

Efficient E-Machine Design: Enhancing Scalability with Transfer Learning and Multi-Fidelity Data

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This paper explores the integration of datasets with various fidelities and transfer learning in designing electric machines (E-machines). By reusing knowledge from prior tasks, transfer learning reduces the cost and time of creating datasets and training models. We test the approach on various E-machine types and fidelity data. The results show that transfer learning enhances efficiency, generalizes well across tasks, and works with smaller and low-fidelity datasets. This provides a scalable and cost-effective solution for the inverse problems of E-machine design.

Index Terms— E-machine design, transfer learning, generative model, generative adversarial network (GAN), inverse problem

I. INTRODUCTION

Deep neural networks (DNNs) are being considered for problems in computational electromagnetics because they have the potential to provide solutions faster than traditional simulations. Designers can use DNNs for applications such as optimizing the topology of E-machines or predicting motor drive key performance indicators (KPIs). These models enable rapid iterative evaluations, speeding up the design process significantly. They reduce the need for slow physics-based simulations at each evaluation [1,2].

Recently, generative AI approaches have introduced a new way of solving design challenges by bypassing traditional optimization altogether [3]. These methods can treat design as an inverse problem, where the desired outcome is specified, and the model generates a potential design candidate to achieve it directly. One example is the Correlation-Diversified Conditional Generative Adversarial Network (CDC-GAN). CDC-GANs learn patterns in the data through a competition between a generator and a discriminator, enabling them to create designs that meet specific KPIs directly. This eliminates the need for iterative optimization or trial-and-error loops. The generator produces high-quality designs by sampling from the learned distribution, while the discriminator ensures these designs align with the required conditions. This process makes the design workflow faster and more efficient, allowing designers to focus on refining and implementing solutions instead of spending time on repetitive adjustments. CDC-GANs provide a straightforward way to handle complex, nonlinear, and high-dimensional design. The concept was applied to an Axial Flux Permanent Magnet (AFPM) machine [4].

However, dataset preparation for a new class of E-machines and training the generative model from scratch remains a major drawback, requiring significant time and computational resources. Transfer learning addresses this challenge by adapting models trained on one problem to new challenges, requiring less data and effort. As for the data creation, various fidelity data are proposed to balance fidelity with cost. High-fidelity data, derived from detailed simulations, provide accurate results but are computationally expensive to generate while low-fidelity data are faster and cheaper to produce while lacking precision. Transfer learning bridges this gap by allowing models to start with knowledge gained from low-fidelity data before refining their understanding using a smaller amount of high-fidelity data [5-7]. This approach significantly reduces the computational burden. Transfer learning offers a promising solution

by leveraging pretrained models to generalize across similar domains, thereby enabling efficient and scalable design processes.

The aim of this work is to use transfer learning to enable efficient adaptation to new E-machine types and conditions without retraining models from scratch. We use low- and high-fidelity datasets to reduce the computational burden of design tasks by reusing existing knowledge. The findings highlight the value of transfer learning for improving scalability and efficiency in the design of E-machines across diverse applications. This work details the methodology, results, and implications of applying transfer learning in this context, demonstrating its potential to develop E-machine design.

II. METHODOLOGY

A. Dataset Preparation

We prepared datasets with various levels of fidelity to reduce computation time. High-fidelity datasets provide detailed and accurate information while are expensive and time-intensive to produce. Low-fidelity datasets, on the other hand, are less detailed but significantly cheaper and faster to generate data. By combining these datasets, we create a balanced approach to training.

For this study, we used Enhanced Latin Hypercube Sampling (ELHS) to generate a comprehensive design space consisting of 5,000 samples [8]. High-fidelity models included 3-D and 3-D quasi E-machine simulations, which were computationally expensive, while low-fidelity models simplified these into a one pole segment component (with a high to low fidelity ratio of 1:5). Both datasets maintained a consistent geometry, physical properties, boundary and solver configurations to ensure comparability.

