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Review

System-Level Optimization in Switched Reluctance Machine Design—Current Trends, Methodologies, and Future Directions

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Abstract: Switched Reluctance Machines (SRMs) are gaining increasing traction within the industrial sector, primarily due to their inherently simple and robust structure. Nevertheless, SRMs are characterized by two major drawbacks—high torque ripple and strong radial forces—both of which render them less suitable for applications requiring smooth operation, such as Electric Vehicles (EVs). To address these limitations, researchers and designers focus on optimizing these critical performance metrics during the design phase. In recent years, the concept of System-Level Design Optimization (SLDOM) has been introduced and applied to SRM drive systems, where both the machine and the controller are simultaneously considered within the optimization framework. This integrated approach has shown significant improvements in mitigating the aforementioned issues. This paper aims to review the existing literature concerning the SLDOM applied to SRMs, highlighting the key methodologies and findings from studies conducted in recent years. Despite its promising outcomes, the adoption of SLDOM remains limited due to its high computational cost and complexity. In response to these challenges, the paper discusses complementary techniques used to enhance the optimization process, such as search space and computational time reduction strategies, along with the associated challenges and potential solutions. Finally, two critical directions for future research are identified, which are expected to influence the development of the SLDOM and its application to SRMs in the coming years.

Keywords: system-level design optimization; switched reluctance machine; multi-level optimization; surrogate models; artificial neural networks; machine learning

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1. Introduction

Electrical machines play crucial roles in industrial applications, and the demand for them is continuously increasing. The largest share of machines in the industry is occupied by Permanent Magnet Synchronous Machines (PMSMs) due to their high power density, which is thanks to permanent magnets, and Induction Machines (IMs) because of their simplicity in construction and operation, as well as their minimal maintenance requirements. However, the scarcity of rare earth metals that are used in permanent magnets in PMSMs and the low power factor of IMs, combined with the significant losses in the rotor, have led the research community in recent years to explore new machine topologies to gain a stronger foothold in industry [1,2].

Switched Reluctance Machines (SRMs) neither incorporate magnets, as found in PMSMs, nor feature windings or bars on the rotor, like IMs. These distinctive characteristics, coupled with their intrinsic fault tolerance, owing to their polyphase structure, high efficiency, and low core losses, render SRMs with a robust and reliable machine topology.

Figure 1 illustrates the various topologies of SRMs. While a detailed discussion of SRMs falls outside of the scope of this paper, interested readers may consult the following textbooks for further information: [3–5]. These attributes make them particularly well-suited for operation in demanding environments, such as those encountered in mining and drilling applications, where extreme temperatures and pressures are present [6,7]. However, due to their high saliency in both the stator and rotor, SRMs exhibit significant torque ripple and generate parasitic acoustic noise because of vibrational forces. These drawbacks render SRMs less suitable for high-speed applications, such as aerospace systems [7], water pumps [8], and superchargers [9], as well as electrical propulsion systems, like Electric Vehicles (EVs) and Hybrid EVs (HEVs), where smooth operation and noise reduction are critical [1,10].

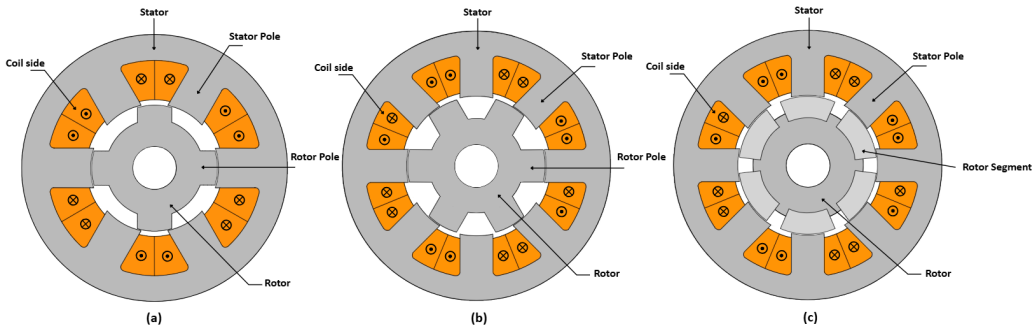


Figure 1. Cross-sectional view of various topologies of SRMs: (**a**) 6/4 and (**b**) 8/6 configurations; (**c**) 8/6 segmented rotor.

Optimization of the design process is the most widely employed strategy by researchers to mitigate torque ripple, acoustic noise, and the overall cost of the SRM structure. Through this approach, the desired objectives can be reduced, leading to an optimized machine that meets the specific requirements of its intended application [11,12]. The design optimization process is generally divided into the following two main categories: design and optimization. In the first category, the objective is to model the machine's structure and operation, define the parameters and goals of the optimization process, and identify feasible candidates that represent the near-optimal performance of the machine. In the second category, optimization algorithms are applied to identify and evaluate the most suitable candidate from the aforementioned set. This is done by searching for a near-optimal solution using single-objective optimization [13,14] or a set of near-optimal solutions, known as the Pareto front, in cases of multi-objective optimization [15,16], within a predefined search space.

However, certain applications, such as EVs and HEVs, necessitate a well-integrated drive system that includes the machine, controller, and power electronics, such as inverters, to function effectively [1]. Optimizing the machine alone does not inherently ensure optimal system performance, as its operation is ultimately governed by the controller. Certain performance metrics of the controller are critical for the smooth operation of the system and should be optimized through appropriate controller algorithms. These include the settling time, which determines how quickly the machine reaches and maintains the desired speed, and the overshoot, which quantifies the maximum deviation from the target value before the system stabilizes. For instance, in Ref. [17], which employed a fuzzy-logic-based PID controller for motor control, the untuned model yields a settling time of 34.5 s, whereas the tuned version achieves a significantly reduced settling time of 10 s, with a trade-off of only 5% in overshoot. This 25-s improvement is crucial for enabling the system to stabilize more rapidly during transient conditions, highlighting the importance of controller optimization. Conversely, a suboptimal controller design may exacerbate torque

ripple or limit the power delivered to the machine [18]. Therefore, optimization at the component level may not ensure the overall performance of the drive system, as the system is strongly interdependent. In these cases, a system-level optimization approach is required to simultaneously optimize the entire drive system to achieve the desired performance and efficiency.

This paper presents the current state of the System-Level Design Optimization Method (SLDOM) for SRM drives, highlighting existing challenges and identifying potential solutions for its implementation. Although the study was conducted with a focus on switched reluctance machines, most of the existing literature concentrates on motor applications, with only a limited number of studies addressing generator configurations. Section 2 maps out the SLDOM, dividing it into the following two categories: single-level and multi-level. Section 3 discusses design space reduction, primarily through the use of surrogate models and parameter criticality assessment, while presenting research conducted on these topics with a focus on SRM drives. Section 4 proposes a method for control enhancement and acceleration of optimization through SLDOM. Finally, Section 5 discusses future research directions based on the SLDOM and Section 6 concludes this paper.

2. System-Level Design Optimization

Unlike conventional design and optimization practices that treat components in isolation, SLDOM treats the system as a whole—the controller, power electronics, and machine—into one single optimization framework. This integrated approach accounts for interdependencies, feedback loops, and cross-coupling interactions that are typically neglected under traditional methodologies. Hence, SLDOM results in an improved and more precise optimization path, especially in large systems such as SRM drives. This method permits engineers to analyze performance metrics not only at the component level but in conjunction with system-level interactions. For instance, design decisions related to the motor can influence control strategies, thermal behavior, and system efficiency overall. System-level optimization is, therefore, required to obtain balanced trade-offs among competing objectives, like cost, performance, and reliability.

2.1. Methodology and Framework

When implementing system-level optimization methods, a consensus has emerged around five key steps, which ensure that the full potential of the approach is realized [19–21]. These seem to offer a well-rounded and systematic procedure that addresses the complexities inherent in optimizing drive systems. The multi-step methodology appears to provide a comprehensive framework for balancing various competing factors between machine and controller, such as efficiency and cost, within the design process. The steps are laid out with a clarity that offers a solid foundation for both further research and practical applications in the field.

Step 1: Definition of the system's overall requirements and design objectives. The system requirements are determined, such as efficiency, torque ripple, average torque, weight, and cost. Constraints are defined, like maximum current, minimum efficiency, and search limits of each parameter for the optimization algorithm, primarily based on the application in which the implementation is carried out.

Step 2: Definition of the drive system characteristics, including both the machine and the controller. In this step, the machine's topology and specifications are selected, alongside the controller, which includes power electronics such as the inverter and control algorithms, to ensure proper functionality. The selection process between the machine and controller can be a complex task, as these two components are highly interdependent and coupled, often requiring expertise and experience.

Step 3: Design of the drive system. Machine design involves modeling and material property selection, as well as multiphysics analyses such as electromagnetic, thermal, and mechanical considerations. The controller design encompasses the selection of the control algorithm, inverter topology, and power electronics.

Step 4: Selection of the optimization algorithms for the entire system. Each level (machine, controller) may employ its own single-objective or multi-objective optimization algorithm, tailored to the specific requirements of that layer.

For the machine level, the optimization procedure is as follows:

$$\begin{aligned} min: \quad & f_m(\boldsymbol{x_m}) \\ subject\ to: \quad & g_{mi}(\boldsymbol{x_m}) \leq 0, \quad i = 1, \ldots, N_m, \\ & \boldsymbol{x_l} \leq \boldsymbol{x_m} \leq \boldsymbol{x_u} \end{aligned} \tag{1}$$

where f_m and g_m represent the machine objective and constraint functions, respectively; $\boldsymbol{x_m}$ denotes the machine design parameters, with $\boldsymbol{x_l}$ and $\boldsymbol{x_u}$ being the lower and upper boundaries of the search space, respectively; and N_m is the number of machine constraint parameters.

Subsequently, for the control level, the optimization procedure is as follows:

$$\begin{aligned} min: \quad & f_c(\boldsymbol{x_c}) \\ subject\ to: \quad & g_{ci}(\boldsymbol{x_c}) \leq 0, \quad i = 1, \ldots, N_c, \\ & \boldsymbol{x_l} \leq \boldsymbol{x_c} \leq \boldsymbol{x_u} \end{aligned} \tag{2}$$

where f_c and g_c represent the control objective and constraint functions, respectively; $\boldsymbol{x_c}$ is the control design parameter, with $\boldsymbol{x_l}$ and $\boldsymbol{x_u}$ as the lower and upper boundaries of the search space respectively; and N_c is the number of control constraints parameters.

To construct the final system-level optimization problem, Equations (1) and (2) should be combined as follows:

$$\begin{aligned} min: \quad & f_{sys}(\boldsymbol{x_{sys}}) = F(f_m, f_c) \\ subject\ to: \quad & g_{mi}(\boldsymbol{x_{sys}}) \leq 0, \quad i = 1, \ldots, N_m, \\ & g_{ci}(\boldsymbol{x_{sys}}) \leq 0, \quad i = 1, \ldots, N_c, \\ & \boldsymbol{x_l} \leq \boldsymbol{x_{sys}} = [\boldsymbol{x_m}, \boldsymbol{x_c}] \leq \boldsymbol{x_u} \end{aligned} \tag{3}$$

where f_{sys} and $\boldsymbol{x_{sys}}$ represent the overall system objective and design parameters, respectively, with f_{sys} being a function of f_m, f_c, and the design parameters. $[\boldsymbol{x_m}, \boldsymbol{x_c}]$ now correspond to the machine and control design parameters, with $\boldsymbol{x_l}$ as the lower and $\boldsymbol{x_u}$ as the upper boundaries of the search space. N_{sys} denotes the number of system constraint parameters.

