

Machine Learning Methods for Hybrid Design Optimization of Electric Machines with Applications for Coreless Axial Flux PM Motors

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Abstract—This paper presents a comparison of machine learning-based surrogate modeling techniques for the prediction of torque constants in example coreless axial flux permanent magnet (AFPM) machine designs. Machine learning was studied for its use as a parallel process to aid in optimization, reducing computational times and complexity. Applied machine learning techniques can be used to accurately predict key parameters electric machine designs and narrow the search space, reducing the necessary amount of finite element analysis (FEA) simulations. An optimized FEA-based set of design candidates is created through differential evolution (DE). The optimized data set was then used to train an artificial neural network (ANN), accelerated random forest (ARF), and gradient boosted regressor (GBR) frameworks to compare applicability. The resulting machine learning models show high accuracy, above 90% R^2 , with trade-offs between data required to convergence, build times, and prediction accuracy.

Index Terms—Electric machines design, coreless axial flux permanent magnet, machine learning, surrogate modeling

I. INTRODUCTION

Machine learning (ML) applied to electric machine design is the newest technique in surrogate assisted design exploration to reduce long computation times and improve the efficiency of design space exploration. Surrogate modeling and data-driven approaches have the potential to accelerate the typically computationally intensive finite element analysis (FEA) electric machine design process [1]. Machine learning models may be used in parallel with FEA to interpolate results, maximally

explore the design search space, and minimize the overall computational cost required for design optimization.

Surrogate methods for aided electric machine design optimization have been explored to capture non-linear complexities [2]. Qiu *et al.* proposed improved design, control, and maintenance of electric motors through AI [3]. Poudel developed a general deep neural network modeling approach for electric machines, with case-studies to flux harmonics and cogging torque prediction [4]. Physics-informed deep learning has been demonstrated by Han *et al.* for design of high efficient and high-power-density induction machines [5]. A comprehensive review of recent ML-based electric machine design optimization developments, opportunities, and challenges are detailed by Li *et al.* [6].

Different machine learning model techniques have been applied to a variety of machine types, with few direct comparisons between models. Sasaki *et al.* studied combined genetic algorithms and convolutional neural networks for fast topology optimizations of electric machines [7], [8]. Variational auto-encoders were utilized by Parekh *et al.* to simultaneously optimize two different machines by predicting key performance indicators (KPIs) [9]. Sakamoto *et al.* propose a physics-assisted neural network to predict the torque ripple of a surface-mounted permanent magnet (PM) motor [10]. Silva *et al.* applied the Gaussian Process Regression surrogate model in conjunction with physics equations to accurately characterize PM synchronous machines [11].

This paper demonstrates and compares the use of multiple machine learning model architectures, including Artificial Neural Networks (ANN), Accelerated Random Forest (ARF), and Gradient Boosted Regressors (GBR) for hybrid electric machine design optimization. Differential Evolution (DE)-based design candidates for a coreless Axial Flux Permanent

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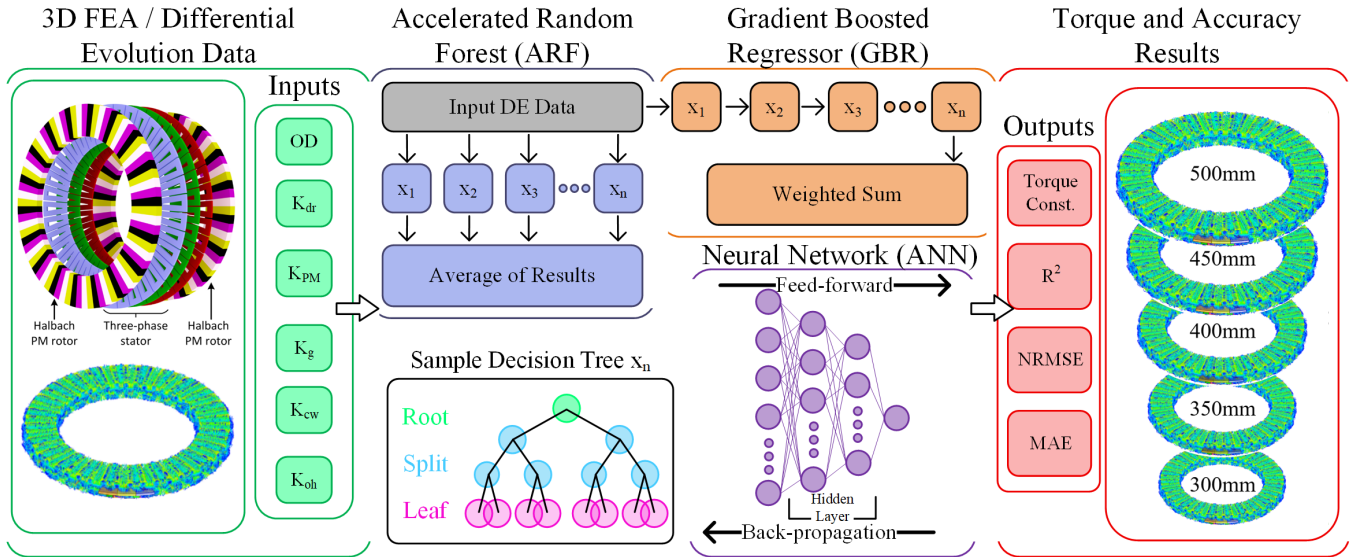


