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Computational Modeling of Electromagnetic Fields in Smart Magnetic Devices and Sensor Technologies

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Abstract
Computational electromagnetic modeling has become an essential component in the design, optimization, calibration, and performance evaluation of smart magnetic devices and sensor technologies. Modern magnetic systems frequently contain nonlinear ferromagnetic materials, permanent magnets, conducting regions, miniature coils, magnetostrictive layers, piezoelectric components, and semiconductor sensing elements. Their behaviour is governed by strongly coupled electromagnetic, mechanical, thermal, and electronic phenomena that are difficult to describe through analytical equations alone. Numerical approaches such as the finite-element method, finite-difference time-domain method, boundary-element method, method of moments, and micromagnetic simulation enable researchers to calculate field distributions, magnetic forces, induced currents, energy losses, resonance behaviour, sensor sensitivity, and cross-axis interference before physical fabrication. This review examines the mathematical foundations, computational techniques, multiphysics coupling strategies, and engineering applications of electromagnetic-field modeling in smart magnetic devices. Particular attention is given to Hall-effect sensors, magnetoresistive sensors, magnetoelectric devices, fluxgate sensors, inductive sensors, microelectromechanical systems, magnetic actuators, and nanoscale spintronic components. The importance of geometry construction, material characterization, boundary conditions, mesh convergence, solver selection, model-order reduction, parameter optimization, and experimental validation is discussed. Emerging approaches involving digital twins, machine learning, physics-informed neural networks, uncertainty quantification, and high-performance computing are also evaluated. Computational models can significantly reduce prototype cycles and support device miniaturization, but their reliability depends on accurate material data, realistic operating conditions, systematic convergence analysis, and comparison with experimental measurements. Future smart magnetic systems will increasingly rely on hybrid physics-based and data-driven models capable of real-time prediction, adaptive calibration, and autonomous design optimization.

Introduction

Smart magnetic devices are systems that sense, generate, guide, transform, or respond to magnetic fields while incorporating electronic processing, adaptive control, communication, or intelligent decision-making. Examples include Hall-effect current sensors, anisotropic and tunnelling magnetoresistive sensors, fluxgate magnetometers, magnetoelectric sensors, inductive proximity sensors, magnetic encoders, magnetostrictive transducers, microelectromechanical resonators, spintronic devices, and magnetic actuators. These technologies are used in electric vehicles, industrial automation, medical instruments, navigation, robotics, smart grids, consumer electronics, aerospace systems, nondestructive testing, and structural monitoring. The design of a magnetic device is rarely determined by magnetic-field strength alone. Sensor output can be affected by flux concentration, leakage fields, nonlinear permeability, hysteresis, eddy currents, temperature, mechanical stress, electrical noise, demagnetization, geometric tolerances, and interference from neighbouring conductors. In magnetoelectric and magnetostrictive devices, electromagnetic fields interact with elastic deformation and structural vibration. In microelectromechanical sensors, small geometric changes may substantially influence resonance frequency and sensitivity. Traditional analytical models are useful for simple coils, magnetic circuits, and uniformly shaped materials. However, closed-form solutions become difficult when devices contain irregular geometries, air gaps, multiple materials, nonlinear constitutive behaviour, or three-dimensional field paths. Computational electromagnetics converts the governing field equations into numerical systems that can be solved over realistic device geometries. The finite-element method is particularly effective for magnetic devices because it can represent complex geometries, localized material interfaces, nonlinear magnetic properties, and coupled physical processes. Magnetic vector-potential formulations allow flux density, current density, force, energy, and loss to be derived from the numerical solution. Finite-element analysis has been successfully compared with experimentally measured field maps above planar coils, including the reproduction of edge and corner effects. At nanometre scales, continuum field modeling must often be supplemented by micromagnetics. Micromagnetic simulation describes spatial variations and dynamics of magnetization while accounting for exchange energy, magnetostatic energy, magnetic anisotropy, and applied fields. The NIST Object Oriented MicroMagnetic Framework is a widely used public-domain system for simulating magnetization processes in ferromagnetic structures. Computational modeling is therefore not simply a visualization tool. It supports material selection, geometric optimization, sensitivity analysis, error prediction, thermal management, signal interpretation, control-system development, and reduction of costly fabrication cycles.

