

Enhancing Transformer Efficiency and Cost-Effectiveness Through Genetic Algorithm and FEMM Analysis

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This research investigates how to improve transformer efficiency and reduce manufacturing costs by combining Genetic Algorithms (GA) and Finite Element Method Magnetism (FEMM) analysis. We present a distinctive approach to optimizing transformer design parameters using GA, with the goal of improving performance indicators such as energy efficiency while minimizing material costs. The FEMM analysis is used to simulate and validate the magnetic properties of optimal transformer designs. Our methodology shows considerable gains in transformer efficiency while also lowering costs, providing a twofold advantage that is critical for long-term electrical engineering practices. The results show that combining GA with FEMM an advanced algorithmic design with electromagnetic simulation, can result in more cost-effective and energy-efficient transformer designs.

Keywords : Cost, Finite Element Method Magnetism (FEMM), Genetic algorithm, Optimization, Transformer efficiency, Three phase transformer

1. Introduction

The promise of optimizing electrical machines and systems lies in the potential to significantly enhance their reliability, efficiency, and overall performance, which has garnered considerable attention in the field of electrical engineering. Among these systems, three-phase transformers are indispensable components in power distribution networks, responsible for stepping voltage levels up or down and ensuring the efficient transmission of electrical energy. As global energy demands continue to rise, optimizing transformer design becomes increasingly critical, offering the possibility of substantial benefits such as improved efficiency, reduced operational costs, and improved system stability and reliability [1, 2].

The endeavor to reduce total losses in transformers is more than just an academic pursuit; even minor improvements can yield considerable economic and environmental benefits. Total loss minimization, a key goal in transformer design, includes both core losses and copper losses, which are critical criteria described in

multiple research studies, industry manuals, and international laws [3]. There are other transformer losses like stray losses and dielectric losses. Stray losses may be caused by the magnetic flux linked to the transformer tank. Stray losses in a transformer are not considered in this research due to the heavy computational load required in FEMM, hence this paper will only cover losses due to hysteresis and eddy current on the core and copper losses on the windings of the transformer.

Traditional optimization techniques for transformer design often involve complex, iterative procedures that can be computationally intensive and time-consuming, relying on intricate mathematical models that may not always capture the full spectrum of real-world operational conditions. These conventional methods, while effective to an extent, may fall short in achieving the desired level of precision and efficiency, particularly when dealing with the intricate electromagnetic behaviors inherent in transformers [4, 5].

In response to these challenges, this paper presents a distinctive approach that integrates the Finite Element Method Magnetism (FEMM) with a Genetic Algorithm (GA) to optimize the design of three-phase transformers. The Finite Element Method (FEM) is a powerful numerical tool widely used in engineering for simulating

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physical phenomena, providing a detailed analysis and visualization of electromagnetic fields within electrical devices. FEMM (Finite Element Method Magnetics), a specialized implementation of FEM for magnetic field analysis, offers an in-depth understanding of the electromagnetic performance of transformers, enabling designers to predict and fine-tune performance parameters with high accuracy [6]. The Genetic Algorithm, inspired by the process of natural selection, is an optimization technique that mimics the principles of biological evolution, including selection, crossover, and mutation [7, 8]. Unlike some other optimization techniques that might require longer convergence times or more computational resources, the GA-FEMM approach has been shown in preliminary assessments to reduce the computational burden, thus streamlining the entire optimization cycle. The Genetic Algorithm (GA) is thought to be more effective than other optimization techniques for a variety of reasons, particularly when used with the Finite Element Method Magnetics (FEMM) in transformer construction. GA is recommended because it successfully searches large and complicated design spaces for optimal solutions, which is critical in transformer design, where various parameters and their interactions have a substantial impact on performance. Furthermore, GA can be efficiently parallelized, enabling it to perform large simulations such as those required for electromagnetic analysis in transformers [9]. This parallel capacity considerably saves calculating time, making it an attractive option in industrial applications where time and resource efficiency are critical. These features make GA ideal for the integrated GA-FEMM technique used in transformer optimi-

zation, which provides a reliable and adaptable strategy for increasing transformer efficiency and performance while minimizing losses.

The objective of this study is to demonstrate how the integration of FEMM and GA can lead to the optimal design of three-phase transformers, with a focus on improving operational efficiency, reducing material costs, and ultimately contributing to the development of more sustainable energy management practices.

This paper is organized to guide the reader through a systematic exploration of our research. We begin with the methodology section that explains the computational techniques used to optimize transformer design through the integration of GA with FEMM. Following this, the results and discussion section presents findings from our simulations, demonstrating how various design modifications impact transformer efficiency and performance, and interprets these results, considering their implications for both transformer design practice and potential areas for further research. Finally, the Conclusion summarizes the study's contributions to the field of transformer design optimization, highlighting the practical benefits and suggesting directions for future research.

