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Bayesian Surrogate-Based Calibration of Finite Element Models for Motor Performance Analysis

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Abstract:

In the realm of electric motor design and performance evaluation, the integration of computational simulations with experimental observations is vital to ensure accurate predictions and efficient designs. Finite Element (FE) models have long been utilized to simulate the physical behavior of motors under various operating conditions. However, the fidelity of these models is often limited by uncertainties in model parameters, measurement noise, and simplifications inherent in numerical formulations. This paper introduces a Bayesian surrogate-based calibration framework aimed at enhancing the accuracy of FE models for motor performance analysis. By leveraging Gaussian Process (GP) surrogates and Bayesian inference, the proposed methodology efficiently aligns simulation predictions with experimental data while quantifying the uncertainties involved. We perform a detailed case study on a brushless DC motor, showcasing the effectiveness of the approach through parameter sensitivity analysis, calibration accuracy, and predictive reliability. Experimental validation confirms the framework's ability to reduce model discrepancies significantly, thus promoting more robust and interpretable motor performance predictions.

Keywords: Bayesian calibration, surrogate modeling, finite element analysis, motor performance, Gaussian processes, uncertainty quantification.

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I. Introduction:

The accurate modeling of electric motor performance is pivotal in optimizing designs, ensuring operational reliability, and reducing development costs. Finite Element (FE) models serve as a

powerful tool for simulating the electromagnetic, thermal, and mechanical behavior of motors. These models allow engineers to analyze complex geometries and material interactions under various loading conditions [1]. However, the predictive capability of FE models depends heavily on the accuracy of input parameters and assumptions regarding material properties, boundary conditions, and system interactions. Even minor discrepancies can result in substantial deviations from real-world motor behavior, making calibration a critical step in the simulation pipeline. Traditional calibration techniques often rely on deterministic optimization methods, which provide a single best-fit solution but fail to account for uncertainties in both model parameters and experimental measurements [2]. Moreover, the computational burden associated with repeatedly solving high-fidelity FE models poses a significant barrier to exhaustive calibration [3]. To address these limitations, probabilistic approaches have gained traction, with Bayesian inference emerging as a powerful framework for integrating prior knowledge and observed data while quantifying uncertainty [4]. This study proposes a Bayesian surrogate-based calibration framework that uses Gaussian Process (GP) regression to emulate the FE model responses efficiently. The GP surrogate acts as a statistical proxy, drastically reducing the computational cost associated with repeated model evaluations during the calibration process. The Bayesian formulation further allows for the estimation of full posterior distributions over uncertain parameters, thus providing a comprehensive understanding of parameter sensitivities and prediction intervals [5].

