

Exploring Multi-Static Numerical Techniques for IPM Motors: AI-Powered Review

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ABSTRACT

The technical aspects of the multi-static computation of interior permanent magnet (IPM) motors, focusing on algorithms, simulation techniques, and computational efficiency, are studied in detail. The design optimization by reducing the computational time and memory is presented. The algorithmic advances, benchmark simulation methods, analyzing surrogate model integration are addressed in this review paper. The optimization strategies leveraging the multi-static computation are assessed by selecting research papers, based on relevance, using the SciSpace platform assisted by artificial intelligence (AI). Studies include the finite element, surrogate modeling, model order reduction, and hybrid analytical approaches, along with their comparative and critical analyses. The parallel-in-space-and-time algorithms combined with model order reduction significantly enhance scalability and simulation speed without compromising accuracy are studied. Surrogate modeling techniques are studied in detail, such as the Gaussian processes and neural networks for reducing the computational complexity and enabling the rapid multi-objective optimization, though they require extensive training data and careful validation. Multi-static computation methods are compared with traditional finite element approaches in computational efficiency, particularly when integrated with advanced optimization algorithms, in generalizability and handling the nonlinear transient phenomena. The paper

demonstrates the multi-static computation frameworks, augmented by surrogate models and optimization algorithms for a robust pathway for efficient and accurate IPM motor design.

Keywords: Artificial Intelligence, Chat GPT, Electrical Machines, IPM Motor, Numerical Analysis, Permanent Magnet Machines, Research Review, SCISPACE.

1. INTRODUCTION

Recently, the research on the technical aspects of a multi-static computation of interior permanent magnet (IPM) motors has emerged due to the increasing demand for efficient and accurate motor design methods in electric vehicle (EV) and industrial applications (Takahashi et al., 2022) and (Sizov et al., 2012). The advances in finite element analysis (FEA) and surrogate modeling have significantly evolved, enabling faster and more precise electromagnetic simulations (Ionel et al., 2009) and (Yamaguchi et al., 2019). However, the practicality of this research is underscored by the demand to optimize the motor performance parameters, such as, electromagnetic torque, efficiency, and thermal behavior while reducing computational costs, which directly impacts the development cycle and energy efficiency of electric machines (Güneş, 2023) and (Du et al., 2025). For example, the computational efficiency improvements of up to two times have been reported to support the comprehensive motor design space exploration (Sizov et al., 2012) and (Sizov, 2013).

The challenges of accurately modeling due to the nonlinear magnetic saturation, cross-coupling effects, and multi-operating point behaviors persist in the IPM motors (Praslicka et al., 2022) and (Cheng et al., 2024). There are trade-offs between computational speed and accuracy during the multi-static or multi-parametric electromagnetic field computations (Sancarlos et al., 2021) and (Liu et al., 2023). Knowledge gaps persist in integrating the parallel-in-time and space algorithms, surrogate modeling techniques, and reduced-order models (ROM) to achieve efficient simulations (Takahashi et al., 2022), (Cheng et al., 2024), and (Sancarlos et al., 2021). Moreover, issues persists about the optimal balance between analytical, numerical, and data-driven approaches, with some studies favoring hybrid methods combining finite element and surrogate models, while others emphasize purely data-driven machine learning frameworks (Kumar et al., 2020), (Guo et al., 2024), and (Shimizu et al., 2024). These gaps hinder the rapid and reliable design optimization of the IPM motors, thus delaying the innovation and increasing the manufacturing costs (Kiani et al., 2023).

There are three interrelated areas, the multi-static computation techniques, surrogate modeling approaches, and computational efficiency metrics (Henneron et al., 2022), (Ionel et al., 2009) and (Ebrahimi et al., 2016). The multi-static computation involves simultaneous or overlapping spatial and temporal discretization to accelerate the electromagnetic field solutions (Takahashi et al., 2022), whereas, the surrogate models approximate the high-fidelity simulations to reduce computational cost, such as, proper orthogonal decomposition (POD), radial basis functions (RBF), and machine learning regressions (Henneron et al., 2022) and (Chen et al., 2024). The computational efficiency is examined through simulation time, parallel scalability, and accuracy (Sizov et al., 2012) and (Yamaguchi et al., 2019). Therefore, understanding these three

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interrelated research areas is essential.

The presented systematic review critically analyzes the development of algorithms, simulation techniques, and computational efficiency strategies. The comparative analyses of the multi-static methods with other computational approaches address the existing knowledge gaps and provide future research directions. After the recent advancements and identifying limitations, the review paper contributes to optimizing motor design processes by enhancing the practicality of computational tools (Takahashi et al., 2022), (Ionel et al., 2009) and (Parekh et. al. 2023). Using the AI assisted SciSpace platform, the peer-reviewed studies are selected focusing on the multi-static computation, surrogate modeling, and computational efficiency. Therefore, the presented AI assisted review framework includes performance benchmarking, algorithmic innovation assessment, and comparative evaluation of the modeling techniques.

2. LITERATURE REVIEW

2.1 Technical landscape

The technical aspects of the multi-static computation of the IPM motors, focusing on algorithm developments, simulation techniques, and computational efficiency are provided in Table 1. The literature landscape about the multi-static computation techniques reveals a broad spectrum of approaches, such as FEA methods, surrogate modeling, model order reduction, and hybrid analytical techniques. The literature emphasizes the computational efficiency improvements and the accuracy validation through experiments or high-fidelity models. The detailed review addresses the algorithm effectiveness, efficiency gains, surrogate integration, and optimization strategies. Thus, a comprehensive overview of the current methodologies and their relative merits are summarized in Table 1.

TABLE 1: Literature review landscape.

