

Article

Physics-Informed Optimization of a Printed Circuit Board Stator Axial-Flux Motor for Robotic Actuators

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Abstract

This paper proposes a physics-informed neural network (PINN)-based design optimization framework for a compact smart actuator motor in physical artificial intelligence (Physical AI) robotic systems, where artificial intelligence is integrated with sensing, actuation, and physical interaction to perceive and act in the real world. To improve integration density and joint compactness, a printed circuit board (PCB) stator axial-flux permanent magnet (AFPM) motor is adopted as a thin and highly integrated topology. Because its performance is strongly affected by coupled design variables, including outer diameter, PCB count, turns per slot, trace width, and magnet thickness, an efficient and physically consistent optimization method is required. The proposed framework constructs a finite element analysis (FEA)-based design database and trains a physics-reconstructed PINN surrogate model to predict torque and loss components. Unlike purely data-driven models, the proposed PINN reconstructs output power and efficiency using physical power-balance relations, thereby improving consistency among torque, loss, output power, and efficiency. The trained surrogate is coupled with the nondominated sorting genetic algorithm II (NSGA-II) to maximize torque and efficiency while minimizing AC loss under dimensional and performance constraints. The optimized candidates are further verified by high-fidelity FEA. The results demonstrate that the proposed framework provides an effective Physical AI-oriented design methodology for compact robotic smart actuators by integrating PCB stator AFPM motor topology, physics-informed learning, and multi-objective optimization.

Keywords: axial-flux permanent magnet motor; printed circuit board stator; physics-informed neural network; multi-objective optimization; finite element analysis; robotic smart actuator; physical artificial intelligence



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1. Introduction

The rapid progress of physical artificial intelligence (Physical AI) is transforming robotic systems from pre-programmed machines into physically interactive agents that perceive, decide, and act in real environments. Unlike conventional artificial intelligence, which mainly focuses on digital information processing, Physical AI requires the integrated design of computation, sensing, actuation, materials, and mechanical structures [1,2]. In this context, the actuator is a key hardware component that determines force density, response bandwidth, backdrivability, compactness, and thermal robustness. Previous studies on legged and articulated robotic systems have shown that actuator and joint motor design

strongly affect dynamic interaction, impact mitigation, joint load response, and force control performance [3–5]. Therefore, compact and high-performance smart actuators are essential for next-generation robotic systems.

In robotic smart actuators, the motor occupies a significant portion of the axial length and volume, making motor miniaturization critical for joint-integrated systems such as humanoid, wearable, collaborative, and service robots. Although radial-flux permanent magnet motors have been widely used, their axial length is constrained by winding, stator core, end-turn, and housing structures. These structural limitations become more critical as the required actuator thickness decreases. AFPM motors are promising for compact and high-torque-density applications because their magnetic flux path is arranged in the axial direction and their active electromagnetic area can be expanded radially [6–8]. In addition, coreless AFPM motors can reduce cogging torque and iron loss, which is beneficial for smooth robotic motion and high-speed operation [8,9]. However, conventional wire-wound AFPM stators still suffer from manufacturing complexity, end-turn volume, and radial geometric variation.

A printed circuit board (PCB) stator provides an effective solution to these limitations by implementing the winding as copper traces on multilayer PCB substrates. This enables a flat, repeatable, and highly manufacturable stator structure. Previous studies have demonstrated that PCB stator AFPM motors can reduce axial length, simplify assembly, and precisely realize winding patterns in high-speed and low-power applications [10–13]. Moreover, the PCB winding topology can be systematically modified by changing the trace width, winding pattern, number of layers, and end-turn connection structure [13–15]. These characteristics make PCB stator AFPM motors suitable for compact robotic smart actuators requiring thin structure, high integration density, and design repeatability.

Despite these advantages, PCB stator AFPM motor design is highly coupled. Motor performance depends on both electromagnetic variables, such as outer diameter and magnet thickness, and PCB-related variables, such as the number of PCB stators, turns per slot, trace width, and layer-dependent current paths. For example, increasing the trace width can reduce dc copper loss but may affect AC loss and routing space, whereas increasing the number of turns can improve torque capability but increase resistance, copper loss, and layout complexity. Therefore, simple parametric sweeps or single-objective optimization methods are insufficient to identify a balanced actuator motor design.

Physics-informed machine learning provides a way to improve the physical reliability of surrogate models by embedding governing equations or physical consistency conditions into the learning process [16,17]. Liu et al. [18] developed a mechanics-based reduced-order model to support real-time prediction of soft-actuator motion. In contrast, the present method embeds torque–speed and power–balance relations into the surrogate output structure by reconstructing output power and efficiency from predicted torque and losses. Its purpose is offline design optimization of a PCB stator AFPM motor for robotic actuators rather than real-time actuator control. This is particularly useful for motor design because key performance quantities are physically coupled; output power must be consistent with torque and speed, and efficiency must satisfy the power–balance relation. Meanwhile, finite element analysis (FEA) is widely used for accurate electric machine evaluation, but FEA-based optimization becomes computationally expensive when many design variables and multiple objectives are considered. To reduce this burden, surrogate models have been widely investigated for electromagnetic device and electric machine optimization [19–22]. When combined with multi-objective algorithms such as the nondominated sorting genetic algorithm II (NSGA-II) [23], recent studies have further demonstrated the effectiveness of neural network-based and surrogate-assisted optimization for electrical machine design [24,25].

However, conventional surrogate-based electrical machine optimization primarily focuses on prediction accuracy and computational efficiency, while the physical dependence among multiple predicted performance quantities is not necessarily guaranteed. In the present PCB stator AFPM motor, torque, output power, efficiency, and loss components are mutually coupled through the torque–speed and power–balance relations. Independently predicting these quantities may therefore produce physically inconsistent combinations during large-scale design exploration. In addition, the strong coupling among PCB-specific design variables, including trace width, number of PCB stators, turns per slot, and magnet thickness, has not been explicitly addressed using a physics-reconstructed surrogate framework. To address this gap, the present study introduces a surrogate structure in which only the physically primary quantities are predicted, and the dependent quantities are reconstructed through deterministic physical relations before multi-objective optimization.

In this paper, a physics-reconstructed physics-informed neural network (PINN) surrogate model is proposed for the design optimization of a compact PCB stator AFPM motor for Physical AI robotic smart actuators. The proposed model predicts torque and loss components from the design variables, while output power and efficiency are reconstructed using physical power–balance relations. This prevents physically inconsistent combinations of torque, loss, output power, and efficiency. The trained surrogate model is coupled with NSGA-II to maximize torque and efficiency while minimizing AC loss under dimensional and performance constraints. Finally, the optimized design candidates are verified using high-fidelity FEA.

Figure 1 shows the overall framework of the proposed PINN-assisted multi-objective design optimization. The design space of the PCB stator AFPM motor is first defined using the outer diameter, number of PCB stators, turns per slot, trace width, and magnet thickness. An FEA-based database is then constructed and used to train surrogate models. The proposed physics-reconstructed PINN reconstructs output power and efficiency from power–balance relations to improve physical consistency. The validated surrogate is finally coupled with NSGA-II, and the selected optimal design is re-evaluated using high-fidelity FEA. The surrogate model comparison includes response surface modeling (RSM), a multi-layer perceptron (MLP), and the proposed PINN. Prediction accuracy is evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE).

