

A Two-Step Hybrid Deep Learning–FEA Approach for Multi-Physics Optimization of High-Speed EV Traction Motors

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Optimizing electromagnetic performance and mechanical stress is essential in designing high-speed traction motors for electric vehicles. Although research on the motor design using deep learning (DL)-based optimization is actively conducted, it often requires significant data sampling time to achieve accurate predictions. This study proposes a hybrid DL–finite element analysis (FEA) approach to address these challenges and accelerate multi-physics optimization. FEA-generated data from each optimization iteration is used to train the DL model, whose accuracy is evaluated via root mean square error (RMSE) and R-squared metrics. Once the model meets specified accuracy thresholds, the predicted mechanical stress is compared with constraints to narrow the motor design space, eventually replacing mechanical stress FEA at higher accuracy levels. Consequently, the proposed method significantly reduces the time required for multi-physics optimal design.

Index Terms—Deep learning, Electric vehicles, Hybrid Method, Mechanical stress, Narrowing design space

I. INTRODUCTION

WITH the recent trend toward high battery voltage, the demand for high-speed traction motors has been increasing. However, high-speed operation generates substantial centrifugal forces, resulting in significant mechanical stress that must be addressed during motor design. A common approach to mitigating mechanical stress involves increasing the thickness of rotor bridges. Nonetheless, this strategy often increases leakage flux in those regions, compromising power density and efficiency [1]. Therefore, the design process requires a multi-physics optimization approach that simultaneously considers electromagnetic performance and mechanical stress.

Recently, research on motor design using deep learning is being actively conducted [2]–[4]. However, training a DL model generally demands extensive data sampling, which can be highly time-consuming. Moreover, because electromagnetic performance (e.g., power density and efficiency) must be maximized, even a small error from DL predictions may cause the optimization algorithm to converge to suboptimal solutions.

To address these issues, this paper proposes a two-step hybrid DL–finite element analysis (FEA) method. In the first step, a DL model is trained to predict mechanical stress using FEA data accumulated at each iteration of the optimization. The model accuracy is evaluated through root mean square error (RMSE) and R-squared metrics, and once these metrics surpass predefined thresholds, the model begins predicting mechanical stress [5]. Only those motor design variables whose predicted mechanical stress is below the margin-adjusted constraint are retained for further optimization. As iterations continue, additional FEA data are sampled, progressively improving the DL model and allowing the margin to be reduced. Consequently, the motor design space is gradually narrowed.

When the DL model achieves sufficiently high accuracy, the method advances to the second step, in which DL model predictions replace FEA for mechanical stress. By relying on predicted mechanical stress, the number of mechanical

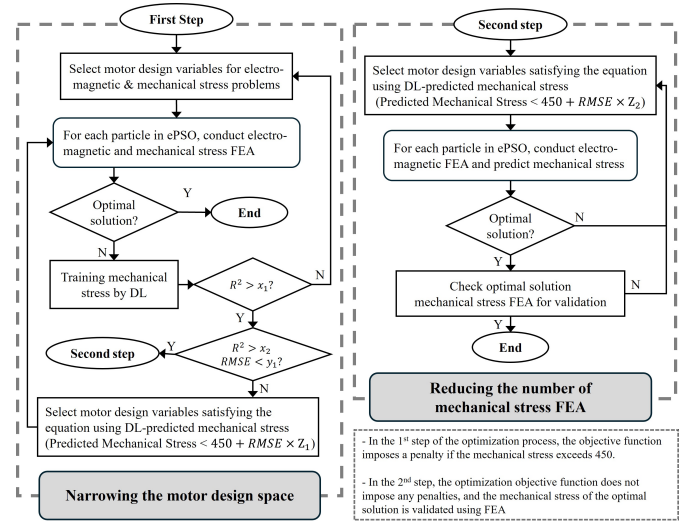


Fig. 1. Proposed multi-physics optimal design flowchart using deep learning.

stress FEAs required during optimization is significantly reduced, thereby shortening the overall design time. This hybrid DL–FEA approach can narrow the motor design space even at early stages with limited data and further reduce the total number of FEA runs once an adequate dataset is obtained. Ultimately, the proposed method significantly decreases the time needed for multi-physics optimal design.

II. PROPOSED METHOD

Fig. 1 illustrates the proposed multi-physics optimization flowchart, which employs the explorative Particle Swarm Optimization (ePSO) algorithm [6].

A. First Step: Adaptive Constraint-Driven Design Space Reduction Using DL

In the first step, motor design variables are selected for multi-physics optimization. Based on these variables, both

TABLE I
OPTIMIZATION PROBLEMS

Item	Problem	Note
Max Torque (T_{max})	Maximize	–
Torque Ripple (T_{ripple})	Minimize	–
Cogging Torque (T_{cog})	Minimize	–
Back EMF THD (THD)	Minimize	–
Mechanical Stress	Constraint	< 450 (MPa) at 22,000rpm

electromagnetic and mechanical stress FEA are performed in each iteration. Afterward, the mechanical stress data are used to train the DL model.

- If the coefficient of determination (R-squared) is less than x_1 , the trained DL model is deemed insufficiently accurate. The next iteration then repeats the same process to increase sampling data.
- If the R-squared is greater than x_1 , the DL model is considered sufficiently accurate. At this stage, when selecting motor design variables, only those values smaller than $450 + (\text{RMSE} \times Z_1)$ are chosen. As more data become available, the RMSE and R-squared improve, leading to a progressively narrower design space.
- Finally, if the R-squared exceeds x_2 (with $x_2 > x_1$) and the RMSE is below y_1 MPa, the DL model is regarded as highly accurate in predicting mechanical stress. The process then advances to the second step.

