Simulation Modeling of the Hall Electromagnetic Transducer for Measuring the Thickness of a Ferromagnetic Film

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Abstract

This paper presents a comprehensive study of 3D magnetic field modeling for a Hall effect-based electromagnetic transducer designed for high-precision, non-contact measurement of ferromagnetic film thickness. The transducer features a solenoidal coil and a sensitive gold Hall plate, with the test material placed between them. Magnetic field interaction with the material causes measurable changes in Hall voltage, correlating with layer thickness. A simulation model was developed in ANSYS Maxwell to visualize magnetic field distribution and study its dependence on geometry, material properties, and sensor positioning. Simulations with and without the specimen allowed analysis of system sensitivity and resolution, leading to the identification of optimal design parameters. The study demonstrates improved measurement accuracy for coating thicknesses from 1 to 400 μm. Additionally, it underscores the importance of computational methods in the development, optimization, and validation of electromagnetic measurement systems. The integration of simulation tools enhances predictive capability and reduces reliance on costly experimental testing, making the approach valuable for industrial applications requiring precise, real-time thickness control.

Keywords

electromagnetic transducer, Hall effect, magnetic field simulation, ferromagnetic film, simulation modeling

1. Introduction

Modern industrial production increasingly requires accurate and reliable sensors and quality assessment systems that are vital for productivity [1, 2]. The development of surface engineering technologies, in particular gas-thermal methods such as plasma and arc spraying, has led to the emergence of advanced coatings that require non-destructive and accurate thickness measurement. Among the most effective approaches are electromagnetic methods that provide high accuracy, operational reliability and seamless integration with automated production systems [3].

High-performance sectors such as aerospace and automotive often rely on multilayer coatings with distinct properties, making it essential to discriminate between layers while maintaining overall measurement accuracy. As these industries adopt Industry 4.0 strategies, the need for intelligent measurement systems with real-time feedback, predictive maintenance capabilities, and automated decision-making has grown. Electromagnetic approaches—especially those based on the Hall effect—are becoming indispensable in this evolving context.

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The Hall effect, discovered by Edwin Hall in 1879, forms the physical basis for many modern electromagnetic sensors. When current flows through a conductor in a magnetic field, a voltage is generated that reflects the magnetic field strength. This measurement principle provides exceptional sensitivity to changes in coating thickness, while remaining robust to environmental influences and surface contamination that typically affect other measurement approaches. Modern Hall sensor technologies have achieved significant improvements in sensitivity, stability, and operating range through advanced semiconductor fabrication techniques and intelligent signal processing algorithms, as presented in the following publications [4, 5].

Advanced Hall sensor configurations employ differential measurement techniques and temperature compensation algorithms to minimize environmental effects and enhance measurement accuracy across varying operational conditions. The development of integrated Hall sensor arrays has enabled spatially resolved thickness mapping, providing comprehensive assessment of coating uniformity and identifying localized variations that may affect component performance.

The evolution of electromagnetic computer modeling began in the 1950s when growing system complexity led engineers to adopt computers for design and virtual testing. Early modeling tools from this period became the foundation of today's advanced simulation environments, supporting design verification, optimization, and predictive modeling. The Finite Element Method (FEM) became a key approach for solving Maxwell's equations in complex geometries and materials [6, 7]. FEM handles nonlinear magnetic behavior, thermal effects, and multiphysics interactions. Techniques like adaptive meshing and efficient solvers enable accurate modeling, validated experimentally for sensor optimization [8, 9]. Electromagnetic coating measurement systems are widely used in aerospace, automotive, marine, and energy industries. For example, aerospace relies on these systems to control thermal barrier coating thickness on turbine blades, directly affecting durability [10], while the automotive sector uses them for corrosion protection assessment [11]. Current research focuses on enhancing measurement range, resolution, and layer discrimination. Multi-element Hall sensors and intelligent signal processing improve accuracy and robustness [12, 13]. Adaptive calibration and machine learning allow systems to compensate for material variability and environmental factors [14, 15]. Signal processing advances, including digital filtering, noise suppression, and real-time data interpretation, enhance performance in harsh conditions. 3D field modeling reveals how coatings redistribute magnetic flux, aiding both transducer optimization and algorithm development [16]. Parametric studies and cloud-based optimization facilitate efficient design exploration [17, 18]. Challenges remain in measuring ultra-thick or ultra-thin coatings and distinguishing multilayer structures. These are addressed by combining advanced hardware with hybrid electromagnetic measurement techniques [19–21].