S. No.	Research Paper	Algorithmic Complexity	Simulation Accuracy	Computational Efficiency	Surrogate Model Integration	Optimization Performance
1.	(Takahashi et al., 2022)	Combines parallel-in-space-time methods for scalability	High accuracy in magnet eddy-current loss analysis	Achieves good parallel performance with 10,000+ processes	Not integrated, focuses on parallel FEM	Not directly addressed
2.	(Henneron & Clénet, 2022)	Hierarchical multilevel surrogate reduces complexity	Surrogate closely matches nonlinear FE magnetostatic results	Surrogate model enables fast approximations	Strong integration of POD and RBF interpolation	Not directly addressed

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3.	(Praslicka et al., 2022)	Surrogate modeling reduces computational steps significantly	Maintains acceptable accuracy vs experimental data	Uses 75% less computational resources than prior methods	Surrogate models map d-q axis parameters and losses	Enables ultra-fast motor performance prediction
4.	(Roomi et al., 2022)	Waveform-targeted surrogate modeling reduces algorithmic burden	Surrogate model accuracy improved over conventional methods	Computational cost significantly reduced	Employs Kriging and Latin-Hypercube Sampling	Enhances surrogate-based design optimization
4.	(Lekić & Vukosavic, 2020)	Uses phase symmetry to reduce simulation steps	Validated against classical time-stepping FE results	Simulation time reduced, especially with more phases	No surrogate model used	Not directly addressed
5.	(Sizov et al., 2012)	Exploits machine symmetries for reduced FE computations	Performance indices satisfactorily estimated vs transient FE	Simulation time reduced by ~100x	No surrogate model, uses Fourier analysis	Enables parametric design optimization
6.	(Sizov, 2013)	Rapid computational FE method for large design spaces	Accurate nonlinear material and geometry modeling	Computational savings up to two orders of magnitude	No surrogate model, but efficient FE solver	Multi-objective optimization with DE algorithm
7.	(P et al., 2014)	CE-FEA with minimum magnetostatic solutions	Accurate multi-objective optimization results	High throughput computing environment	No surrogate model, uses DE algorithm	Multi-objective design optimization
8.	(Partovizadeh et al., 2024)	Reduced-order modeling via Fourier transform and regression	Surrogate models yield accurate torque predictions	Significantly reduces computational cost	Combines dimension reduction with machine learning	Facilitates uncertainty quantification
9.	(Cheng et al., 2024)	ROM combining POD and	ROM closely matches FEM outputs	Much higher computational efficiency	Strong surrogate integration	Enables fast parameter extraction

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		Kriging reduces complexity		than FEM	with POD and Kriging	
10.	(Sancarlos et al., 2021)	PGD-based fully separated representation reduces complexity	Excellent agreement with standard FE solutions	Virtual chart constructed in minutes	Model order reduction fully integrated	Real-time electromagnetic field evaluation
11.	(Ionel & Popescu, 2009)	Surrogate FE model uses minimal FE solutions	Validated against detailed FE and experiments	One to two orders of magnitude faster than time-stepping FE	Surrogate FE model tuned for speed and accuracy	Enables ultra-fast steady-state simulation
12.	(Mazloun et al., 2022)	Gaussian Process surrogate reduces algorithmic load	Surrogate predictions compared favorably with FE results	Reduces computation time for drive cycle calculations	Surrogate model integration strong	Not directly addressed
13.	(Liu et al., 2023)	Hybrid subdomain method reduces computational steps	High accuracy in magnetic field prediction	Prediction model offers extremely high speed	No surrogate model, hybrid analytical approach	Multiobjective optimization improves efficiency
14.	(Liu et al., 2023)	Improved analytical model reduces complexity	Accuracy verified by FE and prototype experiments	Saves time and storage compared to FE	Analytical model without surrogate	Enables fast electromagnetic performance prediction
15.	(Li et al., 2023)	General hybrid analytical model reduces complexity	Verified by FE and experiments with acceptable accuracy	Consumes less time than FE	No surrogate model, uses hybrid analytical	Facilitates design and optimization
16.	(Zhou et al., n.d.)	Hybrid analytical and numerical methods reduce	Validated by FE and experiments	Better computational efficiency than FE	No surrogate model, uses analytical and FDM	Coupled magnetic and temperature field

		complexity				prediction
17.	(Jabbari & Dubas, 2020)	Semi-analytical subdomain method reduces computational steps	Semi-analytical results confirmed by FE	Efficient for performance computation	No surrogate model	Not directly addressed
18.	(Kumar et al., 2020)	Hybrid method combining analytical and static FE reduces complexity	Accuracy comparable to transient FE	Computational time reduced by over 10x	Hybrid method, no surrogate model	Enables torque-speed characteristic optimization
19.	(Guo et al., 2019)	Hybrid FEM and conformal mapping reduces complexity	Good agreement with FEM and experiments	Remarkable computation time reduction	Hybrid model, no surrogate	Not directly addressed
20.	(Ma & El-Refaie, 2020)	FE-based multi-objective optimization with nonlinear models	Good accuracy with 6s per design on PC	Enhanced computational efficiency	No surrogate model	Multi-objective optimization with DE
21.	(Wu et al., 2023)	Layered response surface method reduces complexity	FE validation confirms accuracy	Reduces calculation time	Surrogate models combined with optimization	Multi-objective layered optimization
22.	(Ji et al., 2024)	Surrogate model with SVR reduces algorithmic complexity	SVR model accuracy ensured by Bayesian optimization	Surrogate enables fast torque calculation	Strong surrogate model integration	Multi-objective hierarchical optimization
23.	(Guo et al., 2024)	Machine learning surrogate reduces complexity	Surrogate validated against FEA	Computational time reduced vs FEA	Machine learning surrogate model	Optimization for EV motor performance