The main goal of the first step is to narrow the motor design space by incorporating predicted mechanical stress as a constraint.

B. Second Step: Complete DL-Based Mechanical Stress Prediction

Because the R-squared and RMSE indicate high accuracy in the second step, the DL model replaces mechanical stress FEA, while electromagnetic FEA continues as before. This process is repeated until the optimal solution is found. Once the optimal solution is determined, one final mechanical stress FEA is performed to confirm that stress does not exceed 450 MPa. The primary purpose here is to minimize the number of mechanical stress FEAs required to obtain the optimal design. Even if the predicted mechanical stress goes beyond 450 MPa, no penalty is imposed; instead, mechanical stress FEA is carried out on promising solutions to validate that the stress remains under 450 MPa.

III. OPTIMIZATION PROBLEMS

Table I outlines the objectives and constraints of the optimization problem. There are 35 motor design variables in total. Mechanical stress is evaluated as the maximum value at each of four rotor barriers, resulting in four separate maximum stress values. In training the DL model, 35 inputs (motor design variables) serve as features, and four outputs (maximum stresses at each barrier) are the targets.

$$y = a_1 \left(\frac{300}{T_{max}} \right) + a_2 \left(\frac{T_{ripple}}{15} \right) + a_3 \left(\frac{T_{cog}}{5} \right) + a_4 \left(\frac{THD}{10} \right) \quad (1)$$

TABLE II
ELAPSED TIME FOR OPTIMIZATION

Item	Conventional Method	Proposed Method
Electromagnetic FEA	$11,856 \times 8s$	$8,604 \times 8s$
Mechanical Stress FEA	$5,928 \times 15s$	$1,900 \times 15s$
Train DL Model	–	$19 \times 115s$
Validation Stress FEA	–	$2 \times 15s$
Total Computation Time	≈ 52 hours	≈ 19 hours

$$\begin{cases} \text{Mechanical Stress} \geq 450 & : y = y + P \\ \text{Mechanical Stress} < 450 & : y = y \end{cases} \quad (2)$$

The objective function is defined in (1), where a_1, a_2, a_3 , and a_4 sum to unity. A penalty is imposed if the maximum mechanical stress exceeds 450 MPa, as shown in (2). The penalty P is assigned a large value (e.g., 100), ensuring that any violation significantly inflates the objective function. During the first step, if stress exceeds 450 MPa, y becomes large enough to steer the optimization away from such violations. An Intel i9-10980XE@3.0GHz CPU was used, targeting an objective function value below 0.80 while maintaining $T_{max} > 300$.

IV. CONCLUSION

This paper presents a multi-physics optimization approach for high-speed traction motors requiring simultaneous consideration of electromagnetic performance and mechanical stress. By leveraging a DL model to predict mechanical stress, only motor design variables meeting the margin-adjusted stress limit advance through the optimization, thereby narrowing the design space. In the case shown in Table II, the proposed method began narrowing the design space from the 3rd iteration. By the 19th iteration, the DL model met both RMSE and R-squared requirements, and from the 20th iteration onward, mechanical stress FEA was no longer performed. As a result, the proposed method found its optimal solution at the 2nd particle of the 43rd iteration, taking about 19 hours in total, whereas the conventional method reached its optimum at the 28th particle of the 59th iteration and took about 52 hours—demonstrating a significant reduction in overall multi-physics analysis time. Further details will be provided in the full paper.

REFERENCES

- [1] J.-W. Jung, B.-H. Lee, D.-J. Kim, J.-P. Hong, J.-Y. Kim, S.-M. Jeon, and D.-H. Song, "Mechanical stress reduction of rotor core of interior permanent magnet synchronous motor," *IEEE Transactions on Magnetics*, vol. 48, no. 2, pp. 911–914, 2012.
- [2] Y. Li, G. Lei, G. Bramerdorfer, S. Peng, X. Sun, and J. Zhu, "Machine learning for design optimization of electromagnetic devices: Recent developments and future directions," *Applied Sciences*, vol. 11, no. 4, 2021.
- [3] B. Praslicka, C. Ma, and N. Taran, "A computationally efficient high-fidelity multi-physics design optimization of traction motors for drive cycle loss minimization," *IEEE Transactions on Industry Applications*, vol. 59, no. 2, pp. 1351–1360, 2023.
- [4] S. Barmada, M. Tucci, L. Sani, and C. Tozzo, "Deep neural network-based electro-mechanical optimization of electric motors," *IEEE Transactions on Magnetics*, vol. 59, no. 5, pp. 1–4, 2023.
- [5] D. Chicco, M. J. Warrens, and G. Jurman, "The coefficient of determination r-squared is more informative than SMAPE, MAE, MAPE, MSE and RMSE in regression analysis evaluation," *PeerJ Comput. Sci.*, vol. 7, p. e623, July 2021.
- [6] J. H. Lee, J.-W. Kim, J.-Y. Song, Y.-J. Kim, and S.-Y. Jung, "A novel memetic algorithm using modified particle swarm optimization and mesh adaptive direct search for pmsm design," *IEEE Transactions on Magnetics*, vol. 52, no. 3, pp. 1–4, 2016.