

Physics-Informed Adaptive Gaussian Process Regression Meta-Model for Rapid Characterization of Permanent Magnet Synchronous Machines

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Abstract—Obtaining the best overall performance for an Interior Permanent Magnet synchronous machine (IPM) requires evaluating multiple operating points for the candidate designs in an optimization. With the design domain typically having many variables, this can result in a substantial number of finite element analysis (FEA)-based simulations. This study introduces a novel Physics-Informed Adaptive Gaussian Process Regression (PI-AGPR) framework that significantly reduces computational requirements through a two-module meta-modeling strategy. The first module adaptively selects the optimal operating points using a modified Posterior Standard Deviation criterion that accounts for input-output correlations in multi-output regression. The second module then captures geometric dependencies across designs. Experimental validation confirms the accuracy of the underlying FEA model. Compared with standard Gaussian Process Regression and Artificial Neural Networks using identical training data, the proposed framework PI-AGPR achieves superior accuracy for torque-speed characteristics (2.3% mean absolute percentage error (MAPE)) and flux linkages (1.7–2.0% MAPE), demonstrating its effectiveness for both rapid design characterization and drive cycle optimization.

Index Terms—Artificial Neural Network, Design Optimization, Drive Cycle, Electromobility, Experimental Verification, Gaussian Process Regression, Interior Permanent Magnet Machine, Meta-Model, Physics-Informed Characterization, Traction.

I. INTRODUCTION

Interior Permanent Magnet Synchronous Machines (IPMs) are widely used in high-performance applications that require operation across multiple operating points. Therefore, in the selection of an optimal design, it would be beneficial to evaluate the performance of candidate designs across all prospective operating points. In general, electrical machine optimization most often considers a drive cycle or multiple objectives and

these optimization problems are widely studied [1]. Recent studies applying both well-established and novel optimization algorithms report the need for thousands [2], [3], if not millions [4], of design and operating point evaluations, even when implementing the most efficient optimization algorithms, such as the Newton-Raphson method [2] and the Non-dominated Sorting Genetic Algorithm II (NSGA-II) [4], [5].

While Finite Element Analysis (FEA)-based models are the standard for these evaluations, conducting a large number of FEA simulations can be computationally impractical [1], [2]. To address this challenge, most often, these studies rely on meta-models to partially solve the optimization problem or employ strategies to reduce problem dimensions [3], [4]. These meta-models seek to approximate FEA simulation results at significantly lower computational cost [6], [7]. Early surrogate approaches, such as the FEA-based model in [8], achieved one to two orders of magnitude reduction in solving time, though without addressing performance prediction across a design domain.

Previously proposed meta-models were based on polynomial regression [9], artificial neural networks (ANN) [10], [11], Gaussian Process Regression (GPR) [12], [13], or other approaches [14]. Sequential sampling strategies have also been proposed to reduce the number of FEA evaluations required for constructing surrogate models in PM machine optimization, achieving significant reductions in total computational runtime while maintaining accuracy comparable to direct FEA-based approaches [15]. Studies such as those documented in [9] [16], demonstrate their effectiveness for IPM optimization and characterization across multiple operating points by significantly reducing the number of FEA-based simulations.

These meta-modeling methods, while effective for characterizing individual designs, remain limited in their ability to generalize across different IPM designs [9], [17]. A limitation that becomes especially consequential in drive-cycle optimization, where the surrogate model must evaluate candidate designs across a wide and continuous range of operating points. Recent surrogate-based studies confirm that efficient, generalizable meta-modeling for drive-cycle energy loss optimization of synchronous machines remains an active challenge [18]. This gap can be addressed by a meta-model that adapts to any selection of operating points or drive cycles while accommodating various geometries, enabling both fast design characterization and drive-cycle optimization.

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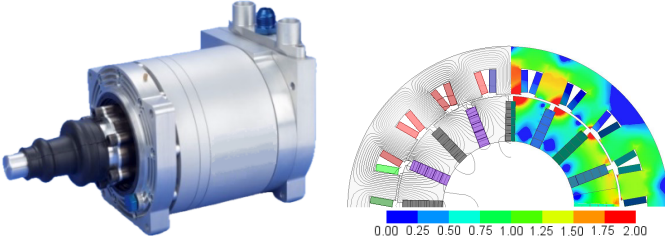


Fig. 1. The ultra-high specific torque IPM motor considered as the reference for the study. The prototype from the original developments for the first generation Formula E (left) and the magnetic field in the motor cross section, flux lines and flux density in excess of 2 T, illustrating the heavy saturation (right).

The proposed approach in this paper, initially presented at IEMDC2025 [19], introduces a novel meta-modeling strategy, Physics-Informed Adaptive Gaussian Process Regression (PI-AGPR), capable of estimating the performance of any design within the design domain and for any control inputs. It also advances a method to handle inputs of different natures when building a GPR-based meta-model. Overall, it aims to evaluate any design for any drive cycle efficiently.

This strategy combines GPR with governing physical equations. A variation of the traditional adaptive sampling policy, Posterior Standard Deviation (PSD), is proposed to account for input-output dependencies and enable a precise adaptive sampling strategy. GPR, previously employed in simpler meta-models [6] or in other IPM-related applications [12], was employed in this study to create a high-performance meta-model. The high fidelity and data efficiency of the proposed meta-modeling strategy are demonstrated through comparisons with standard GPR and a fully connected ANN implementation.

Section II introduces the reference spoke-type IPM machine, the high fidelity FEA model used in this study, and the fundamentals of GPR. Section III presents the proposed PI-AGPR framework and strategy, along with the governing physical equations and the conditions under which the training data were generated. The methodology of the study is described in Section IV, covering both the implementation of the proposed PI-AGPR and the other standard meta-models used for comparison. Section V presents and analyzes the performance of PI-AGPR, comparing it with standard GPR and ANN implementations and discussing its potential applications.

II. REFERENCE IPM MOTOR, FEA SIMULATIONS, AND GAUSSIAN PROCESS REGRESSION

A. IPM Motor Topology

This study employs a reference prototype IPM originally developed for the first-generation Formula E and later optimized, as described in detail in [16], [20]. The 40 kW IPM motor features a spoke rotor with 16 poles and a three-phase winding with concentrated coils placed around 18 teeth, as shown in Fig. 1. Further key design and operating parameters of the reference motor are summarized in the Appendix, Table A1.

The motor achieves a peak torque of 110 Nm within a stator outer diameter of only 80 mm, resulting in a record torque-to-weight ratio [16]. This exceptionally compact envelope was

TABLE I
FEA MODEL PARAMETERS AND DISCRETIZATION SETTINGS

Parameter	Value
Stop time	one electrical period
Time-step Rationale	144 per electrical period
Time-step	$< 104 \mu\text{s}$ (at 500 rpm)
Total mesh elements	12642
Stator element size	4 mm
Rotor element size	4 mm
Permanent magnets element size	2 mm
Air gap	3 layers
Air-gap element size	Air-gap Width/4

enabled by a purpose-designed cooling system comprising forced oil convection through the stator slots and forced air convection across the air gap [16]. The design exhibits extremely large magnetic loading under rated conditions, as illustrated by the flux density distribution in Fig. 1, making it well-suited for a challenging study involving nonlinearities and meta-modeling.

B. FEA Simulations

A high-fidelity FEA model of the reference IPM is developed to characterize its electromagnetic performance across the operating domain; the resulting simulation data serve as the training and testing dataset for the meta-model detailed in Section III. The model is implemented in the commercially available tool *Ansys Electronics Desktop 2023R2* [21] and simulated under 2D transient conditions. The key parameters and mesh settings are summarized in Table I. The core losses, W_{core} , are calculated using the Bertotti formula [22], with coefficients corresponding to the electrical steel material specified in [23]. Regarding copper losses, only Joule's First Law is considered; frequency-dependent effects are disregarded [16].

A torque correction factor of 0.9 is applied to the FEA-predicted torque under the condition $i_q = I_{\text{ph}}$, $i_d = 0$ A, to align the model with the experimental characterization of the prototype reported in [20]. No correction is applied to the flux linkage or loss predictions. The need for this correction is physically grounded: in high-torque density machines with short active stack lengths, three-dimensional end-winding flux contributions are not captured by the 2D transient formulation, and the magnetic properties of the electrical steel laminations are subject to uncertainty both from datasheet tolerances and from degradation induced by the manufacturing process [16], [24], [25]. For this prototype, which features a 74 mm active stack length and laser-cut laminations operating under extreme magnetic loading, these effects are particularly significant [25]. The correction factor use is consistent with the magnitude of FEA-to-experiment discrepancies reported in the broader literature for similar machines and manufacturing conditions [24], [25], where systematic torque offsets of 10–20% have been documented and attributed to the same physical sources.

It is worth noting that within the PI-AGPR framework, which is designed for relative comparison of candidate designs within the same topology and manufacturing process, any systematic FEA offset applies consistently across all evaluated geometries. The relative ranking of candidate designs and the shape of the predicted performance landscape are therefore

preserved, making the framework applicable in design scenarios where experimental calibration data is unavailable.