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24.	(Shimizu, 2023)	Deep learning model reduces algorithmic steps	Accurate iron loss prediction	Computation time reduced by 1/3000 vs FE	Deep learning surrogate model	Efficiency optimization with automatic design
25.	(Hanić et al., 2021)	Neural network metamodel reduces complexity	Good prediction performance	Increased computational efficiency	Neural network surrogate model	Not directly addressed
26.	("Multi-Objective Optimization of Electric...", 2023)	Hybrid data-physics model reduces complexity	Maintains Pareto quality close to FE	Computationally cheap compared to FE	Hybrid surrogate model integrated	Multi-objective optimization
27.	(Kiani & Tahanian, 2023)	Heuristic optimization with parallel processing	Accuracy maintained with FE solver	Parallel processing improves speed	No surrogate model	Automated design optimization
28.	(Park et al., 2023)	Hybrid ABC-SVM algorithm reduces complexity	Verified against conventional algorithms	Faster convergence	Surrogate model via SVM	Optimal design for EV IPMSM
29.	(Li et al., 2024)	Multi-layer surrogate model reduces complexity	Surrogate model validated with FEM	Calculation time reduced by 54.9%	Multi-layer surrogate model	Multi-objective optimization for torque and noise
30.	(Yu et al., 2023)	Combined surrogate and optimization algorithm reduces complexity	FE analysis confirms improved performance	Optimization reduces design time	Combined surrogate models	Multi-objective optimization
31.	(Chen & Doppelbauer, 2024)	Transfer learning modular NN reduces complexity	Accurate prediction capabilities	Fast optimization (~12s)	Transfer learning surrogate model	Multi-objective optimization
32.	(Xia et al.,	Adaptive	Validated	Minimizes	Kriging	Multi-

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	2018)	dynamic Taylor Kriging reduces complexity	through analytic and motor design examples	required sampling data	surrogate model	objective shape optimization
33.	(Amini et al., 2025)	Surrogate-based anisotropic Kriging reduces complexity	FEM verification confirms accuracy	Optimization reduces computational cost	Surrogate model with anisotropic Kriging	Robust combinatorial optimization
34.	(Sarikhani et al., 2010)	Physics-based model with genetic-particle swarm reduces complexity	Performance improvements validated	Fast convergence rate	No surrogate model	Multi-objective optimization
35.	(Liu et al., 2024)	Analytical and surrogate models combined reduce complexity	Validated by simulations and experiments	Minimizes reliance on FE	Surrogate and analytical model combined	Multi-objective optimization
36.	(Du et al., 2025)	Fused surrogate model reduces complexity	Validated by FE simulations	Significant computational savings	Surrogate model integrating RSM and thermal	Multi-objective collaborative optimization
37.	(Zhang & Zhou, 2024)	Surrogate model-based Bayesian updating reduces complexity	High precision calibration	Reduces simulation number	Surrogate model with Bayesian updating	FEM model calibration
38.	(Ge et al., 2023)	Improved equivalent magnetic network reduces complexity	Verified by FE and experiments	Improved computational efficiency	No surrogate model	Dynamic simulation of transient effects
39.	(You, 2020)	Automated	Verified by	Faster than	Metamodel-	Multi-

		design procedure reduces complexity	experiments	conventional methods	based design optimization	objective optimization
40.	(Shimizu & Akatsu, 2024)	Deep learning surrogate reduces complexity	Efficient handling of variable inputs	Faster than FE analysis	Deep learning surrogate model	Design optimization with multiple iterations
41.	(Ebrahimi et al., 2016)	POD-based MOR reduces complexity	High accuracy in nonlinear magnetic analysis	Order-of-magnitude speed gain	Model order reduction with POD	Not directly addressed
42.	(Güneş, 2023)	Machine learning surrogate reduces complexity	Accuracy comparable to FE	Multi-objective optimization in hours	Surrogate model with control inputs	Efficiency maximization design
43.	(Shimizu, 2023)	Deep learning surrogate reduces complexity	Accurate iron loss prediction	Computation time reduced by 1/3000 vs FE	Deep learning surrogate model	Efficiency optimization
44.	(Kang et al., 2021)	Sub-domain algorithm with dynamic sampling reduces complexity	Validated by test functions and motor design	Improved convergence speed	No surrogate model	Multimodal optimization
45.	(Talukder et al., 2022)	Ensemble learning reduces complexity	Improved accuracy over deep CNNs	Faster training than deep CNNs	Ensemble learning surrogate model	Not directly addressed
46.	(Yamaguchi et al., 2019)	Hybrid MPI/OpenMP parallel FEM reduces complexity	Validated by cogging torque analysis	8.7x speedup over non-parallelized	No surrogate model	Parallel FEM performance evaluation

2.2 Analysis and synthesis of the reviewed papers

Recently, the multi-static computation techniques witnesses the significant advancements in the algorithm development, surrogate modeling, and computational efficiency for the IPM motors. The innovative approaches to reducing the

computational space and time, while maintaining or improving the accuracy are presented, such as, the hybrid methods and MOR. There are challenges among balancing model complexity, generalizability, and computational speed. Table 2 presents the trade-offs between multi-static computation and other methods, with some limitations in scalability and applicability to diverse the IPM motor topologies.

TABLE 2: Strengths and weaknesses

S. No.	Aspect	Strengths	Weaknesses
1.	Algorithm development for multi-static computation	The parallel space-and-time FEA methods with time step overlapping demonstrate speedy transient solution convergence and scalability, for an efficient magnetic field analysis for practical IPM motors (Takahashi et al., 2022). MOR techniques with surrogate models such as Kriging method show high accuracy and computational efficiency across wide operating points (Cheng et al., 2024). These algorithmic innovations enable rapid parameter extraction and simulation for early-stage motor design.	However, some algorithms rely heavily on specific assumptions or require extensive computations to build surrogate models, which limit the adaptability to new motor configurations (Cheng et al., 2024). The complexity of coupling the spatial and temporal parallelization introduces the overhead and convergence challenges, in hybrid parallel FEM implementations (Yamaguchi et al., 2019). Furthermore, the generalizability to highly nonlinear or transient phenomena remains underexplored.
2.	Simulation Techniques and Surrogate Modeling	Hierarchical multilevel surrogate models combining POD and radial basis function interpolation provide controlled error bounds and reduced FE solution requirements, enhancing simulation speed without sacrificing accuracy (Henneron & Clénet, 2022). Surrogate modeling approaches, including Gaussian processes and neural networks, have been successfully applied to predict motor performance and losses rapidly, enabling ultra-fast multi-point analysis and drive cycle simulations (Praslicka et al., 2022), (Mazloun et al., 2022) and (Hanić et al., 2021). Hybrid data-physics- driven models further maintain Pareto front quality in multi-objective optimization while	Surrogate models often require large, high-quality training datasets, and their accuracy can degrade outside the sampled parameter space, limiting robustness (Talukder et al., 2022). Some studies report challenges in balancing surrogate model accuracy with computational cost, especially in sensitive input-output relationships (Roomi et al., 2022). The integration of surrogate models with physical constraints and nonlinearities is not always straightforward, thus, affecting the prediction fidelity in complex operating conditions (Mazloun et al., 2022).