Mathematical Foundations and Electromagnetic Modeling Regimes

The foundation of computational electromagnetic analysis is Maxwell's equations. Their differential forms are expressed as:

$$\nabla \cdot \mathbf{D} = \rho$$
$$\nabla \cdot \mathbf{B} = 0$$
$$\nabla \times \mathbf{E} = -\partial \mathbf{B}/\partial t$$
$$\nabla \times \mathbf{H} = \mathbf{J} + \partial \mathbf{D}/\partial t$$

where **E** is electric-field intensity, **D** is electric-flux density, **H** is magnetic-field intensity, **B** is magnetic-flux density, **J** is current density, and **ρ** is electric-charge density. Constitutive relations connect the fields to material properties:

$$\mathbf{B} = \mu \mathbf{H}$$
$$\mathbf{D} = \varepsilon \mathbf{E}$$
$$\mathbf{J} = \sigma \mathbf{E}$$

where μ, ε, and σ represent magnetic permeability, electrical permittivity, and electrical conductivity.

The complete Maxwell system is required for high-frequency electromagnetic-wave problems in which electric and magnetic fields propagate through space. Many magnetic sensors and actuators, however, operate at sufficiently low frequencies that wave propagation and displacement current can be neglected. These systems are commonly treated using magnetostatic or magnetoquasistatic formulations. The appropriate approximation depends on excitation frequency, device size, material conductivity, and the timescale of the physical response.

In magnetostatic analysis, currents and permanent magnets are assumed to be time independent. The governing equations reduce to:

$$\nabla \times \mathbf{H} = \mathbf{J}$$
$$\nabla \cdot \mathbf{B} = 0$$

The magnetic vector potential **A** is frequently introduced so that:

$$\mathbf{B} = \nabla \times \mathbf{A}$$

This definition automatically satisfies the condition that magnetic flux has zero divergence. In a linear isotropic material, the finite-element equation may be represented as:

$$\nabla \times (\nu \nabla \times \mathbf{A}) = \mathbf{J_s}$$

where ν is magnetic reluctivity and $\mathbf{J_s}$ is the applied source-current density.

For conducting devices under time-varying excitation, induced electric fields create eddy currents. A simplified magnetic vector-potential equation is:

$$\nabla \times (\nu \nabla \times \mathbf{A}) + \sigma \partial \mathbf{A}/\partial t = \mathbf{J_s}$$

Eddy-current analysis is essential for conductive targets, magnetic cores, metallic shields, current sensors, high-frequency inductive sensors, and magnetostrictive transducers. Eddy currents alter field penetration, phase response, power loss, heating, and sensor sensitivity.

Skin effect becomes important as frequency increases. Alternating current becomes concentrated near the surface of a conductor, reducing the effective conducting area. The skin depth may be expressed as:

$$\delta = \sqrt{[2/(\omega \mu \sigma)]}$$

where ω is angular frequency. Finite-element meshes must contain sufficient elements across the skin depth to reproduce induced-current distributions accurately. Inadequate resolution can underestimate loss and incorrectly predict coil impedance or sensor output. Material nonlinearity presents a further challenge. Ferromagnetic permeability is not constant but changes with magnetic-field intensity. Saturation limits the maximum useful flux density, while hysteresis causes the magnetic state to depend on previous excitation. Accurate models may therefore require measured B–H curves, hysteresis formulations, remanent magnetization, coercivity, and frequency-dependent loss parameters. Permanent magnets can be represented using remanent-flux-density or magnetization vectors. The operating point depends on magnet geometry, temperature, demagnetizing fields, and surrounding magnetic circuits. A computational model can identify regions in which reverse fields may cause partial demagnetization. Force and torque are important outputs for magnetic actuators, encoders, levitation systems, and mechanical sensors. They may be calculated using Maxwell's stress tensor, virtual work, magnetic co-energy, or equivalent force-density methods. The numerical domain and integration surface must be selected carefully because force predictions can be sensitive to mesh quality and field discontinuities.