The primary objective of this research is to develop a comprehensive three-dimensional magnetic field model of an electromagnetic transducer utilizing Hall effect principles for precise measurement of ferromagnetic coating thickness. This investigation aims to establish optimal design parameters for the Hall sensor element through detailed computational analysis, enabling enhanced measurement accuracy for heat-resistant protective films in industrial applications. The modeling approach seeks to characterize the complex electromagnetic interactions within the sensor system and determine the functional relationships between transducer geometry, material properties, and measurement sensitivity.

The main objective of this study is to simulate the operation of a Hall effect electromagnetic transducer specifically designed for accurate measurement of ferromagnetic coating thickness. This study aims to establish optimal design parameters through detailed computational analysis using advanced finite element methods, characterize complex electromagnetic field distributions in the transducer system, and determine functional relationships.

2. Computer modeling as a tool for developing a simulation model of a Hall effect-based sensor

Computer modeling represents a powerful methodology for studying real systems through their replacement with more convenient experimental models that preserve essential characteristics of the original object. In the context of Hall effect-based sensors, this approach enables the approximation of complex physical phenomena through simplified and practically manageable mathematical functions. The development of simulation models for Hall effect sensors requires substantial intellectual, financial, and temporal investments, making the decision to create new models justified only when simpler solutions or modifications of existing models are unavailable. Mathematical models, particularly those utilizing numerical methods, demand significant resources for their creation and validation. The process of investigating the modeling object and compiling its mathematical description involves establishing relationships between process characteristics, identifying boundary and initial conditions, and formalizing the process through systems of mathematical relationships. The comprehensive approach to mathematical modeling can be represented as a sequence of stages that systematically guide the development process from initial concept to final implementation.

Table 1
Classification of information models in computer simulation

Model Type	Characteristics	Application in Hall Effect Sensor Modeling
Mathematical Models	Symbolic models that describe specific numerical sequences and relationships	Fundamental equations governing electromagnetic field distributions, charge carrier transport, and sensor response characteristics
Graphical Models	Visual representation of objects and processes, particularly useful when other descriptive methods are inadequate	3D geometric representations of sensor structures, magnetic field visualization, current density distributions
Simulation Models	Enable observation of behavioral changes in system elements through computational experiments and parameter modification	Virtual sensor prototypes allowing investigation of design variations, operating condition effects, and performance optimization

The investigation phase of the modeling object requires several critical actions including analysis of object interaction with the external environment, identification of input influence characteristics and object responses, and classification of these parameters as measurable or unmeasurable, controllable or disturbances. The decomposition and investigation of the object's internal structure, along with studying the order of object functioning and identifying input-output relationships, forms the foundation for creating accurate mathematical representations. Collection and verification of existing experimental data about analogous objects, conducting additional experiments when necessary, and classifying the modeling object as stationary or non-stationary provide essential information for model development. The theoretical foundation of computer modeling encompasses different categories of information models, each serving specific purposes in the simulation process. These models can be systematically classified according to their characteristics and applications, as presented in Table 1. The systematic approach to computer modeling implementation follows a comprehensive workflow that ensures thorough development and validation of simulation models.

The complete sequence from initial problem analysis through final model application is demonstrated in Figure 1, which illustrates the methodological framework encompassing problem statement, information model construction, software tool selection, algorithm development, and result validation. Mathematical models provide symbolic representations that describe numerical sequences and specific relationships, forming the quantitative backbone of sensor analysis. Graphical models offer visual representations of objects and processes, particularly valuable for complex geometries where alternative descriptive methods prove inadequate. Simulation models enable direct observation of behavioral changes in system elements through computational experiments, allowing parameter modification and performance analysis.