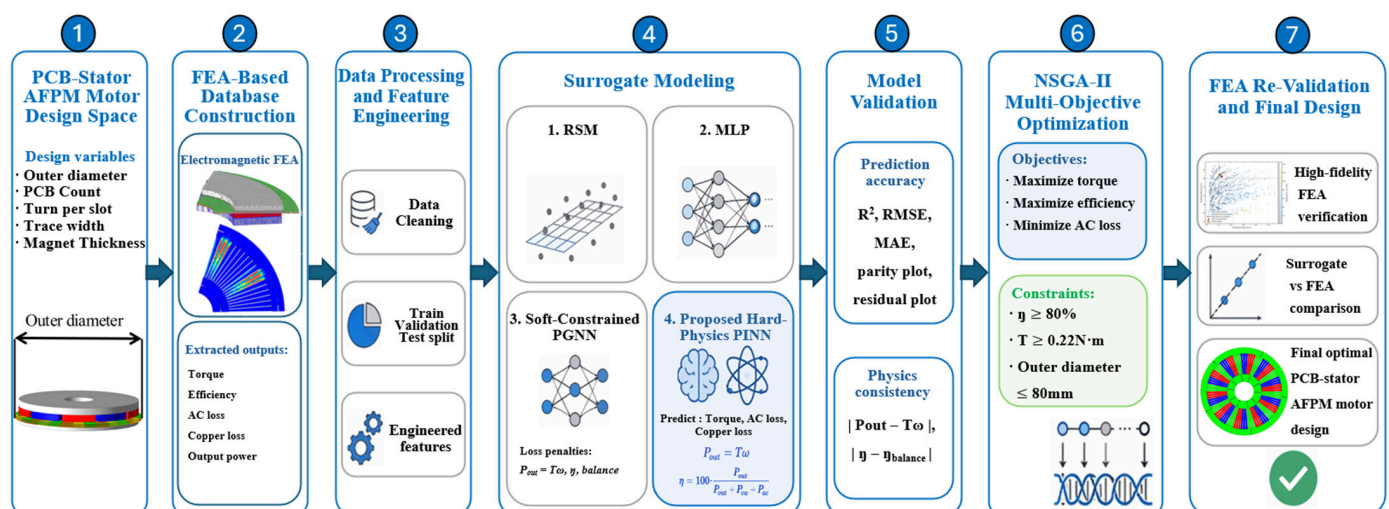


Figure 1. Overall design optimization framework.

2. PCB Stator AFPM Motor and FEA-Based Design Database

This section presents the motor topology, design variables, and FEA-based database construction used in the proposed design optimization framework. The PCB stator AFPM motor is first introduced as a thin motor topology suitable for robotic smart actuators that require axial compactness and high structural integration. The main design variables are then defined to describe the geometric and winding-related characteristics of the motor. Based on these variables, an FEA-based database is constructed by extracting the torque, efficiency, AC loss, copper loss, and output power of each design candidate. The resulting database provides the training and validation data for the surrogate models described in the following section.

2.1. Motor Topology for Robotic Smart Actuators

In robotic smart actuators, the motor must be integrated with transmission components, sensors, bearings, and drive electronics within a limited installation space. Therefore, reducing the axial length of the motor is an important requirement for improving actuator compactness and integration density. Although radial-flux motors have been widely used in robotic actuator systems, their axial miniaturization is inherently limited by the stator core, winding region, and end-turn structure. As the required actuator package becomes thinner, these structural components occupy a significant portion of the available axial space and restrict further miniaturization. To overcome this limitation, this paper adopts a PCB stator AFPM motor topology for compact robotic smart actuators. In the AFPM topology, the main magnetic flux is formed along the axial direction, while the effective torque-producing area is distributed over the radial direction. This configuration is advantageous for thin motor structures because a relatively large active radius can be maintained even when the axial length is reduced. As a result, the AFPM topology is well suited to applications in which compactness and structural integration are more critical than those of conventional motor layouts.

Figure 2 shows the topology of the proposed PCB stator AFPM motor. The permanent magnets were modeled using N45UH, while 35PN230 was assigned to the ferromagnetic back yoke components. As illustrated in Figure 2a, the motor consists of a rotor back yoke, permanent magnets, a PCB stator, and a stator back yoke. The PCB stator contains planar copper trace windings implemented on the PCB substrate, enabling a thin and highly integrated winding structure. Compared with conventional wound coils, the PCB-based winding configuration offers improved geometric repeatability and allows systematic adjustment of the winding layout through PCB design parameters. Figure 2b presents the axial stack configuration of the proposed motor, where the rotor back yoke, magnet, air gap, PCB stator, and stator back yoke are arranged along the axial direction. The total axial length is therefore determined by the thicknesses of these main stack components. In the proposed topology, electromagnetic torque is generated by the interaction between the axial air gap flux produced by the permanent magnets and the current flowing through the PCB trace windings. Because the winding geometry is defined by PCB layout parameters, the motor performance can be adjusted through variables such as the number of PCB stators, turns per slot, trace width, and magnet thickness. These characteristics make the PCB stator AFPM motor a suitable candidate for compact robotic smart actuators. Based on this topology, the main design variables and performance targets are defined in the following subsection.

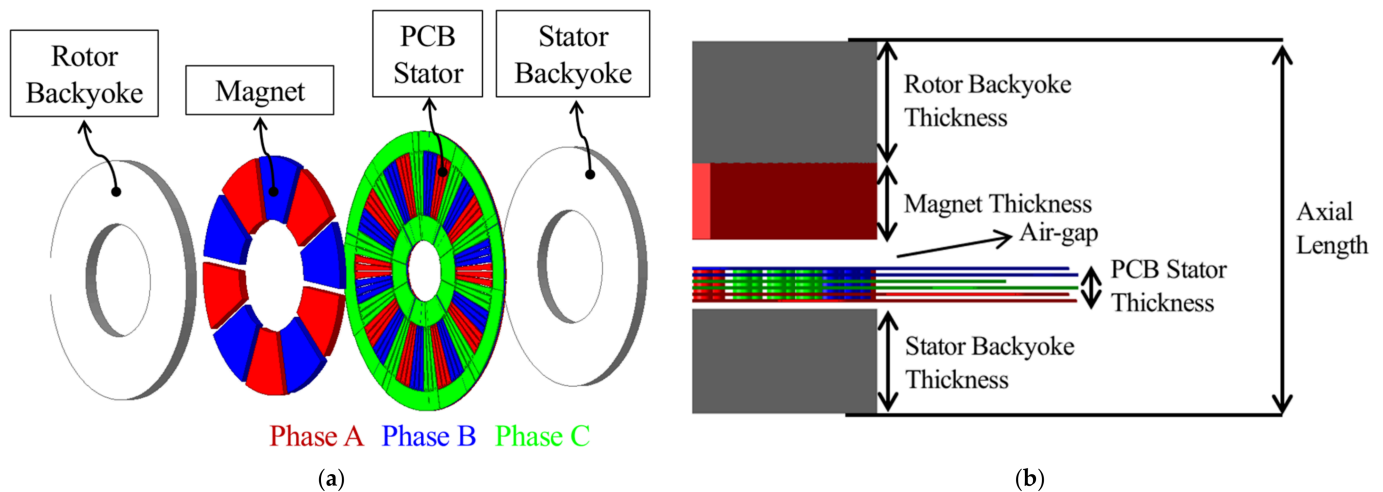


Figure 2. Proposed PCB stator AFPM motor topology for robotic smart actuators: (a) exploded view of the motor structure and (b) axial cross-sectional schematic showing the main stack components and axial length.

2.2. Design Variables and Performance Targets

The electromagnetic performance of the proposed PCB stator AFPM motor is governed by both geometric and winding-related design variables. To define the design problem in a compact and physically meaningful form, the major design variables are selected as the outer diameter, trace width, number of PCB stators, turns per slot, and magnet thickness. These variables are chosen because they directly affect the active electromagnetic area, winding configuration, magnetic loading, and overall motor dimensions.

Figure 3 illustrates the main design variables considered in this study. The outer diameter D_{out} determines the effective active radius and the overall motor size. The trace width w_{tr} defines the width of the PCB copper trace and influences the available copper area, current path configuration, and loss characteristics. The number of PCB stators N_{PCB} represents the number of stacked PCB stator layers used in the motor. In the proposed configuration, the PCB stators are electrically connected in series. Therefore, increasing N_{PCB} increases the effective total series turns of the winding. The turns per slot N_{Turn} defines the number of winding turns assigned to each slot pattern on a single PCB stator. Accordingly, the effective total series turns increase with both N_{PCB} and N_{Turn} . The magnet thickness t_{mag} determines the axial thickness of the permanent magnet and directly affects the air gap flux density and magnetic loading of the motor. A three-dimensional representation of the stacked PCB stators and their winding configuration is provided in Figure 3c, while Figure 3b and 3d further illustrate the PCB trace width and turns-per-slot configurations, respectively.

The design vector is defined as:

$$x = [D_{out}, W_{tr}, N_{PCB}, N_{Turn}, t_{mag}] \quad (1)$$

where each variable represents one of the major geometric or winding-related design parameters. Among these variables, D_{out} and t_{mag} mainly determine the electromagnetic loading and motor dimensions, whereas W_{tr} , N_{PCB} , and N_{Turn} primarily define the PCB winding topology and copper utilization. Since these variables are strongly coupled, a systematic design optimization approach is required to obtain a balanced motor design.