Step 5: Evaluation of the overall system performance, which includes an assessment of both the steady-state and dynamic performances as follows:

1. In the steady state, the evaluation focuses on the machine's performance, including the efficiency, weight, average torque, and cost.
2. In the dynamic state, the evaluation examines the performance of the controller and the overall drive system, considering factors, such as speed overshoot, settling time, torque ripple, and system cost.

The course of the methodology and the steps developed previously are also presented schematically in Figure 2. Each colored section corresponds to a step in the methodology, which provides more detailed information for each step, with the first one being the "drive system design" block.

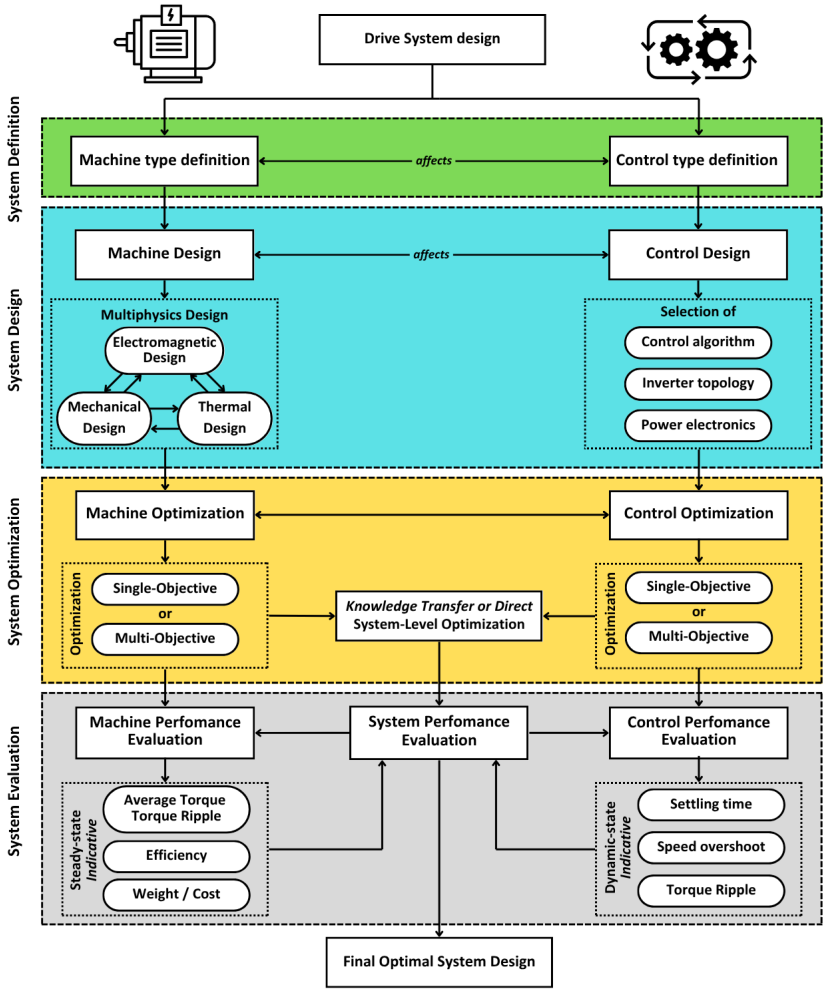


Figure 2. System-level design optimization framework.

In summary, the optimization problem is structured into the following three main branches: the machine level, control level, and the system level. At each level, the system-level optimization methodology conducts an optimization process aimed at maximizing the overall system performance. The first two levels, referred to as the component level, focus on refining their respective elements. While individual components may not be optimized independently, the methodology ensures the near-optimal performance of the overall system.

2.2. System-Level Optimization Methods

There are two approaches regarding system-level optimization based on the procedure of optimization and evaluation. These are the Single-Level Optimization Method (SLOM), which treats the system as a unified entity, and the Multi-Level Optimization Method (MLOM), which optimizes each component sequentially and evaluates the system holistically [19,22]. Both methods aim to optimize the entire system, with the latter being computationally less expensive due to the division of the optimization process into the following two separate parts: machine and controller. Nevertheless, both methods have been utilized in relevant studies, with the former approach being preferred due to its simplicity in implementation.

2.2.1. Single-Level Optimization Method

The logic behind the single-level optimization method is that both the machine and the controller are optimized simultaneously, and the results are evaluated at the same time. The SLOM framework steps are as follows [23]:

Steps 1–3: Identical to the general framework described above;

Step 4: Selection of the optimization method. In this step, an optimization method is chosen that will simultaneously optimize both the machine and the controller;

Step 5: Implementation of the optimization method and evaluation. The final step involves implementing the optimization algorithm for the selected drive system parameters and evaluating the performance of the drive system. This step is repeated until the optimization goals are met.

The aforementioned steps are also illustrated in Figure 3, which outlines the general structure of the methodology. It should be noted that, in the last two steps, the optimization and evaluation of both the machine and the controller are carried out simultaneously. The selection of the optimal design is thus performed holistically for the entire system, rather than independently for each component. The main distinction of this general framework lies in the optimization and evaluation stage, where these processes are executed at the system-level, as explicitly shown in Steps 3 and 4.

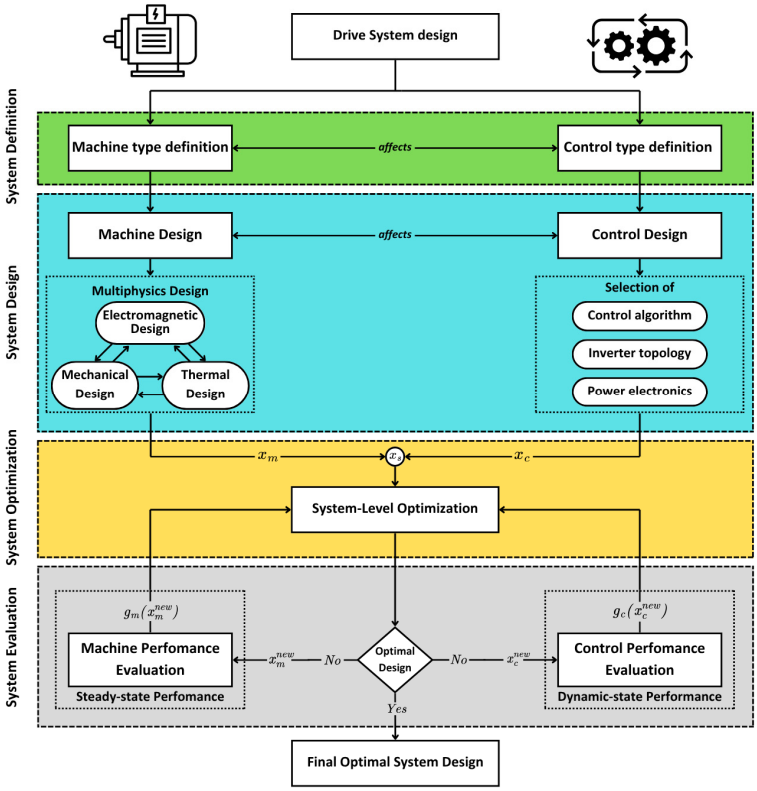


Figure 3. Single-level optimization framework.

The primary drawback of this optimization method is the significant computational burden placed on the computer due to the complexity of the problem and the simultaneous optimization of both the machine and controller. This challenge is particularly evident when numerical methods, such as the Finite Element Method (FEM), are employed. Below, relevant studies based on this method are presented. Their analysis reveals that the choice of this approach was primarily driven by its simplicity rather than the reduction in computational time.

The authors of [24] proposed a method that integrates Mamdani fuzzy inference system for drive system modeling with the Non-Dominated Sorting Genetic Algorithm III (NSGA-III) for application in the switched reluctance generator. This new approach, called Fuzzy Inference NSGA-III, performs the simultaneous optimization of both the machine and the controller through the adjustment of geometric parameters of the generator and turn-on angle, θ_{on}, and the conduction angle, θ_c, of the controller. The NSGA-III was chosen due to its superior ability to handle many-objective optimization problems, and because it naturally facilitates the integration of the designer's fuzzy preferences into the optimization process. It uses a reference-point-based non-dominated sorting approach that not only maintains a well-distributed, diverse Pareto front but also inherently supports the processing of many objectives. By extracting the results, a comparison is made between the outcomes of the proposed method and those of NSGA-II. The results of the former show greater improvement but not significantly. However, the study does not specify the software used for analysis and simulation, which could provide valuable insight into the implementation process. Moreover, the algorithm does not yield a global optimum value but rather a range of values within which the near-optimal value lies. Additionally, the authors could have included wider parameter ranges for the optimization process in order not to limit the algorithm's ability to identify the true near-optimal value.

In [25], the authors investigate the design of an SRM drive system for application in vertical transportation using JMAG software for system modeling. They perform optimization using the Genetic Algorithm (GA) on the motor, selecting one of four possible motor models, and on the controller, optimizing both the geometric characteristics of the motor and the turn-on, θ_{on}, and turn-off, θ_{off}, angles of the controller. The choice of GA is well-suited to the multi-objective nature of the problem, and it has the ability to handle the non-linearities inherent in the system more effectively than traditional gradient-based methods. Their objective is to optimize the RMS current, torque ripple, and torque output. Finally, they evaluate the system's performance under both steady-state and dynamic conditions using MATLAB/Simulink. However, the study does not provide details on the optimization process of the motor's geometry, focusing solely on the control optimization.

Reference [26] proposes a modeling and optimization framework for an SRM drive system, which utilizes FEA-based method through ANSYS simulation software for steady-state operation and analytical equations to describe the system's dynamic behavior. Optimization is performed using the Particle Swarm Optimization (PSO) algorithm to determine the near-optimal current values that minimize torque ripple and voltage peaks and extract the corresponding current profile. PSO was selected over other algorithms such as GA and Differential Evolution (DE) due to its ability to efficiently explore the solution space while maintaining low computational cost, making it well-suited for this application. The current profiling construction and methodology allow for the dynamic state of the motor to be estimated solely through its static analysis. This approach significantly reduces the time required for holistic optimization. However, there is a slight trade-off in accuracy, as not all transient state phenomena are considered during the dynamic analysis. To account for real-world effects, the authors base the optimization on experimentally validated material data, recognizing deviations such as increased iron loss due to manufacturing. The results show very low torque ripple and an almost square current waveform.

Reference [27] focuses on the design of an SRM for aerospace applications by utilizing a field-circuit-coupled FEM and incorporating a loss density function as a constraint for thermal properties. The multi-objective problem is transformed into a single-objective one through the loss density function applied to efficiency. The FEM is employed for the motor, while a field-circuit analysis is used for the inverter, which utilizes the Asymmetric Half-Bridge Converter (AHBC). In the controller, the switching angles θ_{on} and θ_{off} are considered

parameters, and the design parameters are optimized simultaneously with the help of the GA. The results, presented through static analysis, demonstrate improvements, including a slight increase in efficiency and reductions in torque ripple, mass, and loss density.

In [28], the authors discuss the design of an SRM for an in-wheel application in EVs by conducting a static analysis using the FEM through MotorSolve and MATLAB. The NSGA-II algorithm is employed as an optimizer to enhance the average torque, torque ripple, and motor efficiency by modifying both motor and controller variables. The results indicate that the initial design objectives were successfully met, ensuring that the motor fulfills the required operational criteria set by the designer, with a slight improvement over the initially defined targets.