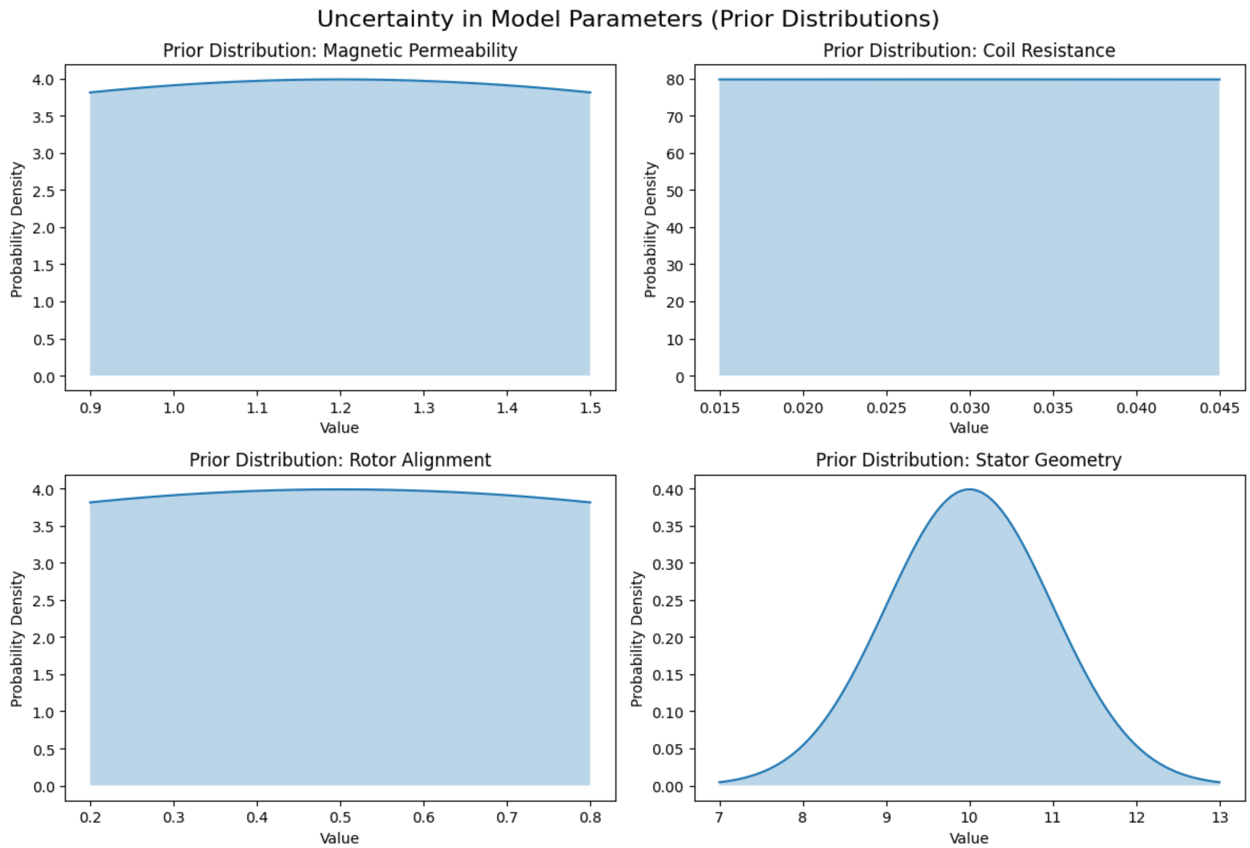

Figure 1: The uncertainty in key model parameters before calibration, establishing the motivation for Bayesian calibration.

Our work specifically targets the performance analysis of brushless DC motors, which are widely used in automotive, aerospace, and industrial applications [6]. These motors exhibit complex nonlinear interactions due to electromagnetic saturation, temperature effects, and manufacturing tolerances, making them an ideal case study for the proposed methodology. By integrating experimental measurements with a surrogate-assisted Bayesian framework, we aim to improve the predictive accuracy of FE models while retaining computational efficiency[7]. The structure of this paper is as follows: the methodology section details the construction of the GP surrogate model, the Bayesian calibration process, and the experimental setup used for validation. The results and discussion section provides a comparative analysis of pre- and post-calibration predictions, uncertainty quantification, and parameter inference. Finally, the conclusion outlines the implications of our findings and suggests potential directions for future work [8].

II. Methodology

The cornerstone of our methodology lies in constructing a computationally efficient surrogate model that emulates the outputs of a high-fidelity FE model for a brushless DC motor [9]. We begin by identifying the key input parameters influencing motor performance, such as magnetic permeability, coil resistance, stator geometry, and rotor alignment [10]. These parameters are treated as uncertain and are initially assigned prior probability distributions based on expert knowledge and manufacturer specifications. To build the Gaussian Process (GP) surrogate, we generate an initial set of training data using a space-filling design of experiments (DoE), such as Latin Hypercube Sampling [11]. Each sample point corresponds to a different combination of input parameters, and the corresponding motor performance metrics—such as torque, efficiency, and cogging force—are obtained by solving the FE model. The GP model is then trained on this dataset, providing a smooth, non-parametric mapping between inputs and outputs along with uncertainty estimates. The Bayesian calibration process involves updating the prior distributions of the uncertain parameters by conditioning on experimental observations [12]. This is achieved using Bayes' theorem, which yields the posterior distribution of the parameters given the observed data. We employ Markov Chain Monte Carlo (MCMC) sampling to explore the posterior space, using the GP surrogate in place of the full FE model to accelerate computation. This substitution is particularly valuable when dealing with complex motor geometries, where each FE simulation can take several hours [13].