The FEA model shows satisfactory agreement with the experimental data recorded by the extended research group [16], [20], as shown in the Appendix. The low deviation confirms that the simulation data are representative of the ground truth and suitable for training the meta-model.

C. Gaussian Process Regression

The GPR formulation used in this study follows the framework established in [19], to which the reader is referred for full derivations. A GP models an unknown function through a mean function $m(\mathbf{x})$ and a covariance function $k(\mathbf{x}, \mathbf{x}')$ [26]:

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')), \quad (1)$$

where $m(\mathbf{x}) = \mathbf{W}\mathbf{x} + B$ with weight matrix $\mathbf{W}$ and bias B learned during training. The key property exploited in this work is that GPR provides not only a predicted mean but also a posterior variance $\mathbb{V}$, which serves as the basis for the adaptive sampling strategy described in Section III.

III. NOVEL META-MODELING FRAMEWORK AND STRATEGY: PI-AGPR

The proposed PI-AGPR, based on GPR and governing physical equations, consists of two modules, as illustrated in Fig. 2. The framework can be applied for any electrical machine, including those with strong nonlinearities. In its current form, the framework is implemented for a fixed motor topology, within which geometric parameters are varied across a predefined design domain; the implementation presented here is conducted on a spoke-type IPM with strong magnetic nonlinearities, which represents a challenging and practically relevant test case. Extension to a multi-topology environment is conceptually possible with a substantially larger dataset [14]. Variations in pole or slot count, would alter the fundamental input–output relationships of the model and would be possible to include with a broader dataset.

The first module determines which operating points are required to efficiently compute the flux linkage maps in the Q-axis, $\psi_q(i_d, i_q)$, and D-axis, $\psi_d(i_d, i_q)$, as well as the different loss components. The components of the loss matrix, $\mathcal{W}$, can be described as:

$$\mathcal{W} = [W_{\text{copper}}, W_{\text{core}}, W_{\text{PM}}], \quad (2)$$

where W_{copper} are the stator winding copper losses, W_{core} are the core losses, and W_{PM} the are eddy-current losses in the permanent magnets, which are disregarded in this study due to effective segmentation of the PMs, as detailed in the Appendix. These losses are quantified using the experimentally verified FEA model from Section II-B. This stage is executed for a single design, and the operating points defined here are used for the designs considered in the second module. In this study, the operating points are defined as $[i_d, i_q, \omega_e]$, where:

$$i_d = -I_{\text{ph}} \sin(\gamma), i_q = I_{\text{ph}} \cos(\gamma) \quad (3)$$

and ω_e is the electrical speed; γ is the stator current angle relative to the rotor D-axis; and I_{ph} is the phase current.

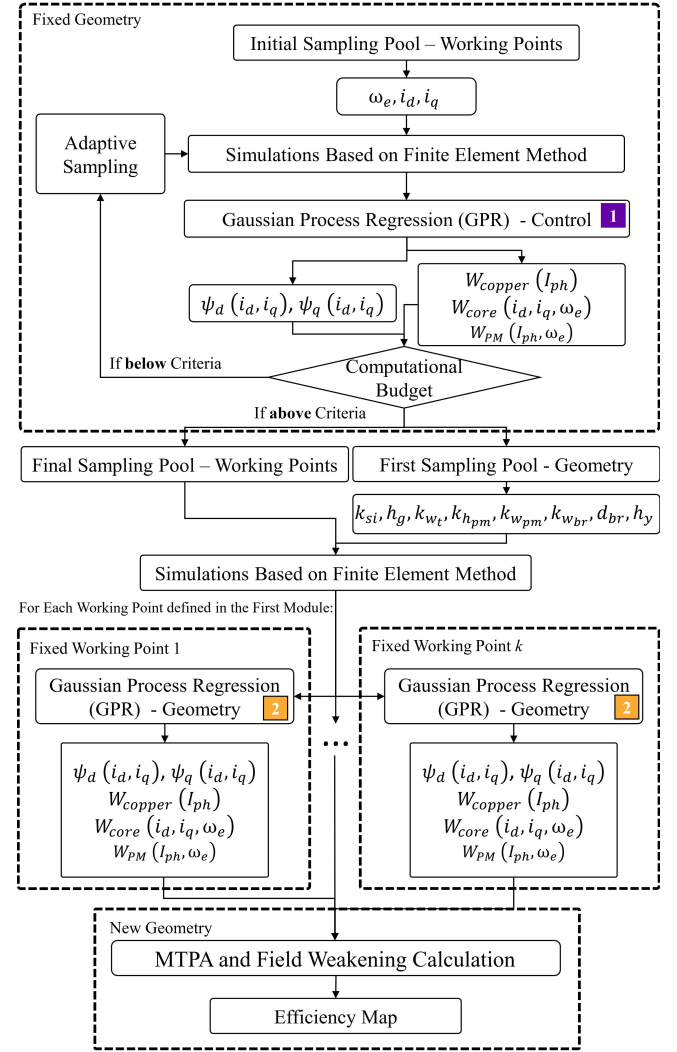


Fig. 2. Illustration of the PI-AGPR strategy.

The second module aims to establish a relationship between geometric variables, identified in Table III, $\psi_q(i_d, i_q)$, $\psi_d(i_d, i_q)$ and $\mathcal{W}$. The goal of this module is to capture the geometric dependencies of the outputs used to compute the performance of a specific design. This relationship combines data from different designs at the same operating points and fits independent geometry-based GP models for the operating points determined in the first module. By running several GPR models, the meta-model is then able to compute loss maps (or the losses for a given set of operating points) for any geometry within the design domain.

Regarding sampling techniques, in the first module the initial sampling was defined using Latin Hypercube Sampling (LHS), along with sampling at the domain limits. The adaptive sampling strategy was based on the output variance of the GPR. The adaptive sampling continues until the defined computational budget is reached. For single-output GPR problems, PSD is a common approach to adaptive sampling. However, given the independent outputs ($\psi_q(i_d, i_q)$, $\psi_d(i_d, i_q)$, and $\mathcal{W}$) in this problem, a standard application of PSD would result in multiple new sampling points for each iteration, which does

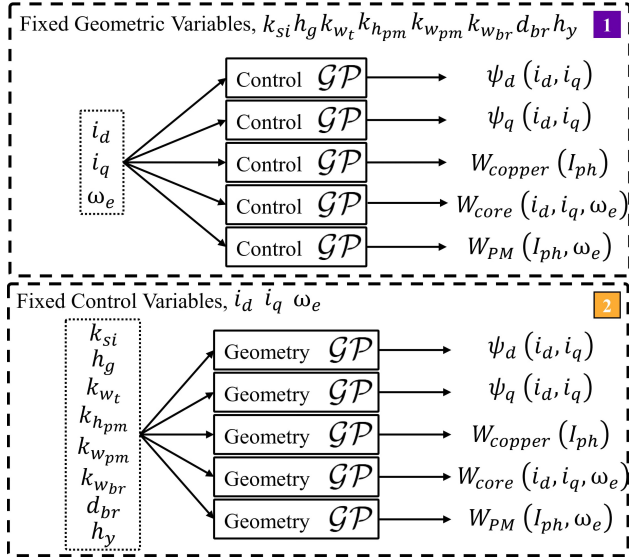


Fig. 3. Illustration of the independent control $\mathcal{GP}$ s (a). Illustration of the independent geometry $\mathcal{GP}$ s (b). The number in the upper right corner identifies where these $\mathcal{GP}$ s fit in Fig. 2.

not allow for a precise adaptive sampling strategy. Furthermore, not all outputs are affected by the three inputs (i_d , i_q , ω_e) in the same way, as presented in Fig. 3.

To quantify the relationship between inputs and outputs, Pearson Correlation Coefficients (PCC) were computed based on the widely accepted reference [27]. The PCC measures the linear correlation between two variables as the ratio of their covariance to the product of their standard deviations, yielding a dimensionless value in $[-1, 1]$. In this study, the PCC matrix $\mathbb{P}$ is computed from the normalized inputs and outputs of the initial LHS samples generated in Module 1, quantifying how strongly each control input (i_d , i_q , ω_e) correlates with each GP output (ψ_d , ψ_q , W_{copper} , W_{core} , W_{PM}), as detailed in Table II.

Additionally, for each $\mathcal{GP}$ from the first module, the output variance $\mathbb{V}$ was calculated across the entire input domain. The selection of the input coordinates that result in the highest output variance is described as:

$$\mathbf{x}_{\mathbb{V}_{\max}}^j = [i_{d(\mathbb{V}_{\max})}^j, i_{q(\mathbb{V}_{\max})}^j, \omega_{e(\mathbb{V}_{\max})}^j], \quad (4)$$

where j corresponds to the outputs of the $\mathcal{GP}$ models from the first module, resulting in one $\mathbf{x}_{\mathbb{V}_{\max}}^j$ for each output.

