

Review

A Review of Core-Loss Modeling in Electrical Machines Under Complex and Rotational Magnetization Conditions

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Abstract

Accurate core-loss prediction in electrical machines is difficult when local magnetic flux follows elliptical, circular, irregular, harmonic-rich, or three-dimensional trajectories. This structured review examines empirical and loss-separation formulations, vector and hysteresis models, flux-locus methods, finite-element (FE)-assisted workflows, analytical and magnetic-network field solvers, reduced-order control models, and machine learning (ML) extensions. The literature is compared using common engineering criteria: required material data and parameters, applicable excitation and material conditions, reported error, computational burden, rotational-field capability, and suitability for machine-level design or control. The evidence shows that scalar alternating-field models remain useful for rapid estimation, but their reliability deteriorates under strong rotationality, minor loops, DC bias, saturation, and pulse-width-modulated excitation. Vector and hysteresis models offer stronger physical fidelity but require richer data and substantially greater calibration and computational effort. Recent reduced-order and data-driven approaches can accelerate FE-level prediction; however, their validity is limited to the training or calibration domain. The review therefore recommends a layered framework in which vector-field extraction and flux-locus classification select an appropriate physics-based baseline, while ML is used for residual correction, surrogate prediction, and uncertainty estimation. Priority research needs include standardized multidimensional datasets, anisotropic and grain-oriented material models, transparent quantitative benchmarks, and loss-aware models suitable for optimization and control.

Keywords: core loss; rotational core loss; flux locus; complex magnetization; hysteresis model; finite-element analysis; electrical machines; machine learning (ML); physics-ML modeling



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1. Introduction

Core loss is a fundamental loss component in electrical machines and remains one of the major determinants of efficiency, temperature rise, power density, and reliability. Although copper loss is often dominant at rated load, the share of iron loss becomes increasingly important in high-speed, high-frequency, high-efficiency, and inverter-fed drives, where local magnetization states are strongly time-varying and spatially nonuniform [1–6]. In rotating electrical machines, the local flux density in teeth, tooth roots, yokes, corners, and bridge regions may deviate significantly from the one-dimensional (1D) alternating magnetization assumed in most conventional loss formulas [7–15]. Consequently, high-fidelity

iron-loss evaluation is no longer a secondary correction but a central part of electromagnetic and thermal design.

Historically, iron-loss prediction in electrical machines was based on scalar empirical equations derived from 1D alternating-field measurements, most notably the Steinmetz family and later the loss-separation formulations associated with hysteresis, classical eddy-current, and excess-loss components [1,5,16–23]. These models remain attractive because of their low computational cost, ease of parameterization, and compatibility with the design data normally supplied by steel manufacturers. However, the main limitation of these formulations is not merely numerical accuracy; it is that they reduce a multidimensional vector magnetization process to a small set of scalar descriptors, such as frequency and peak flux density. This simplification becomes increasingly inadequate when local flux trajectories are elliptical, circular, or irregular, or when significant harmonics and DC-bias effects are present [2,3,6,15,24,25].

A second development line concerns rotational magnetization. Work on rotational power loss predates many modern machine models and can be traced back to very early measurements of rotating fields in ferromagnetic materials [26,27]. Later studies clarified that rotational loss does not scale in a trivial way from alternating loss, and that the relationship depends on flux-density level, frequency, material class, saturation state, and the geometry of the flux locus [2,9,28–32]. These insights are important because real machine cores are vector-field environments: the flux density at a point is a function of both time and a two-dimensional (2D) or three-dimensional (3D) trajectory. This is particularly evident in electrical machines with 3D magnetic flux paths, such as claw-pole and transverse-flux machines [7–15].

A third development line is the increasing use of finite-element (FE)-assisted post-processing. Time-stepping FE analysis allows the extraction of local magnetic field waveforms, harmonic content, phase relationships, and flux loci. These local descriptors can then be processed using empirical, semi-empirical, or hysteresis-based models to estimate regional and total core loss [5–8,13–16,24,33,34]. This strategy does not remove the need for material modeling; rather, it creates an interface between machine-level field computation and material-level loss description. As a result, modern iron-loss analysis has become a layered problem involving materials characterization, vector magnetization modeling, harmonic representation, and numerical integration.

An additional driver for more rigorous iron-loss analysis is the broader shift toward integrated multiphysics design. In contemporary electrical-machine development, electromagnetic performance is optimized alongside thermal, mechanical, acoustic, and manufacturability constraints. Because iron loss is both a source term in the thermal problem and a proxy for magnetic overloading, any significant modeling error propagates into neighboring disciplines. For example, underestimated tooth-root loss may lead to an underestimated hot-spot temperature, which in turn affects winding aging, insulation-class margins, and magnet temperature predictions. This systems view has strengthened the role of iron-loss modeling in machine development far beyond traditional efficiency calculation alone [5,6,16,24,25,33–37].

As illustrated in Figure 1, the evolution of core-loss modeling in electrical machines shows a transition from conventional alternating-field empirical formulations toward more advanced approaches capable of addressing rotational magnetization, complex flux loci, multidimensional magnetic excitation, and FE-assisted evaluation. The revised five-stage roadmap also makes explicit the emerging transition from high-fidelity physics to reduced-order and physics-ML acceleration.

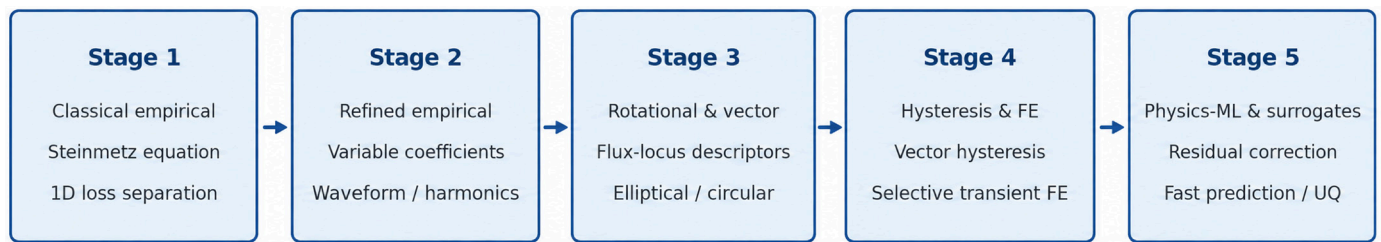


Figure 1. Five-stage evolution of core-loss modeling in electrical machines, from classical empirical and waveform-refined models to rotational/vector descriptions, hysteresis- and FE-assisted analysis, and physics-ML or surrogate acceleration.

Machine learning (ML) is also becoming an important complementary direction for iron-loss modeling. Its relevance is not that it replaces electromagnetic theory, but that it can learn nonlinear corrections, accelerate FE-based workflows, and connect flux-locus descriptors with design-oriented prediction. In the present review, ML is therefore treated as a future-oriented extension of empirical, hysteresis-based, vector, and FE-assisted modeling routes.

Accordingly, this paper provides a structured review of core-loss modeling under complex and rotational magnetization conditions. Rather than treating a small set of papers as the complete evidence base, representative benchmark studies are used to illustrate the development of each model family and are interpreted within a broader body of literature. The comparison is organized around a common machine-oriented question: what field information, material data, parameters, computational effort, and validation evidence are required before a model can be trusted for a given material, excitation waveform, and design task?

The remainder of this paper is organized as follows. Section 2 defines the review methodology and scope. Section 3 explains the engineering importance and physical difficulty of complex and rotational magnetization. Section 4 reviews the main modeling families and integrates recent analytical, magnetic-network, reduced-order, and material-characterization developments. Section 5 compares their accuracy, data requirements, engineering usability, and recent quantitative evidence. Section 6 focuses on ML methods for rotational-loss prediction and physics-guided acceleration. Section 7 concludes the paper and identifies priority research directions.

2. Review Methodology and Scope

This article is a structured technical review rather than a formal meta-analysis. The search framework targeted IEEE Xplore, Scopus, Web of Science, ScienceDirect, and publisher databases, using combinations of “core loss” or “iron loss” with “electrical machine”, “rotational magnetization”, “vector magnetic property”, “flux locus”, “hysteresis”, “finite element”, “magnetic network”, “subdomain”, “grain-oriented steel”, “soft magnetic composite”, “machine learning”, and “control-oriented model”. The principal publication window was January 2019 to August 2026 so that recent developments were emphasized; earlier publications were retained when they introduced a foundational equation, measurement method, or rotational-loss concept that remains in current use.

Studies were included when they (i) proposed, evaluated, or reviewed a core-loss model; (ii) supplied material-level or machine-level evidence relevant to complex excitation; or (iii) provided a field-solution, reduced-order, or data-driven method that could be coupled directly to loss evaluation. Papers concerned only with electromagnetic performance, control, or material processing were excluded from the core comparison unless they clarified how operating trajectories, anisotropy, manufacturing, or computational speed affect loss-oriented modeling. The included evidence was classified by model family

and then extracted against a common set of fields: material or machine, magnetization condition, input data, parameter burden, frequency, and flux-density range when reported, validation level, reported error, and computational information.

Because the reviewed studies employ different materials, excitation waveforms, operating envelopes, reference measurements, and accuracy metrics, their numerical errors are not directly comparable. “Not reported” in the comparison tables means that the cited publication did not provide a transferable value for that field, not that the model was unvalidated. This distinction prevents a low error obtained inside a narrow calibration domain from being interpreted as universal superiority. The overall identification, screening, classification, and evidence-extraction process is summarized in Figure 2.

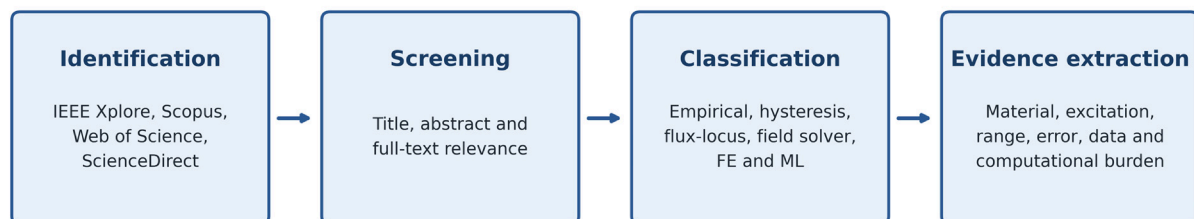


Figure 2. Structured review workflow used to define the evidence base, classify model families, and extract comparable engineering information.

