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Abstract

Typical electric motor design process involves time- consuming finite-element simulations. In recent years, machine learning and deep learning techniques have been investigated for the development of surrogate models which provide rapid evaluation of motor designs. One drawback of these techniques is the requirement of large dataset in order to achieve reasonable prediction accuracy. In this paper, we present strategies in developing data-efficient machine learning and deep learning surrogate models for electric motors: reducing input dimensions, utilizing physics knowledge for hybrid models, and applying feature extraction methods using geometrical and topological data analysis tools.

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***Abstract*—Typical electric motor design process involves time-consuming finite-element simulations. In recent years, machine learning and deep learning techniques have been investigated for the development of surrogate models which provide rapid evaluation of motor designs. One drawback of these techniques is the requirement of large dataset in order to achieve reasonable prediction accuracy. In this paper, we present strategies in developing data-efficient machine learning and deep learning surrogate models for electric motors: reducing input dimensions, utilizing physics knowledge for hybrid models, and applying feature extraction methods using geometrical and topological data analysis tools.**

***Index Terms*—Electric machines, surrogate model, machine learning**

I. Introduction

Electric machines are widely used in households and various industries, and their technologies and design principles are well established. However, the requirements for motor design and customization, especially for new applications such as electric vehicles and aircraft, and factory automation, always pose new challenges to motor designers. Parameter sweeping or iterative optimization methods are often utilized in order to evaluate a large number of design candidates before identifying the optimal design for a specific task. Thee accurate analysis of each motor design candiate often relies on finite-element analysis (FEA) based numerical simulations, which are time-consuming, especially when various operating points are evaluated for one design. It is therefore desirable to seek alternative analysis methods of FEA to rapidly predict motor performances. Surrogate model based optimization has been investigated to speed up the process [1]. Due to the highly nonlinear nature, the accuracy of conventional surrogate models suffers when predicting certain motor performances such as torque waveform and efficiency map. In recent years, machine learning and deep learning methods have found many applications and been applied to motor design [2], [3], due to their capability of emulating highly nonlinear functions. One main challenge with this approach is the large dataset size often required to achieve reasonable prediction accuracy. In this paper, we present three strategies for data-efficient machine learning models for electric motor design optimization purposes: One, reduce input dimension of machine learning model for motor design; two, combine with physics-based methods for hybrid modeling; three, apply advanced feature extraction with geometrical and topological data analysis methods.

II. Data-Efficient Machine Learning Methods

A. Reducing Input Dimension

With the popularity of convolutional neural network (CNN) for image recognition and classification, one commonly used approach is to represent a motor design with a 2D image, which is fed into a CNN based deep learning model, to predict the motor performance [4]. It has been shown that such deep learning models can achieve very good accuracy for highly nonlinear current-dependent torque profiles. However, one main drawback is the large amount of data needed to train the deep models, which typically have millions of trainable parameters. One main reason is that the image-based input has high dimension. A highly involved model is need to extract features in these images. Alternatively, one can represent a motor design with a list of parameters that are most relevant to the motor characteristics. With parameter-based input, the dimension can be reduced significantly. Simpler machine learning models can be built and trained to make predictions with much less amount of data.

In [5], the surrogate models of a surface-mount permanent magnet (SPM) motor are tested and compared. An SPM motor is described as a 2D RGB image of dimension 224×224 for image-based models, while a list of 9 parameters is used for input for parameter-based models. While image-based models can achieve higher accuracy especially for highly nonlinear cogging torque, they require more data, dedicated hardware, and longer training time. On the other hand, parameter-based models are much lighter weight, requires less data, much faster to train, and can achieve comparable accuracy for multiple performance metrics.

Even when image is preferred input method for complicated geometry, it is still possible to reduce the dimension for example by considering symmetry in the design, and image resizing and transformation techniques. By doing so we can remove redundant information from the input and best utilize the available data to effectively train our surrogate models.

B. Hybrid Modeling

Another effective strategy for data-efficient machine learning models is to combine with physical knowledge and build hybrid models. For electric motors, simplified analytical and semi-analytical models have the advantage in computation speed, while suffering in calculation accuracy when saturation is involved. Nonetheless, the output of these physics-based models can be used as a good estimation for a more accurate machine learning model.

In [6], we proposed a physics-assisted neural network (PANN) surrogate model for SPM motor cogging torque prediction. The hybrid model combines a NN with a physics-based model using semi-analytical subdomain method. The subdomain model first provides an approximation of the cogging torque for a given motor design, which is used as an additional input to the NN, which is further trained with dataset generated from FEA simulations to make more accurate predictions. We implemented the method for SPM cogging torque prediction, which is very challenging as it is highly nonlinear and extremely sensitive to small changes in geometry near the air gap. We showed that the trained PANN model can achieve much improved accuracy compared with the subdomain model calculation, as well as the conventional NN approach, especially when the size of the training dataset is small. Depending on the design task, different physics-based models can be used for the hybrid modeling process.

C. Applying Advanced Feature Extraction Methods

For designs with irregular geometries such as topologically optimized motors, it is preferable to represent them as images instead of geometrical parameters. In this case, CNN based deep learning models are typically needed to make reasonable predictions on the motor performance. While one main advantage of CNN based network is the capability of extract features automatically through the training process, it falls short in the explainability as to what features are exactly learned, and the generalization capability to unseen data. In addition, they are susceptible to noisy data and tend to overfit with training data, and can have difficulty in generalizing over unseen data. On the other hand, geometric data analysis methods offers a mathematically rigorous way of extracting the geometry information from a data space. In particular, topology data analysis (TDA) deals with qualitative geometric information, which studies the connected components of a space, such as the classification of loops and higher dimensional surfaces within the space. Compared with other straightforward geometric methods, which quantitatively describe geometric properties such as curvatures, topology describes geometric properties in a much less sensitive way to the choice of metrics [7]. Therefore TDA offers a way of analyzing data that is insensitive to particular choices of metrics, robust to noises, and can withstand transformations and distortions of images.

We have proposed to apply TDA for deep learning based electric motor design, in particular, the prediction of nonlinear 2D flux map of interior permanent magnet (IPM) motor with random rotor structures [8]. We extracted topological features, namely, persistence diagrams and Betti sequences, from the cross-section images of motor design candidates; together with the cross-section images, we trained a two-channel deep learning model for the prediction of 2D flux map of a motor design. The two-channel model includes one branch of deep CNN model with images as input, while the topological features extracted from the images are fed into the second branch of a multi-layer perceptron (MLP) model; the output of the two branches is concatenated and fed into a set of dense layers before finally connecting to the flux map parameters. We showed that the prediction accuracy using topological features combined with cross-section images is consistently better compared with models using motor cross section images only, indicating that the model generalizes better with unseen data with TDA. Other geometric data analysis methods can be explored as well.

III. Conclusions

Deep learning techniques are recently investigated by researchers for electric motor design surrogate modeling and optimization purposes. One major challenge is the large amount of data required to train such models, especially for highly nonlinear motor performance prediction. In this paper, we address this issue by proposing three strategies to best utilize the available training data and improve the model prediction accuracy. We showed with examples that by reducing input dimension, applying physical knowledge for hybrid models, and coupling with effective feature extraction techniques in geometric and topology data analysis, data-efficient deep learning models can be constructed.

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