Fig. 1. Proposed machine learning-based framework for assisted machine design including results from ANSYS Maxwell 3D FEA simulations and visual representations of studied machine learning model architectures.

Magnet (AFPM) motor data are used to train and test each models' ability to accurately predict torque constants. The use of machine learning for parallel processing is prioritized and applicable to alternative electric machines.

II. MACHINE LEARNING AIDED DESIGN

The proposed framework for ML-aided machine design is depicted in Fig. 1, which uses a DE optimized dataset simulated via 3D FEA to train and evaluate a set of surrogate models. Surrogate models can "learn" to approximate the computationally expensive FEA simulations through correlations between results and design parameters, enabling fast prediction of key performance parameters such as the torque constant. This approach substantially reduced the computational overhead associated with high-fidelity machine design optimization by replacing simulations during design exploration. Implementation of the machine learning techniques were completed using open-source libraries Keras and scikit-learn [12], [13].

Artificial neural networks are a multi-layer perceptron (MLP) consisting of interconnected layers and neurons. Each neuron applies a weighted combination and bias of its inputs, enabling the network to model highly complex mappings between inputs and outputs. Training proceeds through a feed-forward and back-propagation process, in which prediction errors are propagated backwards and used to iteratively update weights and biases by gradient descent [14]. The ANN is an established surrogate modeling technique [15], valued for its flexibility and capacity to generalize high-dimension spaces.

The accelerated random forest architecture is an ensemble method comprising numerous decision trees trained independently and in parallel on randomized subsets of the training data. Predictions are created by averaging the outputs of all trees, reducing variance and improving generalization. This model is particularly well-suited for an electric machine aided design workflow as its parallel nature allows inference to be

performed concurrently while FEA simulations are running, enabling interpolation of intermediate results in real time [16], [17]. The ARF represents an advancement in ensemble learning and has seen increased adoption in mechanical and electromagnetic applications due to its robustness and low sensitivity to hyperparameter tuning [18].

Gradient boosted regression shares the same fundamental decision tree structure as the ARF, but differs in its training strategy. Rather than constructing trees in parallel, the GBR trains estimators sequentially, with each successive tree training on the residual errors of the previous one. This iterative mechanism allows the model to progressively reduce bias, producing high accuracy on structured regression tasks [19].

III. EXAMPLE APPLICATION TO ELECTRIC MOTOR

A coreless stator Axial Flux Permanent Magnet (AFPM) machine is selected as the case-study application for the proposed ML techniques. This topology comprising double-sided Halbach array PM rotors and a three-phase coreless stator with overlapping windings, shown in Fig. 1, is particularly well-suited for surrogate modeling since its electromagnetic non-linearity arises from the different nature of more prevalent cored radial-flux electric machines. The non-linearity is from the geometry, rather than material B-H curves, as it has a coreless stator and axial flux configuration [20]. A huge computational effort was required to produce the data design candidates shown in Fig. 2, taking more than 40 hours to produce the entire dataset.

