher accuracy and better robustness compared to random sampling (RS), with size-limited training datasets.



Fig. 1. 3D inductor model. 8-dimensional feature vector $\mathbf{x} = [d, l, h, w, N, x, y, z]$ for describing its structure. 5-dimensional label vector $\mathbf{y} = [L_{0A}, L_{2A}, L_{4A}, L_{6A}, L_{8A}]$.

II. INDUCTOR DESIGN MODEL

A 3D inductor model is constructed as shown in Fig. 1, featuring 8 design parameters that describe its structure: wire diameter d , height of leg l , core space height h , core space width w , number of turns N , and the 3D size of the inductor package x, y, z . An 8-dimensional vector $\mathbf{x} = [d, l, h, w, N, x, y, z]$ is defined as the feature vector for each design.

Considering the non-linear B-H curve of the magnetic material used in the inductor, a total of 5184 models are simulated with varying $\mathbf{x}$. For each design, the label vector is defined as $\mathbf{y} = [L_{0A}, L_{2A}, L_{4A}, L_{6A}, L_{8A}]$, consisting the inductances under 5 current excitations ranging from 0 to 8A. The inductances range from 40 to 3000nH, and most distribute between 70 and 1000nH, with the average value is about 350nH. All simulations take about 1.5 months using the commercial software FEMTET®, running on a computer with Intel(R) Core i7-9700@3.0 GHz.

III. PROPOSED METHOD

In this section, the sampling algorithm and the surrogate modeling method used in this work are introduced.

A. Improved Greedy Sampling (iGS)

Proposed in [5], Improved Greedy Sampling (iGS) is a kind of pool-based AL regression algorithm, in which a pool including all the unlabeled training samples is given in advance, and the task of algorithm is to pick samples from the pool sequentially for labeling, then added them to the training dataset for regressor.

ALGORITHM I
IMPROVED GREEDY SAMPLING (IGS) [5]

Input: Unlabeled samples $\{\mathbf{x}_n\}_{n=1}^{N=5184}$.
 $T = \emptyset$, training dataset.
 $K_0 = 8$, number of training data for initialization
 $K = 1000$, maximum training dataset size

Initialization

Pick the sample closest to the centroid of all $\{\mathbf{x}_n\}$.
Compute d_n^x of remaining samples in $\{\mathbf{x}_n\}$.
Sort samples in $\{\mathbf{x}_n\}$ by d_n^x .

while $k = 1, \dots, K_0-1$ **do**

Pick the sample with largest d_n^x .
Label the picked sample. Add it into T .

Train initial regressor $f_{K_0}(\mathbf{x})$ using T .

Update

while $k = K_0, \dots, K$ **do**

Compute d_n^{xy} of remaining samples in $\{\mathbf{x}_n\}$.
Pick the sample with largest d_n^{xy} .
Label the picked sample. Add it into T .
Train new regressor $f_k(\mathbf{x})$ using T .

Output: Final trained regressor $f_K(\mathbf{x})$.

Three kinds of space distance used in iGS are introduced here. d_n^x is the Euclidean distance in input-vector space between labeled samples and unlabeled samples. For example, after k samples have been labeled and used as training data, d_n^x of unlabeled samples are calculated by follows:

$$d_{nm}^x = \|\mathbf{x}_n - \mathbf{x}_m\|, m = 1, \dots, k; n = k+1, \dots, N \quad (1)$$

$$d_n^x = \min. (d_{nm}^x), n = k+1, \dots, N \quad (2)$$

where $\mathbf{x}_n$ and $\mathbf{x}_m$ denote the feature vectors of unlabeled and labeled samples, respectively. Thus, d_n^x is defined as the shortest distance from unlabeled $\mathbf{x}_n$ to labeled samples.

Similarly, d_n^y , the distance in output-vector space is defined as:

$$d_{nm}^y = \|f(\mathbf{x}_n) - \mathbf{y}_m\|, m = 1, \dots, k; n = k+1, \dots, N \quad (3)$$

$$d_n^y = \min. (d_{nm}^y), n = k+1, \dots, N \quad (4)$$

where $f(\mathbf{x}_n)$ is the prediction for $\mathbf{x}_n$ of trained regressor, and $\mathbf{y}_m$ denotes the label vectors of the labeled samples. Finally, we can define a distance named d_n^{xy} , which contains the information from both input and output-vector space.

$$d_n^{xy} = \min. (d_{nm}^x \cdot d_{nm}^y), n = k+1, \dots, N \quad (5)$$

The whole process of iGS applied in this work is shown as ALGORITHM I.