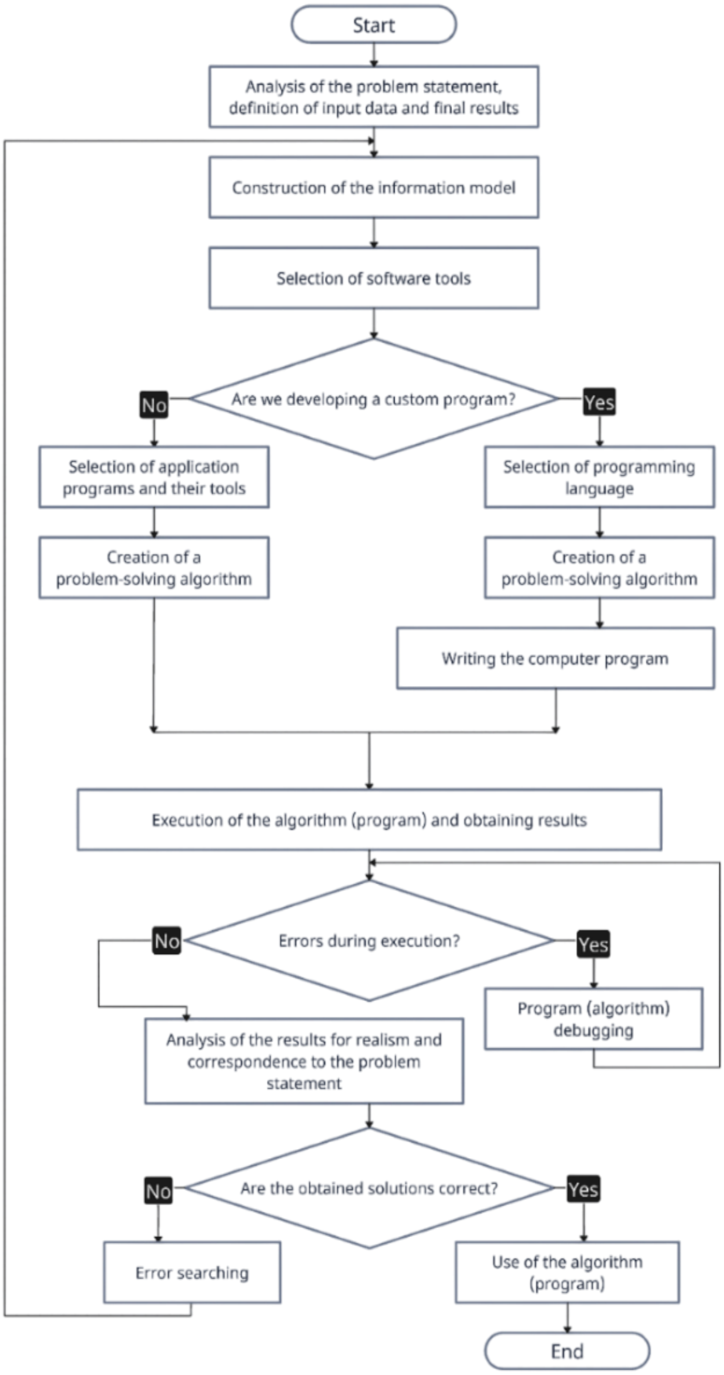

Figure 1: Block diagram showing computer modeling stages.

Mathematical model description utilizes various mathematical disciplines, with algebraic equations and systems, ordinary differential equations, partial differential equations, and matrix algebra being most widely applied for deterministic models. Stochastic modeling additionally employs probability theory methods, mathematical statistics, and random process theory. When a priori information about the object is insufficient, mathematical model forms are refined using multidimensional statistics methods including regression, correlation, multifactor analyses, and passive or active experiment planning.

For most complex objects, model structure contains parameters reflecting specific object characteristics. Parameter value determination occurs through parametric identification methods based on passive or active experiments. The concept of problem correctness holds important significance in the modeling process, as numerical solution methods should be applied only to correctly formulated problems. Mathematical models are correct when they yield positive results in all control checks including dimensionality, order, dependency characteristics, boundary conditions, and physical meaning. One of the solution methods is selected for the mathematical model, enabling the obtainment of output variable values for given input variable values. Method selection is justified based on model properties, variable measurement accuracy data, and solution accuracy and speed requirements. The necessary condition for transitioning from object investigation to model investigation and subsequent result transfer to the modeling object is the requirement of model adequacy to the object.