In the aforementioned studies [24–28], the authors do not present the computational time required to complete the simulation, and given that the data are extracted using the FEM, the computational time is expected to be substantial. A comprehensive search across the entire design space as defined by the designer based on the selected parameters can be prohibitive when using the FEM for every iteration. One potential solution would be to incorporate a complementary space reduction technique or to impose narrower parameter limits. However, this approach carries the risk that an acceptable solution may not exist within the predefined constraints.

2.2.2. Multi-Level Optimization Method

The multi-level optimization method differs from the single-level approach by dividing the process into the following distinct stages: machine level, control level, and system level. Optimization and evaluation are performed independently until the final level, where the entire drive system is evaluated. This staged approach helps distribute the computational workload, preventing excessive strain on the computer at each step [20,29].

The following steps outline the process of implementing the MLOM:

Step 1: Definition of the machine- and control-level models and objectives. At each level, specific objectives are defined—for example, efficiency, average torque, torque ripple, mass, and cost for the machine and the settling time, overshoot, and cost for the controller. Additionally, constraints such as the maximum current, minimum efficiency, and search space are specified, along with the optimization algorithms to be employed.

Step 2: Optimization of each level independently. In this step, the machine and control levels are optimized separately from one another. First, the optimization process is applied to the machine, followed by the optimization of the controller.

1. Machine Level: Design optimization is carried out for the machine, and the steady-state performance of the machine is evaluated, including efficiency, weight, average torque, and cost. Key machine parameters, such as resistance, flux linkage, and inductance, are then passed on to the next step to be used as inputs at the control level.
2. Control Level: At this level, the optimization of the controller is performed based on the output parameters from the previous level. The dynamic performance of the drive system is then evaluated, focusing on speed overshoot, settling time, and torque ripple.

Step 3: The final step is the system level, where the overall drive system is evaluated, and the results are verified.

It should be noted that each step concludes and proceeds to the next when the optimization algorithm has achieved the defined objectives. As a result, both the steady-state and dynamic performances are optimized in the final step, ensuring that the methodology follows a sequential logic. However, this sequential logic ensures a near-optimal solution for each individual component; nevertheless, these component-level solutions may not align with the overall near-optimal performance of the system. As a result, this method

can easily yield suboptimal solutions compared to single-level design optimization if not thoroughly accounted for, which considers the system holistically from the beginning. Moreover, if the evaluation stage does not yield satisfactory results, the methodology must be restarted from the beginning with different design parameters. This iterative reinitialization highlights the primary distinction between this approach and the single-level design optimization method. Figure 4 shows the MLOM framework, highlighting this sequential logic applied during the optimization and evaluation steps mentioned earlier.

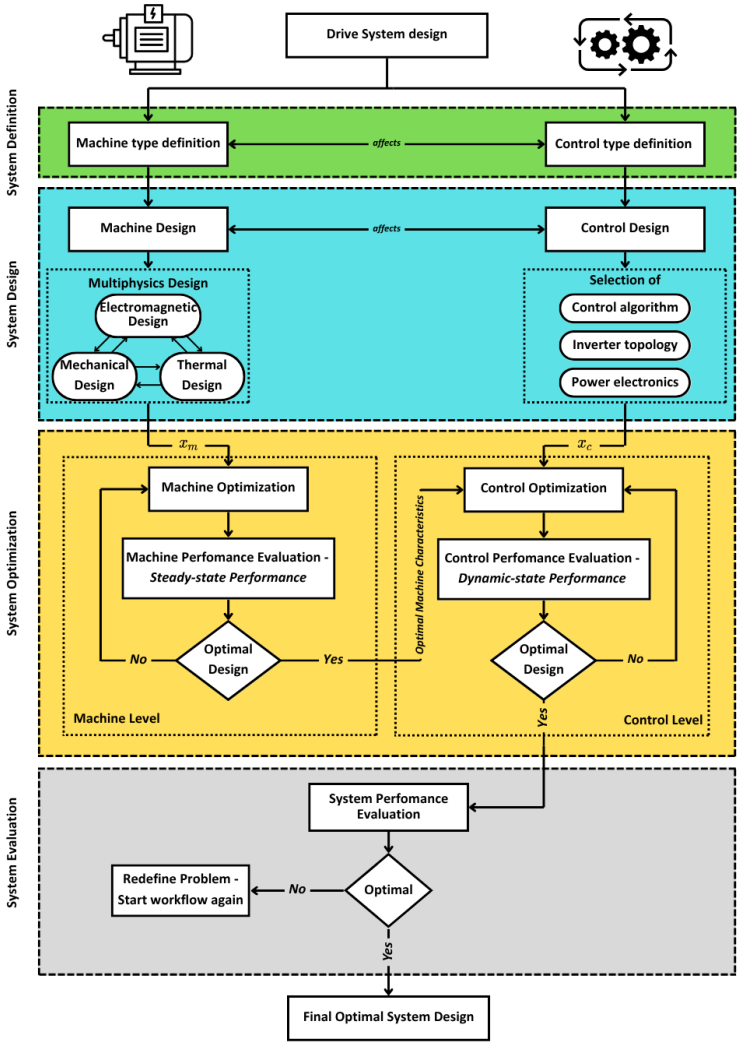


Figure 4. Multi-level optimization method framework.

In [30], the authors propose a novel approach for the design and optimization of an SRM for EV application using a novel Multi-Objective Design Optimization (MODO) algorithm. Their methodology couples the Kriging surrogate model, constructed in ALTAIR FLUX, with MATLAB/Simulink to simulate motor operation and utilizes the NSGA-II algorithm for optimization. Initially, the algorithm optimizes the geometric characteristics of the motor, selecting the best design that maximizes the average torque. Subsequently, it optimizes the turn-on, θ_{on}, and turn-off, θ_{off}, angles. However, the study evaluates only the dynamic performance, arguing that the steady-state condition does not significantly impact the overall system performance. While it is true that certain applications predominantly operate under dynamic conditions, the inclusion of steady-state analysis can offer valuable insight into key performance aspects, such as efficiency, losses, and thermal behavior, which are often not fully captured in transient simulations. Furthermore, steady-state

evaluations are typically computationally efficient, enabling their integration into the design and optimization processes without imposing significant additional complexity.

Reference [31] focuses on the design of an SRM using a non-linear electromagnetic analysis model combined with circuit theory for an EV application. The proposed model is validated through the FEM, and random variables are introduced to define the wind resistance coefficient, rolling resistance coefficient, and slope in order to simulate various road conditions in the dynamic operation of an EV. The torque, efficiency, and torque ripple are optimized using single-objective optimization carried out by the GA. The torque ripple and controller efficiency are optimized by adjusting the turn-on, θ_{on}, and turn-off, θ_{off}, angles. This approach qualifies as an MLOM, since the parameters are optimized in successive steps rather than simultaneously. Typically, control optimization is performed under dynamic conditions. However, the study reports a very high torque ripple coefficient of approximately 1.55, which translates to 155%, while the efficiency remains below 90%. Additionally, the computational time of the method is not discussed.

In the previous references, with both the SLOM and MLOM, the optimization process utilizes the entire solution search space, even if some solutions are neither feasible nor exploitable by the optimization algorithms. This approach imposes a computational burden on the optimization algorithm in terms of processing power and time. Therefore, these solutions and the search space should be reduced accordingly.

3. Model Complexity and Space Reduction Techniques for System-Level Optimization

System-level design optimization can be conducted exclusively using the FEM; however, its massive computational requirements renders it an expensive method. Therefore, several techniques have been proposed and employed to mitigate computational burden. Figure 5 illustrates various techniques that have been adopted in the literature to reduce the computational time of the optimization process by reducing the overall model complexity by adopting surrogate models such as interpolation-based methods, like the Kriging model and the response surface method, as well as machine learning-based algorithms such as neural networks. In addition, the reduction in the critical design parameters prior to optimization through the use of search space reduction techniques is commonly achieved with techniques such as sensitivity analysis, Design of Experiments (DoE), and the Taguchi method.

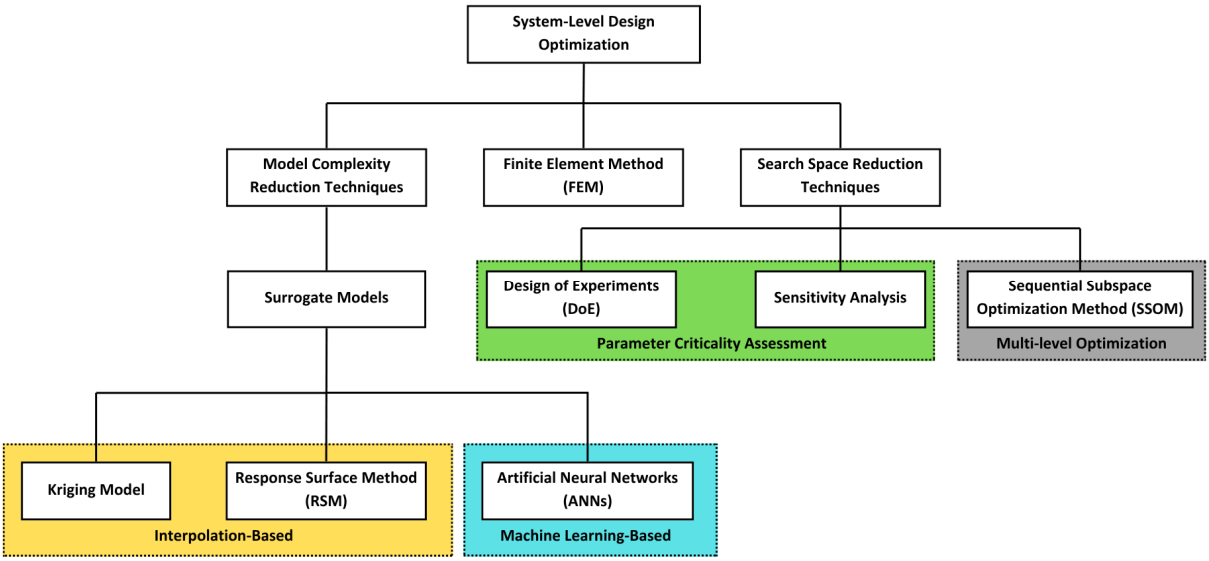


Figure 5. System-level techniques and algorithms most commonly employed for a reduction in model complexity and search space.

3.1. Surrogate Modeling

Surrogate models aim to establish a relationship between the input and output parameters of the problem they are attempting to solve. In the design and optimization of electrical machines, the input parameters are the design parameters used in the optimization process, while the output parameters are those that require optimization, such as efficiency, cost, weight, average torque, and torque ripple. Their main advantage lies in the significantly reduced computational time required to simulate an optimization problem. For this reason, they are often preferred over the FEM due to the excessive computational time demanded by the latter method. However, since surrogate models are constructed through analytical formulas, they lack the precision of the FEM, particularly in their inability to accurately simulate the non-linear behaviors of electrical machines, especially SRMs, such as saturation and mutual coupling between phases. Despite this disadvantage, their use is widespread in the field of electrical machine design optimization, as the reduction in computational time is considerably important relative to the accuracy they sacrifice, especially at the system level, where the optimization of both the motor and controller is required. Popular surrogate models include Kriging model, Radial Basis Functions (RBFs), Response Surface Method (RSM), and Artificial Neural Networks (ANNs) [32,33].