The inputs, $[i_d, i_q, \omega_e]$, corresponding to the highest uncertainty for each output (i.e., each $\mathcal{GP}$ from the first module— $\psi_q(i_d, i_q)$, $\psi_d(i_d, i_q)$, and $\mathcal{W}$) are stored in the maximum variance matrix, $\mathbb{V}_{\max}$. Each input coordinate i of the new sampled point is then computed as:

$$x_i' = \sum_j \mathbb{P}_{ij} \mathbb{V}_{\max, ij} x_{\mathbb{V}_{\max}, i}^j, \quad i \in [0, 2], \quad (5)$$

where $\mathbb{P}$ is the PCC matrix; i is the index identifying the input coordinate; and j is the index identifying the outputs of the $\mathcal{GP}$ models from the first module. For the adaptive sampling process, both $\mathbb{P}$ and $\mathbb{V}_{\max}$ are normalized.

Regarding the second module, the operating points defined in the previous module using adaptive sampling were simulated for each set of geometric inputs. The set of geometric

TABLE II
PEARSON CORRELATION COEFFICIENT

	i_d (-)	i_q (-)	ω_e (-)
ψ_d (-)	1.00	-0.03	0.00
ψ_q (-)	-0.02	1.00	0.00
W_{copper} (-)	-0.67	0.67	0.00
W_{core} (-)	0.02	0.51	0.73
W_{PM} (-)	-0.41	0.41	0.55

inputs was defined using LHS. In the second module, one $\mathcal{GP}$ is defined per operating point and performance output ($\psi_q(i_d, i_q)$, $\psi_d(i_d, i_q)$, and $\mathcal{W}$). These second module $\mathcal{GP}$ s use the geometry parameters described in Table III as inputs with the same outputs defined for the $\mathcal{GP}$ models from the first module. The schematic of the entire meta-modeling strategy and all the different $\mathcal{GP}$ models are illustrated in Fig. 2. Furthermore, the details of the $\mathcal{GP}$ models used in the first and second modules are presented in Fig. 3.

The GP models in both modules predict flux linkages and loss components only; the remaining performance metrics (torque, voltage, and operating-point feasibility) are derived analytically from these predictions using the governing electromagnetic equations, as follows. The electromagnetic torque, T_e , is defined as:

$$T_e = 1.5p[\psi_d(i_d, i_q)i_q - \psi_q(i_d, i_q)i_d], \quad (6)$$

where p is the number of pole pairs. Additionally, the voltage equations are:

$$v_d = R_s i_d + \frac{d\psi_d(i_d, i_q)}{dt} - \omega_e \psi_q(i_d, i_q), \quad (7)$$

$$v_q = R_s i_q + \frac{d\psi_q(i_d, i_q)}{dt} + \omega_e \psi_d(i_d, i_q), \quad (8)$$

where v_d and v_q are the peak fundamental voltages on the d - and q -axes, respectively, R_s is the phase resistance, and ω_e is the electrical speed. For each operating point in the efficiency maps, i_d and i_q values were determined using Maximum Torque per Ampere (MTPA) and field weakening strategies.

Thus, the “Physics-Informed” designation reflects the broad spectrum of physics-integration strategies described in the widely cited reference [28]. The two-module architecture encodes the physical distinction between control and geometric inputs; the adaptive sampling criterion is guided by known electromagnetic input–output dependencies; and the equations computing torque are systematically integrated to derive all final performance metrics from the predicted flux linkages and losses.

For both modules of PI-AGPR, the mean function $m(\mathbf{x})$ is defined as the linear function given in $m(\mathbf{x}) = \mathbf{W}\mathbf{x} + \mathbf{B}$, where the weight matrix $\mathbf{W}$ and bias $\mathbf{B}$ are learned independently for each input dimension during hyperparameter optimization. Consequently, for the GP models in Module 1, which take three control inputs (i_d , i_q , ω_e), the mean function contains three independent linear components; for the GP models in Module 2, which take eight geometric inputs (Table III), it contains eight independent linear components. This per-dimension formulation avoids imposing cross-input linear trends, which

would be physically unwarranted given the distinct roles of the control and geometric variables.

For the covariance function $k(\mathbf{x}, \mathbf{x}')$, the Matérn 5/2 kernel was selected based on cross-validation performance. This kernel provides twice-differentiable sample paths, which is physically consistent with the smooth variation of electromagnetic quantities in IPMs, while avoiding the overly smooth assumptions of the squared exponential kernel that can lead to overfitting in high-dimensional spaces [26]. Additionally, the Matérn 5/2 kernel's finite differentiability produces better-conditioned covariance matrices in the presence of small data irregularities than infinitely smooth kernels, making the GP formulation more robust to residual numerical noise without requiring an explicit noise term [26].

FEA simulations are subject to numerical noise arising from mesh discretization; at the refinement levels employed (Table I), mesh-induced numerical variation is expected to be substantially smaller than the physical signal variation across the operating domain, based on standard practice of this class of 2D transient simulations [29]. Its effect on GPR performance is further mitigated by the finite differentiability of the Matérn 5/2 kernel, as discussed above. Under this condition, treating the data as noise-free eliminates the inter-task noise term in the GP formulation [30], and each output is therefore modeled as an independent GP, with all models fitted using normalized data.

IV. STUDY IMPLEMENTATION

A. Design Domain

Based on the prototype used as a reference in this study, eight geometric variables were included in the design domain. These were selected taking into consideration their impact on performance and manufacturability. The range of values for these variables is detailed in Table III, where k_{si} is the ratio between the stator inner and outer diameters; h_g is the air-gap length; k_{wt} is the ratio between the stator tooth width and its maximum; $k_{h_{pm}}$ is the ratio between the permanent magnet (PM) height and its maximum; $k_{w_{pm}}$ is the ratio between the PM width and the rotor pole pitch; $k_{w_{br}}$ is the proportion of the rotor slot opening relative to the PM width; d_{br} is the distance between the rotor surface and the top of the PM; and h_y is the distance between the top of the stator slot and the outer stator diameter. These geometric variables form the input vector for the $\mathcal{GP}$ models defined in the second module of the proposed meta-modeling strategy, illustrated in Fig. 3.

B. Performance Comparison with Standard Meta-Modeling Strategies

The performance of each meta-model can be evaluated individually. However, given the variety of strategies available for building meta-models, it is valuable to provide a comparative analysis. Thus, in this study, PI-AGPR performance is compared with some standard approaches.

The first approach included in this study is the use of standard GPR, referred to as *GPR*. This method consists of a group of independent $\mathcal{GP}$ models, since inter-task transfer effects are eliminated due to the noise-free nature

TABLE III
DETAILS ON GEOMETRIC VARIABLES

Variables	Maximum	Minimum	Prototype	Alternative
k_{si} (-)	0.75	0.6	0.704	0.652
h_g (mm)	2.5	0.7	1.00	1.78
k_{wt} (-)	0.75	0.45	0.662	0.535
$k_{h_{pm}}$ (-)	0.95	0.55	0.775	0.775
$k_{w_{pm}}$ (-)	0.6	0.2	0.388	0.438
$k_{w_{br}}$ (-)	0.65	0.35	0.5	0.52
d_{br} (mm)	3	1.5	2.50	2.42
h_y (mm)	15	7	10.7	11.4

of the data. These models take as inputs both the control variables $[i_d, i_q, \omega_e]$ and the geometric variables $[k_{si}, h_g, k_{wt}, k_{h_{pm}}, k_{w_{pm}}, k_{w_{br}}, d_{br}, h_y]$. The outputs include $\psi_q(i_d, i_q)$, $\psi_d(i_d, i_q)$, and the loss components. This approach is simpler than the proposed solution; however, it lacks the two-module structure of PI-AGPR. Consequently, it does not distinguish between control and geometric inputs, resulting in an input domain with 11 dimensions.

Another widely used meta-modeling approach is the fully connected ANN, referred to in this study simply as *ANN*. The *ANN* consists of an input layer with 11 neurons, three fully connected hidden layers with 2048, 128, and 16 neurons, respectively, and an output layer with 5 neurons. The activation function for all layers is the Rectified Linear Unit (ReLU). To determine the best structure for the problem described in this study, hyperparameter optimization was performed. This optimization was carried out using Brute-Force Search [31]. For training these standard solutions, 90% of the dataset was used, while the remaining 10% was reserved for testing. The training dataset contains the same number of data points used to build the PI-AGPR solution.

C. FEA-Based Simulations

The data used to build the PI-AGPR were derived from the FEA-based model experimentally verified in Section II-B. The overall computational budget for the first module of the proposed meta-modeling strategy was set to 16 FEA simulations, with 8 defined initially based on LHS and domain limits. The remaining budget was allocated using the adaptive sampling strategy described in Section III. This combination of initial FEA sample size, s_i , and total computational budget, s_t , was chosen based on the first module's performance, detailed in Section V and illustrated in Fig. 5. For the second module of the proposed meta-modeling strategy, 512 different sets of geometric inputs, described in Table III, were defined using LHS to ensure efficient coverage of the geometric domain.