3. Importance of Core Loss and the Problem of Rotational Core-Loss Modeling

3.1. Importance of Core Loss in Modern Electrical Machines

From an engineering perspective, the importance of core loss is reflected in at least four aspects: energy efficiency, temperature rise, optimization constraints, and reliability. In many high-performance drives, particularly those used in electric vehicles, aerospace, compressors, and high-speed industrial spindles, iron loss contributes significantly to the total loss budget and may be the dominant loss under light-load or high-speed operation [4–6,16,24,25,33]. Even when the average total core loss appears moderate, its local distribution may be highly nonuniform. This matters because hot spots driven by high local loss density often determine insulation stress, thermal aging, demagnetization risk in permanent-magnet (PM) machines, and the calibration of cooling systems [5,16,25,33].

The growing role of inverters further strengthens the need for accurate iron-loss modeling. Pulse width modulation (PWM) excitation produces voltage and current harmonics, as well as local magnetic waveforms, that are not well represented by single-frequency sinusoidal assumptions [4–6,16,17,24,38–45]. High-frequency harmonics can significantly increase eddy-current and excess losses, while DC bias or local saturation can alter the effective magnetization path. Therefore, machine designers increasingly need core-loss models that remain valid outside the narrow envelope of manufacturer loss charts.

Another reason iron loss matters is that it directly affects the interpretation of machine tests. Back-to-back efficiency testing, input–output loss separation, and no-load parameter extraction often rely on assumptions regarding iron loss and its variation with voltage, frequency, and temperature. If the assumed loss law is poor, not only is the iron-loss estimate wrong, but the inferred copper loss, mechanical loss, or equivalent-circuit parameters may also be biased. This issue is especially important when comparing machine prototypes built from different steels, or when one prototype is measured under sinusoidal supply and another under inverter supply. Thus, iron loss is both a physical quantity and an identification quantity in machine engineering.

3.2. Conventional Alternating-Field Models

A classical starting point is the empirical Steinmetz equation, introduced for sinusoidal alternating magnetization and subsequently generalized in numerous engineering formulations [1,40–43]:

$$P_v = k f^\alpha B_m^\beta \quad (1)$$

where P_v is the specific loss, f is the excitation frequency, B_m is the peak magnetic flux density, and k , α , and β are material-dependent coefficients. Equation (1) is attractive because of its simplicity and low computational cost. However, it fundamentally describes loss as a scalar function of frequency and peak flux density only. It does not explicitly account for waveform distortion, multidirectional magnetization, or changes in flux-locus shape. Therefore, although it remains useful for preliminary estimation under regular alternating-field conditions, its applicability becomes limited in modern machines where local magnetic behavior is considerably more complex.

Following Bertotti's statistical loss-separation framework [18,20–23,31], the total specific core loss is commonly decomposed into hysteresis, classical eddy-current, and excess components:

$$P_v = P_h + P_c + P_e \quad (2)$$

where P_h , P_c , and P_e denote hysteresis loss, classical eddy-current loss, and excess loss, respectively. In engineering practice, Equation (2) is often expressed in a fitted form such as

$$P_v = k_h f B_m^\alpha + k_c f^2 B_m^2 + k_e f^{1.5} B_m^{1.5} \quad (3)$$

where k_h , k_c , and k_e are fitting coefficients associated with the three components. Equations (2) and (3) improve the description of loss mechanisms and remain widely used in engineering-oriented loss evaluation. Even so, they still rely primarily on scalar quantities and therefore do not fully resolve the limitations associated with rotational magnetization and complex flux trajectories.

For one-dimensional nonsinusoidal excitation, generalized and improved Steinmetz formulations evaluate loss from the time-domain waveform [40–43]. The representative form is:

$$P_v = \left(\frac{1}{T} \right) \int_0^T k \left| \frac{dB}{dt} \right|^\mu (\Delta B)^{\nu-\mu} dt \quad (4)$$

where T is the excitation period, ΔB is the flux-density swing, and μ and ν are fitting exponents. Compared with Equation (1), Equation (4) better reflects the influence of waveform distortion and time-varying magnetization processes. Nevertheless, it is still generally formulated for 1D magnetization and does not directly address rotational magnetic behavior.

In practical machine analysis, the main difficulty is not that Equations (1)–(4) are mathematically simple, but that the machine field is not. A point in the stator yoke may experience a flux waveform with multiple harmonics, while a point at the tooth root may experience a rotating ellipse with changing eccentricity across load and speed. Thus, one must ask whether it is acceptable to reduce such behavior to a single B_m or a small number of harmonic amplitudes. The answer depends on the required fidelity. For rough efficiency prediction, yes; for local hot-spot prediction, often no.

3.3. Significance of Rotational Magnetization

Rotational core loss deserves particular attention because the magnetic field inside real electrical machines is fundamentally a vector field, not a simple scalar field. Under

rotational magnetization, a scalar peak value alone cannot describe the local magnetic state. In 2D analysis, the local magnetic flux density can be written as

$$\mathbf{B}(t) = B_x(t)\mathbf{i} + B_y(t)\mathbf{j} \quad (5)$$

where $B_x(t)$ and $B_y(t)$ are the orthogonal components of the magnetic flux-density vector. For a typical elliptical rotating field, these components may be expressed as

$$B_x(t) = B_{maj}\cos(\omega t), \quad B_y(t) = B_{min}\sin(\omega t) \quad (6)$$

and the axis ratio is defined by

$$\lambda = \frac{B_{min}}{B_{maj}} \quad (7)$$

When $\lambda = 0$, the magnetization reduces to a purely alternating case, whereas $\lambda = 1$ corresponds to circular rotation.

The significance of Equation (7) is not only geometric. It quantifies the degree to which the material is forced to change direction, not merely magnitude. Since dissipation in magnetic materials is linked to path-dependent irreversible processes, different values of λ can correspond to qualitatively different loss behavior even when the peak induction is the same. This is why Figure 3 is so central to the present review: it visually summarizes a problem that scalar formulas conceal.

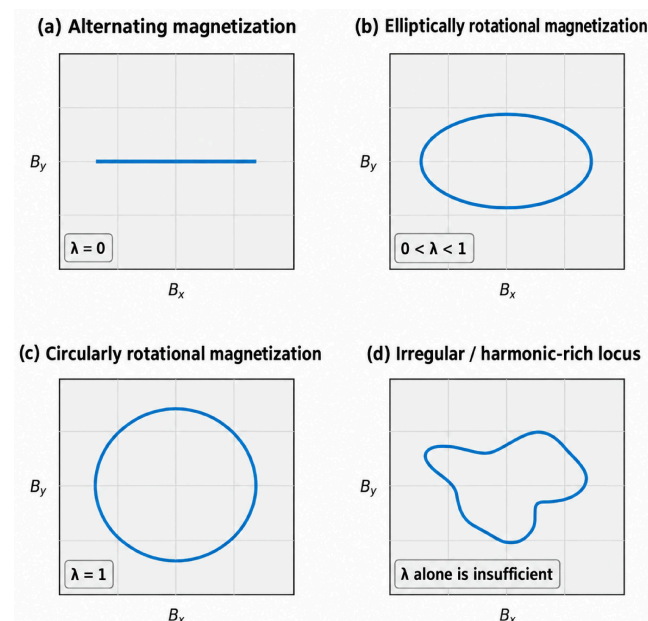


Figure 3. Typical local magnetic flux loci encountered in machine cores: alternating ($\lambda = 0$), elliptically rotational ($0 < \lambda < 1$), circularly rotational ($\lambda = 1$), and irregular harmonic-rich trajectories for which λ alone is not a sufficient descriptor.

In many machine structures, rotational magnetization is not an occasional local phenomenon but a common feature. For example, in brushless doubly fed machines (BDFMs), the coexistence of two stator windings and different pole-pair couplings leads to more complex spatial magnetic-field distributions, making core-loss prediction more challenging than in conventional machines. In induction machines and permanent-magnet machines, clear elliptical loci or rotational magnetization may also appear in tooth roots, yokes, and locally saturated regions. In soft magnetic composite (SMC)-based and claw-pole machines, non-planar 3D magnetization can also occur [8–14].

3.4. Why the Rotational Problem Is Difficult

Rotational-core-loss modeling is challenging because it is simultaneously a measurement, modeling, and calculation problem. Unlike conventional alternating-field loss estimation, rotational loss cannot be described reliably using only frequency and peak flux density. The material response depends on the vectorial evolution of the magnetic field, including its magnitude, direction, phase relationship, flux-locus shape, local saturation, and harmonic distortion. This means that both the experimental data and the modeling framework must be sufficiently rich to represent the effect of rotational magnetic fields. In practice, however, available rotational-loss data remain very limited compared with standard alternating-loss data, which makes accurate machine-level prediction more difficult.

3.4.1. Measurement Challenges in Rotational Magnetic Characterization

The first difficulty lies in measurement. Conventional magnetic-material loss data are usually obtained from Epstein frames, ring specimens, or single-sheet testers under 1D alternating magnetization. These methods are useful for characterizing standard material behavior, but they are insufficient for rotational magnetization, in which both the orthogonal components of magnetic flux density and magnetic field strength must be measured or reconstructed. A rotational magnetic measurement system must therefore control and record vector quantities such as (B_x) , (B_y) , (H_x) , and (H_y) , while also maintaining accurate phase relationships between the two axes [2,3,9–11,31,32].