2. Methodology

In this research, we develop a methodology that intricately combines Finite Element Method Magnetics (FEMM) with Genetic Algorithms (GA) to elevate the design standards of three-phase transformers. Our approach begins with the establishment of a baseline design for the transformer, where essential parameters such as core

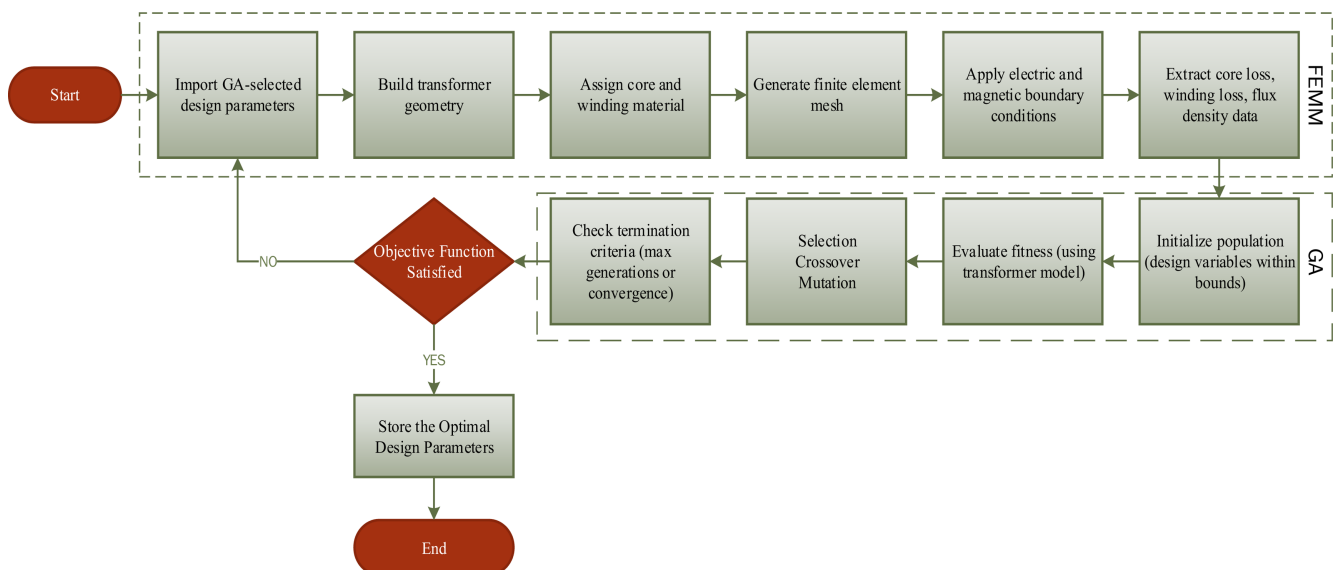


Fig. 1. (Color online) Flowchart of GA+FEMM Optimization.

material, geometry, winding arrangement, and insulation types are meticulously defined. This initial design serves as the groundwork upon which our optimization process builds.

Following the initial setup, we employ FEMM software to conduct comprehensive electromagnetic simulations. These simulations are critical as they provide a deep dive into the baseline characteristics of the transformer, highlighting areas such as magnetic flux distribution and core saturation patterns. By understanding these foundational aspects, we identify potential inefficiencies and areas where improvements are paramount. The precision of FEMM is crucial, as it provides deep insights into the distribution of electromagnetic fields, core losses, leakage inductance, and overall efficiency across various loading conditions [10, 11]. These detailed simulations allow for a thorough analysis of how the transformer will perform under real-world conditions, enabling designers to pinpoint areas for improvement and make informed decisions during the optimization process.

Using the insights gathered from FEMM simulations, the Genetic Algorithm takes the front stage in refining transformer design. The GA iteratively adjusts essential design parameters like as core shape, lamination thickness, and winding configurations to maximize transformer efficiency and reduce material use. GA is a robust optimization technique inspired by the principles of natural evolution, where design candidates (solutions) undergo selection, crossover, and mutation processes to evolve toward optimal solutions [12]. Each iteration of the GA process includes complex selection, crossover, and mutation phases, all guided by fitness evaluations based on the initial and ongoing FEMM investigations. This dynamic and responsive optimization approach is critical for successfully navigating the broad design space, ensuring that each tweak contributes favorably to the overall design objectives.