The standard strategies (*ANN* and *GPR*), developed for comparison with PI-AGPR, uses a dataset of the same size used for train the Module 2 of the proposed approach. However, since the standard strategies do not differentiate between geometric and control variables, the input vector comprises both types of parameters (11 in total). The design space was sampled using the LHS method. In total, for the standard strategies (*ANN* and *GPR*), all 8,192 simulations comprise the shared dataset. For PI-AGPR, this total includes the 8,192 dataset simulations used in Module 2, plus the 16 dedicated Module 1 simulations

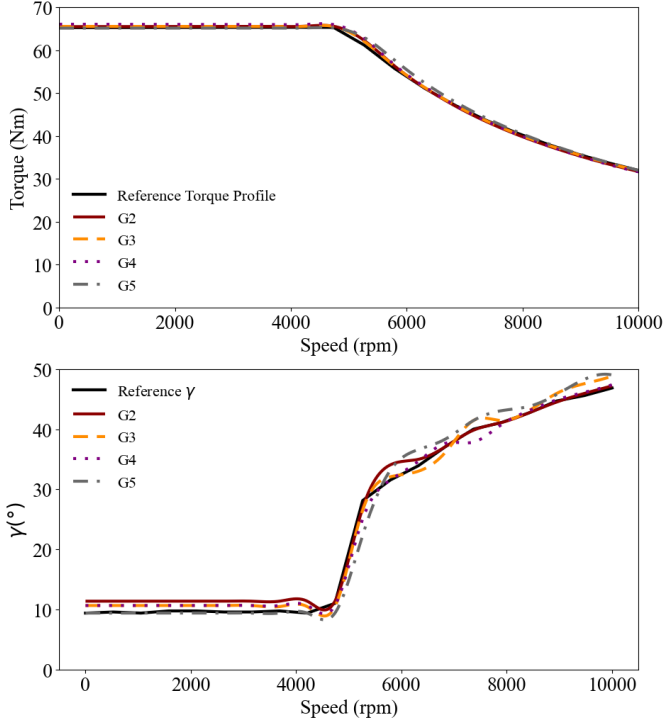


Fig. 4. Effect of the reference geometry selection on the predicted torque-speed characteristic (top) and current advance angle γ (bottom), obtained from the first optimization module using a fixed computational budget of $s_i/s_t = 8/16$. Each curve corresponds to a different reference geometry used to guide the adaptive operating point selection, see Table IV. The black solid line represents the reference solution computed from FEA.

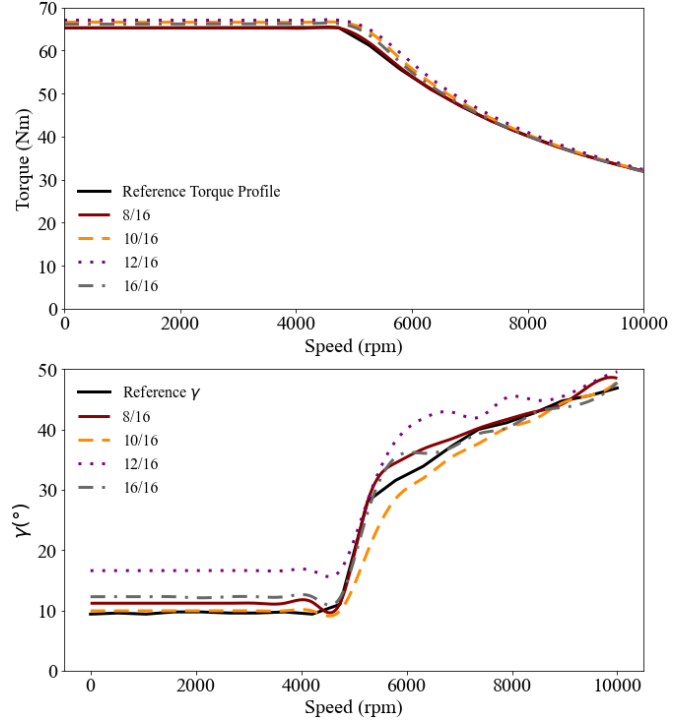


Fig. 5. Effect of the surrogate model sampling strategy on the predicted torque-speed characteristic (top) and current advance angle γ (bottom), obtained from the first optimization module. Each curve corresponds to a different ratio of initial FEA sample size s_i to total computational budget s_t , denoted s_i/s_t . The black solid line represents the reference solution.

used for adaptive operating-point selection, giving a total of 8,208 FEA evaluations; this distinction is reflected in Table V. Each 2D transient FEA simulation takes approximately 72.9 s of wall-clock time, as measured on the workstation used throughout this study, giving a total dataset generation time of 166.1 h for standard strategies and 166.4 h for PI-AGPR.

V. RESULTS AND DISCUSSION

An initial analysis focusing on the performance of the proposed meta-modeling strategy, PI-AGPR, including evaluations of its first and second modules is first presented. The discussion then progresses to a comparative performance analysis between PI-AGPR and the standard meta-modeling strategies described in Section IV-B. Finally, PI-AGPR merits and possible applications are discussed.

A. Meta-Model Performance

As detailed in Section III, PI-AGPR consists of two modules. The first module aims to carefully select the operating points that best describe $\psi_d(i_d, i_q)$, $\psi_q(i_d, i_q)$, and $\mathcal{W}$ of a given geometry. The second module aims to establish a relationship between these outputs and the geometric inputs identified in Table III.

The PI-AGPR outputs are compared to FEA results for a single design, corresponding to the prototype. The geometric inputs corresponding to the prototype design were excluded

TABLE IV
FIRST MODULE PERFORMANCE: EFFECT OF REFERENCE GEOMETRY AND SAMPLING BUDGET ON PREDICTED TORQUE-SPEED CHARACTERISTICS AND γ DEVIATION

s_i/s_t	Ref. Geometry	Torque (MAPE)	$ \gamma $ (°)	Computational Time (s)	
				FEA Runs	GPR Training
8/16	G2 - Min. Saturation	0.6%	1.1°	1168	864
8/16	G3 - Max. Saturation	0.4%	1.1°	1168	864
8/16	G4 - Min. Saliency	1.0%	0.9°	1168	864
8/16	G5 - Max. Saliency	0.8%	1.3°	1168	864
8/16	Alternative	0.2%	1.3°	1168	864
10/16	Alternative	1.9%	1.3°	1168	648
12/16	Alternative	3.0%	5.2°	1168	432
16/16	Alternative	1.2%	1.9°	1168	108

from the training dataset. Therefore, the first module of PI-AGPR was executed using an alternative geometry, selected at random and identified in Table III. The sensitivity of Module 1 to this choice is mitigated by the nature of the adaptive sampling strategy itself: operating points are selected to maximize $\mathcal{GP}$ uncertainty across the full $i_d-i_q-\omega_e$ control space, it inherently promotes broad coverage of the operating domain. The geometric inputs corresponding to the prototype, also identified in Table III, were only used for testing the second module of PI-AGPR and for the overall performance of the standard meta-models.

To empirically validate the robustness of the Module 1 operating points selection with respect to the choice the alternative geometry, identified in Table III, four additional geometries, differing from the alternative geometry only in

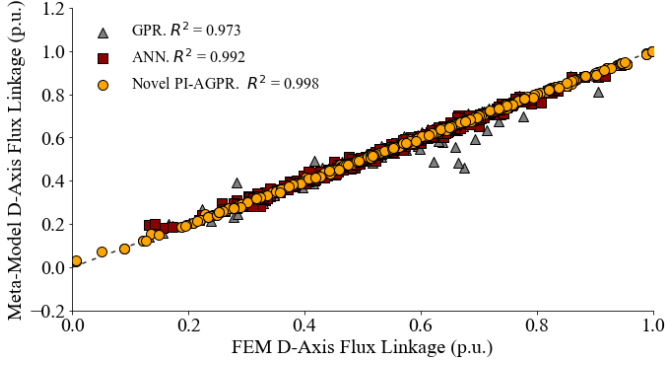


Fig. 6. Parity plot of D-axis flux linkage predictions (ψ_d) for the spoke-type IPM machine. Meta-model outputs from GPR, ANN, and the proposed PI-AGPR are compared against FEA reference solutions. The dashed diagonal represents perfect agreement. Values are normalized with respect to the peak flux linkage.