Numerical Methods and Multiphysics Coupling

The finite-element method divides a complex physical domain into smaller elements connected at nodes. Within each element, the unknown electromagnetic quantity is approximated using interpolation functions. Assembly of all element equations produces a global algebraic system whose solution represents the field throughout the device. Finite-element modeling is well suited to irregular structures, curved magnetic cores, thin air gaps, multilayer sensors, microcoils, permanent magnets, and nonuniform material regions. Two-dimensional models may be used when the geometry is translationally uniform, while axisymmetric models are suitable for rotationally symmetric coils and cylindrical magnetic circuits. Fully three-dimensional models are required when end effects, asymmetric flux leakage, cross-axis fields, or nonuniform winding arrangements are important. The finite-difference time-domain method discretizes both space and time and updates electric and magnetic fields through a time-stepping procedure. It is widely used for transient-wave propagation, electromagnetic compatibility, microwave sensing, and high-frequency structures. Its regular grid is computationally efficient, but curved surfaces and extremely thin layers may require very fine discretization. The method of moments and boundary-element method transform electromagnetic equations into integral equations. These approaches can reduce dimensionality because only material boundaries or conducting surfaces may need discretization. They are especially useful for open-region radiation and scattering problems. However, dense matrix systems and complicated nonlinear materials may reduce their efficiency for some smart magnetic devices. Micromagnetic simulation is required when the internal magnetic-domain structure influences device behaviour. It is particularly relevant to magnetoresistive elements, magnetic random-access memory, nanowires, magnetic nanoparticles, spin-wave devices, and nanoscale sensing layers. The dynamic magnetization response is generally described using the Landau–Lifshitz–Gilbert equation:

$$d\mathbf{M}/dt = -\gamma(\mathbf{M} \times \mathbf{H_e}ff) + (\alpha/M_s)[\mathbf{M} \times d\mathbf{M}/dt]$$

where γ is the gyromagnetic ratio, α is the damping parameter, M_s is saturation magnetization, and $\mathbf{H_e}ff$ is the effective field. The effective field can include applied, exchange, anisotropy, demagnetizing, thermal, and magnetoelastic contributions. Multiphysics coupling is necessary when electromagnetic fields interact with other physical domains. Magnetostrictive materials deform when magnetized, while mechanical stress changes their magnetic properties. Piezoelectric materials produce electrical charge under strain and deform in an electric field. Magnetoelectric sensors combine magnetostrictive and piezoelectric layers so that an applied magnetic field is converted into an electrical output through mechanical coupling. A harmonic finite-element formulation developed for nonlinear magnetoelectric sensors demonstrated that dynamic sensor enhancement is linked to nonlinear magnetic and magnetostrictive behaviour. Such models must simultaneously solve electromagnetic, mechanical, and electrical equations. Thermal coupling is equally important. Coil currents cause Joule heating, while magnetic cores experience hysteresis and eddy-current losses. Temperature changes winding resistance, magnetic permeability, permanent-magnet strength, mechanical stress, and electronic offset. A thermally coupled model can identify hotspots and predict sensitivity drift. Fluid–magnetic coupling is used in magnetic-fluid sensors, biomedical devices, particle separators, and microfluidic systems. Magnetic forces act on particles or ferrofluids, while fluid flow transports the magnetic material. Accurate solutions may require simultaneous treatment of magnetic force, viscous flow, particle concentration, and thermal effects.