		reducing computational cost (Parekh et. al. 2023)	
3.	Computational Efficiency	Computationally efficient FEA methods exploiting the machine symmetries and waveform reconstruction have achieved simulation time reductions by up to two orders of magnitude, facilitating extensive parametric studies and optimization (Sizov et al., 2012) and (Lekić & Vukosavic, 2020). Similarly, the parallel computing frameworks have demonstrated near-linear speedups in magnetic field computations (Yamaguchi et al., 2019). Whereas, the surrogate-based optimization strategies, including waveform-targeted surrogate modeling and transfer learning-enhanced neural networks, significantly reduce the design cycle times while preserving accuracy (Roomi et al., 2022) and (Chen & Doppelbauer, 2024).	Efficiency gains sometimes are at the cost of model generality or require careful tuning of surrogate or reduced-order models, which may not be trivial for the complex motor geometries (Roomi et al., 2022). The surrogate model training and validation challenges the runtime space, if not managed properly (Zhang & Zhou, 2024). Moreover, some computational efficiency improvements are demonstrated only on the specific motor topologies or operating conditions, thus, raising the concerns about broader applicability (Sizov et al., 2012).
4.	Comparative Analysis with Other Computational Methods	Multi-static computation techniques with parallel-in-time and parallel-in-space methods, outperform the traditional finite element approaches in scalability and speed for steady-state and transient analyses (Takahashi et al., 2022). Whereas, hybrid methods that integrate analytical models with static FEA reduce computational burden while maintaining accuracy comparable to a transient FEA (Kumar et al., 2020). Analytical and subdomain methods offer rapid predictions with acceptable accuracy, providing alternatives for early design stages (Li et al., 2023).	Analytical and hybrid methods often simplify complex rotor geometries or magnetic saturation effects, which limit the accuracy in detailed performance prediction (Liu et al., 2023) and (Li et al., 2023). Multi-static methods often require a substantial computational resources for large-scale parallelization, which might not be accessible in all design environments (Takahashi et al., 2022). Thus, the trade-offs between speed and accuracy are not always quantitatively assessed across diverse motor designs, complicating method selection.
5.	Role of Model Order Reduction	Model order reduction techniques effectively reduce dimensionality and enable near-real-time evaluation of	The reduced-order models are sometimes computationally intensive and require careful selection of

	and Surrogate Integration	electromagnetic fields and torque under varying design parameters (Cheng et al., 2024), (Partovizadeh et al., 2024) and (Sancarlos et al., 2021). Thus, these techniques provide a robust design optimization, and facilitate the rapid parameter extraction and uncertainty quantification.	basic functions or frequency components to maintain the accuracy (Ebrahimi et al., 2016) and (Partovizadeh et al., 2024). The applicability of these models to a highly nonlinear or a transient phenomena is limited, and their extension to a multi-physics remains a challenge (Ebrahimi et al., 2016). Additionally, surrogate integration sometimes lacks systematic error quantification, which can affect confidence in predictions.
6.	Optimization Strategies Leveraging Multi-Static Computation	Multi-objective optimization frameworks combining surrogate models with evolutionary algorithms (e.g., NSGA-II, differential evolution) have demonstrated effective improvements in torque, efficiency, and torque ripple for IPM motors (Ma & El-Refaie, 2020), (Wu et al., 2023) and (Ji et al., 2024). Hierarchical and layered surrogate modeling approaches enable sensitivity-based parameter classification, reducing computational load during optimization (Li et al., 2024) and (Yu et al., 2023). Machine learning-based surrogate models integrated with optimization algorithms accelerate design cycles and improve solution quality (Guo et al., 2024) and (Park et al., 2023).	Optimization methods often depend on the quality and representativeness of surrogate models, which may limit exploration of the full design space (Ji et al., 2024). Some approaches require extensive offline data generation and may not fully capture transient or nonlinear effects critical for certain performance metrics (Ma & El-Refaie, 2020). The robustness under varying operating conditions and manufacturing tolerances is not addressed.
7.	Validation and Practical Applicability	Many studies validate their respective computational methods either by the experimental data or detailed FEA, confirming accuracy and practical relevance (Ionel & Popescu, 2009), (Guo et al., 2019) and (Liu et al., 2024). The surrogate models and reduced-order techniques in a real-world motor design demonstrates	Methods are tested on limited motor topologies or operating points, which does not represent a full complexity encountered (Ionel et al., 2009) and (Guo et al., 2019). Thus, scalability of the surrogate and reduced order models remains a concern, especially for the new designs and materials (Chen &

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		their potential for an industrial adoption (Kiani & Tahanian, 2023) and (Güneş, 2023). Additionally, the design systems employing the deep learning reduce the times while maintaining the performance (Shimizu, 2023) and (Shimizu et al., 2024).	Doppelbauer, 2024). Additionally, these techniques require usability and reliability, especially considering the existing industrial workflows
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2.3 Thematic literature review

The literature on the multi-static computation of the IPM motors reveals several recurring themes focusing on the advanced algorithm development, surrogate modeling, and optimization strategies for improving simulation efficiency and design accuracy. Table 3 provides details for the deployment of parallel FEA methods, hierarchical and hybrid surrogate models, and machine learning approaches to accelerate computations while maintaining the precision. The thematic approach focuses on the multi-static computation techniques related to traditional FEA and analytical models. It highlights the trade-offs between computational cost and accuracy. Recent trends illustrate the integration of MOR, deep learning, and multi-objective optimization to enhance the IPM motor design processes.