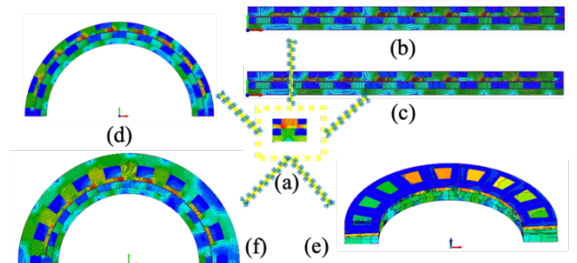


Fig. 1. Transfer learning tasks : (a) source (Low fidelity) ; (b) 3-D quasi model (High Fidelity); (c) large scaled PM linear motor; (d) Double Rotor Radial Flux motors; (e) 3-D AFPM; (f) SPM with Single Rotor Radial Flux motors

B. Transfer Learning Process

The process of transfer learning involves reusing knowledge gained from one domain (source) to improve performance on a related domain (target). We applied transfer learning using CDC-GAN, focusing on the following steps:

- 1) Source knowledge: The CDC-GAN model, was first trained on low-fidelity datasets and demonstrated the ability to learn general patterns. This pretrained model served as a foundation for transfer learning, capturing useful features distributions and correlations from the source task [4].
- 2) Fine-tuning: The pretrained model was then adapted to high-fidelity. A smaller learning rate was used during this stage to refine the model without overfitting the learned patterns from the pretraining phase.
- 3) Evaluation: The performance of the transfer learning model was compared to models trained from scratch to assess its effectiveness.

The generator in CDC-GAN was tasked with generating designs that met specific torque targets, while the discriminator validated the plausibility of these designs [4].

III. RESULTS

A. Target Knowledge

As shown in Fig.1, using the CDC-GAN model on low fidelity data, we transferred its knowledge to high-fidelity datasets across a variety of E-machine types, including 3-D Axial Flux Permanent Magnet (AFPM) motors, PM Linear motors, Double Rotor Radial Flux motors, Surface-Mounted Permanent Magnet (SPM) motor. The TLE-CDC-GAN allowed the model to adapt quickly and achieved stable performance with fewer training epochs when compared to models trained from scratch. The ability to generalize across different machine types and fidelity levels highlighted the robustness of this approach.

B. Performance Metrics

Several metrics were used to evaluate the effectiveness of transfer learning, including the Frobenius norm and Kolmogorov-Smirnov (KS) for the difference of the distribution and correlation matrix of generated and real data distributions, respectively. Key findings indicate Frobenius norm difference for correlation matrices of 0.185 for source training vs. 0.188 for TLE-CDC-GAN and average KS statistic is 0.055 for source training vs. 0.048 for transfer learning. Additionally, training time was significantly reduced. The transfer learning model completed its training on high-fidelity datasets in 28 seconds, compared to 1022 minutes required by the CDC-GAN trained from scratch while preserving model performance.

C. Scalability

The scalability of the TLE-CDC-GAN approach was evident in its ability to handle a wide range of torque requirements and machine types. By fine-tuning the pretrained model, we achieved high performance across different scale scenarios with minimal additional data. This highlights the

potential of transfer learning for addressing diverse design challenges in the E-machine domain. TLE-CDC-GAN proved to be an effective strategy for E-machine design, offering significant advantages in terms of efficiency, generalization, and scalability. By transferring knowledge from low-fidelity datasets, the TLE-CDC-GAN reduced the training time and computational costs for high-fidelity tasks. The approach demonstrated the ability to generalize to various machine types and torque ranges, showing its versatility. Transfer learning enabled the efficient scaling of models to new tasks and domains with minimal additional effort. Despite these advantages, challenges remain. For complex machine types, maintaining stability during fine-tuning involves optimizing hyperparameters to balance model performance and prevent issues such as overfitting or underfitting. Additionally, extending the TLE-CDC-GAN framework to different machine topologies will require further research and development, particularly if the machine to be designed belongs to a distinctly different class, such as a SynRM, rather than variants within the same electromagnetic and topological class.

IV. CONCLUSION

This paper demonstrates how transfer learning combined with multi-fidelity datasets can significantly reduce computational time and improve scalability in E-machine design. We highlight the effectiveness of TLE-CDC-GAN in adapting to diverse E-machine types from axial flux to radial flux models while maintaining performance and efficiency. Techniques such as partial model freezing, integrating more diverse datasets, and applying TLE-CDC-GAN to other domains can address some of the limitations that may arise for different machine classes and domains. These advancements will further enhance the applicability and robustness of this approach, enabling its use in increasingly complex design scenarios.

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