This requirement makes the experimental system more complex than a conventional alternating-loss tester. Small errors in sensor alignment, phase control, excitation waveform, or sample preparation may lead to noticeable differences in the reconstructed flux locus and the calculated loss. In addition, different laboratories may use different specimen geometries, excitation methods, feedback control strategies, and post-processing procedures. As a result, rotational-loss datasets are often less standardized and less widely available than conventional alternating-loss datasets.

The limited availability of reliable vector magnetic data is a major obstacle for model development. Many practical models must still rely on data measured under alternating magnetization and then apply empirical correction factors to account for rotational effects. This can improve engineering usability, but it also limits the model's physical reliability when applied to complex machine regions. Therefore, more accurate consideration of rotational magnetic fields first requires better measurement datasets that cover different materials, frequencies, flux-density levels, axis ratios, saturation states, and waveform conditions.

3.4.2. Modeling Challenges in Rotational Magnetic Characterization

The second difficulty is the modeling problem. Under alternating magnetization, the loss can often be approximated as a function of frequency and peak flux density. Under rotational magnetization, however, the local magnetic state is no longer defined by a single scalar value. The loss may depend on the major-axis flux density, minor-axis flux density, axis ratio, rotation direction, harmonic content, local saturation, DC bias, and temperature [3,5,6,9,14–16,24,33,41]. This makes the model structure much more difficult to define.

A simple empirical correction can introduce the effect of rotationality through a parameter such as the flux-locus axis ratio. However, this does not fully capture irregular or harmonic-rich trajectories. For example, two flux loci may have similar values of λ , but one may be a smooth elliptically rotational locus while the other may contain strong harmonic distortion. These two cases may not produce the same loss. Therefore, the axis ratio alone is useful but not sufficient for all complex magnetization conditions.

Hysteresis-based models provide a more physically meaningful way to describe path-dependent magnetization because they can account for the history of the magnetic state, and not only its peak value. However, these models usually require more parameters, more experimental data, and more careful calibration. Their extension from 1D to vector or rotational magnetization is also nontrivial. The model must describe not only the magnitude of magnetization but also the directional change in the magnetic field. Therefore, the core challenge is to develop a model that is physically meaningful enough to represent rotational effects yet simple enough for practical machine analysis.

3.4.3. Computation Challenges in Rotational Magnetic Characterization

The third difficulty is the calculation problem. Even if a suitable rotational-loss model is available, applying it inside an electrical-machine simulation is computationally demanding. In FE analysis, the magnetic flux density varies from element to element and from time step to time step. A high-fidelity rotational or hysteresis-based model would need to evaluate the local magnetic history for a large number of elements over many time steps. This can significantly increase computational cost, especially in transient simulations and design optimization.

This problem becomes more serious when harmonic excitation, PWM supply, or multiphysics coupling is considered. For example, inverter-fed machines may require small time steps to resolve high-frequency harmonics, while thermal- or stress-dependent loss models may require additional coupling between electromagnetic, thermal, and mechanical fields. If the loss model is too complex, it may be accurate for a single operating point but impractical for full efficiency-map calculation or repeated optimization loops.

Therefore, an important practical issue is the balance between model fidelity and computational efficiency. A possible solution is to use a layered strategy: a simpler empirical or semi-empirical model can be applied during early-stage design and large-scale optimization, while more advanced rotational or hysteresis-based models can be reserved for critical regions or final validation. This approach allows the effect of rotational magnetic fields to be considered more accurately without making the entire simulation workflow computationally prohibitive.

3.5. Additional Practical Factors: Temperature, Stress, and Manufacturing

Beyond excitation topology, machine iron loss is affected by temperature, material grade, cutting and punching damage, residual stress, stacking, bonding, and local mechanical loading [4–6,16,25,34–37,46,47]. These effects are often simplified or neglected in academic loss models but can be material in real products. For example, punching deterioration can increase local loss in teeth and corners, and axial or circumferential stress can alter both permeability and hysteresis behavior. In high-speed machines, this becomes more severe because electromagnetic, thermal, and structural constraints are strongly coupled [16,24,25,33,35].

Temperature changes not only rescale the total loss. They can alter the relative contributions of hysteresis, classical, and excess loss, modify resistivity and hence eddy-current behavior, and change the shape of minor loops under harmonic excitation. In addition, temperature is itself driven by iron loss, creating a feedback loop. A model that ignores this interaction may be adequate for one operating point but not for a full efficiency map.

3.6. Implications for Equivalent-Circuit and System-Level Modeling

Iron loss is increasingly embedded in equivalent-circuit and control-oriented machine models, no longer confined to FE post-processing. A common reduced-order representation introduces an equivalent core-loss resistance or an iron-loss current in the d-q model; this modifies the voltage balance, electromagnetic torque estimate, current allocation, and

efficiency map. The coefficients must vary with speed, flux level, harmonic content, and temperature for the model to remain valid beyond a single operating point. For real-time control, the central trade-off differs from that in offline FE analysis: the model must be fast and sufficiently differentiable for current reference generation or predictive control, while retaining the dominant dependence of the loss on the local or reconstructed flux trajectory. Loss-minimizing control, MTPA/MTPV operation, pole-transition strategies, and disturbance-rejection controllers can all change current harmonics and the resulting flux locus. Consequently, control papers are relevant here as operating-condition evidence, but they should not be misclassified as material-level rotational-loss models.

Control-oriented studies do not necessarily introduce new core-loss constitutive laws, but they define the dynamic operating trajectories that a useful loss model must follow. The optimal pole-transition current distribution reported for variable-pole machines maintains torque while minimizing stator copper loss [48], and adaptive fixed-time PMSM control improves current and speed tracking under parameter mismatch and unknown disturbances [49]. These studies are cited as examples of rapidly changing current trajectories and model uncertainty, not as rotational core-loss models. Their relevance is that current reallocation, transition transients, disturbance compensation, and switching behavior alter harmonic content and local flux loci. A loss-aware controller, therefore, needs either a fast equivalent loss model, a calibrated LUT, or a differentiable surrogate validated over the transient region, not only at steady-state sinusoidal points.

3.7. Why Review-Based Comparison Is Needed

The literature contains numerous iron-loss models, but comparisons between them are often difficult because authors use different materials, test methods, machines, frequencies, and validation procedures. Some models are validated at the material level, others at the machine level; some include temperature or PWM effects, while others focus on rotational magnetization alone. Consequently, the practical question for a machine designer is rarely ‘which model is theoretically the best?’ but rather ‘which model is sufficiently accurate for my machine, data availability, and computational budget?’ This review perspective is therefore valuable because it emphasizes model selection criteria as much as model derivation.

4. Major Modeling Approaches

Representative benchmark studies are summarized in Table 1. They illustrate major development routes from flux-locus and three-dimensional material characterization to hysteresis-assisted and machine-level rotational-loss formulations. The table is not intended as the complete evidence base; recent analytical, reduced-order, magnetic-network, material, and ML studies are integrated into the relevant subsections below and into Sections 5 and 6.

Table 1. Representative benchmark studies for complex and rotational core-loss modeling.

Ref.	Machine/Material	Magnetization Condition	Method	Main Contribution	Main Limitation
[7]	PM motor	Alternating + rotational loci	Flux variation locus + FEM	Introduced locus-based regional loss calculation	Depends on fitted empirical coefficients
[8]	SMC machines	3D excitation	3D FE + loss integration	Extended loss calculation to SMC machine cores	Material data requirements are high
[9]	Soft magnetic materials	Rotational magnetization	Review of measurement and modeling	Established rotational-loss review baseline	Focused more on materials than whole-machine implementation

Table 1. Cont.

Ref.	Machine/Material	Magnetization Condition	Method	Main Contribution	Main Limitation
[13]	BDFM	Rotational + hysteresis	Preisach-assisted iron-loss model	Combined hysteresis and field rotation in BDFM loss prediction	Model complexity and calibration burden
[14]	BDFM	Rotational fields	FE-based rotational iron-loss analysis	Highlighted rotational fields in BDFMs	Limited to a specific machine family
[15]	Induction machines	Alternating + elliptical rotation	Variable-coefficient + elliptical loss model	Improved machine-level accuracy for IMs	Still semi-empirical

4.1. Improved Empirical Models

One major approach is to improve traditional empirical loss equations to better suit high-frequency, harmonic-rich, and rotational-field conditions. In many engineering-oriented formulations, the total local loss under complex magnetization is decomposed into an alternating component and an additional rotational component, as follows:

$$P_v = P_{alt} + P_{rot} \quad (8)$$

where P_{alt} is the alternating-field core-loss component and P_{rot} is the extra loss associated with rotational magnetization. A practical way to include rotational effects is to introduce a correction factor related to the axis ratio of the flux locus [10,16]:

$$P_v = P_{alt}(1 + c_r \lambda^n) \quad (9)$$

where c_r and n are fitting parameters, and λ is the axis ratio defined in Equation (7). For elliptical rotating fields, another useful approximation is to consider the contributions of the major and minor axes separately [8,15],

$$P_{ellip} = P_{maj} + \eta(\lambda)P_{min} \quad (10)$$

where P_{maj} and P_{min} are the losses associated with the major- and minor-axis magnetization components and $\eta(\lambda)$ is a weighting factor related to the locus geometry.

These improved empirical methods retain the simplicity of conventional loss equations while introducing additional terms or corrections to better handle rotational effects. Their main advantages are high computational efficiency and relative ease of implementation, which make them suitable for design-oriented analysis and FE post-processing. However, they remain fundamentally based on fitted relationships and therefore have limited physical interpretability when the magnetization state becomes strongly path-dependent or highly irregular.

The selected induction-machine paper [15] is a good example of this philosophy. It refines the classical alternating model by introducing variable coefficients and then extends the formulation to an elliptical model guided by the flux-locus shape. In engineering terms, this is attractive because it adds just enough complexity to capture a neglected physical effect without incurring the full burden of a multidimensional hysteresis solver. Many successful machine loss studies use this kind of middle-ground approach.