In [34], the authors propose the design of a novel SRM drive topology aimed at minimizing torque ripple. Their approach involves investigating the rotor pole shape by introducing specific grooves. A surrogate model, specifically a proxy model trained using quadratic polynomial regression, is employed, alongside the Multi-Objective Genetic Algorithm (MOGA), for optimization. The objective is to reduce the torque ripple while increasing the average torque, implemented within MATLAB/Simulink. Initially, optimization is performed on the motor, followed by controller optimization through the adjustment of the turn-on, θ_{on}, and turn-off, θ_{off}, angles. The results indicate a significant reduction in torque ripple—up to 72%—with a slight increase in the average torque. However, the study lacks a dynamic-state performance analysis, which is crucial for assessing whether the controller and, consequently, the motor can effectively respond to dynamic conditions. In many cases, dynamic-state performance evaluation is neglected due to the additional computational burden it imposes on the optimization procedure. Nevertheless, it remains a critical analysis that should be incorporated to ensure robust and reliable system performance.

3.1.1. Kriging Model

The Kriging model is an interpolation method based on the Gaussian process that employs a stochastic approach to identify the relationship between optimization variables and objective functions using known data, most often extracted from the FEM simulations. A key feature of the Kriging model is its ability to represent the correlated error and the predictable variance in each simulation [32,35]. Figure 6 illustrates the approximation of the input–output relationship using the Kriging model in comparison to the actual response. In addition, it visualizes the correlated errors (interpolation variance) previously discussed.

In [30,36], the authors employ the Kriging model, coupled with the NSGA-II algorithm, to establish a correlation between variables and optimization parameters to optimize the motor. In [36], they aim to mitigate the mutual coupling between two adjacent phases due to the presence of an even number of phases, which creates asymmetry in the current. To address this issue, they optimize the stator yoke and the controller through the turn-on angle, θ_{on}, and conduction width of the current pulse. While the Kriging model introduces slight deviations compared to the FEM results, it significantly reduces the computational time. The FEM would require on the order of 100,000 simulations; however, the surrogate-based approach reduces this to just 1125 simulations—about 1% of the original number,

achieving a ~99% reduction. This translates to a near 89× speedup in the runtime, cutting the total computational time from approximately 1389 h to just 15.6 h, saving around 1373 h in the process. This reduction in computational time highlights the significance of this method. The experimental results, alongside the simulation data, confirmed the effectiveness of the approach, showing a reduced torque ripple and improved current symmetry in the six-phase SRM design.

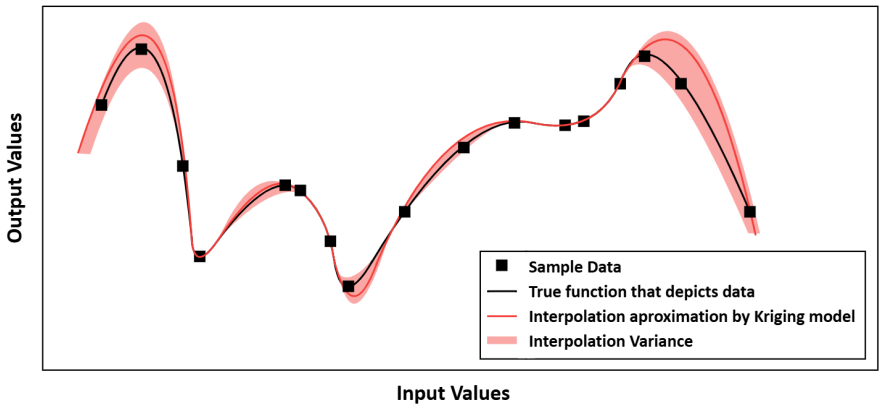


Figure 6. Illustration of the Kriging model structure and its fundamental components.

The authors of [37] discuss the design of an SRM through system-level optimization, specifically Multi-Level Optimization (MLO). A regression-based sensitivity analysis is employed to classify parameters based on their significance, while the motor is modeled using the Kriging method. Shape optimization is applied via a Bezier curve to modify the rotor pole shape and enhance performance, the control optimization is conducted through the turn-on, θ_{on}, and turn-off, θ_{off}, angles, and, as an optimization algorithm, the NSGA-II is utilized. Validation is performed using the ANSYS Suite for the FEM, leading to minimal errors between the Kriging and FEM. Although losses slightly increase, the average torque and torque ripple are marginally optimized. Similarly, in [38], a local sensitivity analysis, along with the Kriging model, is used in conjunction with the NSGA-II algorithm for optimization, with the control parameters being the turn-on, θ_{on}, and turn-off, θ_{off}, angles. The model data are validated once again, and it is concluded that the errors between the Kriging and FEM are small, with a maximum error of 3.17% for the torque ripple, which is considered highly accurate and reinforces the significance of the Kriging model. Both the FEM and surrogate models are experimentally validated using a physical prototype of the SSRM drive system, where the measured data align closely with the simulations, and the surrogate predictions show errors below 1%. However, the entire analysis reduced the initial torque ripple from 93.64% to 47.84%, which remains relatively high, and, additionally, the overall losses increased. Despite these trade-offs, the method proves highly efficient, reducing the number of FEM evaluations by approximately 99.995% and achieving a speedup factor of nearly 20,300× compared to a conventional FEM-based optimization approach.

In [39], the authors focus on the design of a 12/10 SRM for EV applications, utilizing driving cycle data and the Dimension Reduction Optimization Method (DROM) to reduce the solution search space. The authors chose the DROM for its efficiency in managing computationally intensive tasks like finite element simulations. Unlike conventional global optimization techniques (e.g., genetic algorithms or particle swarm methods), the DROM employs a two-stage process—starting with a coarse search to identify promising regions, followed by a refined search within those areas. This strategy reduces computational cost while avoiding local optima. This reduction is performed iteratively at each step until a near-

optimal point is found, progressively narrowing the range of each parameter. The Kriging model is employed using data extracted from the FEM simulations in ANSYS/Maxwell, simulating four different driving conditions. The experimental results from the protype's validation demonstrate errors below 1%. After each simulation, a Pearson correlation analysis is applied to simplify the optimization process and eliminate redundancies. The study highlights that the proposed method significantly reduces the computational time—where a full FEM-based approach would require 750 simulations. The results indicate an increase in torque and a reduction in ripple across all driving conditions.

Finally, in [40], a study is conducted on the design of an SRM using the FEM and the Transient Lumped-Parameter Thermal Model (TLPTM), considering the thermal analysis of the motor. Additionally, a sensitivity analysis is performed through the Sobol method, and the Kriging model is constructed using the FEM in Ansys/Maxwell 2D, with 500 simulations, and the NSGA-II is employed for optimization. The control optimization is performed through the turn-on, θ_{on}, and turn-off, θ_{off}, angles, resulting in a reduction in the torque ripple, an increase in the torque, and a decrease in the temperature of the windings and the stator, all of which are optimized to a satisfactory degree. Experimental validation using a scaled-down prototype of the 12/10 SRM confirms the effectiveness of the proposed design, showing improvements in the torque, temperature reduction, and losses that closely match the simulation results.

3.1.2. Response Surface Method

Similarly to the Kriging model, the response surface method is an interpolation technique that primarily uses data from the FEM to construct a response surface for both known and unknown data. It employs the least squares method to derive a correlation between the input and output parameters [41,42]. Figure 7 illustrates the torque surface based on the response surface method for the input variables rotor position and excitation current for a specific SRM motor. This surface response also qualitatively depicts the relationship between torque, rotor position, and excitation current for the SRM. Warmer tones display higher torques, while cooler tones display lower torques. This is supported by the contour lines, which display constant-torque slices in the X-Y plane.

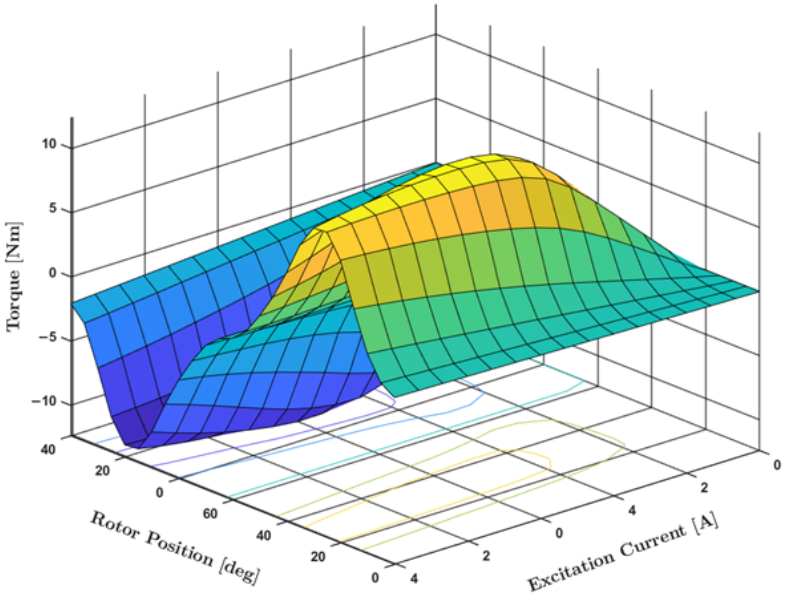


Figure 7. Torque surface of the response surface method for the input rotor position and excitation current.

An analysis is performed in [14] on a 24/16 (number of stator poles/number of rotor poles) SRM motor for application in an in-wheel EV using the FEM and DoE to reduce the solution search space and capture non-linear dependencies, coupled with the RSM and DE. Design candidates are generated through the FEM in ANSYS, and the RSM is implemented via DoE to reduce the search space. Simultaneously, for the control optimization, the near-optimal turn-on, θ_{on}, and turn-off, θ_{off}, angles are determined using a sweep method in MATLAB to optimize the average torque, torque ripple, losses, and RMS current. The results indicate a five-fold reduction in the computational time, from 36 h to 7 h, achieving an 80% reduction in computational time and being about 5 times faster than conventional approaches, while maintaining satisfactory optimization outcomes.

To the best of the authors' knowledge, no other studies have been conducted employing this method for the system-level optimization of SRMs, apart from those focused on component-level optimization. In [43,44], the authors utilize the RSM as a surrogate model for the optimization of a synchronous reluctance machine and a Dual-Permanent-Magnet-Excited (DPME) machine. Notable results include an improvement in the rotor saliency ratio from 2.42 to 3.68, leading to an enhanced torque-to-current ratio and an increase in efficiency from 64.8% to 74.7% in the former, while the latter achieved an 8.9% reduction in permanent magnet material usage. Additionally, improvements in efficiency, a significant reduction in cogging torque, and minimized torque ripple were reported. What is particularly important to highlight is that the implementation of this methodology resulted in a substantial reduction in the computational time, while maintaining a satisfactory level of accuracy, as indicated by the coefficient of determination, R^2. Thus, its application to SRM machines in a broader context of the SLDOM could be highly beneficial.