Applications in Smart Magnetic Devices and Sensors

Hall-effect and current sensors

Hall-effect sensors generate a voltage transverse to the current direction when exposed to a magnetic field. Computational models are used to design magnetic concentrators, current-carrying conductors, air gaps, integrated cores, and shielding structures. The objective may be to improve sensitivity, increase bandwidth, reduce cross-axis response, or produce a linear relationship between current and output voltage. Current sensors often require simultaneous simulation of the primary conductor, ferromagnetic core, air gap, Hall element, and nearby conductors. Saturation analysis determines the maximum measurable current, while thermal simulation predicts offset and gain drift. Hall sensors offer a broad operating range, although detecting extremely weak fields can require alternative sensing principles or flux-concentration structures.

Magnetoresistive sensors

Anisotropic, giant, and tunnelling magnetoresistive sensors change electrical resistance in response to magnetization orientation. Their design may require both device-scale finite-element analysis and nanoscale micromagnetic simulation. Finite-element models calculate the external field and flux-guide behaviour, while micromagnetics determines free-layer rotation, switching, domain formation, and hysteresis. Flux concentrators can increase the field applied to the sensing layer, but they may introduce hysteresis, nonlinearity, noise, and cross-axis sensitivity. Computational optimization can determine pole shape, air-gap dimensions, magnetic thickness, and sensor position.

Magnetoelectric and magnetostrictive sensors

Magnetoelectric sensors convert magnetic excitation into voltage through mechanical coupling between magnetostrictive and piezoelectric

materials. Model parameters include layer thickness, elastic modulus, magnetic bias, damping, bonding quality, resonance mode, electrode geometry, and mechanical boundary conditions. Finite-element models can identify resonance frequencies and regions of stress concentration. Mode localization has been proposed to amplify parameter sensitivity in coupled magnetoelastic resonators. A 2022 modeling study reported that amplitude-ratio output in a localized-mode ΔE-effect sensor could produce substantially greater simulated relative sensitivity than conventional frequency output, illustrating the importance of multiphysics design optimization. Magnetostrictive transducers also require suitable bias fields and control of eddy-current losses. Finite-element analysis has been used to compare core configurations and evaluate slotted structures for loss reduction.

Inductive and eddy-current sensors

Inductive sensors detect changes in coil impedance caused by conductive or magnetic targets. Simulations evaluate coil turns, trace width, spacing, excitation frequency, target distance, conductivity, permeability, and shielding. The induced eddy currents oppose the original field and change coil inductance and resistance. These devices are used for proximity measurement, displacement sensing, wear-particle detection, nondestructive inspection, and rotational-position sensing. Computational analysis can determine the optimum operating frequency and identify whether the response is dominated by conductivity, permeability, geometric distance, or target thickness.

Magnetic MEMS and smart actuators

Microelectromechanical magnetic devices combine miniature mechanical structures with magnetic actuation or sensing. Examples include resonators, switches, microrelays, scanning mirrors, energy harvesters, pressure sensors, and biomedical microdevices. Modeling must account for magnetic forces, mechanical stiffness, damping, fabrication tolerances, residual stress, and pull-in instability. Smart magnetic suspension and proximity systems may combine finite-element-derived dynamic models with sensor-fusion algorithms. A field-sensed suspended system has been modeled using finite elements and an Unscented Kalman Filter to improve proximity estimation under magnetic disturbances.