The pitch factor is a numerical ratio of the coil induced voltage to a fully-pitched coil, based on the configuration of windings. The pitch factor, K_p , for coreless axial flux machines can be expressed as:

$$K_p = \sin\left(\frac{\nu\pi(2-K)}{2N_c}\right), \quad (1)$$

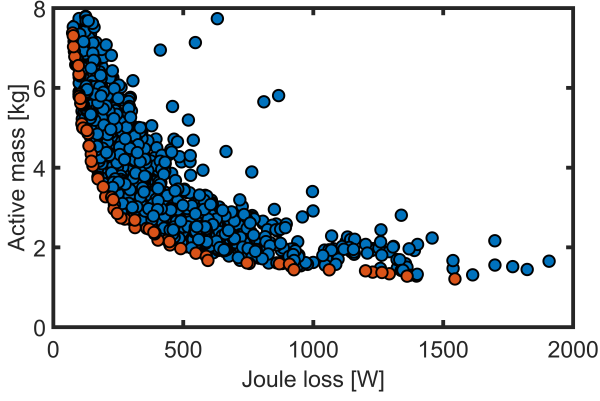


Fig. 2. All electric motor optimization design candidates evaluated using 3D electromagnetics FEA simulations, with orange markers representing the Pareto-optimal designs.

where ϵ is the short-pitch angle in electrical degrees [21]. Voltage harmonics can be suppressed by controlling this ratio, and is a factor in computing the average torque.

The torque generation in this type of machine can be explained using the Lorentz force theorem and is well established in [21]. The average torque provides a reasonably accurate approximation of the coreless AFPM output torque and can be determined through the following equation:

$$T_{avg} = \frac{1}{2w_{cs}} K_M K_{P1} K_{g1} N_c N_t I_p (1 - \lambda) B_1 K_D^2 D_o^3 \sin\left(\frac{w_{cs}}{K_D D_o}\right), \quad (2)$$

where K_M is the periodicity boundary condition coefficient, representing the number of repetitions of the base periodic segment; K_g is the coil group factor; N_c is the coil numbers of the base pole/coil combination; coil group denotes adjacent coils of the same phase coil group denotes adjacent coils of the same phase within one periodicity; N_t is the number of turns per coil; I_p is the peak value of the phase current; λ is the rotor inner-to-outer diameter ratio; B_1 is the fundamental component of flux density ($i = 0$); K_D is a factor that take into account the diameter at which the calculation is performed; D_o is the rotor outer diameter. An important takeaway is that the torque is proportional to the outer diameter cubed D_o^3 . The cubic dependence highlights the strong influence of machine geometry torque capability.

Each phase comprises coils corresponding to the number of poles, with an opposite winding direction for adjacent coils. The stator is constructed using a printed circuit board (PCB), with reduced AC losses through carefully designing the planar copper traces, thereby improving efficiency while maintaining a compact form factor. A coreless AFPM prototype, depicted in Fig. 3, was employed to validate and develop a calibrated 3D FEA model in ANSYS Electronics Desktop [22] [23].

The ML models were trained on successive generations of DE optimized designs, assuming multi-objective optimization as a typical design practice for electric machines, and applied to predict torque constant per design. Each model received

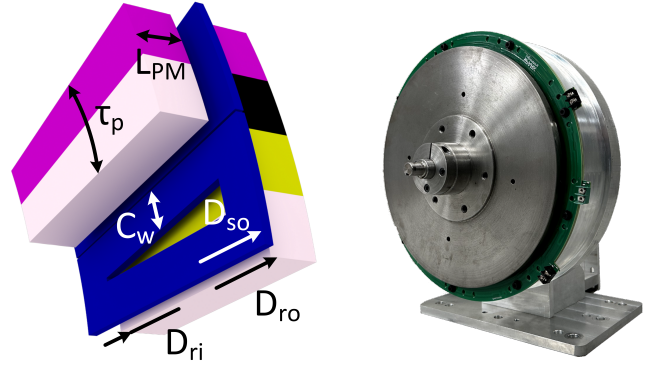


Fig. 3. Geometry and key parameters of the CAFPM machine used for surrogate modeling and the prototype used for electromagnetics model verification.

TABLE I
INDEPENDENT VARIABLES AND CORRESPONDING LIMITS FOR THE CAFPM MACHINE DESIGN OPTIMIZATION AND SURROGATE MODELS.