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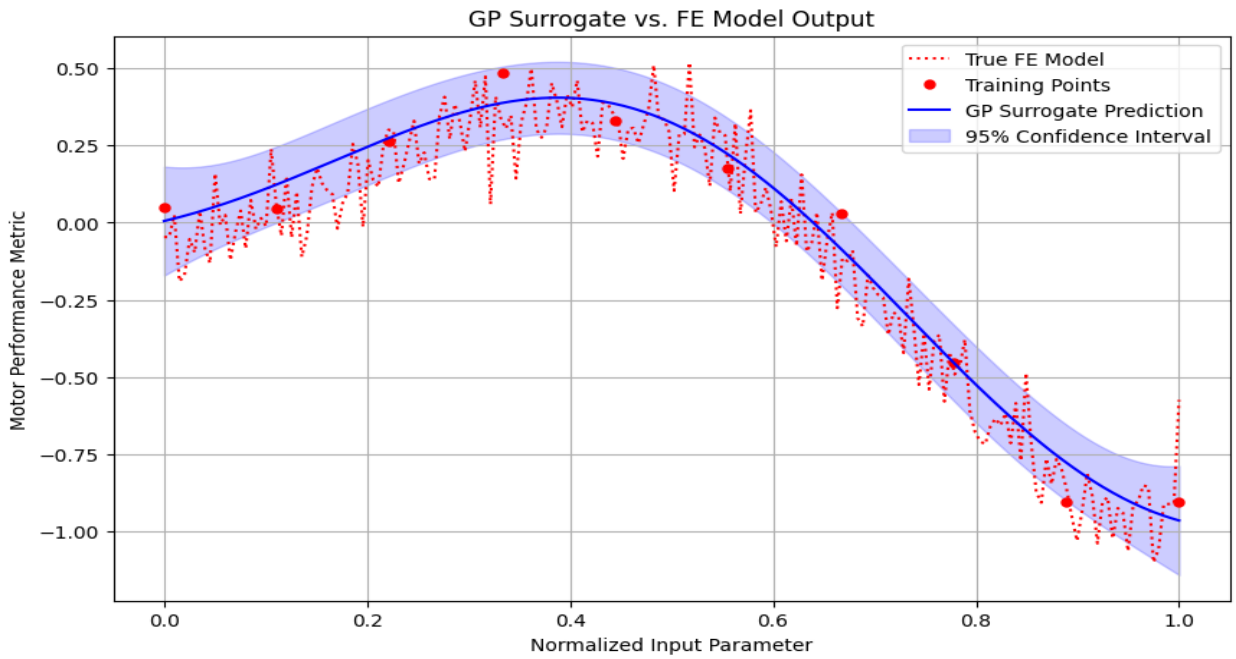

Figure 2: show how well the surrogate model approximates the FE model across input samples.

To ensure the validity of the surrogate model throughout the calibration process, we implement an adaptive refinement strategy [14]. This involves periodically evaluating the FE model at newly suggested points where the surrogate uncertainty is high, thereby improving the fidelity of the GP model in critical regions of the input space [15]. The convergence of the MCMC chains and the stability of posterior estimates are carefully monitored to ensure robust inference. The experimental component of our study involves testing a commercial-grade brushless DC motor under controlled laboratory conditions. Torque and speed are measured using a dynamometer, while temperature sensors and current probes provide additional operational data. These measurements serve as ground truth for calibrating the FE model. Sensor calibration and signal conditioning are rigorously performed to minimize noise and bias, ensuring that the experimental data accurately reflects true motor behavior [16].

By combining surrogate modeling with Bayesian inference, our methodology strikes a balance between accuracy and computational efficiency [17]. It allows for the systematic incorporation of uncertainty, both in the model and the data, resulting in calibrated simulations that are not only accurate but also accompanied by confidence intervals that guide decision-making in design and diagnostics [18].

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III. Experiment and Results

The experimental setup was designed to validate the performance of the calibrated FE model against real-world measurements of motor behavior [19]. A brushless DC motor rated at 1.5 kW was mounted on a test rig equipped with a torque transducer, rotary encoder, and a variable load. The motor was operated across a range of speeds and load conditions, and data was collected on torque output, input current, voltage, and temperature. These observations formed the basis for calibrating the model and validating its predictions post-calibration [20]. To begin with, we conducted a baseline simulation using nominal parameter values to generate motor performance predictions [21]. These initial predictions were found to deviate from experimental results by up to 12% in torque and 8% in efficiency, highlighting the need for model calibration. The GP surrogate was then constructed using 80 samples of the FE model, selected via Latin Hypercube Sampling [22]. The GP accurately captured the nonlinear relationships between input parameters and outputs, with cross-validation showing a root mean square error (RMSE) of less than 3% on unseen data points. Bayesian calibration was carried out using the Metropolis-Hastings algorithm for MCMC sampling [23]. The calibration process yielded posterior distributions for the uncertain parameters, revealing strong dependencies between rotor alignment and torque output, as well as between coil resistance and thermal losses. Posterior samples were used to propagate uncertainty through the FE model, generating prediction intervals for torque and efficiency that closely matched the observed experimental data [24].