Verification, Validation, Calibration, and Optimization

A numerical result should not be considered reliable merely because a solver produces a smooth field plot. Verification determines whether the mathematical equations have been solved correctly, while validation examines whether the equations and material descriptions represent the physical device accurately. Mesh-convergence analysis is a fundamental verification procedure. The model is solved using progressively finer meshes, and quantities such as peak flux density, inductance, force, torque, resonance frequency, or sensor output are compared. The solution is considered sufficiently converged when further refinement produces changes smaller than the selected engineering tolerance. Local mesh refinement is generally required around air gaps, sharp corners, thin conductive layers, sensor elements, magnetic interfaces, and regions of high field gradient. Excessive refinement throughout the entire domain increases computation time without necessarily improving the quantity of interest. Boundary placement can influence the solution. An external air domain that is too small may artificially constrain flux lines. Infinite-element domains, boundary elements, symmetry conditions, or sufficiently distant boundaries can be used to approximate open space. Material data constitute one of the largest sources of uncertainty. Manufacturer-supplied permeability values may not represent the actual frequency, temperature, stress state, or manufacturing condition. Machining, bonding, deposition, and residual stress can alter magnetic behaviour. Whenever possible, measured B–H curves, conductivity, magnetostriction, damping, and thermal properties should be used. Validation requires comparison with experimental measurements. Suitable data may include field scans, coil impedance, sensor voltage, force, displacement, temperature, resonance frequency, or hysteresis loops. Measurements above planar coils have shown strong agreement with three-dimensional finite-element predictions while also identifying practical differences caused by solder joints, dimensional imperfections, and measurement noise. Parameter sensitivity analysis identifies which variables have the greatest influence on performance. It can reveal that sensor output is more sensitive to air-gap width than to core length, or that resonance response is dominated by damping rather than magnetic-film thickness. This information helps establish manufacturing tolerances. Optimization may be performed using gradient-based algorithms, evolutionary methods, particle-swarm optimization, Bayesian optimization, response-surface methods, or topology optimization. Typical objectives include maximizing sensitivity, minimizing power consumption, reducing thermal drift, increasing linear range, lowering cross-axis response, or reducing device volume. A multiobjective problem can be represented as:

$$\textbf{Minimize } \mathbf{F(x)} = [-\mathbf{S(x)}, \mathbf{P(x)}, \mathbf{N(x)}, \mathbf{V(x)}]$$

where **S** represents sensitivity, **P** is power consumption, **N** is noise or error, **V** is device volume, and **x** contains the design variables. Because these objectives can conflict, the result may be a Pareto set rather than one universally optimal solution.

Artificial Intelligence, Digital Twins, and Future Directions

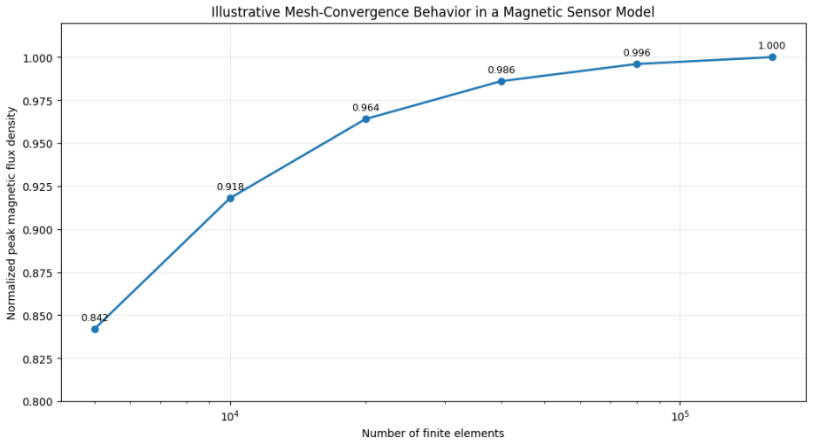
High-fidelity electromagnetic models can require substantial computation when thousands of geometric or operating configurations must be evaluated. Reduced-order models and surrogate models approximate the response of the detailed simulation and permit rapid prediction. A surrogate model may be trained using simulation data generated across a design-of-experiments space. Inputs can include geometry, material properties, current, temperature, and target position, while outputs may include field strength, sensor voltage, inductance, force, or loss. Once trained, the surrogate can evaluate new configurations much faster than a full finite-element solution. Physics-informed neural networks incorporate governing equations into the training process. Instead of learning only from input-output examples, the neural network is penalized when its predicted fields violate Maxwell's equations or boundary conditions. A parametric magnetostatic study demonstrated that a physics-informed network could represent field response as a function of geometry and operating parameters and could be evaluated against finite-element predictions. Physics-informed approaches are promising for repeated optimization, inverse problems, missing-data reconstruction, and real-time control. However, they do not automatically outperform established solvers. Training can be difficult near material discontinuities, sharp field gradients, nonlinear hysteresis, and complex three-dimensional boundaries. Digital twins combine computational models with live sensor data. A digital twin of a smart magnetic system can update its internal state using measured current, temperature, position, vibration, and field information. It may then estimate inaccessible quantities, predict failure, or adapt calibration. For example, a digital twin of a current sensor could compensate for temperature drift and magnetic aging. A magnetic actuator twin could estimate air-gap variation and mechanical wear. A structural-monitoring sensor could distinguish changes caused by stress from those caused by temperature or material degradation. Uncertainty quantification will become increasingly important. A deterministic model generally uses one value for each parameter, but manufactured devices exhibit variations in dimensions, material properties, alignment, and temperature. Probabilistic simulations can predict confidence intervals and manufacturing yield rather than only nominal performance. High-performance computing and graphics-processing units will enable larger three-dimensional transient and micromagnetic calculations. Adaptive mesh refinement can concentrate computational effort near moving interfaces, domain walls, or high-gradient regions. Cloud-based optimization may permit thousands of candidate designs to be evaluated simultaneously. Future smart magnetic devices will likely be designed through hybrid workflows. A high-fidelity finite-element or micromagnetic solver will generate reliable physical data, reduced-order models will provide rapid system-level predictions, and machine-learning algorithms will support optimization and adaptive control. Experimental data will continuously update the model, producing a closed loop among simulation, fabrication, sensing, and operation.