4.2. Hysteresis-Based Modeling

Another important approach is to model loss through hysteresis operators and vector energy dissipation [13,27,38,39,50–56]. For a closed scalar B-H loop, the energy dissipated per cycle is the loop integral; multiplying by frequency gives the hysteresis power loss:

$$P_h = \oint H dB \quad (11)$$

where the closed-loop integral represents the hysteresis-loop area. Under rotational magnetization, a more general vector form may be used:

$$P_h = \left(\frac{1}{T} \right) \int_0^T \mathbf{H}(t) \cdot \frac{d\mathbf{B}(t)}{dt} dt \quad (12)$$

where $\mathbf{H}(t)$ and $\mathbf{B}(t)$ are the magnetic-field-strength and flux-density vectors, respectively. This vector energy expression is meaningful only when $\mathbf{H}$ and $\mathbf{B}$ follow the same physical material trajectory and the sign convention is applied consistently. A general dynamic hysteresis relation may then be written as

$$\frac{dM}{dt} = F(H, M, \dot{H}) \quad (13)$$

where M is the magnetization, H is the magnetic field strength, $\dot{H} = dH/dt$ denotes its time derivative, and $F(\cdot)$ is a model-dependent nonlinear function.

Within this category, Preisach and Jiles–Atherton models are especially influential. Preisach-type models are attractive because of their flexibility in reproducing history-dependent hysteresis loops and minor-loop behavior; Jiles–Atherton models are attractive because their parameters can be linked, at least qualitatively, to material mechanisms such as pinning and reversible/irreversible magnetization [27,38,39,50–55]. In machine applications, these models have been coupled with FE field solutions to estimate local hysteresis loss and improve physical interpretability, as highlighted by the selected BDFM work.

The key strength of hysteresis-based approaches is not merely that they are more physical; rather, they are structurally compatible with path dependence. This matters in rotational and distorted-field cases, where the energy dissipated depends on the path taken in state space, not just on peak values. The corresponding weakness is computational. Parameter identification is usually demanding, multidimensional calibration data are expensive to obtain, and FE coupling can become prohibitive in optimization loops. Therefore, hysteresis-based models are highly valuable for analysis and validation, but they are not automatically the best option for rapid design iteration.

4.3. Flux-Locus and Vector Magnetization Approaches

A central theme in modern machine-loss research is that the local flux locus should be treated as a primary descriptor rather than a by-product of FE simulation. A practical scalar reduction is the equivalent flux density

$$B_{eq} = \sqrt{\frac{1}{T} \int_0^T (B_x^2(t) + B_y^2(t)) dt} \quad (14)$$

which maps a vector trajectory to a single amplitude-like quantity. Although useful, such a reduction inevitably discards information. A richer geometric measure is the enclosed locus area

$$A_{locus} = \oint B_y dB_x \quad (15)$$

which for an ideal ellipse becomes

$$A_{locus} = \pi B_{maj} B_{min} \quad (16)$$

The locus area is related to rotationality and is especially useful when comparing alternating, elliptical, and circular magnetization states.

The flux-variation-locus approach developed for PM motors is influential because it directly links machine-field analysis to region-specific loss modeling. Instead of assuming that a single formula applies everywhere, the method recognizes that different locations may exhibit nearly alternating flux, elliptical rotation, or harmonic-rich, irregular loci. This insight is particularly important for tooth shoulders, yoke corners, and locally saturated regions. Similar ideas extend naturally to SMC machines and 3D-flux topologies, where vector magnetization may not even lie in a single plane [7–12]. The resulting machine-level workflow—from field solution to local flux extraction, locus identification, model selection, and loss integration—is summarized in Figure 4.

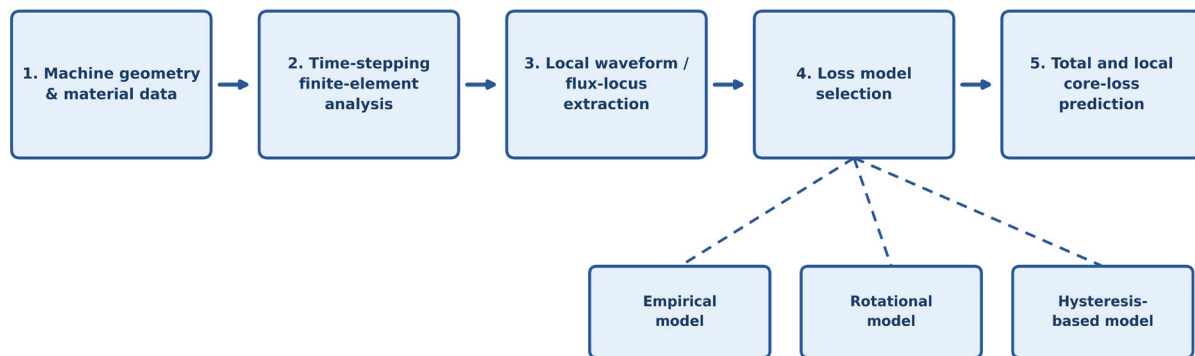


Figure 4. General workflow of FE-assisted core-loss evaluation, including field solution, local flux extraction, locus identification, model selection, and total-loss integration.

An important conceptual advantage of the flux-locus viewpoint is that it separates two questions that are often conflated. The first question is: what is the local magnetization state? The second is: how should loss be computed for that state? Once these questions are separated, one can use the same FE field solution with different material models and thereby study sensitivity to model choice in a more controlled way. This is one reason the locus-based perspective is so useful in review and comparison work.

4.4. FE-Assisted Post-Processing

FE analysis is a major common thread across the selected papers. These studies show that accurate acquisition of local magnetic-field distributions is a prerequisite for high-accuracy core-loss prediction in complex machines. In general, the process begins with time-stepping FE analysis to obtain local flux-density waveforms, phase relationships, and trajectory information. Suitable post-processing models are then applied to calculate local loss densities and total core loss. The generic integration is

$$P_{tot} = \sum_{e=1}^N P_{v,e} V_e \quad (17)$$

where $P_{\{v,e\}}$ is the local volumetric loss density in element e ; V_e is the element volume, and N is the number of elements. For a locally alternating waveform, an engineering harmonic-superposition approximation may be used to evaluate separately identified harmonic components [40–44]:

$$P_{v,e} = \sum_{k=1}^{N_h} \left(k_h f_k B_k^\alpha + k_c f_k^2 B_k^2 + k_e f_k^{1.5} B_k^{1.5} \right) \quad (18)$$

Equation (18) assumes that the loss associated with each harmonic can be evaluated independently using coefficients valid over the relevant frequency and flux-density range. It is most defensible for weakly nonlinear, predominantly alternating waveforms without appreciable DC bias or interacting minor loops. Under strong hysteresis, saturation, PWM-

induced nested loops, DC bias, or genuinely rotational vector excitation, the total loss is generally not equal to the independent sum of harmonic contributions. Time-domain vector hysteresis, waveform-based loss integration, or experimentally calibrated correction should then be preferred. Equation (18) is therefore an engineering approximation rather than a universal superposition law.

More generally, FE-assisted loss evaluation can be viewed as a mapping

$$P_{v,e} = F(B_x(t), B_y(t), f, \lambda, \text{material parameters}) \quad (19)$$

where F encapsulates the chosen empirical, vector, or hysteresis-based material model.

The strength of FE-assisted post-processing is that it provides regional details and enables direct comparison between model classes without changing the field solver. It is therefore particularly well-suited to comparative studies and multiphysics workflows. Its main limitation is that FE analysis alone does not determine the loss: the result depends critically on the constitutive interpretation applied to the local field history. A poor loss model can therefore remain poor even when the field solution is very accurate.

In engineering practice, FE-assisted workflows are also attractive because they support selective refinement. One may use a lower-order loss model in most of the machines and reserve more sophisticated treatment for critical regions such as tooth roots or bridges. This type of adaptive strategy is promising because it aligns model fidelity with engineering importance rather than applying the same computational burden everywhere.

4.5. Analytical, Subdomain, Magnetic-Network, and Reduced-Order Field Solutions

Full transient FE is not the only route for obtaining the local magnetic field required by a loss model. Analytical and subdomain formulations provide rapid field harmonics for regular geometries, whereas equivalent magnetic networks discretize the magnetic circuit into reluctance elements and can retain radial-tangential coupling. A recent two-dimensional generalized equivalent magnetic network for surface-mounted PM machines partitions the yoke, teeth, tooth tips, slots, air gap, magnets, and rotor into reusable network units [57]. Vector magnetic-circuit theory has also been used to couple two-dimensional high-frequency field analysis directly with loss calculation [58]. These approaches can be substantially faster than detailed FE and are attractive for optimization or control, but their loss of accuracy still depends on the embedded material law. Local saturation, slotting, complex leakage, skew, three-dimensional end effects, and irregular flux loci remain the principal limitations. Reduced-order models should therefore be validated against FE and measurement over the intended design and operating domain rather than described as replacements for vector material characterization. For repeated design optimization, flux-locus analysis need not require full element-wise transient FE at every evaluation. A practical hierarchical implementation is to (i) use analytical/subdomain models, magnetic networks, coarse FE, or previously computed field maps to screen for regions likely to exhibit strong rotationality; (ii) perform high-fidelity transient FE only at representative operating points and critical regions such as tooth roots, bridges, and locally saturated zones; and (iii) reuse the resulting locus descriptors through look-up tables or surrogate models during repeated optimization. In this form, flux-locus analysis is a selectively deployed diagnostic rather than a mandatory full-order calculation at every design iteration.

4.6. Measurement and Validation Considerations

No discussion of machine iron-loss modeling is complete without validation. A recurring theme in the literature is that measurement itself is difficult, especially when rotational flux, PWM excitation, temperature variation, and manufacturing deterioration

are present [2–6,9,31,32,56]. Ring specimens, Epstein frames, single-sheet testers, and machine-level calorimetric or loss-separation measurements each provide partial insight, but none serve as a universal standard. This is one reason why different studies often report different levels of agreement, even when the same nominal model family is used.

For review purposes, this point is especially important: the apparent superiority of a model may depend on the validation benchmark. A model tuned to alternating Epstein data may underperform on machine-level tests, while a rotationally corrected model may outperform under specific operating points but lose generality elsewhere. Therefore, high-quality comparative work should ideally combine material- and machine-level measurements with numerical consistency checks.