The main performance quantities extracted from FEA are torque T , efficiency η , AC loss P_{ac} , copper loss P_{cu} , and output power P_{out} . In this study, torque, efficiency, and AC loss are used as the primary optimization objectives. Copper loss and output power are

additionally included because they are required to evaluate the power-balance relation and the physical consistency of the surrogate model.

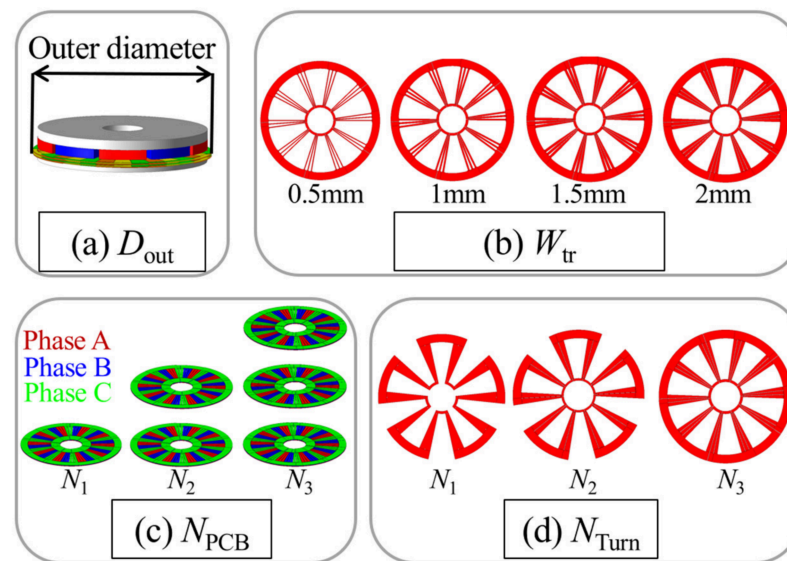


Figure 3. Illustration of the main design variables of the proposed PCB stator AFPM motor: (a) outer diameter D_{out} , (b) trace width W_{tr} , (c) number of PCB stators N_{PCB} , and (d) turns per slot N_{Turn} .

Accordingly, the multi-objective design problem is formulated to maximize torque and efficiency while minimizing AC loss. In minimization form, the objective function is expressed as:

$$\min f(x) = [-T(x), -\eta(x), P_{ac}(x)] \quad (2)$$

Equation (2) represents a vector-valued multi-objective problem rather than a scalar weighted objective. The three objectives are simultaneously optimized in the Pareto sense using NSGA-II.

The dimensional and performance constraints are defined as:

$$\begin{aligned} \eta(x) &\geq 80\%, \\ T(x) &\geq 0.22 \text{ N} \cdot \text{m} \\ D_{out} &\leq 80 \text{ mm} \end{aligned} \quad (3)$$

To incorporate the constraints into the NSGA-II optimization, an exterior penalty function was applied based on the normalized degree of constraint violation. The penalty function is defined as:

$$P_{pen}(x) = 10^3 \left[\frac{\max(80 - \eta(x), 0)}{80} + \frac{\max(0.22 - T(x), 0)}{0.22} + \frac{\max(D_{out}(x) - 80, 0)}{80} \right] \quad (4)$$

The resulting penalty was equally added to each component of the multi-objective function defined in (2), as expressed by

$$f_p(x) = f(x) + P_{pen}(x)[1, 1, 1] \quad (5)$$

Accordingly, $P_{pen}(x) = 0$ for candidates satisfying all three constraints, whereas infeasible candidates receive an increasing penalty in proportion to the normalized degree of constraint violation. The final compromise design was selected only from the feasible candidates satisfying all constraints. These constraints were imposed to obtain a compact smart actuator motor design that satisfies the required torque and efficiency levels while maintaining the allowable motor size.

During NSGA-II, violations of the efficiency, torque, and outer diameter constraints were normalized and incorporated through an exterior penalty term with a coefficient of 10^3 . The final compromise design was selected only from the feasible candidates satisfying all constraints.

These constraints are imposed to obtain a compact smart actuator motor design that satisfies the required torque and efficiency levels while maintaining the allowable motor size.

2.3. FEA-Based Database Construction

The FEA database was constructed to provide physically reliable training data for the surrogate models. For each design point, the geometric and winding-related variables defined in (1) were assigned to the PCB stator AFPM motor model. The resulting motor geometry was then analyzed using electromagnetic FEA under the same operating condition so that the influence of each design variable could be compared consistently. For each design geometry, electromagnetic FEA was performed at a fixed mechanical speed of 3650 rpm to obtain the back-EMF and PM-flux-induced AC loss. A fixed current density of 30 A/mm² was subsequently used for the performance calculation. The same operating conditions were applied to all design cases to ensure a consistent comparison across the design space. A mechanical load torque was not prescribed independently; instead, the electromagnetic torque was obtained as an FEA output under the prescribed speed and current density conditions. The current density of 30 A/mm² was used as a common electromagnetic loading condition for comparative optimization. Although the coreless planar PCB winding provides a relatively large heat-dissipation surface compared with conventional slot windings, a coupled thermal model and specific cooling boundary conditions were not included in the present electromagnetic analysis.

For a given design vector x_i , the corresponding FEA output vector is defined as:

$$y_i = [T_i, \eta_i, P_{ac,i}, P_{cu,i}, P_{out,i}] \quad (6)$$

where T_i , η_i , $P_{ac,i}$, $P_{cu,i}$, and $P_{out,i}$ denote the torque, efficiency, AC loss, copper loss, and output power of the i -th design case, respectively. These quantities were selected because they represent both the electromagnetic output capability and the loss characteristics of the motor.

In this study, the FEA database was constructed based on an electromagnetic analysis to reduce the computational cost of the design space exploration. Therefore, the loss components considered in the surrogate model are limited to the dc copper loss and the AC loss induced in the PCB traces by the time-varying magnetic flux. The iron loss of the back yoke components is not included as a training target in the present database. Because the proposed motor employs a coreless and slotless PCB stator structure with a distributed winding, the stator tooth-related iron loss and slotting harmonics are inherently eliminated. Iron loss may occur in the ferromagnetic back yoke; however, it is expected to be relatively small compared with the winding-related losses considered in this study. In addition, the distributed winding suppresses high-order spatial harmonics, and therefore the permanent magnet eddy-current loss is expected to be negligible within the operating conditions considered in this study. Accordingly, the efficiency used in this study is evaluated from the output power, copper loss, and flux-induced AC loss, and it is used as a consistent comparative indicator within the proposed optimization framework.

The complete FEA database is expressed as:

$$D_{FEA} = \{(x_i, y_i)\}_{i=1}^{Ns} \quad (7)$$

where N_s is the total number of FEA samples. In this database, the input variables describe the design configuration, whereas the output variables represent the corresponding electromagnetic performance obtained from FEA.

After removing duplicated design points, a total of $N_s = 1125$ valid FEA samples were retained. The resulting database was randomly divided into training, validation, and independent test subsets with ratios of 70%, 15%, and 15%, respectively. The design variable ranges used for the FEA database construction are summarized in Table 1.

Table 1. Design variable ranges used for FEA database construction.

Parameter	Unit	Range
Outer diameter [Dout]	mm	60~100
Trace width [mm]	mm	0.5~2.5
Number of PCB stators	-	1~3
Turns per slot	-	1~3
Magnet thickness	mm	2~6

Figure 4 summarizes the FEA database construction procedure. The predefined design cases were analyzed under identical operating conditions, and the resulting electromagnetic and performance quantities were assembled into the surrogate model database.