Singh and Sohail (2026) examined medical negligence in Malaysian hospitals through a qualitative thematic analysis of medico-legal court cases. Their study explored organisational and governance-related factors contributing to healthcare failures, including communication problems, documentation weaknesses, and inadequate risk management systems. The findings emphasized the importance of strengthening healthcare governance and adopting system-based approaches to improve patient safety.

Qazi and Sohail (2026) investigated the factors influencing investors' intention to participate in socially responsible investing among Pakistan Stock Exchange investors. The study focused on attitude, subjective norms, and perceived behavioral control as key determinants of investment intention. The results indicated that investors' positive attitudes significantly influence their willingness to engage in socially responsible investment practices.

Mousumi and Sohail (2026) studied the relationship between service quality, customer engagement, and customer loyalty in the Malaysian telecommunications sector. Their research highlighted that effective service quality dimensions, including reliability, responsiveness, and

customer support, contribute to stronger customer relationships. The study suggested that improving service quality can enhance customer engagement and promote long-term loyalty.



Author-generated illustrative data. The curve demonstrates diminishing changes in the predicted field as the mesh is refined; it is not taken from a specific experiment.

Summary

Computational electromagnetic modeling is central to the development of smart magnetic devices and sensor technologies. Maxwell-based numerical methods allow engineers to calculate field distribution, magnetic force, induced current, impedance, energy loss, temperature rise, structural deformation, resonance behaviour, and sensing response within complex devices. The finite-element method is particularly useful for irregular geometries, nonlinear magnetic materials, air gaps, conductive regions, and coupled electromagnetic–mechanical–thermal systems. Finite-difference, boundary-element, integral-equation, and micromagnetic techniques provide complementary capabilities for transient waves, open regions, scattering problems, and nanoscale magnetization. Applications include Hall-effect current sensors, magnetoresistive sensors, fluxgate magnetometers, magnetoelectric devices, inductive sensors, magnetostrictive transducers, MEMS resonators, magnetic encoders, smart actuators, and spintronic components. Modeling makes it possible to evaluate device behaviour before fabrication and identify the geometric or material variables that control sensitivity and stability. Model credibility depends on mesh convergence, realistic boundary conditions, accurate nonlinear material properties, uncertainty analysis, and experimental validation. Artificial intelligence and physics-informed neural networks may accelerate repeated simulation and inverse design, but they should complement rather than replace validated physical models. The next generation of smart magnetic systems will rely on computationally efficient digital twins capable of real-time calibration, fault prediction, adaptive compensation, and autonomous optimization. Integration of physical modeling, experimental measurements, data analytics, and intelligent control will improve device sensitivity, reliability, manufacturability, and energy efficiency.

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