

Robust Optimization for Electromagnetic Design Based on Neural Networks

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Electromagnetic applications often involve uncertainties, including material property variations, geometric inaccuracies, and environmental fluctuations. Such factors can impact design performance, causing deviations from target specifications. Robust optimization enables to obtain design point almost insensitive to that uncertainties. However, this approach often requires extensive repetitive computations, making the process time-consuming and computationally intensive. To address this challenge, this work proposes the use of neural network surrogate models for robust multi-objective optimization, which can significantly reduce computational time.

Index Terms—Uncertainty quantification, robust optimization, neural network.

I. Introduction

TO ENSURE the precision and stability of electromagnetic devices, it is crucial to account for random variations in dimensions and material properties, as well as performance fluctuations caused by environment changes [1]. Addressing these uncertainties at the early stages of design is essential for achieving reliable outcomes. The design process for such devices typically involves complex multi-objective optimization, necessitating extensive evaluations. Incorporating random errors such as manufacturing errors and temperature-dependent material properties further increases this complexity, as robust multi-objective optimization (RMOP) must evaluate numerous random samples. To address these challenges, surrogate models are often employed to alleviate computational demands, for example, the dual-level surrogate model is used in [1]. However, traditional surrogate models struggle to predict multiple outputs from mixed material and geometrical input data, while NN-based surrogate models[3-4] show great potential in optimizing electromagnetic performances. This study introduces an RMOP framework that uses a neural network (NN)-based surrogate model. The proposed method facilitates the identification of Pareto fronts that meet the design requirements for precision and stability. A saturable coil is studied in order to evaluate the proposed approach.

II. NN-based RMOP

Assume a RMOP has d -dimensional robust objective function $\tilde{\mathbf{F}}(\mathbf{x}) = [\tilde{f}_1(\mathbf{x}), \dots, \tilde{f}_m(\mathbf{x})]$, and $\mathbf{x} = [x_1, x_2, \dots, x_d]^\top$ is a d -dimensional variable vector within the feasible set $\mathcal{X}$. The optimization problem is expressed as:

$$\min_{\mathbf{x} \in \mathcal{X}} \tilde{\mathbf{F}}(\mathbf{x}), \quad (1)$$

To account for uncertainty, we introduce the random vector ξ_j , which has the same size as $\mathbf{x}$. Here, ξ_j represents the j -th realization of a sample of size N . All random vectors

satisfy the same probability density function $P(\xi)$. To be considered robust, an optimal solution must satisfy the following inequality for each component f_j of the objective function F , ensuring that the variation of f_j does not exceed a predefined noise scale ϵ_i :

$$\max_j f_i(\mathbf{x} + \xi_j) - \min_j f_i(\mathbf{x} + \xi_j) \leq \epsilon_i, \quad (2)$$

where $i = 1, 2, \dots, m$, and $j = 1, 2, \dots, N$.

The robust value of the i -th objective function, $\tilde{f}_i(\mathbf{x})$, is computed as the average:

$$\tilde{f}_i(\mathbf{x}) = \frac{1}{N} \sum_{j=1}^N f_i(\mathbf{x} + \xi_j). \quad (3)$$

As shown in Fig. 1, each individual $\mathbf{x}$ will be sampled based on the noise introduced by manufacturing errors $P_m(\xi)$ or environmental disturbances $P_e(\xi)$. The realizations are evaluated using the NN which enables to obtain surrogate models for the functions f_j which originally have to be calculated by high fidelity models like finite element (FE) models. This approach allows designers to select an appropriate Pareto front based on the variation threshold in objective functions. Pareto front A in Fig. 1 has better robustness compared to front B but worse expected objective values.

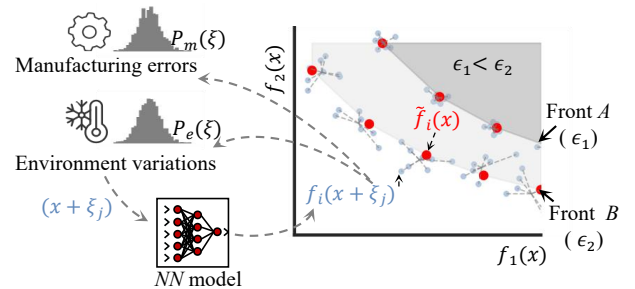


Fig. 1. Conceptual diagram of the proposed method.