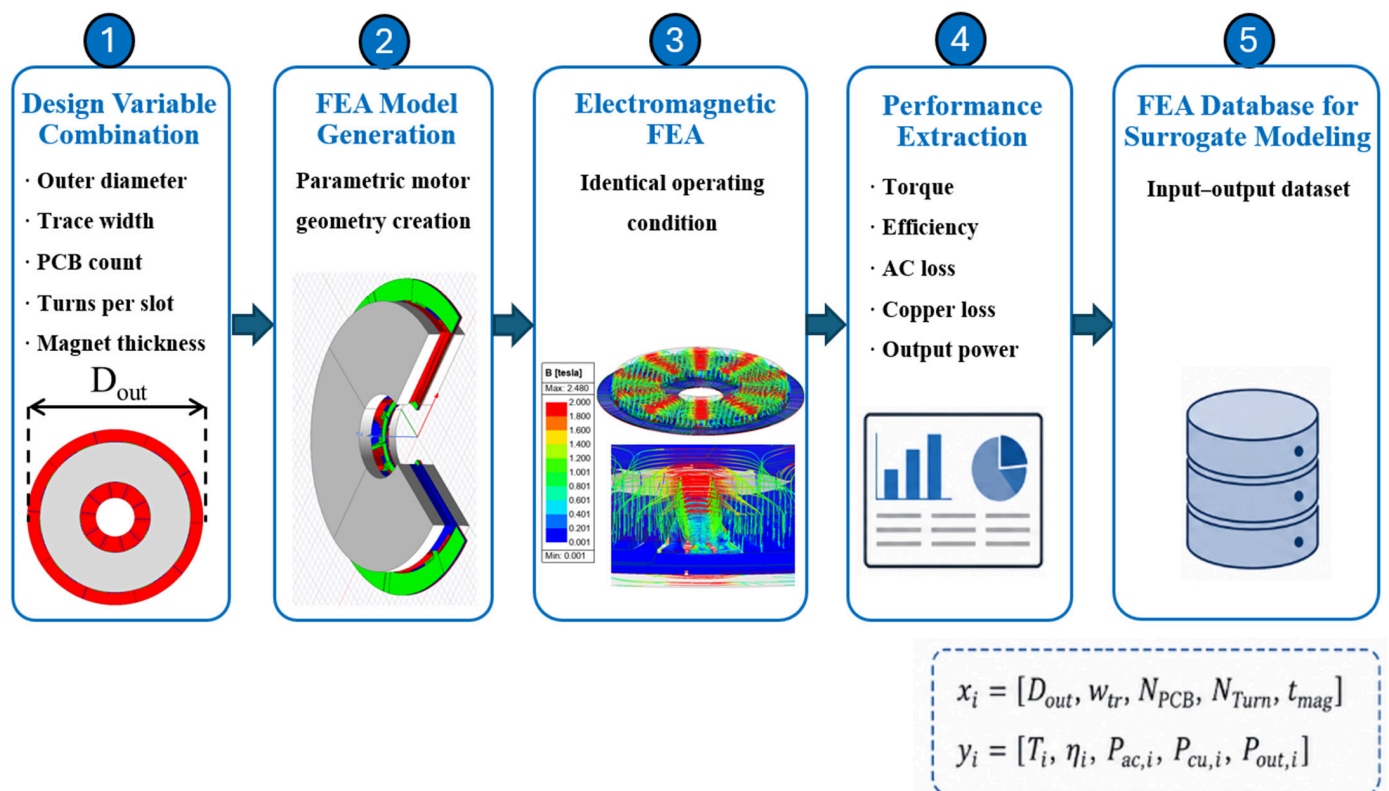


Figure 4. FEA database construction procedure for the proposed PCB stator AFPM motor. Candidate designs are generated from the selected design variables, analyzed using FEA, and organized into an input–output database for surrogate modeling.

The database was subsequently used for model training, validation, and testing. Before training, invalid or incomplete simulation cases were removed, and duplicated design points were excluded to prevent biased learning. This process ensures that the surrogate models are trained using consistent and physically meaningful FEA data. The constructed

database serves as the foundation for the physics-informed surrogate modeling described in Section 3.

3. Physics-Informed Surrogate Modeling

This section presents the surrogate modeling strategy used to approximate the FEA-based motor performance database described in Section 2. Since direct FEA-based optimization is computationally expensive, surrogate models are introduced to rapidly predict the performance of each design candidate. First, conventional data-driven surrogate models, including RSM and MLP, are considered as baseline models. Then, the proposed physics-reconstructed PINN surrogate is introduced to improve the physical consistency of the predicted motor performance. In the proposed model, torque and loss components are predicted from the design variables, whereas output power and efficiency are reconstructed using physical power-balance relations. Finally, the training procedure and validation metrics are described.

3.1. Baseline Surrogate Models

To evaluate the effectiveness of the proposed physics-reconstructed PINN surrogate, conventional data-driven surrogate models are first considered as baseline models. In this study, response surface modeling (RSM) and multilayer perceptron (MLP) are selected as reference models because they are commonly used for surrogate-assisted design optimization. All baseline models are trained using the same FEA-based database described in Section 2, and their prediction results are later compared with those of the proposed PINN. RSM approximates the relationship between the design variables and motor performance using polynomial regression. In this study, the RSM baseline is constructed using second-order polynomial features of the design vector. This model provides a simple and interpretable approximation of the design space. However, its prediction capability can be limited when the motor performance varies nonlinearly with strongly coupled design variables, such as trace width, number of PCB stators, turns per slot, and magnet thickness.

The MLP model is used as a nonlinear data-driven surrogate. Unlike RSM, MLP can represent complex nonlinear relationships between the input design variables and output performance quantities through hidden layers and nonlinear activation functions. Therefore, it can provide better approximation capability than a low-order polynomial model when sufficient training data are available. However, because MLP does not explicitly include physical constraints among the predicted output quantities, it may generate physically inconsistent predictions. For example, the predicted output power may not satisfy the torque–speed relation, or the predicted efficiency may not be consistent with the predicted loss components. Therefore, RSM and MLP are used as baseline models to clarify the benefit of the proposed physics-informed surrogate. The comparison is performed not only in terms of prediction accuracy, such as R^2 , RMSE, and MAE, but also in terms of physical consistency among torque, output power, efficiency, and loss components.

3.2. Proposed Physics-Reconstructed PINN Surrogate

The proposed PINN surrogate is designed to improve the physical consistency of the predicted motor performance by modifying the output structure of the neural network. In a conventional data-driven surrogate, all performance quantities are predicted directly and independently from the design variables. Although this direct-output structure can approximate the FEA database, it does not explicitly guarantee that the predicted output power and efficiency satisfy the physical power-balance relations. Therefore, even when the numerical prediction error is small, physically inconsistent combinations of torque, loss, output power, and efficiency may occur.

Figure 5 compares the output structures of the direct-output surrogate and the proposed physics-reconstructed PINN. In the direct-output surrogate, the neural network maps the design vector directly to all target quantities. In contrast, the proposed PINN first predicts only the torque and loss components and then reconstructs output power and efficiency using deterministic power-balance relations. This reconstruction step is the main difference between the proposed surrogate and conventional direct-output prediction.

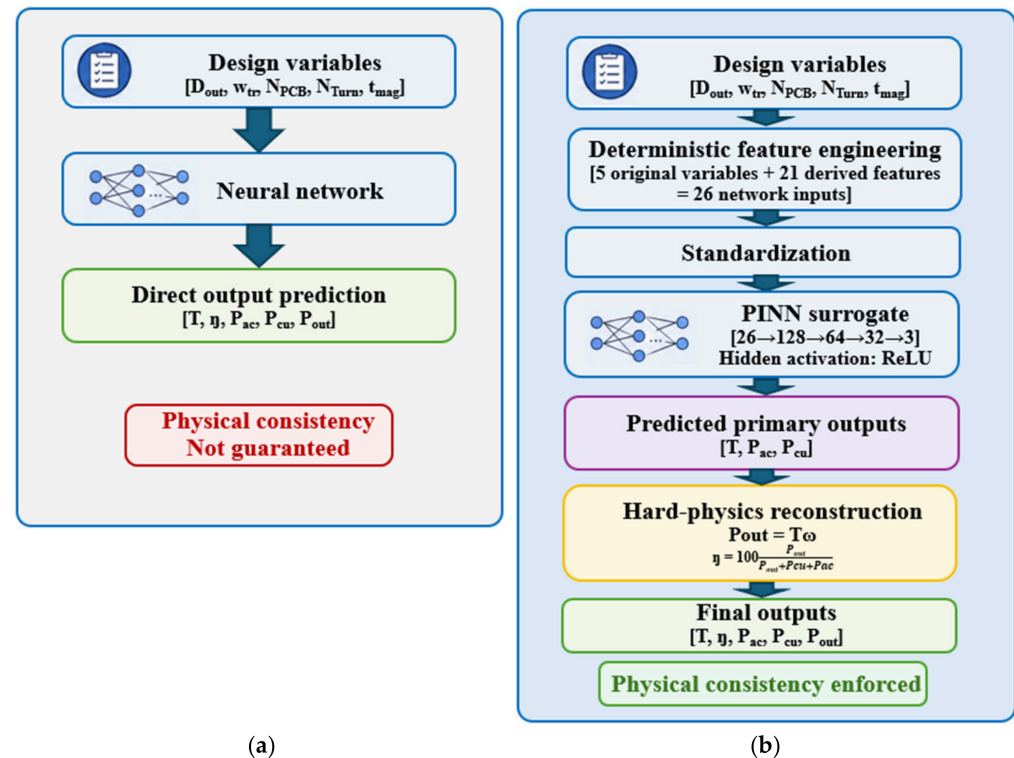


Figure 5. Output structure comparison between the direct-output surrogate and the proposed physics-reconstructed PINN: (a) conventional direct-output surrogate and (b) physics-reconstructed PINN surrogate.