3.1.3. Artificial Neural Networks

Artificial Neural Networks (ANNs) are Machine Learning (ML)-based models that have been increasingly developed in recent years for the design and optimization of electrical machines, as they can significantly reduce the computational burden associated with FEM-based design processes [45,46]. Their fundamental concept involves establishing a mapping between input and output parameters through a fitting process. They consist of the following three layers, as illustrated in Figure 8: input, output, and hidden. The variables x and y are the input and output values, respectively. The accuracy of the model typically increases with the number of hidden layers; however, additional hidden layers may also lead to longer training times or overfitting. The accuracy can also be increased through model complexity and feature engineering [45,47]. A widely used procedure for improving model accuracy is hyperparameter tuning, where the parameters constituting the ANN are optimized. This process can be carried out using various optimization techniques such as PSO and GA. The authors of [48] propose a hybrid approach that combines both methods to mitigate PSO's tendency to become trapped at the local minima while also accelerating convergence, addressing the typically slower performance of the GA. Architectures commonly used for electrical machine optimization include a Feedforward Neural Network (FNN), Backpropagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), and Generalized Regression Neural Network (GRNN) [49].

The authors of [50] propose an optimization method for a high-power-density SRM drive, dividing the process into two stages. In the first stage, a static analysis is conducted to identify the parameters that yield the highest static torque. In the second stage, a dynamic analysis is performed on these parameters to optimize the average torque, torque ripple, and radial forces. This is achieved using a RBFNN as a surrogate model in combination with optimization algorithms, such as the GA, PSO, and Global Response Surface Method (GRSM). An FEA is conducted using ALTAIR software, with the model fitting performed

either with the RBFNN through ALTAIR HyperStudy or with an ANN via Python. The study concludes that the fastest method is an ANN combined with the GRSM. For the control optimization, the conduction angles are optimized using the GA, and the results indicate that, while the average torque and radial forces are improved, the torque ripple remains unchanged. Additionally, the study provides comparative observations suggesting that the GA offers inclusiveness at the expense of time, whereas PSO provides faster convergence with a broad range of solutions.

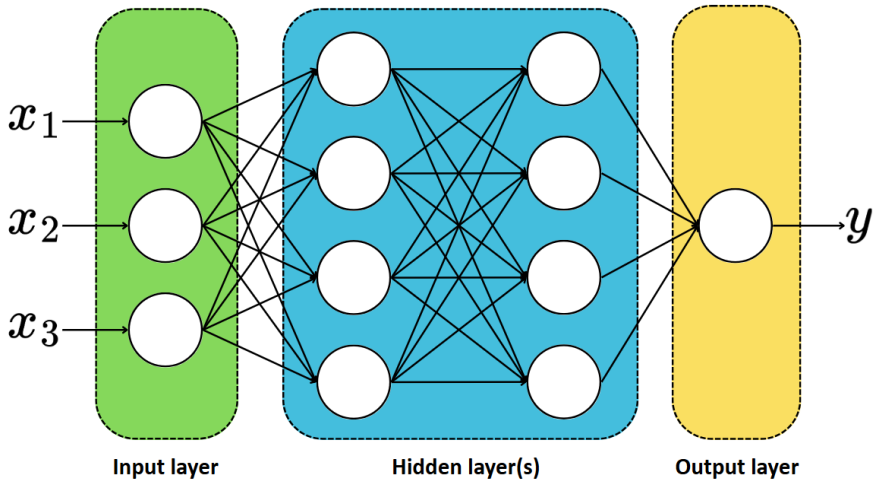


Figure 8. Basic structure of an artificial neural network. The three primary layers—input, hidden, and output—are illustrated.

As with the case of the RSM, as well as according to research conducted by the authors, there is limited literature regarding the use of neural networks in the SLDOM, with most studies focusing on component-level optimization instead. In [51,52], the authors focus on optimizing the motor by employing neural network models such as the GRNN and Multilayer Perceptron Neural Network (MLPN), in combination with PSO and the Fly Optimization Algorithm (FOA), in order to reduce the computational time. For instance, in [53], the computational time for optimization is reduced to just half an hour and an improvement is observed in the critical motor parameters, such as average torque, torque ripple, and efficiency. Additionally, the use of these methods facilitates the simulation of non-linearities inherent in the SRM, making them ideal for further implementation in the SLDOM.

3.2. Parameter Criticality Assessment

In this chapter, two essential space reduction methods—sensitivity analysis (SA) and Design of Experiments (DoE)—are categorized under the broader concept of Parameter Criticality Assessment. These methods analyze the influence each design parameter has on the overall system performance. If a parameter is found to have minimal impact, it is excluded from the optimization process, allowing only the critical parameters to remain. Ultimately, these techniques contribute to a significant reduction in computational time and provide the designer with valuable insight into which parameters need greater attention during the optimization process. They are particularly important in enabling the use of the FEM in SLDOM.

3.2.1. Sensitivity Analysis

The sensitivity analysis approach is aimed at classifying the parameters intended for optimization based on how small variations in these parameters influence system performance. These variations may arise from inherent material imperfections, manufacturing

defects, or constraints introduced by tolerances during the manufacturing process [53]. Essentially, this method allows the designer to eliminate parameters that have minimal or no impact and focus solely on optimizing the critical ones, thereby reducing the parameter space. Indicative methods include One-at-a-Time (OAT), Pearson correlation coefficient, regression-based sensitivity analysis, variance-based decomposition (VBD), and the Sobol method. The latter two are particularly widespread due to their ability to account for model non-linearities and higher-order interactions among parameters, whereas the former methods are limited in capturing such complexities unless combined with complementary techniques such as DoE. Based on the above discussion, and the illustration in Figure 9, the most critical parameter is x_1 , while x_2 appears to be the least influential for the output variables, y, as indicated by the qualitative "sensitivity" metric.

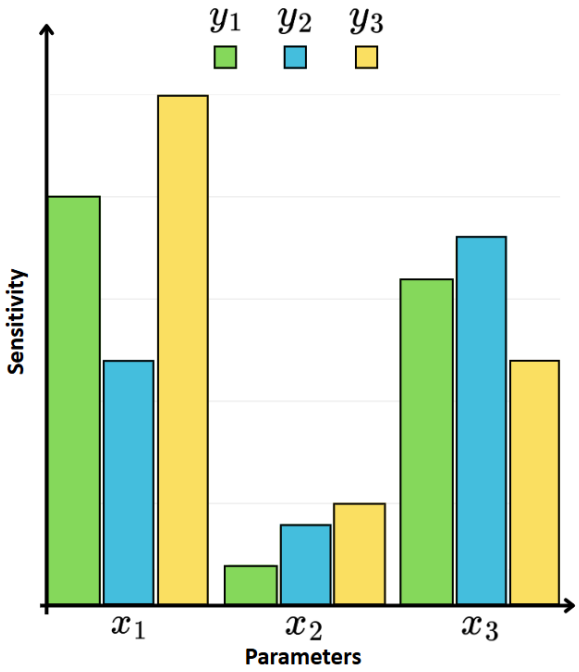


Figure 9. Sensitivity analysis of the output variables, y, based on the input parameters, x.

In the studies [14,37–40,50] analyzed previously, a sensitivity analysis served as the fundamental pillar for further analysis. In [54], a study was conducted utilizing the magnetic parameter design methodology, which is based on the non-linear properties of magnetic materials combined with analytical equations. Variance-based sensitivity analysis is performed to determine the criticality of various parameters and capture their non-linearities and higher-order dependencies. Following this, the analysis identifies the turn-on, θ_{on}, angle as the critical parameter for the controller and the number of turns, N, as the critical parameter for the motor, optimizing both simultaneously. The proposed method is applied to the following three SRM topologies: five-phase 10/8, nine-phase 18/20, and three-phase 12/8. The results are compared with the FEM analysis, leading to the conclusion that minor errors exist but are justified.

Reference [55] serves as a continuation of [26], where the proposed method is experimentally validated. Additionally, a form of sensitivity analysis is employed, utilizing a systematic down-selection process to determine the parameters for optimization. As a result, although the number of design parameters increased from six in [26] to eleven in [55], only the most critical parameters are selected at each iteration for further optimization. The study further compares the results obtained from the voltage-fed analytical equations and the FEM-based simulations under dynamic conditions. The findings indicate that the dis-

crepancies between the two approaches remain within an acceptable range. Experimental validation is carried out using a scaled 5 hp SRM prototype tested on a dynamometer setup, where voltage, current, and torque waveforms closely match simulation results, with minor deviations attributed to practical factors.

In [56], the authors focus on the design of an External Rotor Switched Reluctance Motor (ERSRM) by implementing a sensitivity analysis through the Pearson correlation coefficient, Latin hypercube sampling to extract candidate models, and an improved version of the NSGA-II algorithm, referred to as CD-NSGA-II. This enhanced optimizer incorporates the chi-square distance metric in contrast to the standard NSGA-II and is applied through MATLAB/Simulink and ANSYS. The sensitivity analysis identifies the critical parameters as the θ_{on} and θ_{off} angles, along with key geometric parameters of the motor. The optimization process targets torque ripple, average torque, and efficiency as the primary performance metrics. The paper selects CD-NSGA-II for its superior performance in handling complex, high-dimensional multi-objective optimization problems. Key merits include enhanced population diversity through Sobol sequence initialization, improved convergence and robustness via directional mutation and normal crossover, and adaptive solution ranking using a weighted chi-square distance metric with gradient sensitivity. A comparative analysis between the two optimization algorithms is conducted, revealing that while CD-NSGA-II leads to a slight decrease in efficiency and an increase in losses, it achieves a significant reduction in torque ripple compared to NSGA-II. However, the study does not consider the effects of friction and windage losses in its analysis. The same team of authors of [57] extend their novel topology for the ERSRM featuring an asymmetric stator for application in E-Bikes. The optimization process employs the NSGA-II algorithm in conjunction with a sensitivity analysis and FEM simulations to minimize torque ripple. The analysis and results align with their previous findings, demonstrating a significant reduction in the torque ripple. However, similar trade-offs are observed, including a slight decrease in efficiency and a corresponding increase in losses.

3.2.2. Design of Experiments

The systematic method of designing and evaluating controlled experiments to assess critical variables in optimization procedure is known as design of experiments. This technique improves efficiency by eliminating non-critical parameters and accuracy by allowing designers to gather as much information as possible from fewer experimental runs [14,50]. The DoE's key techniques include the following: the Taguchi method [58], which emphasizes robust design by minimizing variation; fractional factorial designs, which minimize the number of runs while maintaining crucial information; and full factorial designs, which examine every possible combination of factors. Another method, Central Composite Design (CCD), constructs a response surface in order to fit a second order polynomial model and capture non-linearities between factors and responses. Alongside these, Latin Hypercube Sampling (LHS) and Monte Carlo analysis are widely used to sample points to construct surrogate models and account for non-linearities. DoE is widely used in the electronics, automotive, and aerospace manufacturing sectors to optimize the design parameters for increased efficiency and reliability [59,60].

In [14], as previously discussed, successfully implements the DoE methodology, resulting in a notable reduction in the overall computational time of the optimization process. In [61], the authors discuss the design of a 12/10 hybrid excitation segmented-rotor SRM (HESRSRM), where magnets are placed in front of the openings in the stator slots. The paper selects the Taguchi optimization method for its exceptional efficiency and practicality in handling multi-objective motor design problems. By replacing a full factorial design (15,625 trials) with just 25 simulation runs using an orthogonal array, the approach achieves

a 99.84% reduction in computational effort. Taguchi's framework also supports multi-objective optimization, enabling the authors to balance improvements in average torque, torque ripple, and torque density. Alongside the Taguchi method, a One-at-a-Time (OAT) sensitivity analysis is employed to limit the search space and optimize the parameters. The optimization focuses on reducing torque ripple, improving average torque, and minimizing losses using equations developed for the geometric characteristics, while the turn-on, θ_{on}, and turn-off, θ_{off}, angles are indirectly calculated using these equations. Thus, this process can be considered an indirect system-level optimization. However, this approach does not account for the non-linear characteristics of the system, which may affect the accuracy of the optimization results. For the static analysis of the single phase, ALTAIR FLUX software is used to extract the torque profile and the coupled flux, and ALTAIR FLUX is coupled with MATLAB/Simulink for dynamic operation of the motor. The optimization results indicate a significant increase in torque and power density, with only a slight reduction in ripple.