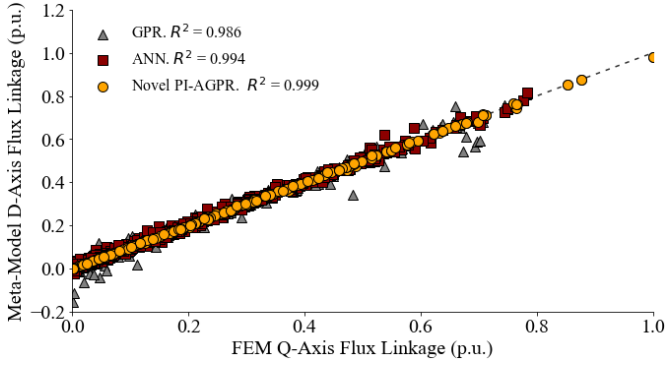


Fig. 7. Parity plot of Q-axis flux linkage predictions (ψ_q) for the spoke-type IPM machine. Meta-model outputs from GPR, ANN, and the proposed PI-AGPR are compared against FEA reference solutions. The dashed diagonal represents perfect agreement. Values are normalized with respect to the peak flux linkage.

the geometric variables defining their saturation and saliency characteristics, were evaluated: two representing the extremes of the saturation range (G2, minimum saturation: $h_g = 2.5$ mm, $k_{h_{pm}} = 0.55$; G3, maximum saturation: $h_g = 0.7$ mm, $k_{h_{pm}} = 0.95$) and two representing the extremes of the saliency ratio (G4, minimum saliency: $k_{w_{pm}} = 0.6$; G5, maximum saliency: $k_{w_{pm}} = 0.2$). For each case (G2, G3, G4 and G5), Module 1 was run independently to determine the set of 16 operating points. These points were then used to compute the torque-speed characteristic and the corresponding γ of the alternative geometry, identified in Table III. The results, presented in Fig. 4 and Table IV, show that the torque MAPE remains below 1.03% and the γ deviation below 1.25° when using any of the 16 operation points generated for each case (G2, G3, G4 and G5). The narrow performance band of Module 1, 0.61%pp in torque and 0.32° in γ , across geometries spanning the electromagnetic extremes of the design domain confirms that the adaptive operating point selection is robust and is not materially sensitive to the saturation or saliency characteristics of the geometry used.

The hyperparameters of the first module, in addition to the implementation details described in Section III and the robustness study, include the initial FEA sample size, s_i , and the

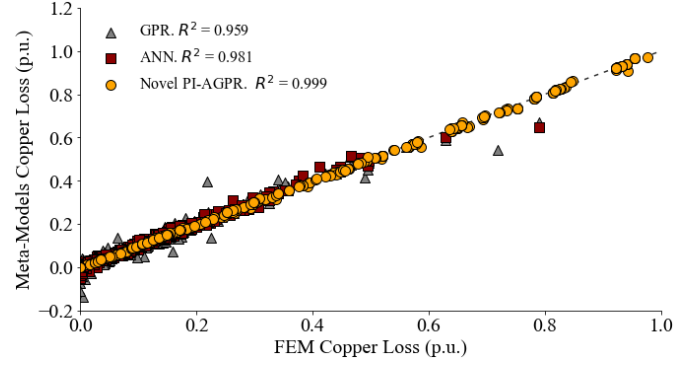


Fig. 8. Parity plot of W_{copper} for the spoke-type IPM machine. Meta-model outputs from GPR, ANN, and the proposed PI-AGPR are compared against FEA reference solutions. The dashed diagonal represents perfect agreement. Values are normalized with respect to the peak copper loss.

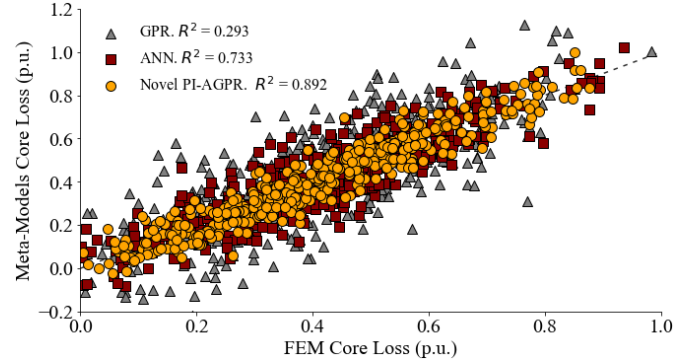


Fig. 9. Parity plot of W_{core} for the spoke-type IPM machine. Meta-model outputs from GPR, ANN, and the proposed PI-AGPR are compared against FEA reference solutions. The dashed diagonal represents perfect agreement. Values are normalized with respect to the peak core loss.

total computational budget, s_t . The metrics used to select these hyperparameters were s_t and the mean absolute percentage error (MAPE) of the torque, as well as the deviation of γ when compared with FEA-based results. The predicted torque-speed characteristics and γ for each s_i/s_t configuration are shown in Fig. 5, with average deviations detailed in Table IV. In terms of computational cost, the FEA computation time is identical across all s_i/s_t , since the number of simulations is fixed; the adaptive strategy therefore reduces prediction error at no additional FEA cost relative to a one-shot LHS approach of equivalent budget, with GPR training representing an overhead compared to the dominant FEA cost. The first module performs better when the s_i/s_t ratio is lowest for the same s_t , which demonstrates the effectiveness of the adaptive sampling strategy described in Section III and contributes to enhancing the performance of the proposed PI-AGPR.

The high performance of Module 1 is essential to ensure that Module 2 of PI-AGPR achieves equally strong results, because they guarantee that the operational points selected are descriptive enough to characterize a set of geometric variables. Evaluating the Module 2 effectively means evaluating the entire PI-AGPR, since it depends on the first module. Therefore, the proposed meta-modeling strategy is assessed both in terms of its generalization capability, by computing $\psi_d(i_d, i_q)$,

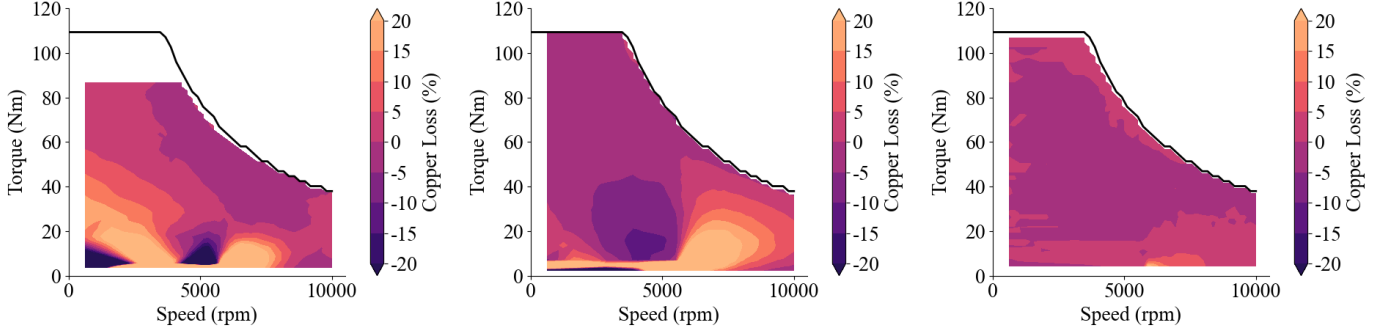


Fig. 10. Prediction error of W_{copper} relative to FEA results for (a) GPR, (b) ANN, and (c) Novel PI-AGPR.

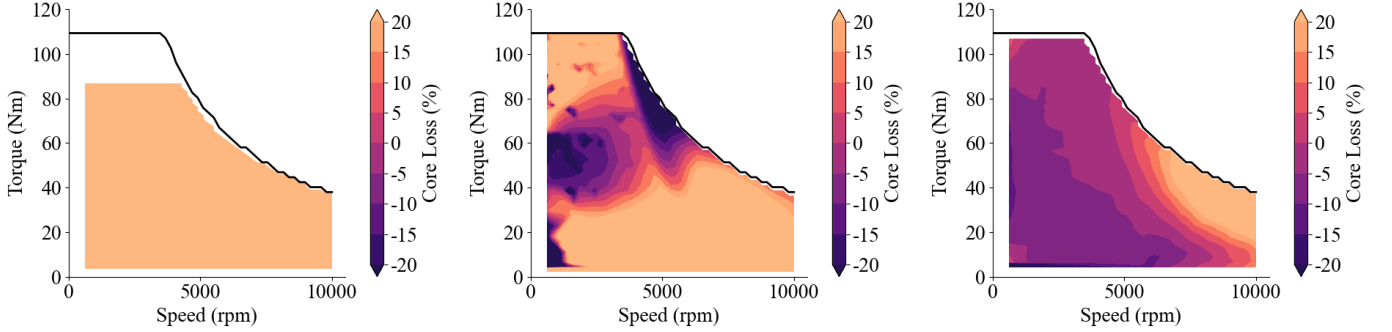


Fig. 11. Prediction error of W_{core} relative to FEA results for (a) GPR, (b) ANN, and (c) Novel PI-AGPR.

$\psi_q(i_d, i_q)$, and $\mathcal{W}$ for random input sets not included in the training dataset; and its ability to estimate the prototype's performance with high accuracy compared to FEA results.