The five physical design variables were deterministically expanded into 26 input features, including polynomial and interaction terms, before network training. This feature construction does not introduce additional independent design variables. The neural network consists of three hidden layers with 128, 64, and 32 neurons using the rectified linear unit (ReLU) activation function. The network directly predicts T , P_{ac} , and P_{cu} , whereas P_{out} and η are reconstructed through the physical relations in (10) and (11). The main configuration of the proposed physics-reconstructed PINN is summarized in Table 2.

Table 2. Configuration of the proposed physics-reconstructed PINN.

Parameter	Value
Physical design variables	5
Network input dimension	26
Hidden layers	128-64-32
Activation	ReLU
Dropout	0.05
Direct outputs	T, P_{ac}, P_{cu}
Optimizer	AdamW
Learning rate	1×10^{-3}
Batch size	64
Maximum epochs	2500

For notational simplicity, the output variables in this subsection denote surrogate-predicted quantities unless otherwise stated. In the direct-output surrogate, the neural network output is expressed as:

$$y_D = N_\theta(x) = [T, \eta, P_{ac}, P_{cu}, P_{out}] \quad (8)$$

where N_θ denotes the neural network and θ represents only its trainable weights and biases. No physical motor parameter is identified during network training. The variables D_{out} , W_{tr} , N_{PCB} , N_{Turn} , and t_{mag} are prescribed motor design variables that are subsequently varied during the NSGA-II optimization. In this formulation, torque, efficiency, AC loss, copper loss, and output power are treated as independent outputs. Therefore, the torque–speed relation and the efficiency–balance relation are not structurally imposed on the final prediction.

In the proposed PINN surrogate, the neural network first predicts the physically primary components as:

$$[T, P_{ac}, P_{cu}] = N_\theta(x) \quad (9)$$

The output power is then reconstructed from the torque–speed relation as:

$$P_{out} = T\omega \quad (10)$$

where ω is the mechanical angular speed. The efficiency is subsequently reconstructed using the power–balance relation as:

$$\eta = 100 \frac{P_{out}}{P_{out} + P_{cu} + P_{ac}} \quad (11)$$

Accordingly, the final output vector of the proposed surrogate is given by

$$y_P = [T, \eta, P_{ac}, P_{cu}, P_{out}] \quad (12)$$

Although the final output vector has the same form as that of the direct-output surrogate, the way the dependent quantities are obtained is different. In the direct-output surrogate, P_{out} and η are independently learned from data. In the proposed physics-reconstructed PINN, these two quantities are deterministically reconstructed from T , P_{ac} , and P_{cu} using (10) and (11). Therefore, the final prediction is constrained to satisfy the prescribed power–balance relations by construction. This reconstruction-based formulation is suitable for the PCB stator AFPM motor considered in this study because its performance is strongly affected by coupled design variables, including trace width, number of PCB stators, turns per slot, and magnet thickness. By combining the nonlinear approximation capability of a neural network with the deterministic reconstruction of physically dependent quantities, the proposed PINN surrogate provides a physically consistent prediction model for subsequent multi-objective optimization.

3.3. Training and Model Validation

The FEA database constructed in Section 2 was divided into training, validation, and test subsets to evaluate the surrogate models under identical data conditions. The training subset was used to update the model parameters, the validation subset was used for early stopping and model selection, and the test subset was reserved for the final performance evaluation. Before training, the input design variables and output performance quantities were standardized to improve numerical stability. The RSM and MLP models were trained as baseline surrogate models, while the proposed physics-reconstructed PINN was trained using the final output vector defined in (12). In the

proposed model, the neural network predicts torque and loss components, whereas output power and efficiency are reconstructed using the power-balance relations in (10) and (11). Therefore, the training loss was calculated from the difference between the FEA target values and the reconstructed PINN outputs. Additional penalty terms were used to suppress physically invalid predictions, such as negative torque, negative loss, or efficiency values outside the range of 0–100%. Since output power and efficiency are reconstructed by the physical relations, additional soft penalty terms for the torque–speed and efficiency–balance relations are not required.

Figure 6 shows the prediction accuracy of the proposed PINN surrogate on the test set. Prediction accuracy is assessed using the correlation coefficient (R), coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). Figure 6a, 6b and 6c present the parity plots for torque, efficiency, and AC loss, respectively. In each plot, the horizontal axis represents the FEA result, and the vertical axis represents the PINN prediction. The dashed line indicates the ideal prediction line, $y = x$, while the solid line represents the fitted regression line. As shown in Figure 6a, the predicted torque agrees well with the FEA result, with $R = 0.9990$, $R^2 = 0.9977$, RMSE of 0.0089 N·m, and MAE of 0.0064 N·m. The efficiency prediction in Figure 6b also shows high accuracy, with $R = 0.9977$, $R^2 = 0.9948$, RMSE of 0.5499%, and MAE of 0.4169%. For AC loss, Figure 6c shows $R = 0.9974$, $R^2 = 0.9947$, RMSE of 1.1972 W, and MAE of 0.7870 W. These results indicate that the proposed PINN surrogate accurately reproduces the FEA-derived motor performance on unseen test data.

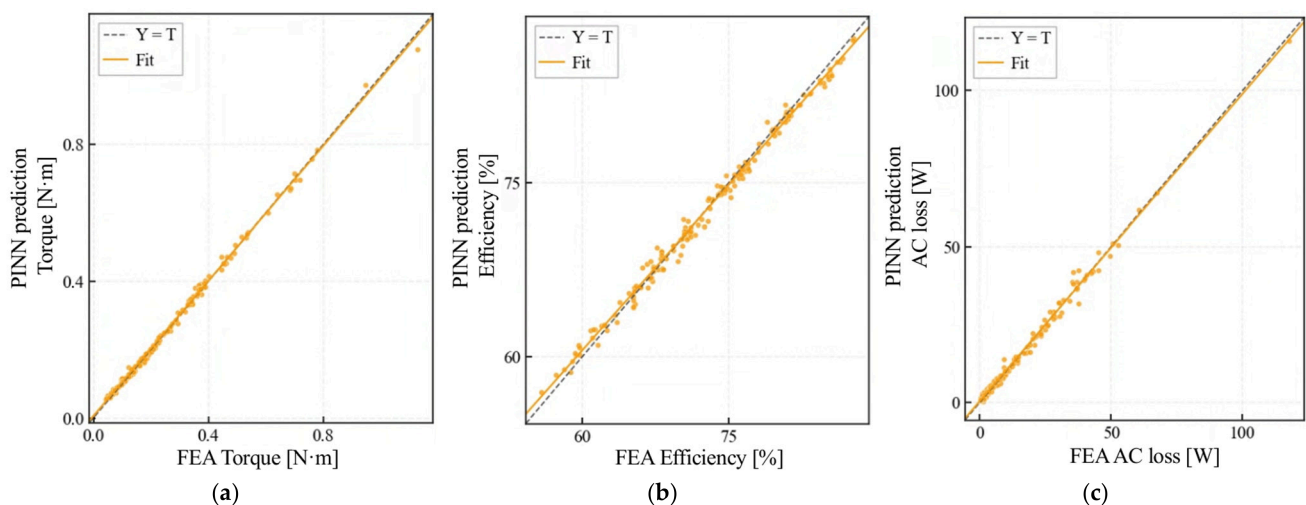


Figure 6. Prediction accuracy of the proposed PINN surrogate on the independent test subset. Each marker represents one FEA-generated motor design sample that was not used for neural network training or model selection: (a) torque, (b) efficiency, and (c) AC loss.