Reference [62] addresses system-level optimization using a sensitivity analysis from the perspective of robustness. The authors propose a method that incorporates the driving cycle and multiple driving modes into the analysis. This method utilizes variance-based sensitivity analysis to eliminate non-critical parameters, combined with the Taguchi method for optimization. A case study of a 12/10 six-phase SRM is conducted to validate the method, where each design parameter, whether of the controller or the motor, affects different driving modes. The analysis is completed after four iterations, and the results show a significant reduction in torque ripple with a slight decrease in torque. To improve real-world feasibility, the study adopts a robust design strategy by modeling manufacturing tolerances, such as air gap variation, as noise factors and optimizing based on signal-to-noise ratios, ensuring the final design performs reliably under production variability. Overall, if the two driving modes are combined, the full factorial approach would require 180 simulations per iteration, whereas the proposed method performs only 24 simulations. This results in an overall reduction in the simulation count by approximately 86.7%, highlighting the substantial computational savings achieved through this approach.

Based on the review of the aforementioned papers, it can be concluded that most studies do not explicitly incorporate higher-order interactions among the design factors in their analysis and instead focus primarily on first-order effects of individual variables. Furthermore, in cases where no dedicated sampling method for capturing non-linearities, such as LHS or CCD, is employed, the identification of non-linear behavior is deferred to the FEM simulations conducted prior to the surrogate model construction.

3.3. Sequential Subspace Optimization Method

The Sequential Subspace Optimization Method (SSOM) is an approach that falls under the category of multi-level optimization, as it performs optimization across multiple levels by dividing the overall search space. In contrast to the single-space optimization method, which conducts optimization on a single level considering all design parameters simultaneously, the multi-level approach divides the problem into separate yet related subspaces in which the parameters defined for optimization are placed into based on their significance, with each subspace being optimized separately. This process is sequential, and at each level, the parameters of the other levels remain fixed. The entire process is iteratively repeated until a convergence criterion is met [11]. Figure 10 shows the SSOM framework, with the most critical parameters placed in the first level, and the least critical ones assigned to the final level.

This method is particularly useful in cases where the number of optimization parameters and the solution search space are extensive, such as in System-Level Optimiza-

tion [11,63,64]. Classification of parameters based on their significance is performed through sensitivity analysis, which evaluates the impact of small variations in each parameter on the overall system performance [63].

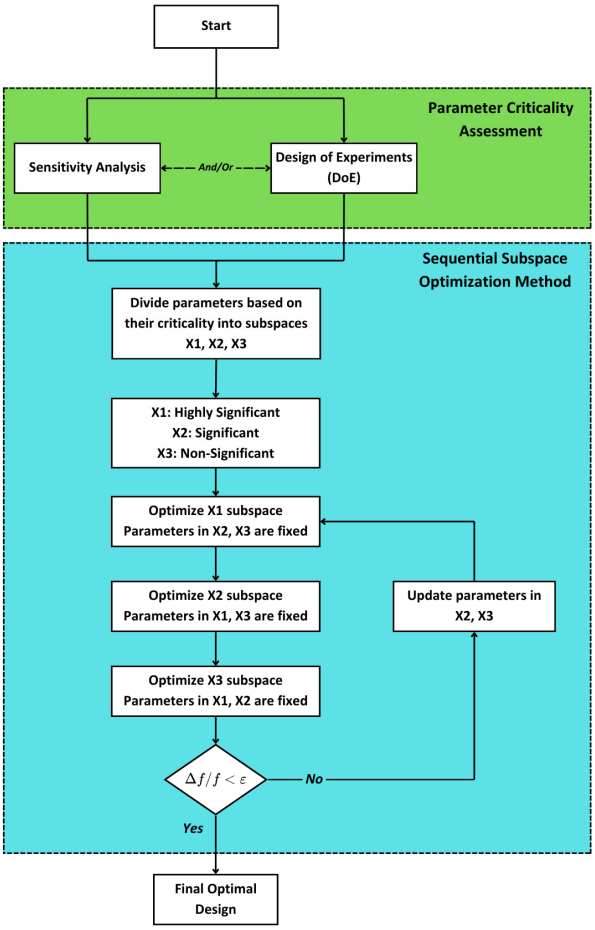


Figure 10. Sequential subspace optimization method.

Initially, the authors of [20,65] mapped the SLDOM framework and enhanced it with the SSOM and surrogate models, such as Kriging, combined with a sensitivity analysis. In [20], the optimization results are promising, showing an increase in output power, torque, and efficiency, while reducing cost, torque ripple, and losses. Additionally, the computational time with the SSOM has been reduced by up to five times for the motor and twice for the control compared to a single-level optimization method.

In references [37,38,40], system parameters are categorized into three levels—highly significant, significant, and non-significant—based on their criticality, followed by sequential subspace optimization. In [37], the sensitivity analysis identifies the controller turn-on, θ_{on}, and turn-off, θ_{off}, angles as the most critical parameters, placing them in the X1 subspace. Conversely, in [38], the control and motor parameters are distributed across the three levels, with each level requiring fewer FEM simulations for optimization and only three iterations for the whole optimization process, highlighting the significance of the SSOM approach. Finally, in [40], the Kriging model is utilized in combination with sensitivity analysis and the SSOM to accelerate the optimization process. The parameters identified through sensitivity analysis are divided into three levels, with the most critical being the turn-off θ_{off} angle and the air gap g. Only two iterations are required for the optimization algorithm to converge based on the termination criterion defined by the authors, resulting in a 16.17% improvement in overall system performance.

In [66], the SSOM is utilized alongside the Kriging model and a local sensitivity analysis to optimize an SRM drive system. The design parameters are classified into the three subspaces, while the NSGA-II generates Pareto-optimal solutions through optimization. A termination criterion, based on the relative error between two successive iterations, determines the best design, leading to a 42% increase in torque and a torque ripple reduction of around 65%. Only three iterations are required for the termination criterion to be satisfied, with each subspace requiring significantly less time for optimization compared to the first. This is logical, as the most critical parameters, which have the greatest impact on system performance, are placed in the first subspace. The last comment highlights the significance of parameter criticality assessment, which refers to identifying the critical parameters and downplaying the influence of those with limited impact. The results are validated by comparing the FEM simulations with experimental data from a prototype SSRM drive system. Torque measurements at 6000 rpm align closely with simulation predictions. Finally, this paper serves as a preliminary study for [38], by the same authors, which refines the approach by introducing multi-level optimization, better Kriging model validation, and a more adaptable method for selecting the near-optimal design based on specific application needs.

Having reviewed the studies focused on techniques for computational time and model complexity reduction, Table 1 presents the quantitative impact of these methods on simulation time, number of simulations, and model accuracy, benchmarked against the FEM. A substantial reduction in computational burden is observed, while model accuracy is compromised minimally. Among the surrogate modeling techniques, the Kriging model emerges as the most commonly adopted, owing to its ability to significantly reduce computational effort with only minor deviations from the true model. It is also noted that for studies lacking explicit numerical data, estimations have been conducted based on the reported outcomes and discussions.

Table 1. Comparison of surrogate modeling techniques in terms of computational efficiency and accuracy relative to the FEM.

	Kriging Model	**RSM**	**ANN**	**Models Employing SA**	**Models Employing DoE**	**Models Employing SSOM**
Computational time/number of simulations compared to FEM	[30] from 30 min to a few seconds	[14] 559 simulations from 3000 ones (~80% reduction), from 33 h to roughly 6 (~5 times faster)	[50] from 900 candidate models to a fraction of them	[54] 33% fewer parameters in simulations	[61] from 15,625 to 25 simulations (~99.84% reduction)	[66] from 50,000 to 3993 simulations (92% reduction)
	[36] from 100 thousand to 1125 simulations (~99% reduction)			[55] from 1–3 min to 0.5–3 s		
	[37] from 1331 to 726 simulations (~45% reduction)				[62] from 81 to 18 simulations (78% reduction)	
	[38] from 27 million to 1331 simulations (~99.995% reduction)			[56] 90% down in computation time		
	[40] from a few million to a few thousands					
Model accuracy compared to FEM	[30] 1–2% discrepancies	[14] almost 100% accuracy	[50] average error 1.5%, maximum error 3%	[54] max 23% overprediction	[61] maximum error 1%	[66] errors well within 1% in the convergence measure
	[36] decent accuracy			[55] maximum error 2%		
	[37] 1.79% maximum error				[62] maximum error 5%	
	[38] average error 1%, maximum error 3.1%			[56] maximum error 5%		

Table 2 provides a summary of the research papers that have been classified under the category of SLDOM and discussed in detail in the previous sections. It outlines the specific content of each study, along with the techniques employed to achieve SLDOM. Regarding the "Optimization Parameters" section, the term "Geometrical Parameter" refers to various geometric features of the motor. Due to their abundance and in order to maintain the table's clarity, these parameters have been grouped under a single category rather than listed individually. Moreover, the studies referring to SRM/SRG drives employ a general terminology, allowing their findings and methodologies to be applicable across a wide range of industrial applications.

Table 2. Summary of references on system-level design optimization of SRMs.

Ref.	Modeling	Optimization Algorithm	System-Level Algorithm	Optimization Parameters Machine/Control	Optimization Goals	Application
[14]	RSM with SA	DE	Single-Level	Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Torque Ripple, Mass, Copper Losses	In-Wheel application EV
[24]	RSM	FIS–NSGA-III		Geometrical Parameters/ θ_{on}, θ_c	Efficiency, Torque Ripple, Power Density	SRG Drives
[25]	FEM	GA		Candidate Models/ $\theta_{on}, \theta_{off}$	Average Torque, Torque Ripple	Vertical Transportation
[26]	FEM	PSO		Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Efficiency, Torque Ripple, Power Density	SRM Drives
[27]	Field-Circuit-coupled FEM	GA			Efficiency, Mass	Aerospace Applications
[28,31]	[28] FEM, [31] FEM with SA	[28] NSGA-II, [31] GA	[28] Single-Level, [31] Multi-Level		Average Torque, Torque Ripple, Efficiency	[28] In-Wheel application EV, [31] EV
[30]	Kriging	NSGA-II	Multi-Level		Average Torque, Torque Density, Losses	EV
[34]	PR Model	MOGA		Rotor pole shape/ $\theta_{on}, \theta_{off}$	Average Torque, Torque Ripple	SRM Drives
[36]	Kriging	NSGA-II	Single-Level	Yoke width ratio/ θ_{on}, θ_c	Average Torque, Torque Ripple, RMS Current	
[37,38,66]	Kriging with SA	[37,38] NSGA-II, [66] SSOM–NSGA-II		[37] Rotor pole shape, [38,66] Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Average Torque, Torque Ripple, Losses	
[39]	Kriging with SA	GRA with TOPSIS	Multi-Level	Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Average Torque, Torque Ripple, Losses	EV
[40]	FEM with TLPTM–Kriging with SA	NSGA-II	Single-Level		Average Torque, Torque Ripple, Losses, Temperature Rise	