TABLE 3: Thematic overview.

S. No.	Theme	Theme Description
1.	Surrogate Modeling and Machine Learning for Computational Efficiency	Surrogate modeling techniques such as proper POD, RBF, Gaussian processes, support vector regression (SVR), and neural networks are widely applied to reduce the computational costs in IPM motor design. These models enable rapid approximation of FEA solutions across multiple operating points with a minimal accuracy loss to facilitate multi-objective optimization under constraints (Henneron et al., 2022), (Praslicka et al., 2022), (Roomi et al., 2022), (Cheng et al., 2024), (Mazloun et al., 2022), (Guo et al., 2024), (Hanić et al., 2021), (Du et al., 2025), (Zhang et al., 2024), and (Shimizu et al., 2024). Integration of deep learning further enhances the prediction speed, and enable automatic design systems (Shimizu, 2023) and (Talukder et al., 2022).
2.	Computationally Efficient Finite Element Analysis and Parallelization	Advances in FEA methods focus on improving the computational efficiency through parallel-in-space-and-time approaches, domain decomposition, and hybrid parallel computing. These methods drastically reduce simulation times for magnetic field and loss analyses without compromising the accuracy, enable large-scale design space exploration and optimization of the IPM motors (Takahashi et al., 2022), (Lekić et al., 2020), (Sizov et al., 2012), (Sizov, 2013), (Ionel et

		al., 2009), and (Yamaguchi et al., 2019). Time step overlapping and multi-threading accelerates the convergence and performance (Takahashi et al., 2022).
3.	Multi-Objective Optimization Leveraging Surrogate and Reduced-Order Models	Multi-objective optimization employ surrogate or reduced-order models combined with algorithms such as NSGA-II, differential evolution, and genetic algorithms (GA). The sensitivity analysis and response surface methods (RSM) guide parameter selection to improve the design robustness and convergence speed (Ma et al., 2020), (Wu et al., 2023), (Ji et al., 2024), (Kiani et al., 2023), (Li et al., 2024), (Yu et al., 2023), (Amini et al., 2025), (Sarikhani et al., 2010), (Liu et al., 2024), (Du et al., 2025), (You, 2020), and (Güneş, 2023). While Bayesian learning strategies enhance the surrogate model's adaptability and predictive capability (Chen et al., 2024), (Zhang et al., 2024).
4.	Hybrid and Analytical Modeling Methods for Fast and Accurate Performance Prediction	To balance the accuracy and the computational cost, the hybrid approaches integrate analytical subdomain methods with FEA or magnetic equivalent circuit (MEC) models. These models account complex IPM rotor structures, saturation effects, and nonlinearities. Thus, the fast prediction of the electromagnetic performance such as back-EMF, electromagnetic torque, and cogging torque is enabled. Hybrid models are quick relative to a full FEA while maintaining acceptable accuracy for IPM design and optimization (Liu et al., 2023), (Li et al., 2023), (Jabbari et al., 2020), (Kumar et al., 2020), (Guo et al., 2019), and (Ge et al., 2023).
5.	Model Order Reduction Techniques and Proper Orthogonal Decomposition	MOR and POD techniques reduce the dimensionality of magnetic field data and parameter spaces, for a rapid evaluation in nonlinear and dynamic analyses. MOR combined with surrogate modeling enables efficient parameter extraction and real-time simulations for IPM motor design and optimization (Cheng et al., 2024), (Sancarlos et al., 2021) and (Ebrahimi et al., 2016).
6.	Surrogate Model Integration in Drive Cycle and Transient Analysis	Surrogate models including the Gaussian process regressions accelerate the drive cycle simulations and transient analyses. These approaches maintain accuracy while drastically reducing the computational time, for the IPM motor design under realistic operating conditions (Mazloun et al., 2022), (Ge et al., 2023), and (Güneş, 2023).
7.	Deep Learning and AI-Based Automatic Design Systems	Recent developments focus on deep learning models, including generative adversarial networks and vision transformers, to predict the iron losses and efficiency in IPM motor designs. These models enable ultra-fast automatic optimization with computation times reduced by orders to traditional FEA, supporting iterative design processes with a high fidelity (Shimizu, 2023) and (Shimizu et al., 2024).
8.	Multi-Static Computation	The multi-static computation techniques are compared with traditional FEA and analytical methods, demonstrating better parallel scalability

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	Versus Traditional Methods	and efficiency of multi-static approaches while highlighting limitations in their standalone capabilities. Hybrid methods combining the multi-static and classical techniques show promising results to overcome these limitations for a practical IPM motor design (Takahashi et al., 2022), (Guo et al., 2019), and (Ge et al., 2023).
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2.4 Agreement and divergence across studies

The reviewed literature largely agrees on the importance and effectiveness of surrogate modeling and MOR techniques to enhance the computational efficiency in the IPM motor design, while maintaining acceptable accuracy. Thus, the multi-static computation methods and hybrid approach significantly reduce the computational time compared to traditional FEA methods. However, divergence exists regarding the degree of accuracy retention and scalability of these methods, especially in complex motor topologies or transient analyses. Differences in algorithmic approaches, problem scope (steady state vs. transient), and integration of optimization strategies contribute to these variations.

TABLE 4: Comparative analysis and scope of the research.

