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Abstract

Multi-objective optimization is frequently employed in electric motor design, where iterative numerical simulations are required to evaluate a large number of design candidates. A trial-and-error design methodology like this is very time-consuming. In this paper, we propose learning-based surrogate models that use trained deep neural networks (NNs) to accomplish the rapid evaluation of motor designs. A motor design candidate can be described with either a list of geometrical parameters of the motor design, or a colored image of the motor cross-section. Different deep learning models can be constructed with either parameter-based input or image-based inputs. Our analysis reveals that deep convolutional neural networks (CNNs) utilizing image-based inputs exhibit a higher degree of predictive accuracy for more intricate responses, such as cogging torque, in comparison to models employing parameter-based inputs, albeit at the cost of increased training time.

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Comparison of Learning-based Surrogate Models for Electric Motors

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Multi-objective optimization is frequently employed in electric motor design, where iterative numerical simulations are required to evaluate a large number of design candidates. A trial-and-error design methodology like this is very time-consuming. In this paper, we propose learning-based surrogate models that use trained deep neural networks (NNs) to accomplish the rapid evaluation of motor designs. A motor design candidate can be described with either a list of geometrical parameters of the motor design, or a colored image of the motor cross-section. Different deep learning models can be constructed with either parameter-based input or image-based inputs. Our analysis reveals that deep convolutional neural networks (CNNs) utilizing image-based inputs exhibit a higher degree of predictive accuracy for more intricate responses, such as cogging torque, in comparison to models employing parameter-based inputs, albeit at the cost of increased training time.

***Index Terms*—Deep Learning, Surrogate Model, Finite Element Analysis, Electrical Motors**

I. INTRODUCTION

MULTI-OBJECTIVE OPTIMIZATION (MOO) is often used by motor designers to identify the best designs considering different objectives such as higher torque generation, lower torque ripple and lower material cost. Evolutionary algorithms such as genetic algorithm are often utilized to iteratively update the design parameters in the process, while finite-element simulations are conducted to evaluate the performance of each design candidate within the optimization loop [1]. The present methodology is limited by its time-consuming nature, with the primary bottleneck residing in the simulation phase.

Our intention is to make use of the robust machine learning and deep learning models, which have witnessed a lot of success in various fields, to facilitate such procedures and improve the effectiveness of motor designs[2], [3], [4], [5]. We investigate two different ways of describing the geometries of motor design candidates, namely parameter-based and image-based methods, and construct various machine learning and deep learning surrogate models suitable for each input method, and compare their performances in predicting multiple motor responses. We show that feed-forward neural networks combined with parameter-based input are easier to train, while deep convolutional neural networks (CNNs) with image-based input can achieve higher prediction accuracy for more complicated responses.

II. DATASET GENERATION

A surface permanent magnet (SPM) motor design problem is investigated in this paper. We first generate a dataset of SPM motors with 10 poles and 12 slots, whose topology is shown in Fig. 1. The dataset comprises 8916 different motor designs created by sweeping 9 independent geometrical parameters (among 18 parameters in total) as shown in Fig. 1. A quarter of the cross-section can be used to fully describe the motor design due to rotational symmetry. Therefore, we can use either a vector of parameters or an RGB image of the cross-section to describe one motor design, and feed them to machine learning model for training and testing. The motor designs are simulated in JMAG, a commercial finite-element analysis (FEA) software, to compute the responses, which include the Fourier components of induced voltage, the harmonic distortion of the induced voltage and the Fourier components of the cogging torque.

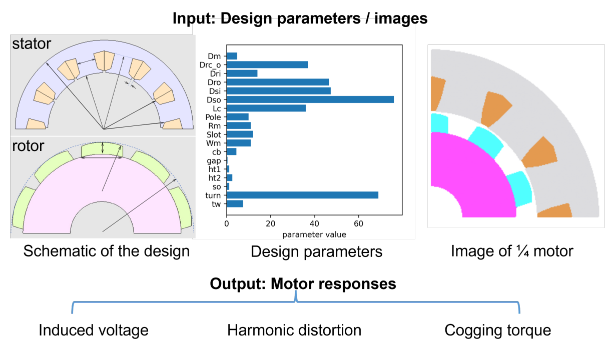

Fig. 1. Generated data structure of SPM motors, which consists of 9 independent parameters and 3 responses.

III. PARAMETER- AND IMAGE-BASED MACHINE LEARNING MODELS

We first develop machine learning models using a vector of 9 geometrical parameters as input. A standard fully-connected neural network (FCNN) with one input layer, one output layer, and one hidden layer serves as our foundation, as depicted in Fig. 2(a).Nine independent design parameters are supplied from the input layer to the hidden layer via connections between neurons. Then the data flow is coupled to a single node in the output layer to get a prediction for the individual responses after a $\tanh(\cdot)$ activation. This simple model configuration is comprised of a degree of freedom large enough considering the small input and output dimensions. The root-mean-square-error (RMSE) between the predicted responses and the ground truth is calculated and minimized iteratively during the training process.