For the generalization capability, 450 sets of the eight geometric inputs were selected at random from the test dataset. For each geometric input set, the tested meta-models generate predictions for one of the operating points determined in Module 1 (not the same operating point for all the 450 sets), which are then compared with FEA results. This comparison is shown for $\psi_d(i_d, i_q)$, $\psi_q(i_d, i_q)$, W_{copper} , and W_{core} in Figs. 6, 7, 8, and 9, respectively. The MAPE, computed using normalized data, for these outputs are presented in Table V.

PI-AGPR is highly reliable for predicting ψ_d , ψ_q , and W_{copper} , presenting extremely low error values. The higher error for W_{core} is primarily attributable to its nonlinear dependence on all three control inputs, particularly the coupling with electrical speed ω_e through the spatial harmonic content of the flux density waveform [32], [33] a dependency that the operating point selection in Module 1 may not fully capture across the speed range.

However, two considerations reduce the practical impact of this limitation. First, as shown in Fig. A2 and discussed in the Appendix, core losses constitute a small fraction of total losses at the high-current operating conditions that dominate energy consumption in drive-cycle applications; at rated and near-rated current levels (0.6–1.0 p.u.), their share remains below 20% of total FEA losses across all evaluated speeds, see Table A2. Their relative contribution grows at light load and high speed, where copper losses are smaller, but these operating conditions carry lower energy weight in typical drive cycles [16].

Second, since the same operating points are used to evaluate all candidate designs, any residual error in W_{core} prediction applies consistently across the design space, preserving the relative ranking of designs. An adaptive sampling weighted toward ω_e , or a hybrid approach combining GPR with an analytical Bertotti-based prior [22], represents a promising direction for future work.

B. Comparison with Standard Meta-Modeling Strategies

The performance of PI-AGPR is compared with standard meta-modeling approaches, namely ANN and GPR, as detailed in Section IV-B. The generalization capability is an important metric when evaluating the performance of most meta-models. To assess this for both ANN and GPR, 450 sets of the eleven inputs (control and geometric inputs) were selected from the test dataset randomly. The outputs of both GPR and ANN were compared with FEA results, as shown in Figs. 6, 7, 8, and 9. Additionally, the performance of PI-AGPR is compared with these two standard approaches in Table V.

Based on the results from the test data points, and using the same amount of training resources, PI-AGPR performs significantly better when computing $\psi_d(i_d, i_q)$, $\psi_q(i_d, i_q)$, W_{copper} , and W_{core} . As discussed previously, W_{core} depends not only on i_d and i_q but also on ω_e , making it a strictly more complex function than ψ_d and ψ_q , yet PI-AGPR achieves a significant improvement over standard solutions on this metric.

Following the evaluation and comparison of the generalization capabilities of PI-AGPR, ANN, and GPR, their effectiveness in characterizing a specific design is further analyzed. For this study, W_{copper} and W_{core} maps of the prototype design

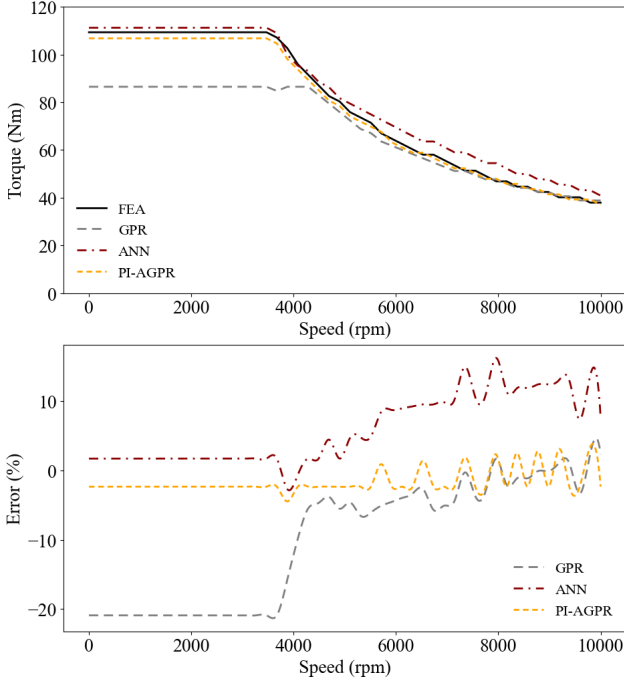


Fig. 12. Torque-speed characteristic calculated using PI-AGPR and the standard methods included in this study. The geometry is from the prototype, identified in Table III.

were computed using all three meta-models. The geometric input values corresponding to the prototype design were never included in either the training or test datasets. The differences between the loss components computed by the different meta-models (PI-AGPR, ANN, and GPR) are presented in Figs. 10 and 11. The black line in these figures corresponds to the FEA calculation of the torque-speed characteristic, allowing for a visual observation of the deviation for all the outputs.

PI-AGPR predicts loss components with substantially higher fidelity than GPR and ANN, with the vast majority of loss map values computed within 5% absolute error (Figs. 10 and 11). The relatively higher MAPE for W_{core} (Table V) is consistent with its nonlinear dependence on all three control inputs, particularly the coupling with electrical speed ω_e [32], [33], which the operating point selection in Module 1 may not fully capture across the speed range. The torque-speed comparison in Fig. 12 reinforces this picture: only PI-AGPR maintains consistent accuracy across the full torque-speed range, with 2.3% MAPE at both base and maximum speed (Table V).

C. Discussion

The accuracy and computational efficiency of all three strategies are summarised in Table V. The direct FEA reference per candidate design comprises 16 simulations at 72.9 s each (one flux linkage map and seven drive-cycle representative points identified via k-means clustering [9], [16]), totalling 1,168 s per candidate and 227.1 h for a full 700-candidate campaign. The offline dataset of 8,192 FEA simulations (166.1 h) is shared by ANN and GPR and constitutes the only investment required before any campaign can be run. PI-AGPR requires an additional 16 FEA simulations for the adaptive operating

TABLE V
META-MODELING STRATEGIES: ACCURACY AND COMPUTATIONAL EFFICIENCY. DIRECT FEA REFERENCE PER CANDIDATE: 16 SIMULATIONS TIMES 72.9 s = 1,168 s. DIRECT FEA CAMPAIGN REFERENCE: 227.1 h (700 CANDIDATES).

	ANN	GPR	PI-AGPR
<i>Accuracy (MAPE)</i>			
ψ_d (-)	2.0%	2.5%	2.0%
ψ_q (-)	33.8%	84.8%	1.7%
W_{copper} (-)	16.4%	121.9%	1.6%
W_{core} (-)	160.6%	169.8%	17.0%
Torque, base speed (-)	1.7%	20.8%	2.3%
Torque, max. speed (-)	7.7%	2.4%	2.3%
<i>Computational efficiency</i>			
Model training time	5.9 min	1.90 h	1.40 h+0.24 h
Evaluation time (ms)	2.9	113	82
<i>Optimization using Trained Meta-Models</i>			
Candidate Performance Evaluation	2.0 s	79.1 s	57.4 s
Speedup vs. direct FEA	$\sim 4 \times 10^5 \times$	$\sim 10^4 \times$	$\sim 1.4 \times 10^4 \times$

point selection in Module 1 (0.56 h), bringing its total offline cost to 8,208 simulations (166.7 h), a marginal increase of 0.4% relative to the standard strategies, which is based on the results from Table IV and reflected in Table V. The reported times cover FEA simulations, model training, and forward-pass evaluation; operations common to all approaches (such as MTPA calculations, field-weakening strategies, and efficiency map computation) are excluded since their cost is strategy-independent and does not affect the relative comparison.

The results in Sections V-A and V-B consistently demonstrate the superiority of PI-AGPR over standard GPR and ANN, with MAPE values below 3% for the majority of outputs. While all three meta-modeling strategies share a comparable offline dataset cost, the per-candidate evaluation time of PI-AGPR (82 ms) is achieved without the accuracy degradation observed in GPR at base speed (20.8% torque MAPE) or in ANN at maximum speed (7.7% torque MAPE), both of which would make those models unreliable for full-speed-range drive-cycle optimization. Only PI-AGPR maintains consistent 2.3% torque MAPE across the operating range.

The computational implications for a full multi-objective drive-cycle optimization run are summarized in Table V, for a representative Differential Evolution (DE) algorithm with 70 generations and 10 individuals per generation [34]. It is worth emphasizing that the direct FEA baseline already reflects a highly optimized evaluation strategy, informed by prior studies on large-scale IPM optimization [16], [34], and the speedup figures reported therefore reflect a conservative estimate of PI-AGPR's advantage. On first use, all three meta-modeling strategies offer a modest speedup (1.35–1.37) because the one-time offline dataset cost dominates the total. Once trained, however, PI-AGPR is reusable across any drive cycle or objective without additional FEA simulations: for each subsequent optimization run, PI-AGPR evaluates all 700 candidate designs in 57 s, compared to 227 h for direct FEA, a speedup of approximately 14,000 times.