B. Random Sampling (RS)

In this work, Random Sampling (RS) is used as the baseline method compared with iGS. All the sample are selected randomly. After selecting K_0 randomly for training the initial regressor $f_0(\mathbf{x})$, samples for every update are picked randomly as well, until size of total training dataset reach K .

C. Random Forest Regressor (RFR)

Random Forest Regressor (RFR), implemented via Scikit-Learn is chosen as the regression modeling method for its robustness against overfitting. The root mean squared error (RMSE) and R2 score metrics are used to evaluate the model accuracy.

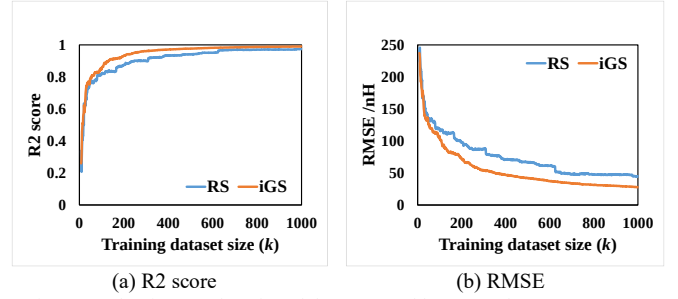


Fig. 2. Evaluation results of models generated by AL and RS.

IV. EVALUATION RESULTS

Because iGS and RS would select different samples to label, using the remaining unlabeled samples as test dataset is not a fair way for comparison. Therefore, the trained models are evaluated using all the 5184 samples, in which k labeled samples are with their true $\mathbf{y}$ and the other samples are with the predicted labels $f(\mathbf{x})$ by the trained regressor.

To prevent the influence on the evaluations from the randomness in RS and RFR, both iGS and RS were executed 5 times with different random seeds, whose average results are shown in Fig. 2. It shows that iGS outperformed RS as the training dataset exceeded 100 samples. With 1000 samples selected, model by iGS reaches a R2 score of 0.99, and an RMSE of 28nH, one-tenth of the average inductance value. Meanwhile, RS only reaches 0.97 and 44.5nH, same as what iGS obtained with about 445 data. It means that iGS can save half of the computation cost so far, which equals to half a week's computation time for 500 data. Moreover, iGS also exhibited smoother learning curves, demonstrating better robustness.

V. CONCLUSION

This study proposed a new method to accelerate the surrogate modeling of FEM for EM device. Focusing on a 3D inductor design problem, regressor is trained to fit the non-linear relationship between the inductances and the design parameters. Using iGS, the proposed approach obtained models with better accuracy and robustness than those by RS, which makes it a promising tool for computationally expensive FEM problems.

REFERENCES

- [1] J. Kudela, R. Matousek, "Recent advances and applications of surrogate models for finite element method computations: a review," *Soft Computing*, vol. 26(24), pp. 13709-13733, 2022.
- [2] Y. Sato, K. Kawano, H. Igarashi, "Direct inverse modeling for electromagnetic components using Gaussian kernel regression," *IEEE Transactions on Magnetics*, vol. 58(5), pp. 1-8, 2022.
- [3] X. Kong, S. Yin, Y. Gong, H. Igarashi, "Multi-objective optimization and uncertainty quantification for inductors based on neural network," *COMPEL-The international journal for computation and mathematics in electrical and electronic engineering*, vol. 43(4), pp. 890-903, 2024.
- [4] Z. Wen, O. Pizarro, S. Williams, "Feature Alignment: Rethinking Efficient Active Learning via Proxy in the Context of Pre-trained Models," *Transactions on Machine Learning Research*, 2024.
- [5] D. Wu, C. T. Lin, J. Huang, "Active learning for regression using greedy sampling," *Information Sciences*, vol. 474, pp. 90-105, 2019.
- [6] L. Zhang, Y. Xie, Y.R. Feng, et al, "Active-Learning-Based Sparse Near Field Scanning with Time-Domain Current Measurement for Conductive Coupling Path Visualization," *IEEE Transactions on Instrumentation and Measurement*, vol. 73, 2024.