Table 2. *Cont.*

Ref.	Modeling	Optimization Algorithm	System-Level Algorithm	Optimization Parameters Machine/Control	Optimization Goals	Application
[50]	RBFNN with SA	GA, PSO, GRSM	Multi-Level	Candidate Models/ $\theta_{on}, \theta_{off}$	Radial Force Harmonics, Torque Ripple, Average Torque	SRM Drives
[54]	Analytical Equations with SA	DE	Single-Level	Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Average Torque, Current Density, Torque Ripple	
[55]	Voltage-fed Analytical Equations and FEM	PSO	Single-Level	Geometrical Parameters/ $\theta_{on}, \theta_{off}$	Average Torque, Torque Ripple, Efficiency	SRM Drives
[56,57]	FEM with SA	[56] CD-NSGA-II [57] NSGA-II			[56] Efficiency, Average Torque, [56,57] Torque Ripple	E-Bikes
[61,62]	Taguchi with SA	Taguchi			Average Torque, Torque Ripple, Torque Density	

Regarding the optimization algorithms employed, the most widely used are NSGA-II and GA, due to their strong capabilities in handling non-linearities and their robust search ability and adaptability, making them well-suited for multi-objective problems. On the other hand, various innovative algorithms can be introduced to SRM drive system optimization to reduce computational time. One such method is the Decentralized Stochastic Recursive Gradient (DSRG) algorithm, which has the ability to split the overall problem into smaller, manageable subproblems, solving them in parallel and thereby significantly reducing computational effort. Furthermore, its stochastic gradient updates are particularly effective in navigating the non-linear nature inherent in SRM design [67]. Another promising approach is the Black Widow Optimization (BWO) algorithm [68], which offers fast convergence and can address both non-linearities and multi-objective problems, features especially relevant in complex SRM drive systems.

All the aforementioned studies fall under the category of System-Level Optimization, as they analyze and optimize both the machine and the controller simultaneously or sequentially using various methods discussed earlier. However, these studies primarily focus on optimizing machine-related parameters such as torque, losses, efficiency, and torque ripple, while neglecting key controller performance metrics such as speed overshoot, settling time, controller efficiency and losses, which are left to be adjusted by the controller's algorithm. Moreover, the only controller-related parameters considered in the optimization process are the turn-on, θ_{on}, turn-off, θ_{off}, and conduction, θ_c, angles.

To the authors' best knowledge, there are no existing recent studies that incorporate a broader range of controller performance metrics in SLDOM for SRM drives. This gap likely stems from the high computational cost and complexity associated with such an analysis due to the strong coupling between the machine and the controller, thereby necessitating a multiphysics-based approach for a more comprehensive optimization process. Furthermore, most of the reviewed studies either overlook transient electromagnetic and thermal effects or, in cases that involve dynamic-state simulations, do not explicitly consider them. This is mainly due to the added complexity and computational effort required to include such detailed simulations.

To address these computational challenges and facilitate the integration of emerging methodologies, we propose a structured roadmap aimed at overcoming key limitations in current SLDOM practices. First, by incorporating ML-based algorithms into the modeling of the machine, its electromagnetic, thermal, and mechanical characteristics with minimal loss in fidelity are shown to be captured, thereby enabling offline training. Model complexity is to be controlled through dimensionality reduction techniques, such as sensitivity analysis and DoE. Second, the integration of Model Predictive Control (MPC) is particularly advantageous due to its predictive nature and its ability to directly incorporate dynamic controller performance metrics, such as overshoot and settling time. MPC can continuously update control actions based on predicted system trajectories, making it well-suited for coordinated machine–controller optimization. Accordingly, the proposed roadmap follows the following sequence: offline generation and validation of ML-based surrogate models; integration of these models into an MPC-based co-optimization framework.

4. Proposed Solution–Machine Learning Modeling Coupled with Model Predictive Control

ML-based modeling has already shown promising results, primarily in reducing computational time, while its accuracy can be further improved by using larger models and more training data. Naturally, these two aspects are contradictory, making it essential to find a balance between them. Nevertheless, the excessive computational burden required by the FEM can be significantly reduced by replacing it with ML models. Most studies focus on supervised learning, while reinforcement learning has not yet been widely applied to motor design but has shown potential in control strategies [69].

Multiphysics analysis of an SRM is crucial for determining the final design, but it is also highly complex and time consuming [70]. In most cases, the electromagnetic analysis is performed using the FEM, while the thermal aspect is either neglected or a coupled electromagnetic-thermal analysis is conducted, and the mechanical aspect is entirely omitted [71]. The latter approach remains relatively time-consuming and does not account for the mechanical analysis, which determines the radial forces, vibration, and acoustic noise, which are in turn further influenced by the power converter and its switching frequency [72]. One common approach adopted by several of the aforementioned studies is the incorporation of thermal and mechanical factors as constraints in the optimization process, either simultaneously, as in [24,25,27,37,50], or sequentially, as in [14,40,55], following the electromagnetic analysis. This is typically achieved by considering parameters such as current density, iron and copper losses, and torque–current density, which indirectly assist in regulating temperature rise and torque ripple for radial forces reduction. While this method effectively mitigates the high computational cost associated with full thermal and mechanical analyses, it does not fully capture the actual operational behavior of the motor. As such, a primary suggestion is to evaluate candidate topologies using the constraints, and perform thermal and mechanical analysis with the promising designs. The integration of ML algorithms in the design process aims to reduce the implementation time of these analyses and to map a relationship between the three domains. However, one downside is that numerous FEM simulations are required to train the model. Nevertheless, the number of simulations needed is significantly lower compared to those required for a full simulation involving all three types of analysis. Along with the FEM, Computational Fluid Dynamics (CFD) is specifically used for the three analyses [73,74]. By employing ML algorithms, their use is limited to training and evaluating the model through simulations, as well as to the final validation of the optimization process.

The authors of [71] describe a method that combines electromagnetic/thermal analysis with an ANN to accelerate the optimization of a Surface Permanent Magnet machine. The

ANN is used to determine the maximum current density for each design generated during the optimization process. Training of the ANN is performed using data from the first 10 generations of simulations, representing 70% of the simulations, with the remaining 15% used for validation and 15% for testing. The results show improvements compared to using the FEM alone, with the simulation time reduced by up to three times. This analysis demonstrates that the proposed approach yields positive outcomes and can also be applied to SRM, particularly if controller parameters such as switching frequency are considered for mechanical analysis. This would enable a comprehensive SLDOM analysis.

The most prominent control strategies proposed for SRM drives are Direct Torque Control (DTC), Field-Oriented Control (FOC), Current Chopping Control (CCC), Angle Position Control (APC), and MPC [75]. CCC is the most widely used due to its simplicity, low complexity, and minimal computational burden. However, despite its advantages, CCC has notable limitations. It struggles to effectively mitigate torque ripple, exhibits relatively low efficiency, and lacks the capability to handle constraints such as voltage, torque, and speed. These drawbacks make it less suitable for applications requiring precise control and optimization in drive system design [76]. The authors of [77] have conducted a comprehensive analysis of MPC for application in SRM drives, covering all its subcategories. They highlight that MPC offers high accuracy, can account for non-linearities, can easily handle constraints, and has the potential to replace conventional PID controllers.

Based on the above points, the integration of ML algorithms with MPC can have a positive impact on the design and optimization of SRM drives. Figure 11 illustrates that the proposed scheme, on one hand, enables efficient machine modeling through ML, with training, testing, and evaluation performed using data from the multiphysics analysis, while on the other, MPC provides advanced machine control, utilizing the predictive model, with inputs like rotor position $\theta_r(k)$, and current $i(k)$, and minimizing the error between the reference current i^*, or torque T^*, and the actual output value $\hat{T}$ or $\hat{i}$. Although multiphysics analysis is a simulation-based approach, it demonstrates a high level of accuracy and can effectively be used to train neural networks. When combined with real-world data, it enables a robust validation process, enhancing the overall reliability and applicability of the developed model [78,79].

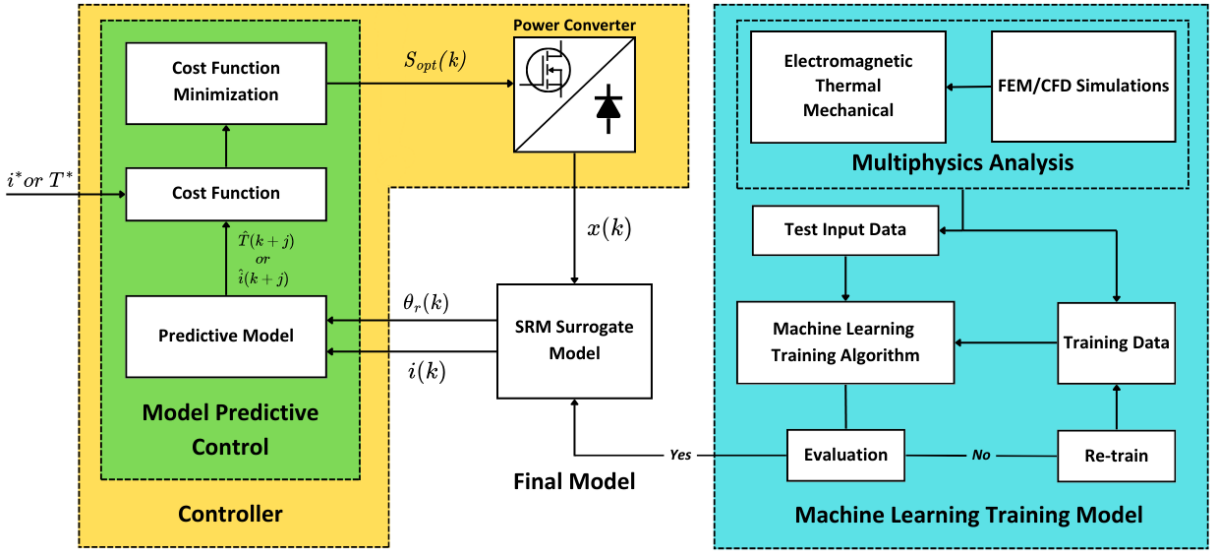


Figure 11. MPC control strategy integration with machine learning modeling for SRM.

Figures 12 and 13 show the application of the ML-MPC for the single-level and multi-level SLDOM, respectively. This representation highlights how ML models assist the MPC

and contribute in optimizing both the machine and controller parameters. Specifically, ML algorithms supply MPC with the necessary data for accurate predictions, such as relationships between torque, current, flux, and rotor position. Switching states can be optimized to mitigate torque ripple, enhance dynamic response time, and reduce computational burden. Additionally, MPC proves highly valuable in system-level design, as it performs online optimization during the control optimization phase [78,79]. This is expected to reduce the number of required steps and dynamic performance simulations needed to determine the near-optimal operating conditions.