4.7. Material Dependence, Anisotropy, and Rotational Characterization

The reviewed literature also demonstrates that machine iron-loss modeling is inseparable from material choice. Conventional non-oriented electrical steels, grain-oriented steels, amorphous alloys, ferrites, and SMCs exhibit different hysteresis characteristics, different eddy-current sensitivities, and different responses to rotational excitation [1–3,9–12,17–20]. SMCs are particularly informative in this respect because they enable true 3D flux paths while also introducing different conductivity and loss-separation behavior compared with laminated steels. As a result, the development of SMC-focused models has served as a useful testbed for multidimensional magnetization ideas that are now increasingly relevant to advanced machine topologies.

Material anisotropy requires explicit treatment because a single scalar loss curve cannot represent the rolling, transverse, and intermediate directions of grain-oriented or strongly textured sheet. Recent rotational single-sheet work has measured non-oriented B25AV1300 and grain-oriented B30P100 under alternating, circular, and elliptical excitation and proposed separate one-dimensional angular and two-dimensional rotational-loss models [59]. Together with earlier controlled-locus measurements [60], this evidence shows why “material type” is not a sufficient input: rolling direction, magnetization angle, locus ellipticity, rotation direction, frequency, flux-density level, stress, and temperature can all alter loss. Bidirectional or segmented-core machine designs, therefore, require anisotropic vector data or a direction-dependent surrogate; a coefficient identified from the rolling direction alone should not be applied indiscriminately to transverse or rotating flux. Earlier controlled-locus measurements reported that rotational loss under controlled circular H can reach up to about 2.5 times that under controlled circular B and up to about six times the alternating loss for anisotropic steel [60]. Together with the recent NO/GO steel study [59], in which the one-dimensional relative error was generally below 3%, while the optimized two-dimensional model reduced the reported error to 0.73% compared with 2.11% for the preceding model. These values are study-specific rather than universal, but they demonstrate that anisotropy and locus geometry can materially change the loss estimate.

4.8. Data-Driven Opportunities and Their Limits

Although the core discussion of this paper focuses on physics-based and semi-empirical models, recent trends in electrical-machine research increasingly include data-driven and hybrid surrogate approaches. In principle, machine learning models could map local field histories to local loss densities without requiring explicit analytical decomposition. In practice, however, the success of such approaches still depends on the quality of the training data and on whether the model extrapolates robustly outside the calibration envelope. For this reason, data-driven approaches should presently be regarded as complementary tools rather than replacements for physically interpretable models. They are potentially valuable for reduced-order approximation of expensive FE-assisted or

hysteresis-based models, especially in optimization loops, but their reliability still depends on the same foundational issue emphasized throughout this review: the need for accurate vector magnetization data and careful validation.

5. Comparative Discussion

A comparative overview of the major modeling approaches is provided in Table 2, in which the methods are evaluated with respect to rotational-field capability, physical interpretability, computational cost, FE compatibility, and practical applicability. As shown in the table, no single approach is optimal in all aspects. Instead, different methods offer different trade-offs between accuracy, physical meaning, and engineering efficiency.

Table 2. Comparison of major core-loss modeling approaches.

Approach	Expected Accuracy Within Calibration Domain	Physical Meaning	Computational Cost	FE Compatibility	Typical Use
Classical empirical (Steinmetz)	Low	Low-to-moderate	Very low	Very high	Preliminary estimation
Loss separation/refined empirical	Low-to-moderate	Moderate	Low	Very high	Design iteration, harmonic correction
Alternating + rotational correction	Moderate	Moderate	Low	High	Machine-level rotational-loss estimation
Flux-locus/vector description	High (descriptive)	Moderate	Moderate	High	Region classification, post-processing
Hysteresis-based (Preisach/J-A)	High	High	High	Moderate	Mechanism study, high-fidelity analysis
FE-assisted hybrid workflow	Depends on embedded model	Moderate to high	Moderate to high	Intrinsic	Detailed design and validation

First, in terms of prediction accuracy, when the machine is mainly under regular alternating magnetization conditions, improved empirical models are often sufficient for engineering purposes. However, when local magnetic fields exhibit clear rotational characteristics or highly complex flux trajectories, conventional empirical corrections are usually not enough, and flux-locus analysis, rotational core-loss models, or even hysteresis-based models become necessary. In other words, the more faithfully a model reflects the real magnetization path, the higher its theoretical accuracy tends to be, but also the more difficult it is to implement.

Second, in terms of physical interpretability, hysteresis-based models are clearly superior to purely empirical models. These approaches offer stronger physical grounding by starting from material magnetization behavior, whereas empirical approaches, although very practical in engineering, still rely primarily on fitted corrections. Thus, if the purpose is to understand the mechanism of rotational core loss, physically motivated models are preferable; if the goal is rapid and stable prediction of total machine loss, empirical models and FE-based post-processing remain more practical.

Third, in terms of computational efficiency, empirical models and empirical post-processing methods still have obvious advantages. These methods require relatively few parameters and are easy to implement, making them well-suited to repeated iterations in machine design. Once complex hysteresis-based or higher-dimensional dynamic material models are introduced, computational cost increases rapidly, which becomes a practical obstacle in optimization procedures.

Fourth, in terms of engineering applicability, the FE analysis framework combined with post-processing is the most flexible. This is because it can leverage existing machine-analysis platforms to obtain local magnetic-field information while allowing different loss-model levels to be connected based on the required accuracy. In this sense, it acts as a unified carrier platform: empirical models, rotational-loss models, and hysteresis-based models can all be integrated into it. This is also one of the most common and expandable routes in current engineering research.

5.1. Accuracy Versus Usability

The tension between accuracy and usability is perhaps the single most important theme in the entire field. A model may perform very well against a carefully controlled material-level experiment and still be impractical for design optimization because the required calibration data are unavailable or the computation is too expensive. Conversely, a simple model may be less accurate in absolute terms but far more useful in iterative design because it captures trends correctly and can be evaluated thousands of times. This is why the field has not converged on a single dominant iron-loss model despite decades of study. The evaluation criteria are task-dependent. If the aim is machine ranking, rapid topology selection, or sensitivity analysis, a low-cost refined empirical model may be entirely appropriate. If the aim is thermal hot-spot prediction in a final design, a vector or hysteresis-enhanced model may be necessary.

5.2. The Importance of Validation Hierarchy

Another key comparative issue is the hierarchy of validation. Material-level validation is necessary because machine-level disagreement can otherwise be caused by multiple confounding factors. However, material-level agreement alone is insufficient because the machine environment introduces local harmonics, rotational flux, slotting effects, and manufacturing-induced deterioration. Therefore, the strongest evidence for a model usually comes from a hierarchy: first, validation on material measurements; then, validation on local or component-level data; and finally, validation against complete machine experiments. Models that are validated only at one level should be interpreted with greater caution, especially when proposed for broad engineering use.

5.3. Implications for Design Optimization

From an optimization perspective, the most promising route is often hybridization. A practical strategy is to use a refined empirical or semi-empirical model during large-scale optimization, and then apply a more accurate FE-assisted or hysteresis-based model to the final candidate designs. In this way, computational effort is concentrated where it has the highest value. Such layered use of models is consistent with the broader development of electrical-machine optimization and is likely to become even more important as designers seek to include efficiency maps, thermal constraints, acoustic behavior, and robustness in unified optimization frameworks.

5.4. Quantitative Evidence and Cross-Study Comparison

Recent work has moved in three parallel directions: a broader synthesis of the physical assumptions underlying simplified loss models [61]; faster machine-level representations calibrated from FE and measurements [62]; and data-driven prediction across wide operating conditions [63,64]. Table 3 reports quantitative information only when the cited study provides a transferable value. The entries should not be interpreted as a universal ranking because the materials, waveforms, machines, reference models, and error metrics differ. Additional context is useful for judging when this added complexity matters. Earlier rotational-loss review literature reports that the rotational component

can account for up to roughly 50% of total core loss in some rotating-machine conditions [9], while the literature does not provide a single representative percentage that is transferable across machine classes, materials, speeds, loads, and flux-locus distributions. Many studies validate total core loss without separately reporting a machine-level rotational fraction. In the present comparison, the PMSM study [65] shows deviations from approximately -80% to $+20\%$ over parts of the d-q operating map when empirical approximations are compared with the numerical reference; the reduced-order state-space/LUT study [62] reports approximately $120\times$ acceleration relative to time-stepping FE; and the ANN study [63] reports a minimum MAPE of 2.58%, MAPE below 5%, and 93.33–98.48% of predictions within $\pm 10\%$, depending on material. These examples reinforce that both accuracy and computational benefit must be interpreted within the stated validation domain.

Table 3. Quantitative evidence reported by representative material-, machine-, and data-level studies.

Ref.	Material/System	Excitation or Range	Model/Validation	Reported Quantitative Result	Interpretive Limit
[60]	NO, conventional GO and high-permeability GO steel	10, 50, and 250 Hz; circular B radius 0.5–2.0 T	Rotational single-sheet measurement	Loss under controlled circular H up to $2.5\times$ controlled circular B and up to $6\times$ alternating loss for anisotropic steel	Material-level circular loci; not a machine-level prediction error
[62]	150 kVA and 200 kW synchronous-machine cases	Sinusoidal and PWM supplies; operating-domain LUT	FE-derived state-space/LUT model; calorimetric comparison	Approximately $120\times$ faster than time-stepping FE	Speedup depends on LUT construction and covered state space
[65]	PMSM operating maps	Multiple speeds and d-q operating points	Two- and three-term empirical approximations versus ANSYS Maxwell 2D (AEDT 2021 R1) loss	Published contour scales show deviations of approximately -80% to $+20\%$ in parts of the map	Error is operating-point dependent and model/reference dependent
[63]	Four high-frequency magnetic materials	Sinusoidal excitation; frequency, B, and temperature inputs	ANN compared with Steinmetz and KNN	Minimum MAPE 2.58%; MAPE below 5%; 93.33–98.48% of predictions within $\pm 10\%$ depending on material	Scalar sinusoidal data; rotational transfer not demonstrated
[59]	B25AV1300 NO and B30P100 GO steels	Alternating at multiple angles; circular and elliptical loci; 400–800 Hz examples	Improved RSST; 1D anisotropic and 2D elliptical models	1D relative error generally below 3%; optimized 2D error 0.73% versus 2.11% for the preceding model	Two material grades and laboratory specimens; machine-level transfer remains to be tested

Complementing the quantitative comparison, Table 4 summarizes emerging developments across analytical, reduced-order, material-characterization, control-oriented, and data-driven approaches, clarifying how each contribution extends the current evidence base and where rotational-loss limitations remain.