S. No.	Comparison Criterion	Studies in Agreement	Studies in Divergence	Potential Explanations
1.	Algorithmic Complexity	Many studies agree that combining parallel-in-space- and-time FEM or subdomain methods with surrogate modeling reduces complexity significantly (Takahashi et al., 2022), (Sancarlos et al., 2021), and (Liu et al., 2023). Hierarchical and multi-level surrogate models are effective in managing high-dimensional parameter spaces (Henneron et al., 2022) and (Xia et al., 2018).	Some papers emphasize the complexity of applying these methods to highly nonlinear or multi-physics problems, noting challenges in extending them to transient or multiphase simulations (Lekić et al., 2020) and (Ebrahimi et al., 2016).	Variations arise due to focus on steady-state vs. transient simulations, model linearity assumptions, and problem dimensionality.
2.	Simulation Accuracy	Surrogate and reduced-order models generally maintain good accuracy relative to full FEM, validated by experiments and high-fidelity simulations (Praslicka et al., 2022), (Cheng et al., 2024), (Ionel et al., 2009) and (Liu et al.,	Discrepancies exist where analytical or hybrid models may lose accuracy for complex rotor structures or saturation effects	Differences stem from model assumptions (linear vs nonlinear), treatment of

		2024). Improvements in error control and iterative refinement are commonly reported (Henneron et al., 2022) and (Zhang et al., 2024).	(Liu et al., 2023), (Li et al., 2023) and (Guo et al., 2019). Some deep learning models face accuracy challenges without large datasets (Talukder et al., 2022).	saturation, and availability of training data or experimental validation.
3.	Computational Efficiency	Broad consensus that multi-static computations, surrogate models, and hybrid methods drastically reduce computational time (often by 50-75% or more) compared to full FEM (Takahashi et al., 2022), (Praslicka et al., 2022), (Roomi et al., 2022), (Sizov et al., 2012) and (Shimizu, 2023). GPU/parallel implementations further enhance speed (Yamaguchi et al., 2019).	Contrasting views on efficiency gains when applied to multi-physics or transient problems, where surrogate construction or model order reduction overhead may reduce net gains (Ebrahimi et al., 2016) and (Zhou et al., n.d.).	Efficiency depends on problem scope, with steady-state analyses benefiting most; transient and coupled field analyses pose higher challenges.
4.	Surrogate Model Integration	Majority highlight integration of surrogate models (Kriging, RBF, POD, Gaussian processes) as pivotal in enabling fast multi-point and multi-objective optimization (Henneron et al., 2022), (Roomi et al., 2022), (Cheng et al., 2024), (Mazloun et al., 2022) and (Chen et al., 2024). Transfer learning and machine learning models also support adaptability (Hanić et al., 2021), (Chen et al., 2024).	Some divergence in surrogate model choice and training strategies; e.g., interpolation-based vs. machine learning; sampling strategies influence performance (Xia et al., 2018) and (Talukder et al., 2022).	Differences arise from surrogate model methodology, sampling design, and intended optimization use cases.
5.	Optimization Performance	Most studies confirm that multi-static computation frameworks combined with surrogate models enable efficient multi-objective optimization, improving torque, efficiency, and reducing torque ripple (Ma et al., 2020), (Wu et al., 2023), (Li et al., 2024), (Amini et al., 2025) and (Güneş, 2023). Bayesian updating and	Some papers note limitations in optimization accuracy due to surrogate fidelity or computational resource constraints in large design spaces (Parekh et al., 2023) and (Kiani et	Variations depend on optimization algorithm robustness, surrogate model accuracy, and computational resources available for

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	evolutionary algorithms show robust results (Ji et al., 2024), (Zhang et al., 2024).	al., 2023).	training and evaluation.
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3. THEORETICAL AND PRACTICAL IMPLICATIONS

3.1 Theoretical implications

The synthesis of the presented research highlights the significant advancements in algorithm development for multi-static computation of the IPM motors, particularly through the integration of parallel-in-space-and-time FEA methods and MOR techniques, such as POD and surrogate modeling. The theoretical understanding is enhanced due to the computational efficiency enhancements without sacrificing accuracy in electromagnetic field simulations (Takahashi et al., 2022), (Cheng et al., 2024) and (Sancarlos et al., 2021). The multi-static and hybrid approaches challenge the conventional time-stepping FEA by offering accelerated convergence with more scalable and efficient simulation framework (Takahashi et al., 2022), (Lekić et al., 2020) and (Sizov et al., 2012).

The surrogate models, including Gaussian processes, Kriging, and machine learning-based metamodels, extends theoretical frameworks. Thus, the rapid approximation of complex nonlinear motor behaviors across multiple operating points are enabled. The data-driven and reduced-order models effectively capture key characteristics while reducing the computational burden (Henneron et al., 2022), (Praslicka et al., 2022), (Partovizadeh et al., 2024) and (Chen et al., 2024). The development of hybrid analytical and numerical models enriches the modeling fidelity of IPM motors having complex rotor topologies and saturation effects. Thus, a comprehensive theoretical basis is provided for understanding the electromagnetic phenomena in the IPM motors (Liu et al., 2023) and (Li et al., 2023).

The multi-static computation and surrogate modeling demonstrate the theoretical feasibility of multi-objective and hierarchical optimization specially for high-dimensional design spaces. Thus, both have an important role of advanced computational techniques in navigating complex trade-offs inherent in the IPM motor design (Wu et al., 2023), (Ji et al., 2024) and (Li et al., 2024). The integration of machine learning and deep learning techniques introduce a new theoretical perspective. Thus automatic and speedy IPM motor design processes are suggested with computational convergence with AI methodologies (Shimizu, 2023), (Shimizu et al., 2024) and (Güneş, 2023).

3.2 Practical Implications

The improvements in computational efficiency through parallel-in-space-and-time FEA and hybrid parallel FEA methods enable practical deployment of a large-scale simulations on the high-performance computing platforms, significantly reducing the design cycle times for the IPM motors in industrial settings (Takahashi et al., 2022), (Yamaguchi et al., 2019). Surrogate modeling techniques, hierarchical multilevel approaches and machine learning-based metamodels, provide rapid performance prediction and optimization for early design decisions and reduce the reliance on FEA

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(Henneron et al., 2022), (Praslicka et al., 2022) and (Mazloun et al., 2022).