To compare the proposed model with conventional surrogate approaches, RSM, MLP, and the proposed PINN were evaluated using the same test set. Figure 7 presents the comparative validation results for torque, efficiency, and AC loss. Each panel compares the parity plots of the three surrogate models, where the horizontal axis represents the FEA result and the vertical axis represents the predicted value. The markers represent individual test samples, while the dashed line indicates the ideal $y = x$ relationship and the solid line represents the fitted regression line. As shown in Figure 7a, all three models accurately predict the torque, and their prediction points are closely distributed along the ideal $y = x$ line. Figure 7b shows that the proposed PINN provides the highest efficiency prediction accuracy among the three models, with $R = 0.9977$, $R^2 = 0.9948$, RMSE of 0.5499%, and MAE of 0.4169%. In Figure 7c, the proposed PINN also shows accurate AC loss prediction, with

$R = 0.9974$, $R^2 = 0.9947$, RMSE of 1.1972 W, and MAE of 0.7870 W. These results indicate that the proposed PINN achieves prediction accuracy comparable to or better than the baseline surrogate models while maintaining the physics-reconstructed output structure.

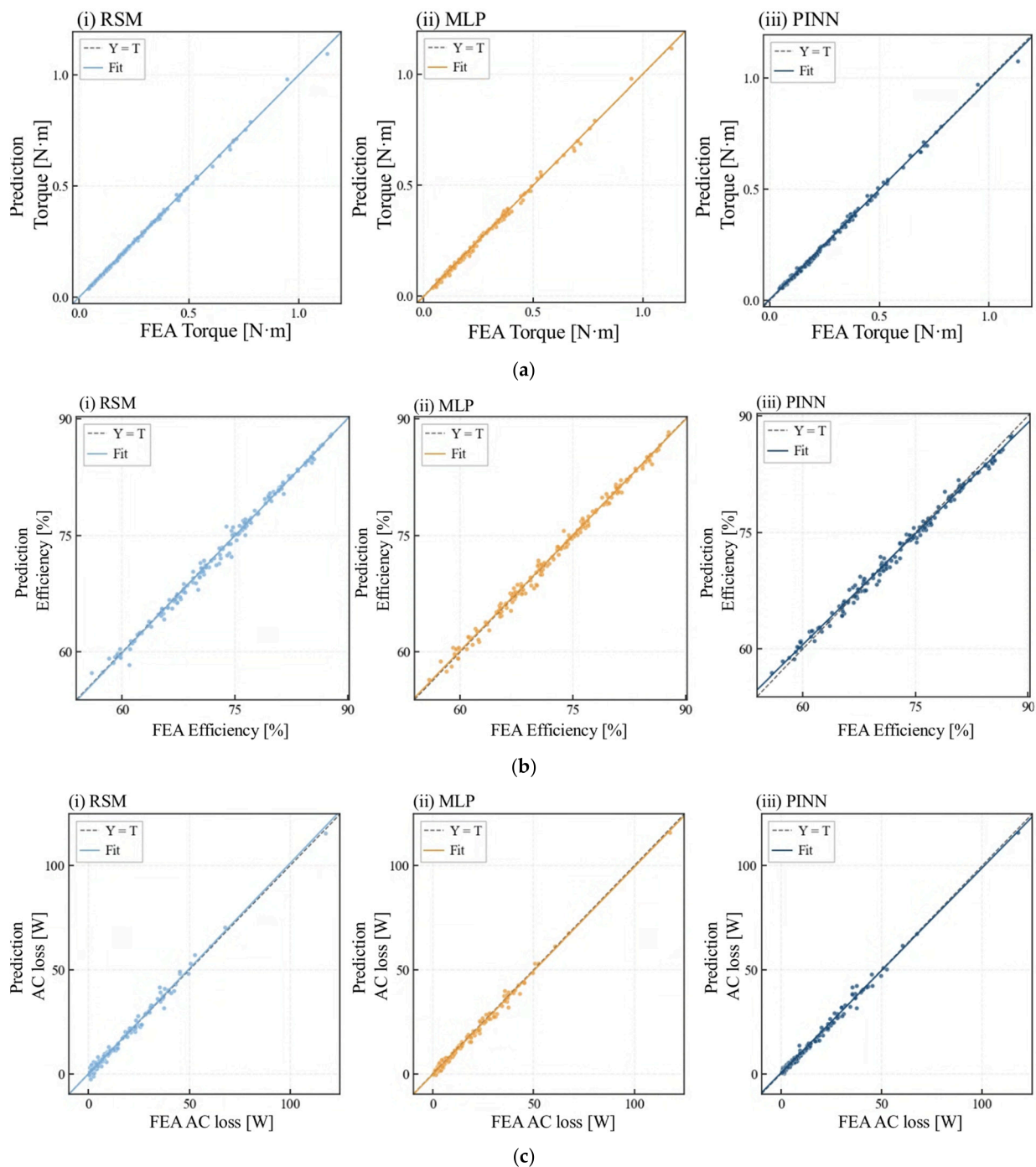


Figure 7. Comparative validation of surrogate models on the test set: (a) torque prediction using (i) RSM, (ii) MLP, and (iii) PINN; (b) efficiency prediction using (i) RSM, (ii) MLP, and (iii) PINN; and (c) AC loss prediction using (i) RSM, (ii) MLP, and (iii) PINN.

Figure 8 compares the test set prediction accuracy of the RSM, MLP, and proposed PINN surrogate models for the three primary performance indices: torque, efficiency, and AC loss. As shown in Figure 8a, all three models achieve high R^2 values for torque and efficiency, indicating that the overall response trends are well captured. However, the prediction of AC loss is more challenging than torque and efficiency because AC loss is

highly sensitive to electromagnetic field variation and trace geometry. In this target, the proposed PINN maintains the highest prediction accuracy among the compared models.

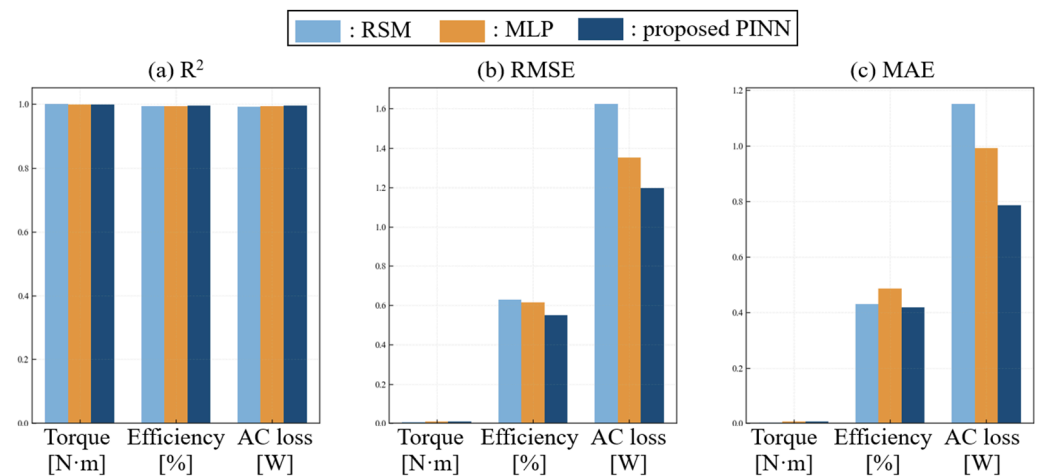


Figure 8. Test set metric comparison of surrogate models: (a) R^2 , (b) RMSE, and (c) MAE.

On the same test set, the efficiency RMSE values of RSM, MLP, and the proposed PINN are 0.6292, 0.6156, and 0.5499 percentage points, respectively. The corresponding AC loss RMSE values are 1.6240, 1.3522, and 1.1972 W, respectively. Although RSM achieves the lowest torque RMSE, the proposed PINN provides the lowest RMSE for efficiency and AC loss. In addition, its output reconstruction enforces the prescribed torque–speed and power–balance relations. These characteristics support its selection for the subsequent multi-objective optimization.