In practice, the offline cost is frequently not incurred as a single upfront investment. In research and industrial workflows involving repeated optimization of machines within the same topology, FEA simulation data of the kind used

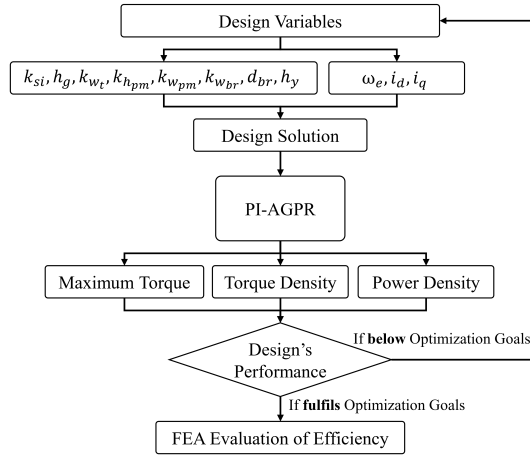


Fig. 13. Implementation of PI-AGPR in an optimization process.

here (gathered following well-established parameterization and sampling workflows [29]) accumulates organically across projects. When such data is already available, PI-AGPR can be trained at no or very reduced additional FEA cost, and every subsequent optimization run operates at the full per-candidate speedup immediately.

More broadly, PI-AGPR is designed to work alongside FEA rather than to replace it. The framework is intended for the computationally intensive screening phase of the design process, where large numbers of candidate designs must be evaluated rapidly and reliably across the full operating range. Candidates that satisfy the screening criteria are subsequently subjected to full FEA evaluation for detailed performance validation, including accurate core loss computation. In this context, the higher uncertainty in W_{core} prediction reported in Table V does not compromise the framework's utility: PI-AGPR's role is to identify promising regions of the design space efficiently, while FEA retains its role as the authoritative source of ground-truth performance data for shortlisted designs, as illustrated in Fig. 13.

VI. CONCLUSION

This study introduces Physics-Informed Adaptive Gaussian Process Regression (PI-AGPR), a novel meta-modeling framework that combines GP regression with governing physical equations to efficiently estimate IPM performance across arbitrary operating points and geometries within a fixed motor topology. The framework introduces two key innovations: a two-module architecture that distinguishes between control and geometric inputs, reducing the dimensional challenge inherent in conventional approaches; and an adapted Posterior Standard Deviation criterion for multi-output regression that leverages Pearson correlation coefficients to enable precise single-point adaptive sampling.

Using an experimentally validated FEA model and the same dataset size as competing methods, PI-AGPR demonstrates consistently superior predictive performance across all target outputs. MAPE values remain below 3% for flux linkages (1.7–2.0%) and torque-speed characteristics (2.3%), compared to errors as high as 84.8% and 20.8% for standard GPR,

and 33.8% and 7.7% for ANN, at base and maximum speed respectively. Once trained, PI-AGPR evaluates a full 700-candidate drive-cycle optimization campaign in under 60 s, representing a significant speedup relative to direct 2D transient FEA evaluation, while maintaining consistent accuracy across the full torque-speed range; a property that neither GPR nor ANN achieves simultaneously.

Accuracy in core loss prediction remains a limitation, primarily due to its nonlinear dependence on electrical speed, and could be enhanced through dedicated sampling strategies or hybrid approaches combining GPR with an analytical Bertotti-based prior. A systematic robustness study of the Module 1 operating point selection was conducted in four reference geometries spanning the electromagnetic extremes of the design domain confirming that torque MAPE below 1.1% and γ deviation below 1.3° regardless of the reference geometry chosen.

It stands that the PI-AGPR framework's ability to reliably predict torque-speed characteristics and flux linkages makes it particularly suitable for multi-objective optimization involving drive cycles, where it can evaluate candidate designs at arbitrary operating points without additional FEA simulations. Thus, the proposed framework provides a computationally efficient pathway for IPM design optimization while maintaining high fidelity to physics-based simulation results.

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APPENDIX

The FEA model described in Section II-B is validated against experimental data published by the extended research group for the reference IPM [16], [20], confirming its suitability as a ground-truth data source for training and testing PI-AGPR. Further details on the experimentally verified machine are presented in Table A1. The torque predicted by the FEA model is compared with experimental data in Fig. A1, for $i_q = I_{\text{ph}}$ and $i_d = 0$ A. The FEA model, incorporating the correction factor described in Section II-B, shows satisfactory agreement across the full current range.

Total losses are compared at 2,000 rpm in Fig. A2, with FEA results separated into copper, core, and PM eddy-current contributions. The complete loss comparison across 2,000–10,000 rpm is provided in Table A2. The FEA model achieves a mean absolute error of 4.2% across all 25 operating points, with a maximum deviation of 11.1% at 0.4 p.u. phase current and 4,000 rpm; the systematic underestimation at low-to-intermediate current levels is consistent with the omission of frequency-dependent copper losses in the 2D transient formulation [16]. PM eddy-current losses remain below 0.4% of total

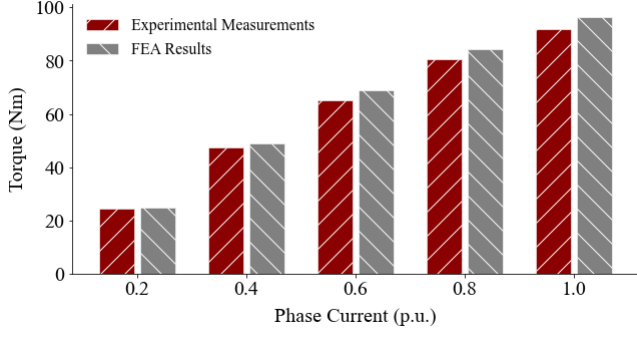


Fig. A1. Torque with $i_q = I_{ph}$ and $i_d = 0$ A for different current levels. Experimental measurements from [16].

TABLE A1
REFERENCE IPM MOTOR RATED PARAMETERS

Parameter	Value
Peak torque	110 Nm
Peak phase current	325 A_{rms}
DC bus voltage	650 V
Phase resistance (20°C)	3.3 mΩ
Base speed	3,500 rpm
Maximum speed	12,000 rpm
Stator outer diameter	80 mm
Rotor hub diameter	30 mm
Active stack length	74 mm
Stator slots / Rotor poles	18 / 16

losses at 2,000 rpm and below 8% at the most demanding condition, consistent with the effective radial segmentation of the PMs [16] and independently confirmed by the tolerance sensitivity analysis of this machine reported in [25], where PM eddy-current losses are not identified as a significant source of performance variability. They are therefore disregarded in PI-AGPR, as stated in Section III. The low overall deviation confirms that the FEA model provides a reliable representation of the reference motor's electromagnetic behavior.

REFERENCES

- [1] G. Bramerdorfer, J. A. Tapia, J. J. Pyrhönen, and A. Cavagnino, "Modern electrical machine design optimization: Techniques, trends, and best practices," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 10, pp. 7672 – 7684, 2018.
- [2] Y. Shimizu, "Efficiency optimization design that considers control of interior permanent magnet synchronous motors based on machine learning for automotive application," *IEEE Access*, vol. 11, pp. 41 – 49, 2023.
- [3] J. Jiang, T. Zou, M. D. Nardo, G. Gallicchio, S. L. Rocca, and A. L. Rocca, "Holistic design optimization of 350 kW high-speed permanent magnet-assisted synchronous reluctance machine for heavy-duty electric vehicle," *IEEE Transactions on Transportation Electrification*, vol. 11, no. 4, pp. 9234 – 9249, 2025.
- [4] B. Cheong, P. Giangrande, X. Zhang, M. Galea, P. Zanchetta, and P. Wheeler, "Evolutionary multiobjective optimization of a system-level motor drive design," *IEEE Transactions on Industry Applications*, vol. 56, no. 6, pp. 6904 – 6913, 2020.
- [5] D. Liu, H. Yang, R. Tu, X. Liu, X. Liu, and H. Lin, "Multi-stage optimization scheme for partitioned magnet pole variable-leakage-flux machine considering flux-adjustable range," *IEEE Transactions on Energy Conversion*, pp. 1 – 10, 2025.
- [6] M. Cheng, X. Zhao, M. Dhimish, W. Qiu, and S. Niu, "A review of data-driven surrogate models for design optimization of electric motors," *IEEE Transactions on Transportation Electrification*, pp. 1 – 1, 2024.

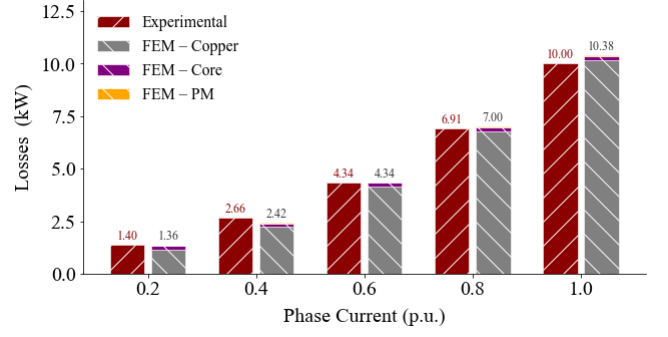


Fig. A2. Total losses at 2,000 rpm with $i_q = I_{ph}$ and $i_d = 0$ A, with FEA loss separation into copper, core, and PM eddy-current components. Experimental measurements from [16].