The multi-objective optimization algorithms combined with surrogate models and reduced-order models offer practical pathways to achieve the improvements in electromagnetic torque, efficiency, and noise reduction, which are critical for the IPM motor applications and other industrial uses (Wu et al., 2023), (Li et al., 2024) and (Amini et al., 2025). The hybrid analytical models with FEA present practical advantages by maintaining accuracy while reducing the computational time, to enable frequent and comprehensive design iterations in engineering workflows (Liu et al., 2023), (Kumar et al., 2020) and (Guo et al., 2019).

The machine learning-driven automatic design systems and transfer learning-based surrogate models are practical for the industry by enabling the scalable and adaptable IPM motor design processes to accommodate varying design parameters and operating conditions with a minimal human intervention (Shimizu, 2023), (Chen et al., 2024) and (Shimizu et al., 2024). The surrogate model-based Bayesian updating frameworks for FEA model offers practical benefits in enhancing the IPM motor model reliability by reducing the number of required simulations, time and memory (Zhang et al., 2024).

3.3 Research gaps and limitations for future research directions

The limitations in the reviewed literature are provided in Table 5. Research areas are highlighted with their limitations. These limitations provide insight into the lapses in the current research papers and suggest to continue investigation in the particular research gap with suitable direction, as provided in Table 6.

TABLE 5: Limitation in the reviewed literature.

S. No.	Area of Limitation	Description of Limitation	Papers with limitation
1.	Limited Experimental Validation	Several studies rely on simulation and surrogate models with a limited experimental validation. This affects the practical applicability of the findings, hence limits confidence in real-world performance predictions.	(Praslicka et al., 2022), (Ionel et al., 2009), (Liu et al., 2023), (Guo et al., 2019) and (Liu et al., 2024)
2.	High Computational Cost	Despite recent improvements, many FEA and multi-static computation methods are computationally intensive, restricting their use in large-scale or real-time applications. Therefore, the scalability and rapid design iteration is affected.	(Takahashi et al., 2022), (Lekić et al., 2020), (Sizov et al., 2012), (Ma et al., 2020), (Kiani et al., 2023) and (Yamaguchi et al., 2019)
3.	Surrogate Model Accuracy and Generalizability	Surrogate models face challenges in balancing the accuracy and computational efficiency, especially during the diverse motor topologies or operating conditions. This affects the reliability and generalizability of the surrogate-	(Henneron & Clénet, 2022), (Roomi et al., 2022), (Mazloun et al., 2022), (Chen & Doppelbauer,

	lity	based predictions.	2024) and (Güneş, 2023)
4.	Insufficient Integration of Multi-Physics Effects	Many researchers focus on the electromagnetic aspects, with limited incorporation of thermal, mechanical, or dynamic transient effects, reducing the comprehensiveness of the IPM motor performance analysis and optimization. This gap limits holistic design insights.	(Zhou et al., n.d.), (Ge et al., 2023) and (Güneş, 2023)
5.	Limited Comparative Analyses	Few papers provide a direct comparative evaluations between multi-static and alternative computational methods, therefore, it is difficult to understand the relative advantages and limitations. This approach does not support the ability to benchmark and select optimal approaches.	(Takahashi et al., 2022), (Kumar et al., 2020) and (Guo et al., 2019)
6.	Narrow Focus on Specific Motor Topologies	Few studies deals with a particular IPM motor designs or configurations, which limit the external validity and applicability to broader motor types or novel designs. This focus restricts generalization across the motor design.	(Liu et al., 2023), (Li et al., 2023), (Ji et al., 2024) and (Guo et al., 2024)
7.	Data and Model Complexity Constraints	High-dimensional parameter spaces and complex nonlinearities pose challenges for MOR and surrogate modeling, sometimes lead to oversimplifications that reduce the model fidelity and predictive power. Therefore, the optimization accuracy is impacted.	(Cheng et al., 2024), (Sancarlos et al., 2021) and (Ebrahimi et al., 2016)
8.	Limited Real-Time Application	Some methods improve the computational speed; however, few studies demonstrate the real-time or near-real-time applicability of the multi-static computation techniques. Therefore, their practical use in adaptive control or rapid prototyping environments is limited.	(Praslicka et al., 2022), (Partovizadeh et al., 2024), (Shimizu, 2023) and (Shimizu et al., 2024)

TABLE 7: Research gap in the reviewed literature.

S. No.	Gap Area	Description	Future Research Directions	Justification	Priority
1.	Scalability and Generalizability of Multi-Static	Current multi- static computation algorithms often rely on specific assumptions and	Develop adaptive multi-static algorithms with reduced offline training requirements and enhanced	Existing methods show high efficiency but limited generalizability,	High

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	Algorithms	extensive offline computations, limiting adaptability to diverse motor topologies and nonlinear transient phenomena.	capability to handle nonlinearities and transient effects across varied IPM motor designs. Investigate hybrid approaches combining data-driven and physics-based models for broader applicability.	restricting practical deployment in diverse motor configurations and operating conditions (Takahashi et al., 2022), (Cheng et al., 2024) and (Ebrahimi et al., 2016).	
2.	Surrogate Model Robustness Outside Training Domains	Surrogate models frequently degrade in accuracy when extrapolating beyond their training data, especially in sensitive input-output relationships and complex nonlinearities.	Research on the adaptive surrogate modeling techniques with the uncertainty quantification and active learning. Integrate the physical constraints to improve the model robustness and reliability in real work scenarios.	Surrogate model's dependence on training data quality limits their predictive reliability. Therefore, the optimization and design decisions are impacted (Roomi et al., 2022) (Mazloun et al., 2022) (Talukder et al., 2022).	High
3.	Integration of Surrogate Models with Multi-Physics Simulations	Most surrogate models focus on electromagnetic aspects, with limited integration of thermal, mechanical, and transient phenomena in IPM motor simulations.	Develop multi-physics surrogate modeling frameworks that couple electromagnetic, thermal, and mechanical fields, enabling comprehensive and efficient motor performance prediction under realistic operating conditions.	Multi-physics effects critically influence the IPM motor performance and reliability, however these are underrepresented in current surrogate modeling approaches (Zhou et al., n.d.) (Du et al., 2025) and (Ge et al., 2023).	High
4.	Quantitative Trade-Off	Comparative studies often lack systematic	Conduct benchmark research with	Clear quantification is	Medium