5.5. Practical Model-Selection and Escalation Rules

A universal fixed threshold such as 5% or 10% cannot be justified across all machine classes because the contribution of rotational loss and the error of a simplified model depend on material, topology, operating point, saturation, waveform distortion, and the chosen reference method. A more transferable engineering rule is to define a project-specific allowable core-loss error ε_{design} and, where local thermal risk is important, a local loss-

density tolerance ε_{local} . At representative operating points, a normalized model-discrepancy indicator may be evaluated as $\delta_P = \frac{|P_{advanced} - P_{baseline}|}{P_{reference}}$, where the reference is an experiment or the best validated high-fidelity model available.

Table 4. Cross-study evidence for emerging core-loss modeling approaches.

Ref.	Year	Development	Contribution to This Review	Key Limitation for Rotational-Loss Use
[61]	2024	Review of simplified iron-loss models	Updates the physical and engineering context for model selection	Review evidence is broader than machine-specific rotational validation
[62]	2024	FE-derived state-space/LUT model	Demonstrates control-oriented acceleration and calorimetric validation	Validity bounded by precomputed state space
[57]	2025	2D generalized magnetic network	Adds a non-FE field-solution route for PM machines	Requires coupling to a suitable loss/material model
[58]	2025	Vector magnetic-circuit loss method	Links two-dimensional field analysis and high-frequency loss calculation	High-frequency application; machine-level rotational generality remains limited
[65]	2025	PMSM empirical-versus-numerical comparison	Adds operating-map error evidence	Error varies strongly across the d-q map
[63]	2025	ANN core-loss predictor	Adds reported ML accuracy and baseline comparison	Sinusoidal scalar excitation, not vector rotational validation
[64]	2026	Physics-informed hybrid ML	Adds complex-condition physics-guided prediction	Transfer to rotating-machine vector loss remains to be demonstrated
[59]	2026	NO/GO steel rotational measurement and models	Adds anisotropic, alternating, circular, and elliptical material evidence	Requires broader interlaboratory and machine-level validation
[48,49]	2025–2026	Control-oriented machine studies	Motivate fast loss-aware models under changing trajectories	Not core-loss constitutive models

The simplest model should be retained when δ_P remains within ε_{design} , and the local discrepancy remains within ε_{local} across the relevant operating region. Escalation to a rotational or vector model is justified when directional variation or flux-locus geometry causes the error budget to be exceeded; escalation to a hysteresis-based model is justified when minor loops, DC bias, saturation, or path dependence remain a dominant source of error; and an FE-assisted or surrogate workflow is justified when spatial localization is required but repeated high-fidelity calculations are too expensive. A design team may choose, for example, a 5% or 10% error budget, but such a value should be stated as an application-specific acceptance criterion rather than presented as a universal property of a model family. This rule converts the qualitative statement that no single model is universally best into an explicit model-escalation procedure tied to engineering requirements.

5.6. Synthesis of the Comparison

Taken together, current core-loss modeling research shows a clear development logic: from 1D alternating empirical models, to rotational magnetization correction, to flux-locus analysis, multidimensional material modeling, and FE-coupled implementation. Future valuable advances are therefore likely to arise not from improving a single isolated model, but from establishing a smoother connection between material magnetization mechanisms and machine-level design implementation.

6. ML-Based Core-Loss Modeling

In this review, ML is evaluated only insofar as it supports core-loss prediction under complex excitation. The relevant tasks are: (i) mapping vector waveforms $B_x(t)$ and $B_y(t)$ or flux-locus descriptors to loss; (ii) correcting the residual error of a Steinmetz-, Bertotti-, vector-, or hysteresis-based baseline; and (iii) replacing repeated FE post-processing with a validated surrogate. Generic algorithm descriptions are secondary to evidence that the training data contain rotational, minor-loop, DC bias, PWM, temperature, and material variations.

ML has recently become an increasingly relevant direction in core-loss modeling because it provides a practical way to approximate nonlinear relationships that are difficult to represent using closed-form empirical equations. In conventional models, core loss is usually expressed as a function of frequency, peak flux density, waveform parameters, or separated loss components. However, under realistic electrical-machine operating conditions, local loss may also depend on harmonic content, temperature, material type, stress state, flux-locus geometry, and multidimensional magnetization history. These factors interact in a nonlinear way, making it difficult for a single analytical formula to remain accurate across different machines, materials, and operating regions. ML-based models are therefore attractive because they can learn complex input–output relationships directly from measured data, FE simulation data, or hybrid datasets [66,67].

However, ML should not be regarded as a replacement for electromagnetic understanding. Its value is greatest when used to complement physics-based modeling without removing the problem’s physical basis. In core-loss prediction, the quality of an ML model depends heavily on the quality, coverage, and physical relevance of the training data. If the dataset only covers simple alternating magnetization, the model may not extrapolate reliably to elliptically or circularly rotational conditions, or to irregular flux-locus conditions. Similarly, if the training data do not include the relevant temperature, frequency, saturation, or harmonic range, the learned model may produce accurate interpolation but unreliable prediction outside the calibration domain. Therefore, ML-based core-loss modeling should be understood as part of a broader framework that integrates materials physics, machine-level field data, and data-driven correction. This is especially important in engineering applications, where interpretability and trustworthiness are as important as numerical accuracy [68].

6.1. Motivation and Challenges

The motivation for applying ML to core-loss modeling comes from the limitations of traditional empirical, hysteresis-based, and FE-assisted approaches. Empirical equations are efficient but may be too simple for complex magnetization. Hysteresis-based models are more physically meaningful but often require many parameters and can be computationally expensive. FE-assisted post-processing provides detailed local magnetic-field information, but repeated transient simulations and element-wise loss calculations can be costly in design optimization. ML offers a possible bridge between these approaches by learning an efficient surrogate relationship between magnetic-field descriptors and core-loss values [66,67].

For rotational-loss learning, the minimum physically meaningful inputs extend beyond frequency f and peak flux density B_m . Candidate features include $B_x(t)$, $B_y(t)$, B_{maj} , B_{min} , the axis ratio $\lambda = B_{min}/B_{maj}$, the locus area A_{locus} , rotation direction, harmonic descriptors H_{harm} , DC offset, temperature T , stress, and material identifier M_{id} . If only scalar sinusoidal data are used, the resulting model is a scalar core-loss predictor and should not be presented as a rotational-loss model. At the feature-reduced level, where the local waveform has already been compressed into scalar descriptors, the mapping takes the form

$$P_v = F_{ML}(f, B_{maj}, \lambda, A_{locus}, H_{harm}, T, M_{id}) \quad (20)$$

where F_{ML} denotes the learned nonlinear mapping from selected physical and operating descriptors to the specific core loss P_v . Equations (20), (21) and (27) form a hierarchy that differs in how much of the local magnetization history is retained: Equation (20) compresses the flux locus into scalar descriptors, Equation (21) retains the vector waveform itself, and Equation (27) targets the rotational-loss component directly. A model built on Equation (20) should therefore be reported as a locus-descriptor model rather than as a waveform-level rotational model.

The main challenge is that ML models require sufficient and representative data. In core-loss research, high-quality data are expensive because experimental measurements under rotational or multidimensional magnetization are difficult to obtain, and FE-generated datasets may be computationally expensive or biased by the loss model used to generate them. Another challenge is interpretability. A highly accurate ML model may still be difficult to trust if it does not explain why the loss changes under different magnetization conditions. In engineering design, this is important because designers need not only numerical predictions but also confidence in the model's behavior across operating points [68].

6.2. Data-Driven Regression: ANN, SVR, Random Forest, and GPR

Traditional data-driven regression methods provide a natural starting point for ML-based core-loss modeling. Artificial neural networks (ANNs), support vector regression (SVR), random forests, and Gaussian process regression (GPR) can be trained to map selected magnetic and operating features to measured or simulated loss values. Compared with deep learning methods, these models generally require less data and are easier to implement for structured tabular datasets.

ANNs are widely used because they can approximate nonlinear relationships between inputs, such as f , B_m , T , M_{id} , and P_v . SVR is useful when the dataset is relatively small because it can provide robust nonlinear regression with controlled model complexity. Random forests can handle feature interactions and provide some indication of feature importance, which is useful for understanding whether frequency, flux density, temperature, or locus-related descriptors dominate the prediction. GPR is especially attractive for scientific modeling because it can provide uncertainty estimates together with predictions, although its computational cost increases with dataset size.

For core-loss applications, these regression models are most reliable when the input features are physically meaningful. For example, using f , B_{maj} , λ , A_{locus} , H_{harm} , T , and M_{id} is more informative than using only frequency and peak flux density. A regression model trained only on f and B_m may behave like a more flexible Steinmetz equation, but it will still fail to represent rotational magnetization if no rotational descriptor is included. Recent data-driven core-loss studies have shown that ML and deep learning models can outperform traditional empirical equations when trained on sufficiently broad datasets spanning material, temperature, frequency, and waveform [66]. In the ANN study summarized in Table 3 [63], the minimum reported MAPE was 2.58%, the MAPE remained below 5%, and 93.33–98.48% of predictions were within $\pm 10\%$, depending on material. However, these results were obtained from scalar sinusoidal data and therefore demonstrate interpolation accuracy for that domain rather than validated transfer to rotational magnetization.