Adequacy represents the reproduction by the model of all object properties important for given research purposes with necessary completeness. Model adequacy is typically determined based on statistical evaluations of discrepancies between model and object output variable values at identical input variable values, calculated from modeling object experiment series results. Different experiment series data should be used for adequacy verification than for parametric identification. Differences between model and object output values may be caused by model simplification, numerical method errors, measurement device errors, and computational errors related to decimal and binary number system transitions and computer calculation peculiarities. If the model fails to satisfy adequacy criteria, step-by-step verification of development correctness at all stages becomes necessary, including experiment condition verification, measurement and result recording correctness, software implementation algorithm correctness, parametric identification result adequacy, model solution method selection justification, mathematical description correctness of phenomena and object characteristics, and conceptual model adequacy.

Mathematical modeling methodology enables avoiding the necessity of manufacturing cumbersome physical models associated with material costs, reducing characteristic determination time especially when calculating mathematical models on computers using effective computational methods and algorithms, studying modeling object behavior at different parameter values, analyzing the possibility of applying different elements, and obtaining characteristics and indicators that are difficult to obtain experimentally including correlational, frequency, and parametric sensitivity characteristics. Simulation modeling is a powerful tool that allows researchers and engineers to create digital analogues of real-world systems and processes. By combining logical-mathematical models with numerical algorithms and computer power, it becomes possible to study system behavior over time without the risks or costs associated with real experimentation. The process begins with identifying a real system and constructing a conceptual model that reflects its key elements and dynamics. This model is then translated into a mathematical form, which is further transformed into a simulation algorithm for implementation on a computer.

High-performance computing plays a critical role in modern simulation. Solving large systems of equations, handling complex meshes, or executing stochastic Monte Carlo simulations requires significant computational resources. Technologies like parallel computing, GPU acceleration, and adaptive time-stepping make it feasible to model high-dimensional systems with increased precision [22-23]. Moreover, modern simulation software such as ANSYS, COMSOL Multiphysics, GROMACS, and MATLAB provide extensive toolkits for modeling fluid dynamics, thermomechanics, molecular behavior, and control systems. One of the most effective techniques is adaptive mesh refinement (AMR), which allows the computational grid to automatically adjust its resolution in regions where the solution exhibits rapid changes or high gradients [24].

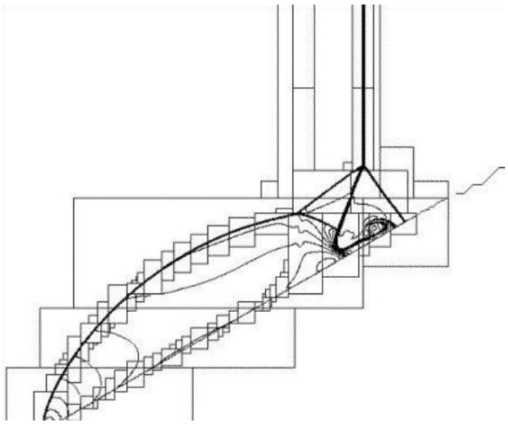

Figure 2: Grid structure in an AMR simulation of a shock wave interacting with an inclined surface.

This significantly increases accuracy without proportionally increasing the computational cost. AMR is widely applied in problems involving shock waves, turbulent flows, and chemical reactions, where localized phenomena must be captured with high precision. In AMR simulations, the computational grid is dynamically refined in response to local features of the solution. For example, during the simulation of a shock wave impacting an inclined surface, the algorithm automatically increases the resolution in regions where sharp gradients or discontinuities occur. The computational domain is divided into nested grids, with each successive level providing finer spatial detail. This hierarchical structure, as illustrated in Figure 2, ensures that high-resolution computations are performed only in areas where they are physically required, significantly improving efficiency while maintaining accuracy in critical regions.