	Analysis Between Accuracy and Efficiency	quantification of trade-offs between computational speed and simulation accuracy across different multi-static and hybrid methods.	standardized metrics to evaluate the accuracy and efficiency trade-offs for the multi-static, surrogate, and hybrid analytical methods across diverse IPM motor designs and operating points.	required for the method selection and balancing design cycle time with prediction fidelity (Takahashi et al., 2022) (Sizov et al., 2012) and (Kumar et al., 2020).	
5.	Surrogate Model Training Cost and Data Efficiency	High computational cost and data requirements for surrogate model training can offset runtime savings, especially for high-dimensional parameter spaces.	Investigate data efficient training strategies, such as transfer learning, modular neural networks, and adaptive sampling to reduce the training cost while maintaining the accuracy. Explore the meta-learning approaches for the rapid surrogate adaptation to the new IPM motor designs.	Training overhead remains a bottleneck to limit the surrogate model scalability and practical use in iterative design processes (Chen et al., 2024), (Zhang et al., 2024) and (Talukder et al., 2022).	High
6.	Extension of Model Order Reduction to Transient and Nonlinear Regimes	Current model order reduction (MOR) techniques excel in steady-state or linearized problems but struggle with highly nonlinear and transient IPM motor behaviors.	Develop MOR methods incorporating nonlinear model reduction and time-dependent basis functions to accurately capture transient dynamics and saturation effects in IPM motor simulations.	MOR limitations restrict the real-time and multi-objective optimization under realistic transient operating conditions (Partovizadeh et al., 2024), (Ebrahimi et al., 2016) and (Sancarlos et al., 2021).	Medium
7.	Optimization Robustness Under Manufacturing Variability	Optimization frameworks often neglect the impact of manufacturing tolerances and	Integrate uncertainty quantification and robust optimization techniques within surrogate-based multi-	Addressing the variability is critical for an industrial adoption and ensuring the	High

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		material variability on motor performance and surrogate model predictions.	static computation frameworks to ensure design reliability under real-world variability.	optimized designs performance as expected in production (Cheng et al., 2024), (Ji et al., 2024) and (Liu et al., 2024).	
8.	Seamless Integration into Industrial Design Workflows	Many advanced computational methods lack user-friendly interfaces and automation for integration into existing industrial motor design and validation pipelines.	Develop standardized software tools and automated workflows that incorporate multi-static computation, surrogate modeling, and optimization, facilitating adoption by motor designers and engineers.	Bridging the gap between research prototypes and industrial practice is necessary for widespread impact (Kiani et al., 2023), (You, 2020) and (Shimizu et al., 2024).	Medium
9.	Comparative Evaluation of Multi-Static vs Hybrid Analytical Methods	Limited comprehensive comparative analyses exist evaluating multi-static computation against hybrid analytical and semi-analytical methods in terms of scalability, accuracy, and computational cost.	Perform systematic comparative studies across multiple motor topologies and operating conditions to delineate the strengths and limitations of multi-static and hybrid analytical approaches.	Such evaluations recommend the method selection by highlighting the opportunities for the method hybridization (Liu et al., 2023), (Li et al., 2023) and (Kumar et al., 2020).	Medium
10.	Surrogate Model Integration with Real-Time Control and Monitoring	Few studies address the use of surrogate models derived from multi-static computations for real-time motor control, monitoring, or fault diagnosis.	Explore surrogate model deployment in embedded systems for real-time parameter estimation, control optimization, and predictive maintenance of IPM motors.	Real-time applications demand fast as well as accurate models during the changing conditions, to extend the utility of computational advances (Cheng et al., 2024), (Güneş, 2023) and (Zhang et al., 2024).	Medium

4. CONCLUSION

The presented research review presents the marked progress in the multi-static computation techniques for the IPM motors, specifically in algorithm development, simulation methodologies, and computational efficiency enhancements. Recent advancements and innovations in parallel-in-space-and-time FEA methods and MOR have increased the transient and steady-state electromagnetic simulations of the IPM motor. Thus, the algorithmic advances have facilitated the scalable, high-fidelity analysis across huge design spaces for a rapid model evaluation. Additionally, the surrogate modeling integrated with the reduced-order techniques balance the accuracy and efficiency by approximating the complex as well as nonlinear behaviors, therefore, demand for the full FEA is reduced.

Combined simulation frameworks of hierarchical surrogate models including Gaussian processes, neural networks, and advanced interpolation schemes demonstrate robust accuracy, and are validated against experiments as well as high-fidelity models. These models provide details about salient physical phenomena, such as magnetic saturation, eddy current losses, and IPM rotor topology effects with reduced computational time and space. The challenges persist in maintaining surrogate reliability outside the trained parameter domains, therefore, a careful dataset generation and error control strategies are needed. The surrogate model along with hybrid analytical and FEA methods provide fast and reliable, suitable for the early IPM motor design.

The simulation time through parallel processing, waveform-targeted surrogate modeling, and machine learning approaches is significantly reduced. Thus, the extensive multi-objective optimization that simultaneously refine the electromagnetic torque, efficiency, torque ripple, mechanical and thermal characteristics are improved. The surrogate models including the Bayesian updating, and evolutionary algorithms exhibit an enhanced convergence speed and quality. However, the dependency on the surrogate training data and complexity in representing nonlinear transient effects are a challenge on the optimization robustness.

The multi-static computation methods are better than the traditional FEA approaches in scalability and speed; however, their applicability is limited due to model assumptions. Analytical and subdomain techniques provide a conceptual design, however, there are tradeoffs in model's detail and accuracy. Thus, the integration of MOR and surrogate modeling mitigates these trade-offs, however systematic error quantification and Multiphysics domains are yet to be explored.

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