III. Case Study of Inductor Design

A. NN Surrogate Model

Three neural networks (NNs) were independently trained to predict inductance (L), core loss (P), and saturation current (I_s), using $B(H)$ curves and dimension scales as six input variables. The $B(H)$ curve here is described by the Fröhlich-Kennelly equation:

$$B = \frac{H}{\alpha + \beta H} + \mu_0 H, \quad (4)$$

For dimension parameters, w and d represent the coil width and spacing, while W and T represent the core width and thickness. The training data is obtained from the two-dimensional FE calculations. Fig. 2 illustrates the architecture of the NNs, which comprise three hidden layers, each containing 40 neurons. The size of the training dataset is 4000. The training process, implemented using Python's TensorFlow library, employed a Multilayer Perceptron (MLP) model and involved 500 training iterations. Regression analysis between the true values (FE calculations) and the neural network predictions is illustrated in Fig. 3, with the corresponding coefficients of determination (R^2) indicated.

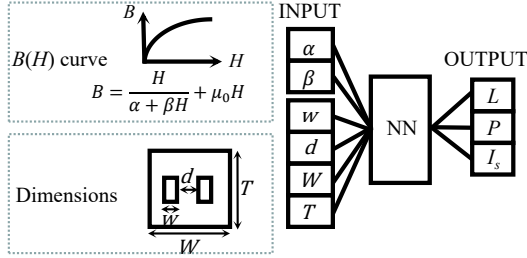


Fig. 2. NN for the prediction of inductors performance.

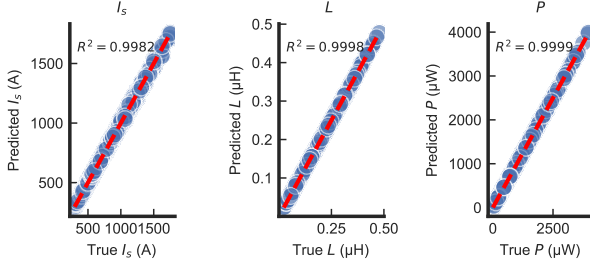


Fig. 3. Regression analysis between the true values (FE calculations) and the neural network predictions.

B. RMOP definition

In this case, the design variables are the structural dimensions given in Fig. 2. The RMOP is defined as:

$$\mathbf{x} = [d, w, T_m, W_m] \quad (5)$$

$$\begin{aligned} \min_{\mathbf{x} \in \mathcal{X}} \tilde{\mathbf{F}}(\mathbf{x}) &= \min_{\mathbf{x} \in \mathcal{X}} [-\tilde{I}_s(\mathbf{x}), \tilde{P}(\mathbf{x})] \\ \text{subject to } \Delta L(\mathbf{x}) &\leq \epsilon_i \end{aligned} \quad (6)$$

where the optimization objectives I_s , P , and the inductance value L all comply with the noise scale ϵ_i . Assume the operating environment has a temperature following a normal distribution centered at 25°C with a standard deviation of 3°C. The $B(H)$ parameters at room temperature are

set to be $\alpha_0 = 7 \times 10^4$ A/m and $\beta_0 = 0.45$ m/A, with only β varying with temperature according to the following relationship:

$$\beta(T) = \beta_0 \cdot (1 + 0.01T). \quad (7)$$

Assume that the dimension scales follow a normal dis-

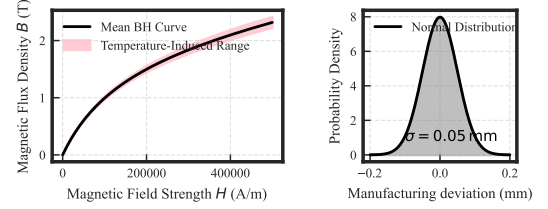


Fig. 4. Variation ranges of the BH curve and manufacturing error.

tribution with a standard deviation of 0.05 mm. Fig. 4 illustrates the variation range of the $B(H)$ curve caused by temperature changes, along with manufacturing errors that follow a normal distribution. Under this assumption, suppose a customer requires the inductance variation to remain within 1%, 2%, or 3%. In this scenario, both temperature disturbances and manufacturing errors are considered. The designer can apply this method to generate the corresponding Pareto fronts as shown in Fig.5.

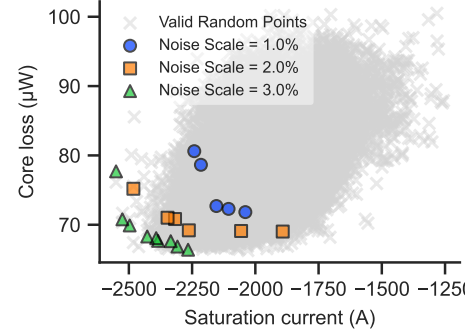


Fig. 5. Pareto fronts under different noise scales.

IV. Conclusion

This study applies to optimizing various electromagnetic devices, including motor topology optimization. To improve the model's resolution for small-scale perturbations caused by manufacturing imperfections, local mesh deformation of the FE model will be carried out in the future to reduce FE computational errors required for constructing the training dataset.

References

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