3. Mathematical analysis and simulation modeling of the operation of the Hall sensor

Hall effect sensors work on the principle that a transverse voltage is induced in a current-carrying conductor when it is placed in a magnetic field. The development of such sensors requires microelectronic technologies, precise calibration, and a deep understanding of semiconductor physics. The Figure 3 shows a computer model of the sensor and its visual element of the Hall plate. Consider a conductor in the form of a rectangular plate through which an electric current I flows. In the absence of a magnetic field, the potential difference between points C and D, which lie on one of the equipotential surfaces, equals zero. When the sample is placed in a magnetic field with magnetic induction B perpendicular to both the current direction and the sample plane, a potential difference V_H develops between points C and D, termed the Hall electromotive force (EMF).

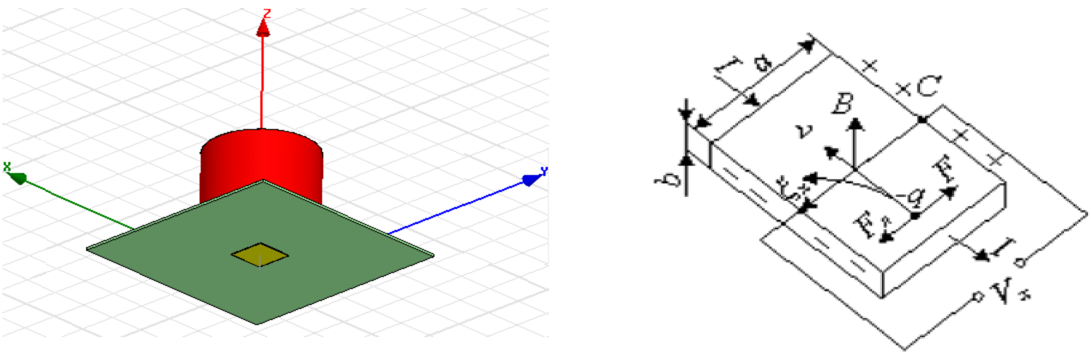

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Figure 3: Hall sensor model: (a) computer model in which a coil is shown in red, a measuring glass containing a sprayed metal layer in green, a hall plate in yellow; (b) Hall plate with physical values.

Experimental observations demonstrate that for moderately strong fields, V_H is proportional to the magnetic induction B, the current I, and inversely proportional to the plate thickness b:

$$V_H = R_H BI/b = R_H Bja, \tag{1}$$

where j represents the current density in the sample and a denotes the sample width. The proportionality coefficient R_h is a material constant called the Hall coefficient. It has dimensions of L^3/Q (where L is length and Q is electric charge) and is measured in m^3/C.

The physical mechanism underlying the Hall effect can be understood as follows. When current flows in the direction indicated by the arrow in Figure 3, electrons drift with velocity ν in the opposite direction.

Each electron experiences a Lorentz force from the magnetic field B:

$$F_L = q[\nu B], \tag{2}$$

where q is the electron charge. The direction of this force is determined by the right-hand rule. Since the angle between ν and B equals 90°, the magnitude of the Lorentz force is:

$$F_L = q\nu B. \tag{3}$$

Under the influence of the Lorentz force, electrons are deflected toward the outer edge of the plate (dashed line in Figure 3), charging it negatively. Uncompensated positive charges accumulate on the opposite face, leading to the establishment of an electric field directed from C to D with magnitude:

$$e_H = V_H/a, \tag{4}$$

where V_H is the potential difference between points C and D (Hall EMF).

The field e_H exerts a force on electrons given by $F = -qe_H$, , directed opposite to the Lorentz force. When $F = F_L$, the transverse electric field balances the Lorentz force, and further accumulation of electric charges on the lateral faces of the plate ceases. From the equilibrium condition:

$$q\nu B = qe_H, \tag{5}$$

we obtain:

$$e_H = \nu B \tag{6}$$

Considering that the current density in the conductor is j = qnν, where n is the electron concentration, we get ν = j/(qn). Substituting this expression into equation (6):

$$V_H = (1/qn)Bja. \tag{7}$$

Theory thus leads to an expression for V_H that coincides with the experimentally established relationship (1). The Hall coefficient is therefore:

$$R_H = 1/qn. \tag{8}$$

The comprehensive analysis of electromagnetic field interactions within the Hall effect measurement system necessitates sophisticated computational modeling approaches. In the work, it was decided to use the Ansoft Maxwell 13.0 system for the numerical modeling of the measuring transducer based on the Hall effect. It is a software for modeling electromagnetic fields, which is used for the design and research of two-dimensional and three-dimensional models of sensors, transformers and other electrical and electromechanical devices of various applications. Ansoft Maxwell is based on the finite element method and calculates static, harmonic electromagnetic and electric fields and transients in field problems with high accuracy. The use of such software significantly reduces the design time, allows to optimize the design of the measuring transducer (thickness gauge) in accordance with the main criteria.