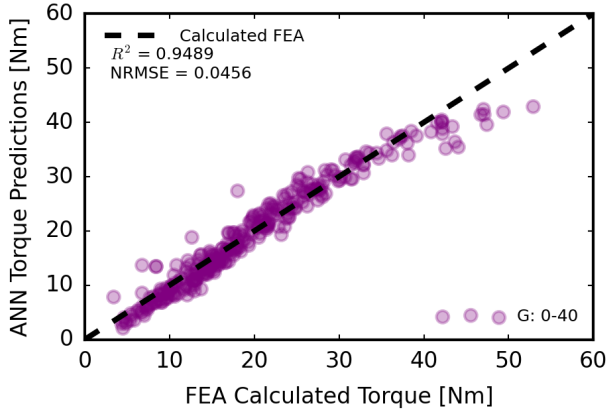
Var.	Description	Min.	Max.
K_{dr}	Rotor diameter ratio = $\frac{D_{ro}-D_{ri}}{D_{ro}}$	0.15	0.35
K_{PM}	PM axial length ratio = $\frac{L_{PM}}{\tau_p}$	0.15	0.50
K_g	Magnet-to-magnet gap ratio = $\frac{g_{M2M}}{\tau_p}$	0.14	0.75
K_{cw}	Coil side width ratio = $\frac{4C_w}{\tau_p D_{ri}}$	0.77	1.00
K_{oh}	Overhang ratio = $\frac{D_{so}-D_{ro}}{2C_w}$	0.00	1.00

the same set of normalized and scaled input geometry ratios, defined in Table I and visualized in Fig. 3. Five-fold cross-validation was applied during training to partition the dataset into training and validation subsets across five non-overlapping folds, mitigating overfitting and providing a more robust estimate of generalization performance.

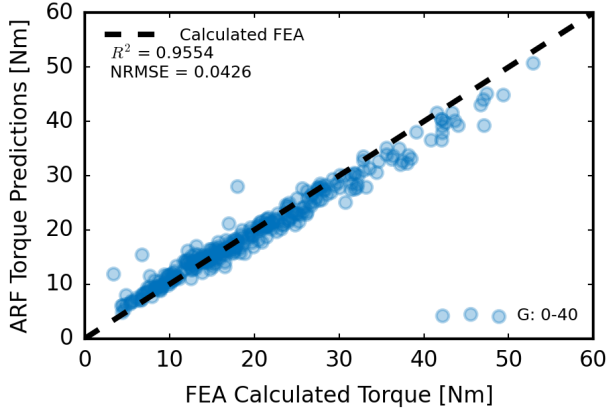
Hyperparameters for each model are initialized to well-established defaults for their respective architectures. All surrogate models were trained on a computing system equipped with a 16-core Intel(R) Xeon(R) Gold 6226R CPU operating at 2.90GHz, an NVIDIA T1000 GPU with 8 GB of memory, and 128 GB of RAM. Model performance is evaluated at each DE design generation grouping using a comprehensive set of metrics: normalized root-mean-square error (NRMSE), (R^2), and mean absolute error (MAE), along with convergence behavior, are used to assess both predictive accuracy and training stability as the dataset grows.

IV. DISCUSSION AND COMPARISON OF METHODS

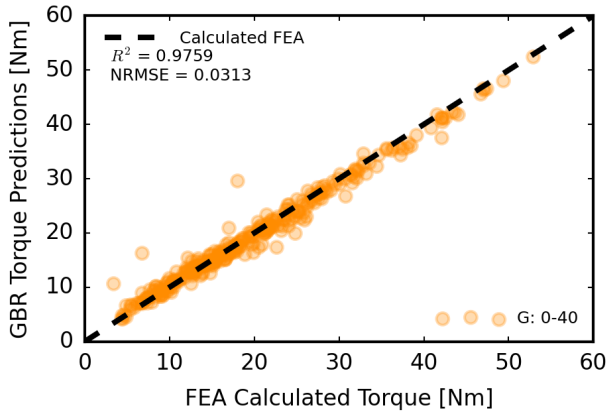
All three ML surrogate models demonstrated a strong prediction accuracy when trained on the full DE optimized dataset, as evidenced by the regression plots in Fig. 4a-4c and the error metrics summarized in Table II. The ARF consistently achieved the highest consistency, with over $R^2 = 0.90$ at and above 5 generations of data, suggesting that the ARF has the highest generalization. The ANN and GBR had high R^2 values across all generation grouping, but both dropped at the 10 generation mark, likely from overfitting.



(a)



(b)



(c)

Fig. 4. Regression plots comparing the simulated vs predicted torque constants from (a) ANN, (b) ARF, and (c) GBR. Each of the models were trained on all design candidates from the DE optimization.