6.3. Deep Learning: Deep Neural Networks, Convolutional Neural Networks, Long Short-Term Memory, and Transformer Models

Deep learning methods become more relevant when the input data are high-dimensional, sequential, or spatially distributed. Deep neural networks (DNNs) can extend conventional ANNs by using multiple hidden layers to capture stronger nonlinearities.

Convolutional neural networks (CNNs) can be used when the input is represented as a spatial map, image-like field distribution, or discretized waveform pattern. Long short-term memory (LSTM) networks are suitable for time-series data because they can learn temporal dependencies in $B(t)$, $H(t)$, current waveforms, or voltage waveforms. Transformer models may also be useful when long-range temporal relationships or complex waveform histories are important.

In core-loss modeling, deep learning can play two roles. The first is waveform-based prediction. Instead of reducing a waveform to a few scalar features, a neural network can use sampled waveforms such as $B(t)$, $H(t)$, $B_x(t)$, and $B_y(t)$ directly as inputs. This is useful under nonsinusoidal excitation, PWM supply, and harmonic-rich operating conditions, where the detailed waveform shape affects losses. The second role is field-distribution-based prediction. For machine applications, FE simulations can produce spatial distributions of flux density, flux-locus parameters, or local loss density. CNN-type architectures may then be used to learn spatial patterns associated with high-loss regions. Waveform-based CNN methods have also been used to estimate magnetic loss under arbitrary excitation, showing the potential of deep models for waveform-sensitive loss prediction [69].

A more general vector-waveform-based ML mapping may be expressed as

$$P_v = F_{ML}(B_x(t), B_y(t), f, \lambda, \text{material parameters}) \quad (21)$$

where $B_x(t)$ and $B_y(t)$ describe the local time-varying vector magnetic flux density, and the material parameters may include material grade, temperature-dependent properties, or fitted coefficients.

However, deep learning also introduces risks. It usually requires larger datasets than traditional regression methods and may yield predictions that are difficult to interpret. If the training dataset is generated only from a narrow set of machine geometries or operating conditions, the model may not generalize to other topologies. Therefore, deep learning is most useful when combined with physically meaningful inputs, carefully designed validation, and clear restrictions on its intended application domain [66,68].

6.4. Hybrid Physics-ML Models

Hybrid physics-ML models are particularly promising for core-loss prediction because they combine the robustness of physics-based equations with the flexibility of data-driven correction. Instead of asking an ML model to predict the full loss directly, a baseline physical or empirical model can first be used to estimate the loss, and the ML model is then trained to predict the residual error or a correction factor. This reduces the burden on the ML model and improves extrapolation, as the main physical trend is already captured by the baseline equation.

A typical hybrid model can be written in additive form as

$$P_{ML-hybrid} = P_{phys} + \Delta P_{ML} \quad (22)$$

or in multiplicative correction form as

$$P_{ML-hybrid} = P_{phys} \cdot C_{ML} \quad (23)$$

where P_{phys} is the prediction from a conventional empirical, loss-separation, or hysteresis-inspired model, ΔP_{ML} is a learned residual term, and C_{ML} is a learned correction factor.

This type of model is well-suited to rotational and complex magnetization problems. For example, P_{phys} may be calculated using a conventional alternating-field model, while

the ML correction accounts for flux-locus shape, axis ratio, harmonic distortion, local saturation, or temperature. In this way, the ML component focuses on the part of the problem that the analytical model cannot capture well. Hybrid strategies are also consistent with data-driven material modeling and waveform-based loss estimation, in which physical structure is retained while data-driven components enhance flexibility [67,69].

6.5. Physics-Informed Neural Networks

Physics-informed neural networks (PINNs) represent another important direction. In a PINN framework, the training loss not only measures the mismatch between predicted and measured data; it also includes physical constraints derived from governing equations, constitutive relationships, conservation laws, or known loss behavior. PINNs were originally developed as a framework for solving forward and inverse problems governed by nonlinear differential equations [70], and they have also been explored for parametric magnetostatic problems [71].

For core-loss prediction, PINNs are attractive because they can reduce the amount of experimental data required and improve physical consistency. A typical PINN-type objective can be expressed as

$$L_{total} = L_{data} + \alpha L_{physics} \quad (24)$$

where L_{data} penalizes the mismatch between predicted and measured or simulated loss values, $L_{physics}$ penalizes violations of physical constraints, and α is a weighting coefficient.

For example, the data term may be written as

$$L_{data} = \frac{1}{N} \sum_{i=1}^N \left(P_i^{pred} - P_i^{meas} \right)^2 \quad (25)$$

where P_i^{pred} and P_i^{meas} are the predicted and measured core-loss values for the i -th data point. The physical term $L_{physics}$ may include constraints such as non-negative loss, consistency with Maxwell-equation-based field relationships, smooth dependence on frequency, or reduction to the alternating-loss case when $\lambda \rightarrow 0$.

Nevertheless, using PINNs for core-loss modeling remains challenging. The physics of magnetic hysteresis and rotational loss is not always easily expressed as a simple differentiable constraint. In addition, if the assumed physical constraint is too simplified, the PINN may inherit the same limitations as the baseline model. PINN training may also suffer from loss-balancing difficulties, non-convex optimization landscapes, and vanishing gradients [72]. Therefore, PINNs are most promising when the physical constraints are carefully selected, and the model is used to complement validated material characterization rather than supplant it.

6.6. FE-Accelerated Surrogate Models

FE-accelerated surrogate models are highly relevant to electrical-machine design because full transient FE simulations are often too expensive for repeated optimization. In this approach, FE simulations are used to generate a dataset across selected geometries, materials, operating points, or control conditions. An ML model is then trained to approximate the FE-based prediction, allowing much faster evaluation during optimization.

For core-loss modeling, such surrogate models may predict total iron loss, regional loss distribution, or local loss-density maps. The input may include machine design variables x_{design} , operating variables x_{op} , material parameters, and selected field descriptors. A generic surrogate model may be written as

$$P_v = F_{sur}(x_{design}, x_{op}) \quad (26)$$

where F_{sur} represents a learned surrogate mapping from design and operating variables to loss prediction.

Compared with direct FE post-processing, surrogate models can substantially reduce computational time once trained. Neural operator methods and Fourier neural operators are particularly relevant because they are designed to learn mappings between function spaces and can therefore approximate families of partial differential equation solutions more efficiently than by repeatedly solving each instance independently [73,74]. This is attractive for future FEM-accelerated machine design, where the target is not only a single loss value but a fast mapping from geometry and operating condition to field and loss behavior. A useful engineering benchmark is provided by the FE-derived state-space/LUT model in [62], which is not itself an ML model but achieves approximately $120\times$ faster evaluation than time-stepping FE within its precomputed state space. This indicates the order of acceleration that a learned surrogate may need to provide to justify its additional training and validation burden, while also emphasizing that speedup must be reported together with the covered design domain.

However, surrogate models must be used carefully. Their validity is limited by the design space covered by the FE training dataset. If the machine geometry, material, or operating point moves far outside the training range, the surrogate prediction may become unreliable. Therefore, FEM-accelerated ML should be combined with active learning, adaptive sampling, or periodic FE validation. Active learning is especially useful because it can select new simulation points where the model uncertainty is high, reducing the number of expensive FE simulations required for reliable training [75].

6.7. ML for Rotational Magnetization

ML is especially relevant for rotational magnetization because the relationship between flux-locus geometry and loss is difficult to capture using simple formulas. A rotational magnetization state can be described by multiple features, including B_{maj} , B_{min} , A_{locus} , f , T , rotation direction, and harmonic content. These descriptors provide a richer input space than f and B_m alone, and ML models can learn nonlinear interactions among them.

For elliptically rotational magnetization, an ML model may learn how the loss varies with λ , B_{maj} , B_{min} , and f . For circularly rotational magnetization, the model may identify saturation-related behavior that differs from the alternating case. For irregular or harmonic-rich loci, the model may use waveform samples, Fourier coefficients, or geometric descriptors to capture trajectory complexity. A rotational-loss-oriented ML mapping can be expressed as

$$P_{rot,ML} = F_{ML}(B_{maj}, B_{min}, \lambda, A_{locus}, f, T) \quad (27)$$

where $P_{rot,ML}$ denotes the ML-estimated rotational-loss component or rotational-loss correction.

A promising direction is to combine flux-locus classification with ML-based correction. The local field can first be classified as alternating, elliptically rotational, circularly rotational, or irregular. Then, an appropriate model or correction factor can be applied to each category. This preserves physical interpretability while allowing data-driven flexibility. Such a framework is especially suitable for FE-assisted workflows, where $B_x(t)$ and $B_y(t)$ are already available at local elements.

6.8. Remaining Challenges, Future Opportunities, and an Integrated Physics-ML Framework

Despite its potential, ML-based core-loss modeling still faces several major challenges. The first is data availability. High-quality datasets spanning different materials, frequencies, temperatures, stress states, waveform conditions, and rotational magnetization patterns

remain limited. The second is generalization. A model trained on one material or machine topology may not work reliably on another unless the training set is sufficiently broad or the model includes physically meaningful descriptors. The third is interpretability. Engineers must understand why the model predicts higher or lower loss in certain regions, especially when the prediction affects thermal safety or design decisions [68].

Another challenge is uncertainty quantification. Most ML models provide a single predicted value, but design engineers also need confidence intervals or reliability indicators. This is particularly important when the model is used outside the original training range. GPR, Bayesian neural networks, ensemble learning, and conformal prediction may be useful tools for estimating prediction uncertainty in future core-loss models. Active learning may also help by identifying operating conditions or geometries where new measurements or FE simulations would be most informative [75]. For deployment, the terminology should also be explicit. The training domain is the set of samples used to fit the ML model, whereas the validated domain is the bounded feature envelope over which independent validation has demonstrated acceptable performance; this review therefore avoids treating “training domain” and “calibration domain” as interchangeable. A practical reliability protocol is to (i) define the validated ranges of frequency, B_{maj} , B_{min} , axis ratio, temperature, harmonic descriptors, material state, and other relevant features; (ii) verify that a new operating point lies inside that envelope and evaluate a distance-to-training-data or uncertainty metric; (iii) accept the ML correction only when the combined validation error and uncertainty remain below the stated engineering error budget; and (iv) revert to the physics-based baseline and request additional FE or measurement samples when those criteria are violated. Predictions outside the validated domain should therefore be identified explicitly as extrapolative rather than treated as reliable by default.