Figure 9 shows the physical consistency evaluation of the proposed PINN surrogate. Figure 9a compares the predicted output power with the physics-derived value calculated from $T\omega$, and Figure 9b compares the predicted efficiency with the physics-derived efficiency obtained from the power–balance relation. The circular markers represent individual design samples, with the blue and orange markers corresponding to output power and efficiency, respectively. The grey dashed lines indicate equality between the horizontal- and vertical-axis values ($Y = T$), while the colored solid lines represent the fitted regression lines. The reference and fitted lines nearly overlap because output power and efficiency are reconstructed using the prescribed physical relations. In both cases, the prediction points lie exactly on the ideal $y = x$ line, resulting in $R = 1.0000$, $R^2 = 1.0000$, and zero RMSE and MAE. It should be noted, however, that these perfect agreement results do not indicate independent prediction accuracy against FEA. Rather, they reflect that P_{out} and η are reconstructed by design using the hard-physics relations in the proposed PINN. Therefore, Figure 9 should be interpreted as a verification of structural physical consistency, whereas the actual predictive accuracy against FEA is evaluated separately in Figures 6 and 7.

These results indicate that the principal advantage of the proposed PINN is not limited to prediction accuracy but also lies in the structural enforcement of the prescribed physical relations. On the independent test set, the mean output power consistency residual was approximately 0% for RSM, 4.449% for MLP, and approximately 0% for the proposed PINN. The corresponding mean efficiency–balance residuals were 0.620, 0.971, and approximately 0 percentage points, respectively. Although RSM also exhibited an almost zero output power residual in the present constant-speed dataset, this agreement results from the direct proportionality between torque and output power at the fixed operating speed and is not structurally imposed in the RSM formulation. In contrast, the proposed PINN guarantees both the torque–speed and efficiency power–balance relations by construction.

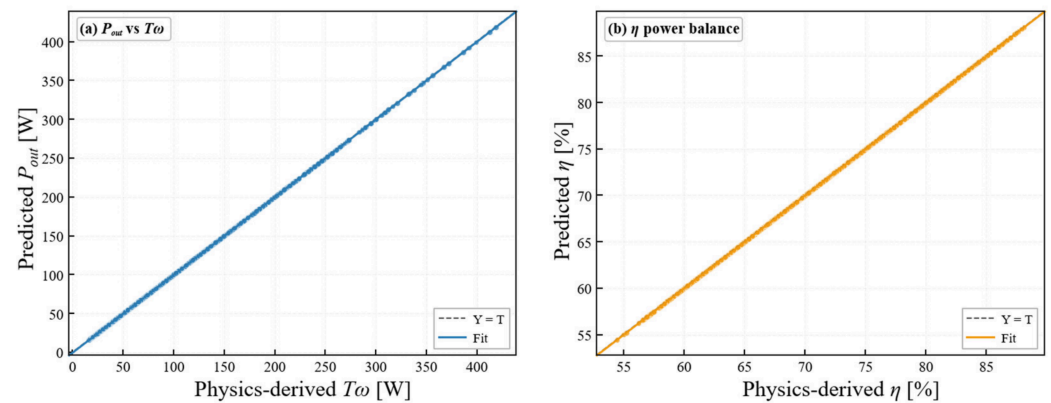


Figure 9. Physical consistency evaluation of the proposed PINN surrogate: (a) output power balance and (b) efficiency balance.

4. NSGA-II-Based Multi-Objective Optimization and FEA Re-Validation

The validated physics-reconstructed PINN surrogate is used as the performance prediction model for multi-objective design optimization. Since the PCB stator AFPM motor involves strongly coupled design variables, a single-objective optimization may lead to an unbalanced design with improved performance in one aspect but degraded performance in others. Therefore, NSGA-II is employed to explore the trade-off among torque, efficiency, and AC loss under the required dimensional and performance constraints. In this section, the optimization problem and NSGA-II procedure are first described. Then, the obtained Pareto-optimal solutions are analyzed, and the selected optimal design is re-evaluated using high-fidelity FEA to verify the reliability of the surrogate-assisted optimization result.

4.1. NSGA-II Optimization Results and Candidate Selection

The validated physics-reconstructed PINN surrogate was coupled with NSGA-II to explore the feasible design space under the dimensional and performance constraints defined in (3). The optimization was performed to maximize torque and efficiency while minimizing AC loss. During the NSGA-II search, each candidate design was evaluated using the proposed PINN surrogate instead of repeated FEA, which enabled efficient exploration of a large number of design candidates.

Figure 10 shows the NSGA-II optimization results and the selected candidate design. Each marker represents a candidate motor design evaluated by the surrogate model. The horizontal axis denotes the predicted torque, and the vertical axis denotes the predicted efficiency. The color scale represents the predicted AC loss, and the marker size reflects the relative AC loss level of each candidate. The dashed vertical and horizontal lines indicate the imposed torque and efficiency constraints, respectively. As shown in Figure 10, the candidate designs are distributed over a wide design space, and only a subset of candidates satisfies both the torque and efficiency constraints. Designs located in the upper-right feasible region are preferred because they simultaneously provide higher torque and higher efficiency. However, the AC loss must also be considered because excessive AC loss can degrade the overall performance of the PCB stator AFPM motor. Therefore, the final design was selected by considering the trade-off among torque, efficiency, and AC loss. The selected design is marked by the star symbol in Figure 10. This candidate satisfies the required torque constraint of 0.22 N·m and the efficiency constraint of 80% while maintaining a relatively low predicted AC loss compared with other feasible candidates.

To clarify the design changes introduced by the optimization, a representative initial design was defined using the mid-level values of the five design variables within the

investigated design space. The initial and optimized designs were evaluated at the same operating speed of 3650 rpm. Table 3 compares their principal design parameters and electromagnetic performance.

Table 3. Comparison of the initial reference and optimized designs.

Parameter	Initial Reference	Optimized
Outer diameter [mm]	80	80
PCB count	2	2
Turns per slot	2	3
Trace width [mm]	1.5	0.5
Magnet thickness [mm]	4	6
Torque [N·m]	0.2809	0.2563
Efficiency [%]	72.41	81.58
AC loss [W]	17.24	2

Compared with the initial reference design, the optimized design increased the efficiency from 72.41% to 81.58% while reducing the AC loss from 17.24 W to 2 W, corresponding to an 88.4% reduction. The torque decreased from 0.2809 N·m to 0.2563 N·m; however, the optimized design satisfied the prescribed torque constraint of 0.22 N·m while substantially improving the efficiency and AC loss characteristics.

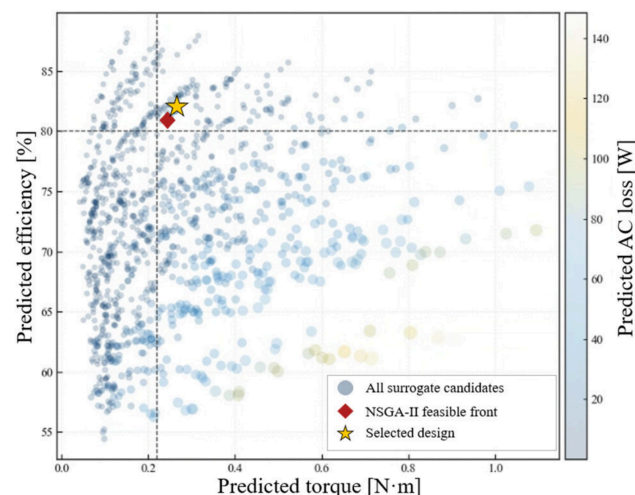


Figure 10. Feasible candidate selection from NSGA-II optimization.