TABLE A2
EXPERIMENTAL AND FEA TOTAL LOSSES (kW) AND RELATIVE ERROR (%) FOR $i_q = I_{ph}$, $i_d = 0$ A ($I_{BASE} = 325 A_{RMS}$). EACH CELL: EXP. / FEA (kW); ERROR = $(W_{FEA} - W_{EXP})/W_{EXP}$.

Speed (rpm)	Phase Current I_{ph} (p.u.)				
	0.2	0.4	0.6	0.8	1.0
2,000	1.40 / 1.36 (−2.9%)	2.66 / 2.42 (−9.0%)	4.34 / 4.34 (±0.0%)	6.91 / 7.00 (+1.3%)	10.00 / 10.38 (+3.8%)
4,000	1.77 / 1.65 (−6.8%)	2.97 / 2.64 (−11.1%)	4.71 / 4.59 (−2.5%)	7.54 / 7.31 (−3.1%)	11.80 / 12.16 (+3.1%)
6,000	2.06 / 1.99 (−3.4%)	3.20 / 2.90 (−9.4%)	4.94 / 4.91 (−0.6%)	7.77 / 7.71 (−0.8%)	11.09 / 11.24 (+1.4%)
8,000	2.43 / 2.38 (−2.1%)	3.49 / 3.20 (−8.3%)	5.26 / 5.28 (+0.4%)	8.03 / 8.19 (+2.0%)	12.17 / 11.85 (−2.6%)
10,000	3.00 / 2.81 (−6.3%)	3.86 / 3.50 (−9.3%)	5.80 / 5.65 (−2.6%)	9.69 / 8.68 (−10.4%)	12.66 / 12.48 (−1.4%)

- [7] Z. Lai, W. Peng, G. Feng, and M. Pan, "Bayesian deep learning for fault diagnosis of induction motors with reduced data reliance and improved interpretability," *IEEE Transactions on Energy Conversion*, vol. 40, no. 3, pp. 2155 – 2168, 2025.
- [8] D. M. Ionel and M. Popescu, "Finite-element surrogate model for electric machines with revolving field—Application to IPM motors," *IEEE Trans. Ind. Appl.*, vol. 46, no. 6, pp. 2424–2433, Nov./Dec. 2010.
- [9] B. Praslicka, N. Taran, and C. Ma, "An ultra-fast method for analyzing ipm motors at multiple operating points using surrogate models," *IEEE Transportation Electrification Conference and Expo (ITEC)*, pp. 868 – 873, 2022.
- [10] B. Poudel and E. Amiri, "Deep learning based design methodology for electric machines: Data acquisition, training and optimization," *IEEE Access*, vol. 11, pp. 18 281 – 18 290, 2023.
- [11] R. Pascual, K. Mahtani, E. Rivero, and C. A. Platero, "Brushless synchronous machine field winding interturn fault severity estimation through deep neural networks," *IEEE Transactions on Energy Conversion*, vol. 39, no. 2, pp. 1341 – 1351, 2023.
- [12] P. Asef and C. Vagg, "A physics-informed bayesian optimization method for rapid development of electrical machines," *Scientific Reports*, vol. 4526, no. 14, 2024.
- [13] V. Bílek, J. Bárta, and L. Aarniovuori, "Multi-objective bayesian optimization of squirrel-cage induction machine," *International Conference on Electrical Machines (ICEM)*, 2024.
- [14] V. Parekh, D. Flore, and S. Schöps, "Deep learning-based meta-modeling for multi-objective technology optimization of electrical machines," *IEEE Access*, vol. 11, pp. 93 420 – 93 430, 2023.
- [15] Y. Yang, C. Zhang, G. Bramerdorfer, N. Bianchi, J. Qu, J. Zhao, and S. Zhang, "A computationally efficient surrogate model based robust optimization for permanent magnet synchronous machines," *IEEE Trans. Energy Convers.*, vol. 37, no. 3, pp. 1520–1532, 2022.
- [16] A. Fatemi, D. M. Ionel, M. Popescu, and N. A. O. Demerdash, "Design optimization of a high torque density spoke-type PM motor for a formula E race drive cycle," *IEEE Transactions on Industry Applications*, vol. 54, no. 5, pp. 4343–4354, 2018.
- [17] S. Stipetic, J. Goss, D. Zarko, and M. Popescu, "Calculation of efficiency

maps using a scalable saturated model of synchronous permanent magnet machines,” *IEEE Transactions on Industry Applications*, vol. 54, no. 5, pp. 4257 – 4267, 2018.

- [18] Y. Gong, A. Gneiting, S. Weigel, N. Parspour, and Z. An, “Surrogate model-based drive cycle modeling and optimization of synchronous reluctance machines for electric vehicles,” *IEEE Trans. Magn.*, vol. 61, no. 9, pp. 1–5, 2025.
- [19] M. D. Silva, O. A. Badewa, R. E. Alden, P. Asef, D. M. Ionel, and S. Eriksson, “A physics-informed gaussian process regression-based meta model for rapid characterization of permanent magnet synchronous machines,” *2025 IEEE International Electric Machines Drives Conference (IEMDC)*, pp. 1311–1316, 2025.
- [20] A. Fatemi, *Design Optimization of Permanent Magnet Machines Over a Target Operating Cycle Using Computationally Efficient Techniques*. (2016). Dissertations (1934-). 662.
- [21] Ansys® *Electronics Desktop, Maxwell, version 23.2, 2023, ANSYS Inc.*
- [22] J. Pyrhönen, T. Jokinen, and V. Hrabovcová, *Design of Rotating Electrical Machines*, 1st ed. John Wiley & Sons, 2013.
- [23] Tata Steel, *Hi-Lite High Performance-Ultra Light Electrical Steel: NO10-1270N Data Sheet*, Tata Steel, 2019, product datasheet.
- [24] A. Credo and P. Pescetto, “A systematic method for the calibration of FEA model of synchronous reluctance machines considering manufacturing effects,” *IEEE Open J. Ind. Appl.*, vol. 6, pp. 539–550, 2025.
- [25] N. Taran, V. Rallabandi, D. M. Ionel, P. Zhou, M. Thiele, and G. Heins, “A systematic study on the effects of dimensional and materials tolerances on permanent magnet synchronous machines based on the IEEE std 1812,” *IEEE Trans. Ind. Appl.*, vol. 55, no. 2, pp. 1360–1371, Mar./Apr. 2019.
- [26] C. E. Rasmussen and C. K. I. Williams, “Gaussian processes for machine learning,” vol. 18, no. 8, pp. 912 – 923, 2006.
- [27] C. M. Bishop, *Pattern Recognition and Machine Learning*, ser. Information Science and Statistics. New York, NY: Springer, 2006.
- [28] G. E. Karniadakis, I. G. Kevrekidis, L. Lu, P. Perdikaris, S. Wang, and L. Yang, “Physics-informed machine learning,” *Nature Reviews Physics*, vol. 3, no. 6, pp. 422–440, 2021.
- [29] M. Rosu, P. Zhou, D. Lin, D. M. Ionel, M. Popescu, F. Blaabjerg, V. Rallabandi, and D. Staton, *Multiphysics Simulation by Design for Electrical Machines, Power Electronics and Drives*. Hoboken, NJ: Wiley-IEEE Press, 2017.
- [30] E. V. Bonilla, K. M. A. Chai, and C. K. I. Williams, “Multi-task gaussian process prediction,” *Proceedings of the 20th International Conference on Neural Information Processing Systems*, pp. 153 – 160, 2007.
- [31] Z. Xing, Z. Zhang, J. Guo, Y. Qin, and L. Jia, “Rail train operation energy-saving optimization based on improved brute-force search,” *Applied Energy*, vol. 330, no. 120345, 2023.
- [32] D. M. Ionel, M. Popescu, S. Dellinger, T. J. E. Miller, R. J. Heideman, and M. I. McGilp, “On the variation with flux and frequency of the core loss coefficients in electrical machines,” *IEEE Transactions on Industry Applications*, vol. 42, no. 3, pp. 658 – 667, 2006.
- [33] S. V. Pathirannahalage, L. Mierczak, and B. Bilgin, “Pre-assembly core loss measurement of electric motor cores: A review of conventional and advanced technologies,” *IEEE Access*, vol. 13, pp. 59 130 – 59 145, 2025.
- [34] N. Taran, D. M. Ionel, and D. G. Dorrell, “Two-level surrogate-assisted differential evolution multi-objective optimization of electric machines using 3-D FEA,” *IEEE Transactions on Magnetics*, vol. 54, no. 11, pp. 1 – 5, 2018.



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