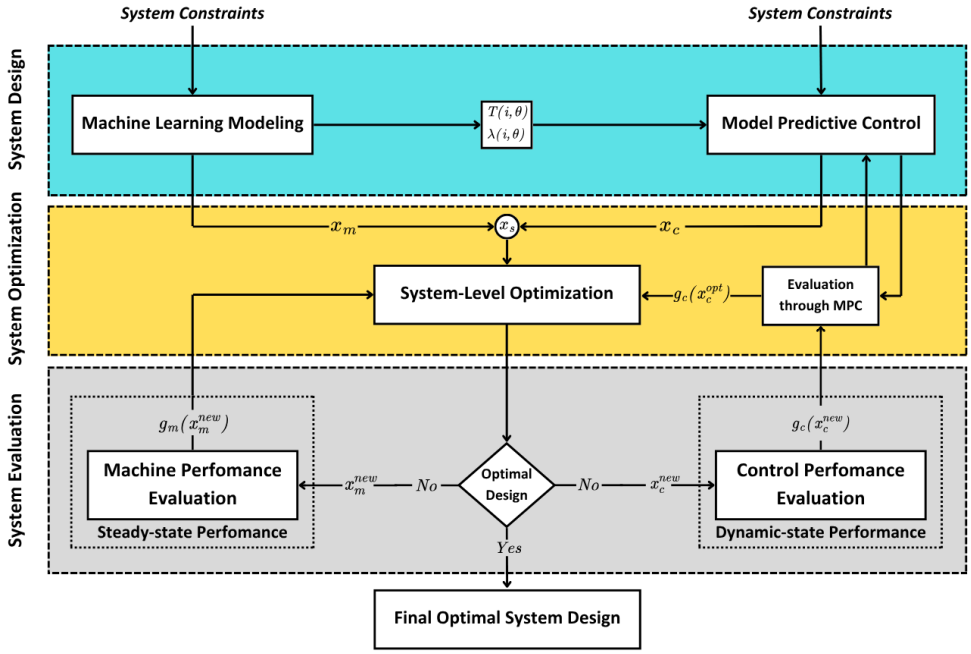


Figure 12. Implementation of ML-MPC on Single-Level System-Level Design Optimization.

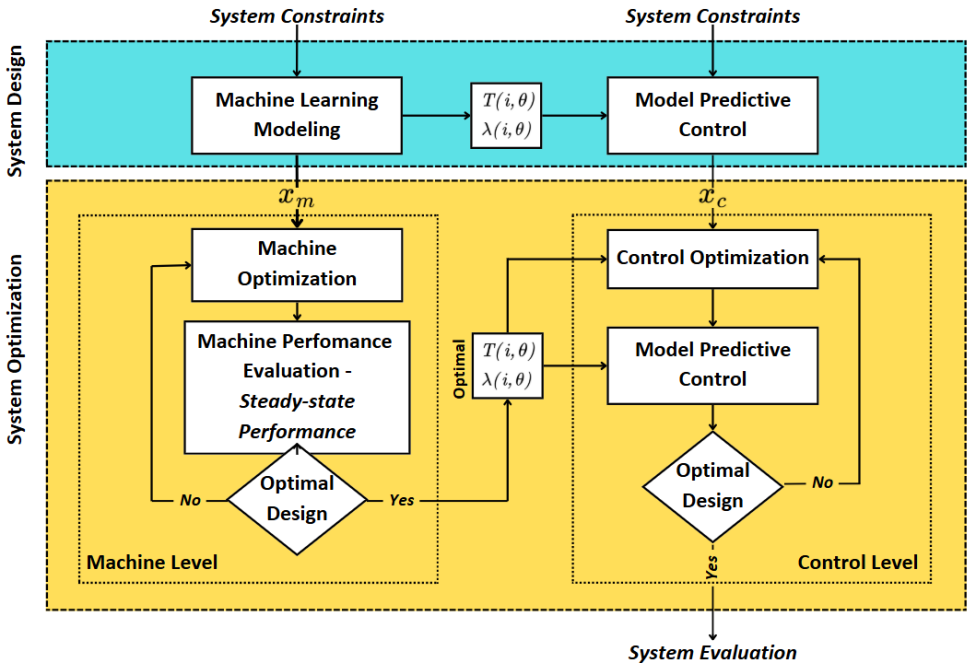


Figure 13. Implementation of ML-MPC in multilevel system-level design optimization.

5. Future Directions in Research

5.1. Integration of Robustness in System-Level Design Optimization

The effects of laser cutting or punching during manufacturing and assembly lead to material degradation in the machine, particularly in areas with sharp edges such as stator and rotor poles. This shape distortion impacts key parameters, like torque ripple, efficiency, and losses [80,81]. In general, manufacturing imperfections should be accounted for during the design phase, especially in drive system design for specific applications like EVs, wind power generation and aeronautical applications, as they also influence controller performance. The robust-oriented approach follows this line of thinking and incorporates these considerations into the design process by minimizing the sensitivity to parameter variations, thereby ensuring that such deviations do not affect the smooth operation of the machine. This is also illustrated schematically in Figure 14, where a minor manufacturing deviation in the deterministic solution results in a significant impact on the outcome, as indicated by Δ_{f1}. In contrast, the robust solution exhibits smaller deviations, which can ensure the reliable operation of the system.

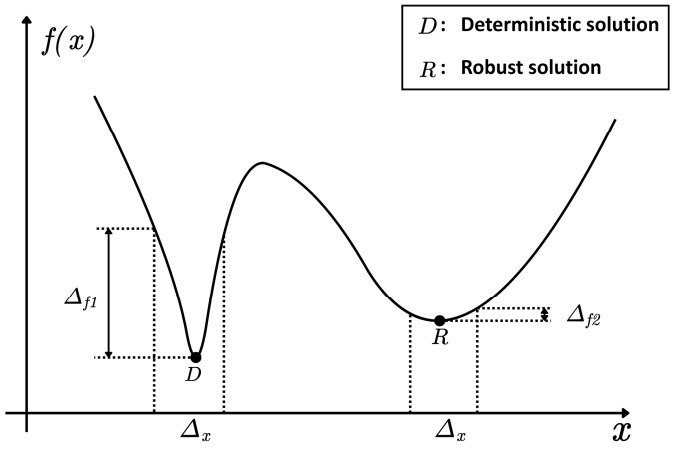


Figure 14. Deterministic and robust solutions in the optimization problem.

Reference [65] is a study that follows up on previous research by integrating the concept of robustness into the SLDOM. The authors introduce the Design for Six Sigma (DFSS) approach to avoid solutions derived from a purely deterministic algorithm, which could lead to high-risk designs for engineers due to higher number of defections and Probability of Failure (POF), influenced by the sensitivity to variations. While the results are slightly inferior to those obtained using a deterministic approach, as can be seen in Figure 14, they exhibit greater robustness and stability. Although this study may not specifically address SRM drive systems, it highlights the significance of system-level optimization in conjunction with the SSOM and its potential implementation in SRM drives.

References [61,62] utilized the Taguchi method for this purpose. In [82] a modification of the Taguchi method is presented for integration into System-Level optimization. This novel System-Level Sequential Taguchi Method (SLSTM) aims to achieve robust optimization of the entire drive by selecting a set of design parameters for both the controller and the machine, using sensitivity analysis and evaluating them through the Signal-to-Noise (S/N) ratio to ascertain robustness. The Taguchi method optimizes this set of parameters, and after just three iterations, the target is achieved. Finally, an analysis of the Component-Level Sequential Taguchi Method (CLSTM) is performed, comparing it with SLSTM. The results indicate that SLSTM outperforms CLSTM in terms of torque ripple, torque, and losses. Similar results are presented in [83]. The authors of this paper anticipate that this method will gain widespread adoption in the future, as SRM drive research continues to

advance and finds industrial applications—particularly in EVs and small electric bikes, where robustness and reliability from a manufacturing standpoint are critical.

5.2. Noise and Vibration Improvement Through System-Level Design Optimization

Noise and vibration are inherent drawbacks of SRMs due to radial electromagnetic forces, which should be minimized as much as possible [84]. The traditional approach to addressing these issues is through the optimization of the machine geometry and the reduction in pole saliency. In [85], there has been an effort to reduce these issues by modifying the geometry of the stator poles, introducing bridges between the poles to reduce the saliency ratio. Similarly, the stator pole bridge design in this study resulted in a 12.52 dBA noise reduction and shifted resonant frequencies, reducing vibration acceleration from 100 m/s^2 to 59.82 m/s^2. Unlike active control strategies, which require real-time sensors, controllers, and energy, this passive solution is robust and energy-free, offering consistent noise and vibration improvements across a wide operational range. For EVs and HEVs, electromagnetic noise in powertrains is particularly noticeable due to a phenomenon known as whistling, which stems from the interactions between the stator and rotor poles across the airgap [86]. In SRMs, this phenomenon is further amplified due to the high saliency of the poles, which intensifies the interactions in the airgap. As a result, noise mitigation becomes critically important for applications in EVs and HEVs, where noise mitigation is a key design constraint.

On the other hand, one form of noise generation is the power electronics from the converter, through which noise is introduced by their switching frequency when there is a PWM technique employed and, often, by design failures. Therefore, they should be designed with the aim of reducing interference and noise in the machine. Several control strategies have been proposed and implemented to mitigate this issue, however there is usually a trade-off between minimizing noise and maintaining high efficiency along with average torque [87]. For instance, in [87], the authors present several NVH mitigation techniques based on the power electronic control Random Hysteresis Band (RHB) and RHB with Spectrum Shaping (RHB-SS). All methods demonstrated a reduction in acoustic noise, with RHB and RHB-SS proving the most effective, achieving a 13–15% decrease relative to the baseline. However, due to the inherent characteristics of high-rotor pole SRM, notably their pronounced saliency, these machines are particularly prone to noise and vibration generation. As a result, the observed reductions may not represent the near-optimal achievable mitigation in this SRM configuration.

Efforts to mitigate Noise, Vibration, and Harshness (NVH) at the component level can often result in negative effects on other parameters, such as efficiency, or fail to achieve sufficient noise reduction, since NVH is influenced by both the machine and the controller. The use of SLDOM could address this issue by optimizing the entire system while setting NVH-related parameters as optimization targets, like mitigating radial forces or optimizing phase commutation timing through the control strategy. This holistic approach allows for the simultaneous optimization of all potential noise sources, both mechanical and electrical, leading to a more comprehensive and effective noise and vibration reduction strategy, especially for transportation applications.

6. Conclusions

This article provides a comprehensive overview of the System-Level Design Optimization Method (SLDOM) and the methodologies employed for its implementation. It introduces two principal optimization approaches—Single-Level Optimization Method (SLOM) and Multi-Level Optimization Method (MLOM)—and presents a classification of the relevant studies. Due to the computational burden associated with FEM-based

optimization, the paper highlights techniques for search space reduction, primarily through the use of surrogate models and a parameter criticality assessment. Furthermore, the paper reviews studies that employed the SLDOM in conjunction with model complexity reduction strategies, such as Kriging models, response surface methods, and artificial neural networks. These approaches have been shown to significantly decrease computational time compared with purely FEM-based procedures.

Despite the advantages of the SLDOM, including the simultaneous optimization of both machine and controller, as well as the consideration of their interdependencies, its application remains limited, particularly regarding the optimization of control strategies beyond current switching angles. This limited adoption is attributed to the multiphysics nature of SRM drives, which substantially increase the computational complexity when coupled with the controller. In response, the article puts forward an integrated approach to the SLDOM that leverages Machine Learning (ML) and Model Predictive Control (MPC) to accelerate the optimization process and enhance control effectiveness. The identified state-of-the-art methodologies show promise for more practical implementation through their holistic evaluation under the SLDOM paradigm. The identified research directions focus on incorporating robustness into the design process and mitigating noise and vibration. These two aspects address inherent challenges that significantly affect Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs). By tackling these critical issues, the proposed methodology could lead to a substantial increase in the broader adoption of SRMs in EV and HEV applications, as well as in other sectors such as aerospace and wind power generation.

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