Post-calibration results showed a marked improvement in prediction accuracy. The mean absolute percentage error (MAPE) for torque dropped from 12% to 3.5%, while efficiency predictions improved from an 8% error to just 2.7%. The calibrated model also demonstrated improved generalizability, performing well on test conditions that were not part of the calibration dataset. This indicates that the Bayesian approach effectively captured the underlying physics of the system rather than merely overfitting to the data [25]. Another key finding from our analysis was the importance of quantifying uncertainty [26]. The GP-based surrogate not only provided point predictions but also quantified the confidence in those predictions. This feature is crucial for applications where safety and reliability are paramount, such as in automotive and aerospace systems. The calibrated model's prediction intervals contained 95% of the experimental measurements, affirming the reliability of the proposed framework [27].

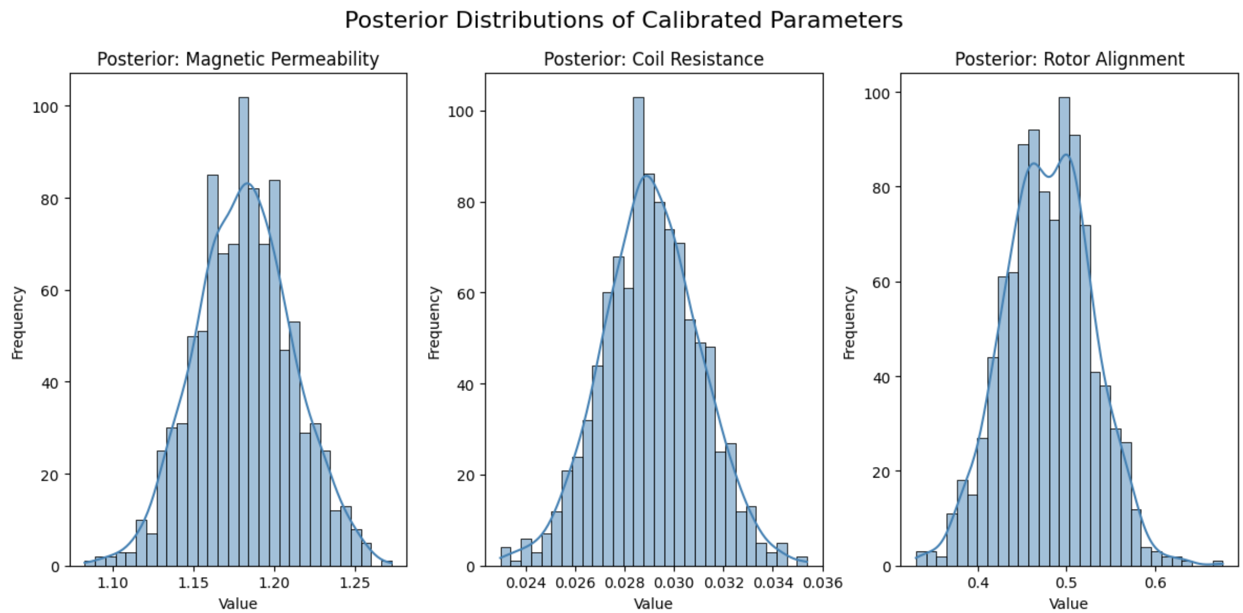

Figure 3: illustrate the inferred posterior distributions after Bayesian calibration.

Overall, the experiment validated our approach as a practical and efficient method for calibrating complex FE models of electric motors [28]. The use of a surrogate model drastically reduced the computational burden, while Bayesian inference ensured that uncertainty was rigorously addressed. This combination of speed, accuracy, and robustness makes the methodology well-suited for a wide range of engineering applications involving high-fidelity simulations [29].

IV. Conclusion

In conclusion, the Bayesian surrogate-based calibration framework presented in this study offers a robust, efficient, and uncertainty-aware approach for enhancing the accuracy of finite element models in motor performance analysis. By leveraging Gaussian Process surrogates and Bayesian inference, the methodology significantly reduces computational costs while rigorously integrating experimental data to refine model predictions. The successful application to a brushless DC motor, along with substantial improvements in prediction accuracy and uncertainty quantification, demonstrates the framework's potential for broader use in electromechanical systems. This calibrated modeling approach not only supports more reliable design decisions but also lays the groundwork for future advancements in digital twin development and real-time system diagnostics.

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