The Hall sensing element is modeled as a gold sheet with dimensions a = 50 mm (length), b = 50 mm (width), and d = 1 mm (thickness). The selection of gold as the Hall sensor material is based on its excellent electrical conductivity, chemical stability, and well-characterized Hall effect properties. The electromagnetic excitation conditions include a constant magnetomotive force of 500 ampere-turns applied to the inductor coil and a measurement current of 30 mA flowing through the Hall plate.

The setup used in Maxwell simulations possesses the following parameters: its maximum number of passes is 10 with a percent error of 1%; refinement per pass is 30; the minimum number of passes is 2; the minimum number of converged passes is 1; and the nonlinear residual was set to 0.001. A calculation accuracy of 1% and modeling condi-tions were also established for vacuum, which in its magnetic properties is close to air, as well as to organic substances that cause surface uncertainties (not of ferromagnetic na-ture). The modeling was carried out for magnetostatics, and the magnetic properties (rela-tive permeability, bulk conductivity) of the materials from which the model was created are fixed according to the Maxwell library.

For numerical modeling, ANSYS Maxwell 13 software was used, which is focused on calculating electromagnetic fields using the finite element method. All calculations were performed on a personal computer with an Intel Core i5-480M processor (2.66 GHz, 2 cores / 4 threads), 8 GB DDR3 RAM and a 500 GB hard drive. Despite the limited hardware resources, the selected model sizes and adaptive grid provided sufficient calculation speed and acceptable convergence time.

The simulation environment was configured to represent vacuum conditions, which closely approximates the magnetic properties of air and organic materials that may be present in the measurement environment. This assumption is valid for non-ferromagnetic materials and eliminates complications arising from complex permeability variations.

The tests and modeling were carried out under normal conditions (temperature and humidity close to standard), therefore the influence of temperature dependence of material properties, as well as geometric inaccuracies and defects of samples, was not specifically considered in this work. The saturation of the ferromagnetic material was considered only in the context of modeling in the Maxwell environment. These factors are supposed to be taken into account in further studies during extended tests.

The magnetic flux density distribution analysis shows significant spatial variation across the measurement volume. On the horizontal cross-section passing through the center of the gold Hall plate (parallel to the xOy plane), magnetic induction values range from 1.78 mT at the center position directly opposite the coil to 0.019 mT at the peripheral regions. This substantial variation in field strength across the measurement area demonstrates the importance of precise positioning and the need for calibration procedures that account for spatial non-uniformities.

The vertical cross-sectional analysis (parallel to the xOz plane through the coil centerline) reveals the three-dimensional nature of the field distribution. The magnetic field strength exhibits values ranging from 1545 A/m near the coil edges to 1062 A/m at positions distant from the coil terminations. These results confirm the expected field concentration near the inductor windings and the gradual field attenuation with increasing distance from the source.

The computational results validate the theoretical understanding of electromagnetic field behavior in solenoid configurations. The highest absolute values of magnetic flux density occur within the coil volume, particularly near the coil edges, while the maximum magnetic field strength is concentrated near the winding periphery. These field distribution patterns correlate well with established theoretical predictions, as illustrated in Figure 4.

A comprehensive parametric study was conducted to evaluate the influence of key design variables on measurement system performance. Three primary parameters were investigated: the air gap distance between the coil and glass substrate (Δ), the Hall plate aspect ratio (b/a), and the Hall plate thickness (d). During each parametric sweep, one variable was modified while maintaining constant values for the remaining parameters.

The theoretical Hall coefficient for the gold measuring plate was calculated using the established relationship, yielding RH = 1.09×10^{-10} m^3/C. As the air gap between the inductor and the coated substrate increases, the magnetic field strength within the Hall plate decreases proportionally, while the Hall coefficient remains essentially constant. This behavior confirms the theoretical predictions regarding the independence of material properties from applied field strength within the linear operating regime, as demonstrated in Figure 5.