Future opportunities lie in hybrid and workflow-oriented ML. Rather than replacing empirical, hysteresis-based, or FE-assisted methods, ML can be used to accelerate them, correct their residual errors, or identify local regions where higher-fidelity modeling is needed. For review-based core-loss research, the most promising direction is therefore an integrated framework in which physics-based models provide structure, FE simulations provide local vector-field information, and ML provides fast nonlinear correction or surrogate prediction. Such a framework could support more accurate and efficient core-loss evaluation under alternating, elliptically rotational, circularly rotational, and irregular magnetization conditions.

Building on these opportunities, Figure 5 summarizes an integrated physics-ML framework for rotational core-loss prediction. The recommended input is not merely frequency and peak flux density, but a vector-field description or physically meaningful locus features. A physics-based baseline first accounts for known scaling and material behavior; ML then learns a residual correction, a fast surrogate, or an uncertainty estimate. This structure makes failure modes easier to diagnose and preserves the alternating-field limit. It also prevents a model trained on scalar sinusoidal data from being presented as rotationally capable without evidence. Rotational capability should be claimed only when the training and validation data include $B_x(t)$, $B_y(t)$ trajectories or equivalent descriptors spanning alternating, elliptical, circular, and irregular conditions.

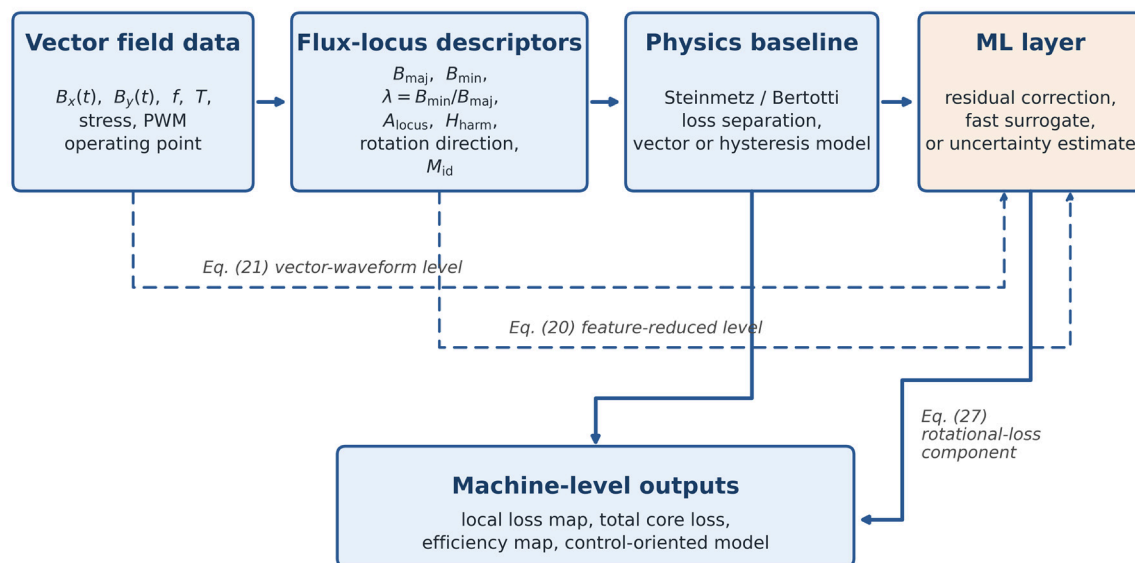


Figure 5. Integrated physics-ML framework for flux-locus-aware machine core-loss prediction. ML is used as a correction, surrogate, or uncertainty layer rather than as an unconstrained replacement for the material model.

7. Conclusions and Future Directions

This paper has presented an expanded review and discussion of core-loss modeling under complex and rotational magnetization conditions in electrical machines. The central conclusion is that modern machine environments have outgrown the assumptions underlying purely alternating-field loss estimation. Although classical empirical models remain useful and often indispensable for rapid design calculations, they are increasingly insufficient in regions where the magnetic flux density exhibits strong directional variation, harmonic distortion, local saturation, or true multidimensional behavior [1–9,13–16,24,25,33]. The review also shows that ML-based modeling is becoming an important complementary route for handling nonlinear correction, surrogate prediction, and data-driven interpretation of complex magnetization.

The reviewed literature shows a clear development trajectory. The first stage consists of classical Steinmetz and loss-separation models calibrated from alternating-field data. The second stage introduces refined empirical methods that incorporate variable coefficients, waveform sensitivity, and harmonic effects. The third stage explicitly addresses rotational magnetization through flux-locus descriptors and alternating-plus-rotational decompositions. The fourth stage introduces hysteresis-based and FE-assisted formulations to capture path dependence and support machine-level implementation. This evolution does not imply that older models are obsolete; rather, it highlights that different models are appropriate for different design and analysis tasks. A fifth emerging stage is the use of ML-based methods, including data-driven regression, physics-ML correction, PINNs, and FE-accelerated surrogate models, to improve prediction speed and nonlinear generalization while retaining physical guidance.

Across the reviewed evidence, improved empirical models offer simple implementation and low cost; flux-locus and vector descriptions provide a practical bridge between local machine fields and material models; hysteresis approaches offer the strongest path dependence at greater calibration and computation cost; and recent analytical, magnetic-network, reduced-order, and ML approaches improve speed without removing the need for representative material data and validation.

The main research gaps identified from the reviewed literature are summarized in Table 5, together with possible future directions for improving core-loss modeling under

complex and rotational magnetization conditions. These gaps indicate that future progress will likely depend on better flux-locus characterization, more unified modeling frameworks, and more efficient implementation in design-oriented workflows. In response to the increasing role of ML in iron-loss modeling, Table 5 also identifies physics-informed and flux-locus-aware ML as important future directions.

Table 5. Main research gaps and future directions.

Current Issue	Why Existing Models Are Insufficient	Potential Direction	Representative Refs.
Irregular flux loci	Axis ratio alone cannot capture harmonic-rich or non-planar paths	Higher-order locus descriptors and data-driven embeddings	[2,3,7,9,12]
Alternating/rotational transition	Many models switch regimes rather than unify them	Continuous vector-loss formulations	[13–15,20–30]
Parameter-identification burden	Vector and hysteresis models require rich datasets	Reduced-order calibration and manufacturer-ready datasets	[5,13,27–39]
Manufacturing and stress effects	Punching, stress, and temperature alter local loss behavior	Multiphysics-aware material models	[16,25,35–37]
Optimization readiness	High-fidelity models are often too slow for design loops	Surrogate or hybrid FE-loss workflows	[5,6,16–25,34]
ML integration	Limited data and extrapolation	Physics-ML, PINNs, FE surrogates	[66–75]
Model-selection thresholds	Machine-class rotational fractions and simplified-versus-advanced model errors are not reported consistently	Report rotational-loss fraction, baseline-to-advanced discrepancy, and application-specific error budgets at representative operating points	[7,9,13–15,61,65]

Several future research directions appear especially important. First, better descriptors are needed for irregular and non-planar flux loci. Axis ratio and equivalent flux density are useful, but they do not fully capture the effects of distortion or 3D trajectories. Second, unified models are needed that recover alternating loss as a limiting case while remaining valid for elliptical, circular, and harmonic-rich rotational magnetization. Third, the identification of vector and hysteresis parameters must become more efficient if advanced models are to enter optimization workflows. Fourth, machine-level loss evaluation should better incorporate stress, temperature, and manufacturing damage, which are often as important in practice as the choice of basic loss equation. Fifth, the growing adoption of SMCs, amorphous alloys, and high-speed inverter-fed machines will continue to push the field toward multidimensional and multiphysics loss modeling [2,3,5,6,9–12,16,24,25,33–37]. Sixth, ML-based modeling should be developed as a complementary layer that can learn residual errors, accelerate FE-assisted workflows, and identify nonlinear interactions among waveform distortion, temperature, material properties, and flux-locus descriptors.

A final point should be emphasized. The future of machine iron-loss research will likely depend as much on standardization as on new equations. Without more consistent, multidimensional material datasets, reference measurement procedures, and benchmarking problems for machine-level validation, it will remain difficult to compare models across publications fairly. Reviews and comparative studies, therefore, play an important role: they help identify where disagreement is due to model structure and where it is due to differences in data, calibration, or testing. In that sense, the field is moving not only toward better models but also toward better model ecosystems.

In summary, future iron-loss models for electrical machines will likely be judged not only by accuracy, but also by portability across materials, compatibility with FE and optimization platforms, and robustness under real operating conditions. The most promising direction is therefore not a single best formula, but an integrated framework that combines

accurate materials characterization, flux-locus-aware interpretation, and efficient design-oriented implementation. In this integrated framework, ML can serve as a fast nonlinear correction and surrogate-prediction tool, provided it remains constrained by physics-based descriptors and validated at the machine level. Accordingly, model complexity should be escalated only when a simpler baseline exceeds a stated global or local error budget, and ML deployment should remain conditional on a clearly defined validated domain and uncertainty criterion.

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Abbreviations

The following abbreviations are used in this manuscript:

1D	One-dimensional
FE	Finite element
ML	Machine learning
3D	Three-dimensional
2D	Two-dimensional
PM	Permanent magnet
PWM	Pulse width modulation
BDFMs	Brushless doubly fed machines
SMC	Soft magnetic composite
PMSMs	Permanent-magnet synchronous machines
ANNs	Artificial neural networks
SVR	Support vector regression
GPR	Gaussian process regression
DNNs	Deep neural networks
CNNs	Convolutional neural networks
LSTM	Long short-term memory
PINNs	Physics-informed neural networks

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