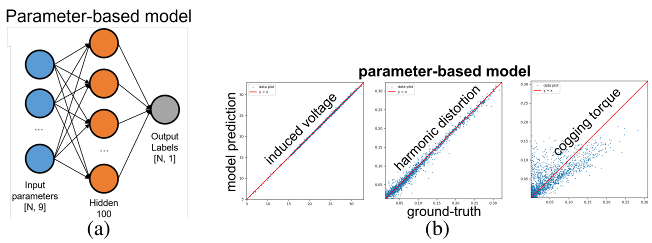

Fig. 2. Model structure with parameter-based input (a) and the prediction vs ground truth plot (b).

The trained model is applied to new test data for prediction, and the response plot is shown in Fig. 2(b). Overall the prediction accuracy is excellent, while cogging torque prediction is significantly worse. The difference can be understood by studying the features of dataset with statistical methods. We calculate the data correlation between all the response and parameter pairs. The correlation matrix is shown in Fig. 3. The absolute value of the data correlation is between 0 (not dependent) and 1 (linearly dependent), and the sign of the data correlation indicate if the two variables are positively or negatively related. From the figure, we can quantitatively analyze the dependence of the responses on the design parameters. Cogging torque, in particular, has a relatively weak dependence on the design parameters, which makes it more challenging to predict with machine learning models.

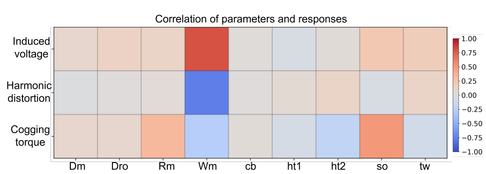

Fig. 3. The correlation matrix of the dataset between parameters and responses

In order to further improve the prediction accuracy, we build models which are more capable of learning highly-nonlinear functions. We first describe each motor design with an RGB image, as shown in Fig. 1, which contains more information of the motor design compared to the parameter-based method. Deep networks built on CNNs have proven to be effective in extracting features in such images. We build an image-based model with customized ResNet [6] as illustrated in Fig. 4(a): an ImageBlock is first used to process the image channels where the weight of the pixel value is adjusted. Then, the data is passed through the convolutional layers with ResNet blocks which consist of two convolutional layers plus an identity mapping. Finally, we reshape the output to vectors and apply three additional fully-connected neural networks where the output will be the responses. The response plot showing the comparison between predicted responses and the ground-truth is visualized in 4(b). The quantitative comparison of the RMSE for the two types of models is shown in Table I.

Overall, the image-based model dramatically improves the prediction accuracy for harmonic distortion and cogging torque, which is ascribed to the enhanced nonlinearity from CNNs. However, it also marginally reduces the accuracy of induced voltage. The reason is that the image resolution is nevertheless constrained by the number of pixels, which prevents extremely high precision due to a certain information loss.

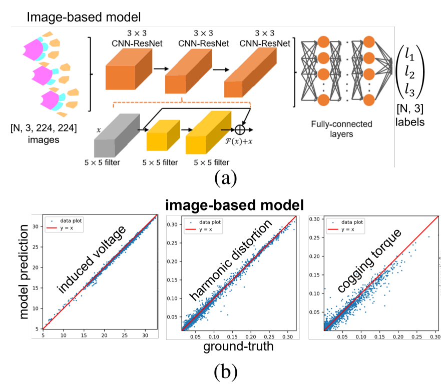

Fig. 4. Model structure with image-based input (a) and the prediction vs ground truth plot (b).

TABLE I

Root-Mean-Square-Error of the response prediction

Response	Parameter-based Model	Image-based Model
induced voltage	0.0248 ± 0.0031	0.0596 ± 0.0062
harmonic distortion	0.1149 ± 0.0131	0.0994 ± 0.0063
cogging torque	0.5455 ± 0.0528	0.2392 ± 0.0100

The responses are normalized to Gaussian distribution $\tilde{p} = (p - \mu_p)/\sigma_p$ before computing the RMSE, where μ_p, σ_p are the mean and standard deviation of responses in the training dataset. All models are trained 6 times to calculate the statistics of RMSE.

IV. Concluding Remarks

In conclusion, we investigated learning-based surrogate models for the rapid prediction of motor performances. We constructed machine learning models with either geometrical parameters or cross-section images as input. Though parameter-based models are much simpler and faster to perform prediction, image-based models have the advantage of better accuracy in predicting highly nonlinear responses. The trained surrogate models can greatly speed up the subsequent design optimization process by replacing the computationally expensive finite-element simulations.

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