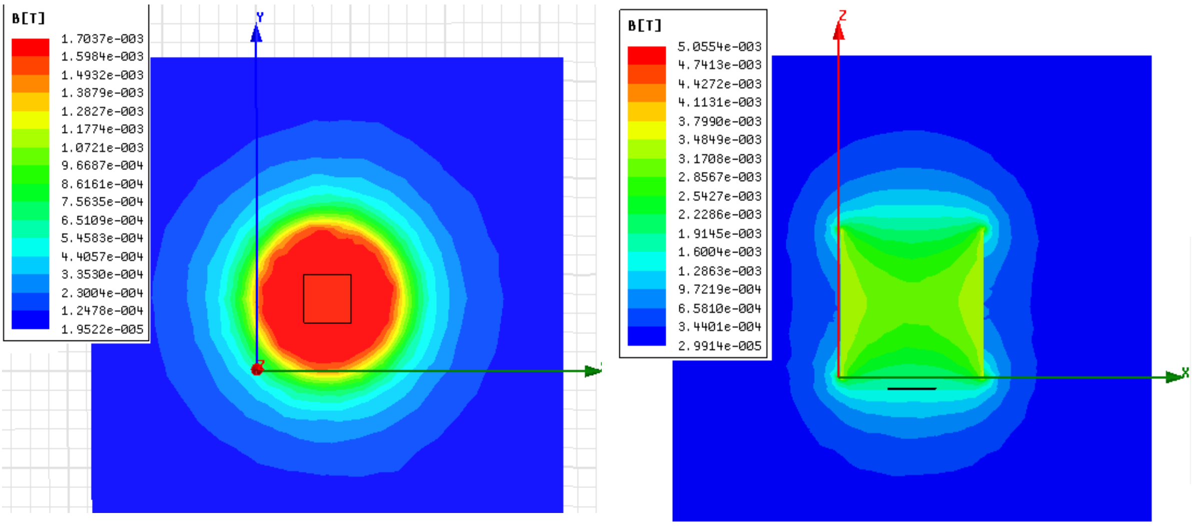

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Figure 4: Magnetic field distribution patterns: (a) magnetic induction on horizontal section through Hall plate center, (b) magnetic induction on vertical section through coil center.

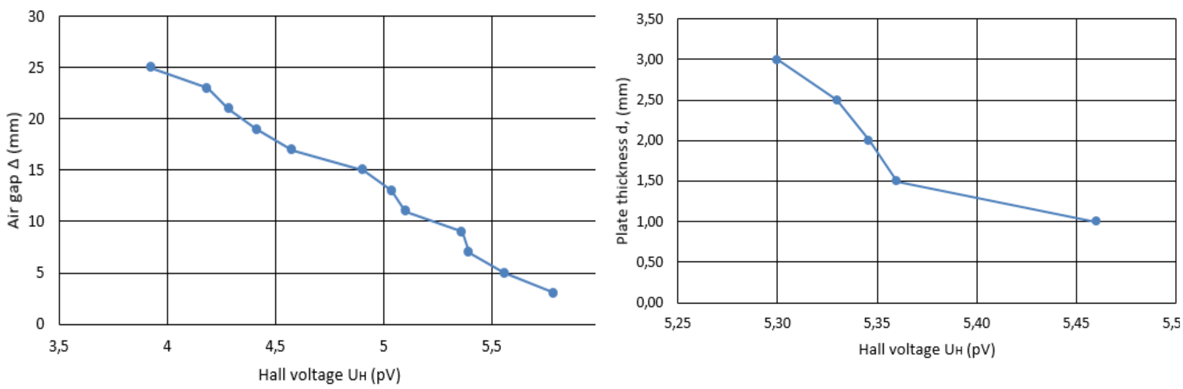

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Figure 5: Hall voltage distribution depending on: (a) air gap, (b) Hall plate thickness.

The computational analysis of various iron coating thicknesses (δ) reveals systematic changes in the electromagnetic field characteristics. For fixed Hall plate parameters (Δ = 4 mm, d = 1 mm, b/a = 100/100), the simulation results demonstrate the direct relationship between coating thickness and the measured electromagnetic parameters across the range from 0 to 400 μm.