The convergence results shown in Fig. 5 further differentiates the models in terms of computational efficiency. The GBR was slower to stabilize, but results in the lowest NRMSE of 2.71%, reflecting its iterative bias-reduction training. The ARF and ANN converged more rapidly, reaching NRMSE values of 8.68% and 3.22%, respectively, indicating that they may be more suitable to parallel prediction and real-time interpolation

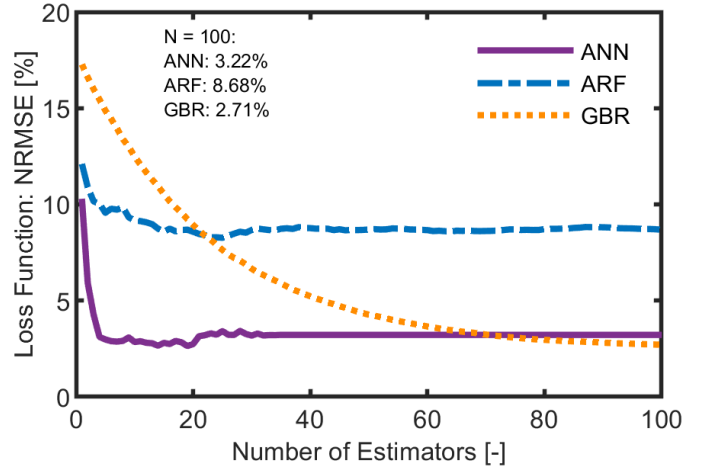


Fig. 5. Convergence of normalized root mean square error (NRMSE) across 100 estimators for the ANN, ARF, and GBR surrogate models using the entire range of design candidates.

of simulation results since they require less estimators to reach a stable prediction. The ARF displayed higher error and some instability, but remains within acceptable error bounds for surrogate-assisted design exploration ($< 10\%$).

The tested surrogate model build times on average required seconds to complete k-fold validation, training, and inferences, making them computationally inexpensive compared to FEA. For the example coreless AFPM machine, simulations for only one pole and half of the total axial length takes approximately 90 seconds on our computing hardware. Establishing surrogate models requires acquiring data and training, but once established are able to instantly produce results in contrast to the complex FEA models. The results demonstrate that surrogate models are orders of magnitude faster than high-fidelity FEA, and well-suited for large-scale design space exploration.

Of the evaluated models, the ANN required the longest computation time for k-fold validation, training, and inference due to the iterative optimization process over multiple epochs. Even with early stopping, the ANN build time was approximately three times greater than the ARF model and thirty times greater than the GBR model. The fast model construction and

TABLE II
PREDICTION ERROR METRICS FOR DIFFERENT SURROGATE MODELS.

Model	Gen.	Designs	R^2	NRMSE	MAE
ANN	5	241	0.93	0.06	1.24
	10	401	0.84	0.07	1.28
	20	708	0.97	0.04	0.95
	40	1243	0.98	0.03	0.74
ARF	5	241	0.90	0.07	1.99
	10	401	0.92	0.05	1.51
	20	708	0.96	0.04	1.27
	40	1243	0.96	0.04	1.52
GBR	5	241	0.91	0.07	1.71
	10	401	0.86	0.07	1.53
	20	708	0.96	0.04	1.26
	40	1243	0.98	0.03	0.98

TABLE III
COMPUTATION TIME FOR ESTABLISHED SURROGATE MODELS.

Model	K-Fold (s)	Train (s)	Inference (s)
ANN	22.92	18.94	0.183
ARF	13.61	0.24	0.052
GBR	1.02	0.21	0.001

accurate predictions of the GBR are especially attractive for parallel iterative optimization where the surrogate model must be retrained multiple times.

The surrogate models may exhibit significant errors at low and high torque, where deviations can exceed 50% in some cases. These errors are unacceptable for direct design evaluation and may lead to incorrect conclusions if the models are not validated or double-checked. Surrogate models should be utilized as tools to efficiently explore design spaces, rather than a direct replacement for high-fidelity FEA. Any design candidate selected through surrogate modeling should be validated using FEA and undergo correction procedures to improve prediction accuracy, as exemplified in [24].

V. CONCLUSION

This paper demonstrates the use of multiple ML surrogate modeling methods for hybrid design optimization of electric machines, with a case study on a fixed OD coreless AFPM. Machine learning is proposed to be used in parallel to reduce high computation requirements for large mesh FEA models and significantly minimize simulation times. The surrogate ML models, ARF, GBR, and ANN, are trained on an example DE optimized coreless AFPM dataset and display satisfactory overall accuracy in capturing non-linearities. The tested machine learning models demonstrate their ability to significantly reduce necessary FEA data, systematically explore design spaces, and each have low training times. Performance was predicted efficiently within the context of the trained CAFPM designs with each model having its own advantages in terms of accuracy, necessary data for convergence, and training times.

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