The FEA database contained 1125 valid design cases, which were divided into 787 training, 169 validation, and 169 independent test samples. The computational costs of the surrogate models were also evaluated under the same computing environment. The training times of RSM, MLP, and the proposed PINN were 0.24, 5.76, and 21.35 s, respectively, while their average prediction times were 0.0106, 0.0013, and 0.0024 ms per design case, respectively. The NSGA-II optimization was performed using a population size of 160 and 120 generations and required approximately 139.1 s using the precomputed PINN predictions. The per-gene mutation probability and uniform crossover probability were set to 0.20 and 0.90, respectively, and the optimization was terminated after the fixed maximum of 120 generations. Because the chromosome consists of five genes corresponding to the five design variables, $p_m = 0.20$ corresponds to $\frac{1}{N_{var}}$, resulting in approximately one gene being subject to mutation per offspring on average. This setting was adopted to maintain population diversity in the discrete design space. Thus, the total PINN training and optimization time was approximately 160.4 s. The PINN training and NSGA-II search

using precomputed predictions required 21.35 s and approximately 139.1 s, respectively, giving a combined time of approximately 160 s. This time excludes initial FEA database generation, data preparation, hyperparameter tuning, prediction precomputation, and subsequent FEA verification. Therefore, it represents the training-and-search cost after the database becomes available, rather than the total computational cost of the complete design process. Table 4 summarizes the training and batch-averaged prediction times. Like recent neural network-based motor design optimization [24], the proposed framework uses a surrogate model to support multi-objective design search. The present approach specifically reconstructs output power and efficiency from torque and loss predictions using physical relations. Although its training and prediction times are longer than those of the MLP baseline, this reconstruction ensures consistency with the prescribed torque–speed and power–balance relations. Comparisons with published methods are qualitative because the motor configurations, datasets, and computing environments differ; no superiority in computational speed is claimed. For a like-for-like comparison with direct FEA-coupled NSGA-II, the initial database preparation and model tuning costs must also be included, and both approaches must be assessed at comparable solution quality within the same design domain. The computational cost of direct FEA-coupled NSGA-II depends on the number of unique designs requiring solver evaluation, accounting for the reuse of previously evaluated results. Therefore, Table 4 characterizes the computational costs of individual stages rather than demonstrating a measured end-to-end speedup at equivalent solution quality.

Table 4. Computational cost comparison of FEA and surrogate models.

Method	Training Time [s]	Prediction/Evaluation Time
RSM	0.24	0.0106 ms/case
MLP	5.76	0.0013 ms/case
Proposed PINN	21.35	0.0024 ms/case
High-fidelity FEA	-	>1 h/case (estimated)

Therefore, it was chosen as the final optimized candidate for high-fidelity FEA re-validation in the following subsection.

4.2. FEA Re-Validation of the Selected Design

The selected design identified from the NSGA-II optimization was re-evaluated using high-fidelity FEA to verify the reliability of the surrogate-assisted optimization result. It should be noted that the generalization capability of the surrogate had already been evaluated over the independent test set in Figures 6–8. Therefore, the purpose of the present re-validation is not to repeat the surrogate accuracy assessment, but to verify that the final design selected through the NSGA-II optimization remains feasible when re-evaluated using high-fidelity FEA. Figure 11 presents the relative comparison between the PINN prediction and the FEA re-validation result, where the FEA values are normalized to 100%. In addition, Table 5 summarizes the corresponding quantitative comparison for torque, efficiency, AC loss, copper loss, and output power. As shown in Figure 11 and Table 5, the PINN prediction shows good agreement with the FEA re-validation result for all considered performance metrics. The predicted torque is 0.2518 N·m, whereas the FEA result is 0.2563 N·m, corresponding to an error of -1.73% . The predicted efficiency is 81.70%, which is very close to the FEA result of 81.58%, with an error of $+0.14\%$. For the loss components, the predicted AC loss and copper loss are 2.073 W and 19.49 W, respectively, whereas the corresponding FEA results are 2.000 W and 20.11 W, respectively, yielding errors of $+3.64\%$ and -3.08% , respectively. The predicted output power is 96.26 W,

compared with the FEA result of 97.95 W, resulting in an error of -1.73% . Surrogate prediction errors may affect the objective values and the dominance ranking of nearby Pareto candidates. For the selected design, the absolute differences between the PINN and FEA results are approximately 0.0045 N·m for torque, 0.12 percentage points for efficiency, and 0.073 W for AC loss. The torque and efficiency differences are smaller than the corresponding PINN-predicted margins above the required limits, which are 0.0318 N·m and 1.70 percentage points, respectively. Both constraints remain satisfied in the FEA results, indicating that the surrogate errors do not change the feasibility determination for this selected design.

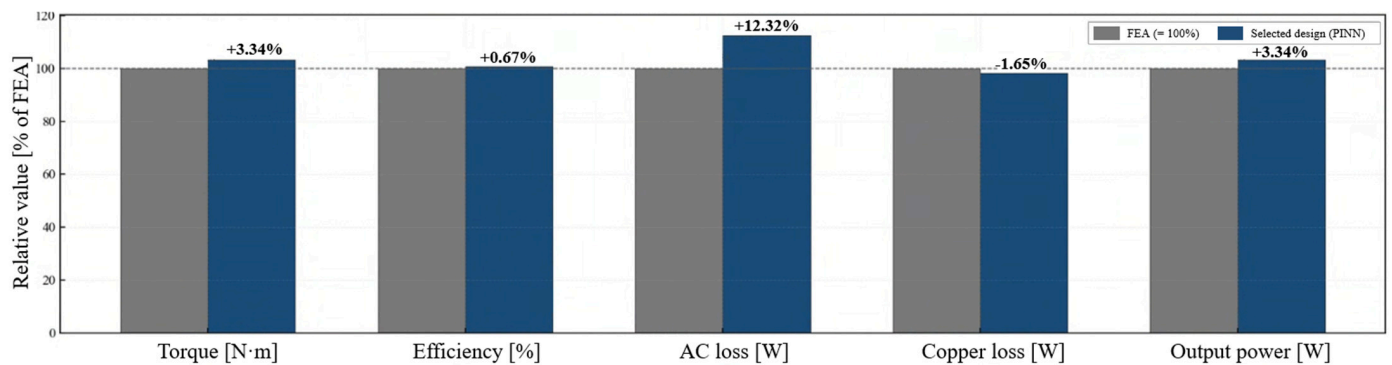


Figure 11. Comparison between PINN prediction and FEA re-validation for the selected design.

Table 5. Quantitative comparison between the PINN prediction and the FEA re-validation results for the selected design.

Metric	Selected (PINN)	FEA	Err. [%]
Torque [N·m]	0.2518	0.2563	−1.73
Efficiency [%]	81.7	81.58	+0.14
AC loss [W]	2.073	2	+3.64
Copper loss [W]	19.49	20.11	−3.08
Output power [W]	96.26	97.95	−1.73

These results indicate that the selected design remains feasible after high-fidelity electromagnetic re-validation and that the proposed physics-reconstructed PINN surrogate provides sufficiently accurate performance estimates for optimization. In particular, the torque and efficiency constraints are still satisfied in the FEA results, confirming that the proposed PINN-assisted NSGA-II framework can effectively guide the search toward a valid high-performance PCB stator AFPM motor design. It should be noted that the present re-validation is performed within the same analysis scope used for the FEA database construction. Since the database is based on electromagnetic analysis, the considered loss terms are limited to copper loss and flux-induced AC loss in the PCB traces, while iron loss is not included. Therefore, the present validation should be interpreted within this modeling scope. The numerical assessment is structured to evaluate the proposed design-optimization methodology at two levels. At the surrogate model level, the held-out test set evaluation and the comparisons with RSM and MLP assess predictive accuracy across the investigated design domain. At the optimization result level, the selected design comparison assesses agreement with the FEA reference results and satisfaction of the prescribed design constraints. These complementary assessments provide a quantitative basis for evaluating the proposed framework as a model-based electromagnetic design tool, rather than relying solely on the predicted performance of a single optimized motor.

5. Conclusions

This paper proposed a physics-reconstructed PINN-assisted optimization framework for a compact PCB stator AFPM motor for robotic smart actuator applications. The proposed surrogate predicts torque and loss components using a neural network, while output power and efficiency are reconstructed through power-balance relations to ensure physical consistency. The model showed high prediction accuracy on the FEA-based test set, achieving $R^2 = 0.9977$, 0.9948 , and 0.9947 for torque, efficiency, and AC loss, respectively. The validated PINN surrogate was coupled with NSGA-II to maximize torque and efficiency while minimizing AC loss under the required constraints. The selected design was re-validated by high-fidelity FEA, and the maximum prediction error was 3.64%, confirming the reliability of the proposed optimization framework. In this study, the database was constructed using electromagnetic analysis because accurate 3D FEA of thin PCB copper traces requires a high computational cost due to their small thickness. Therefore, the optimization focused on copper loss and PM-flux-induced AC loss in the PCB traces, which are the main loss components considered in the present coreless PCB stator AFPM motor model. Accordingly, stator iron loss was outside the scope of the present analysis, which was limited to the electromagnetic quantities defined in the constructed no-load FEA database.

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