The calculated Hall coefficient and resulting voltage variations across the Hall plate dimensions provide quantitative metrics for evaluating measurement sensitivity.

The analysis indicates that the effective measurement range of the proposed sensor system extends from 0.001 mm to 0.2 mm for deposited metallic films, which encompasses the requirements for various industrial applications.

Beyond 0.2 mm thickness, the measurement sensitivity decreases significantly due to magnetic flux saturation effects within the ferromagnetic coating. The detailed results are presented in Table 2. The results demonstrate that the proposed transducer configuration exhibits clear sensitivity to variations in ferromagnetic film thickness within the range of 1 to 400 µm. Notably, thinner coatings preserve stronger magnetic fields in the Hall sensor region, resulting in higher Hall voltages, while thicker films redirect magnetic flux and attenuate the measurable field behind the sample. This effect establishes a functional correlation between film thickness and Hall voltage, enabling precise non-contact measurement.

Table 2
Computational results for different iron coating thicknesses (δ) with fixed parameters Δ = 4 mm, d = 1 mm, b/a = 100/100

δ, mm	*B*, mTl	*H*, A/m	U_{20}, pV
0.001	1.58	1261	5.1666
0.01	1.18	980	3.8586
0.1	0.395	800	1.29165
0.2	0.295	212	0.96465
0.3	0.23	195	0.7521
0.4	0.18	174	0.5886

Potential areas of application are quality control of ferromagnetic coatings in mechanical engineering and instrument making; detection of corrosion and degradation of materials — a decrease in the thickness of protective coatings can be detected at early stages; evaluation of the parameters of ferromagnetic films or coatings in real time without damaging the sample, which is in demand in the energy, aviation and electronics industries

4. Conclusions

A detailed three-dimensional computational model of a Hall effect-based electromagnetic transducer has been successfully developed and analyzed for the purpose of measuring ferromagnetic film thickness. The simulation model incorporated key geometric, electrical, and material parameters of the system, including the coil, Hall plate, and test substrate, and was implemented using the finite element method in ANSYS Maxwell. The simulation results provided comprehensive insight into the spatial distribution of magnetic flux density and field strength under various conditions, including changes in sensor geometry, air gap distance, and coating thickness. The modeling approach enables optimization of sensor design and operational parameters, offering valuable guidance for real-world deployment in high-temperature or corrosion-resistant coating processes, such as turbine blade protection.

Our ANSYS Maxwell modeling allows. Optimize the Hall sensor design — select the coil parameters (number of turns, geometry, excitation current) and the location of the sensing element to obtain a sensitive signal. Predict behavior in various conditions — evaluate the effect of the gap, coating thickness, material heterogeneity and external factors without conducting a large number of expensive experiments. Increase the accuracy of film thickness measurements — using modeling, you can build calibration dependencies, take into account the geometric features of the sample and compensate for systematic errors in advance.

The study confirms the effectiveness of numerical modeling in predicting the electromagnetic behavior of complex sensor systems. The integration of adaptive simulation techniques not only accelerates design iterations but also enhances prediction accuracy and reliability. The approach is adaptable to other coating materials and geometries, positioning it as a promising tool for industrial surface quality control, particularly in scenarios demanding real-time, high-resolution, and non-invasive measurement capabilities.

5. Prospects for Further Research

In the future, it is planned to experimentally test the developed numerical model on a series of reference samples with a controlled coating thickness in the range from 1 to 400 μm (manufacturing error ±0.5 μm). For this purpose, a measuring setup with thermal stabilization (±0.5 °C) and a precision micropositioner for setting the gap between the sensor and the sample will be used. The next step will be the creation and testing of a laboratory prototype of the Hall sensor with an optimized design of the coil and sensing element. In addition, it is planned to study alternative sensor configurations (variations in coil geometry, multi-position measurement schemes, the use of different Hall plate materials) to improve accuracy and expand the range of measured thicknesses. A separate area of work will be taking into account temperature factors, geometric tolerances and possible material defects to bring the modeling conditions closer to real industrial problems.

Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 and Gramby in order to: Grammar and spelling check. After using these tools/services, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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