The strong interplay between GA optimization and FEMM validation creates a constant iterative feedback loop. To validate the effectiveness of each alteration, optimized designs are cycled through FEMM simulations again. This loop continues until the incremental gains in efficiency and cost reductions reach a plateau, suggesting convergence toward an ideal design configuration. Once a potentially optimal design is identified, we move to the prototype testing phase. This stage is crucial for bridging the gap between theoretical simulations and tangible operational performance.

By meticulously integrating advanced simulation tools with evolutionary optimization techniques, our methodology not only enhances the performance of three-

phase transformers but also ensures these improvements are achievable within practical, real-world constraints. This approach allows for a sophisticated exploration of transformative solutions that meet the modern demands of efficiency and cost-effectiveness in transformer manufacturing. Fig. 1. depicts the flowchart for the methodology.

2.1. Transformer Specification

A full description of the transformer's properties is required to improve its efficiency and cost-effectiveness by integrating genetic algorithms with finite element method magnetics (FEMM) analysis. The detailed specification includes numerous key components that are critical for future analysis and optimization processes.

The prototype transformer being studied is a commercial three-phase unit intended for medium to high-voltage applications. This option reflects the typical requirements of modern power distribution networks, which prioritize efficiency and reliability. The core material used is high-grade Cold-Rolled Grain Oriented Steel (CRGO) and its properties are shown in Table 1 and Fig. 2 shows the B-H Magnetization Curve Validation comparing prototype measurements with FEMM simulation results. The excellent agreement (maximum error 2.1%) validates our CRGO material model implementation. The operating points at 1.48T (prototype) and 1.50T (FEMM) demonstrate accurate flux density prediction under nominal conditions. It is known for its exceptional magnetic characteristics and reduces core losses, an important component in transformer performance. In transformer design, core material selection is crucial as it directly influences efficiency and effectiveness in its operation. CRGO is one of the frequently used magnetic materials due to its excellent magnetic properties, especially high magnetic permeability and low power loss, which play a vital role in high-performance trans-

Table 1. Magnetic Characteristics of CRGO Material Used in FEMM Analysis from Non-linear B-H Curve Model.

Property	Symbol	Values
Relative permeability (linear)	μ_{rx}	55,000
Relative permeability (linear)	μ_{ry}	55,000
Maximum B-H curve angle	ϕ_{max}	2.85°
Coactivity	H_c	0 A/m
Electrical conductivity	σ	4.8221 MS/m
Lamination thickness	-	0.27 mm
Lamination fill factor	-	0.97
Number of strands	-	0
Strand diameter	-	0 mm

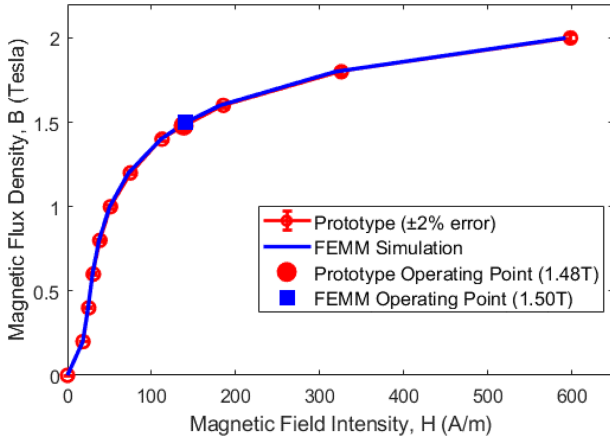


Fig. 2. (Color online) B-H Magnetization Curve Validation comparing prototype measurements with FEMM simulation results.

formers. These inherent qualities, whereby a significant improvement in the transformer efficiency due to a reduction of the core losses is achieved, form the basis for adopting CRGO in the transformer model in the present study.

A distinctive feature of CRGO is its anisotropic magnetic properties, meaning that its magnetic characteristics vary depending on the direction of magnetization. This anisotropy is particularly relevant to transformer core design because it affects how the core handles magnetic flux under operational conditions. The orientation distribution function (ODF) plays a pivotal role in characterizing the anisotropy of these materials. It accounts for the distribution of crystallographic orientations within the steel, which directly impacts its magnetic properties. The ODF method has been successfully applied to CRGO steels, offering a robust framework for predicting and understanding their behavior under various magnetic orientations [13]. Central to the quantification of magnetic anisotropy using the ODF is the ability to determine the magnetic properties along different directions with respect to the rolling direction (RD). For instance, by considering only a few measurement directions, specifically 0° , 45° , and 90° relative to the RD (Rolling direction). It is possible to effectively predict magnetic behaviors across all angles. This is captured in the mathematical relationship which models the magnetic property A as a function of the angle ϕ :

$$A = A_0 + A_1 \cos(2\phi) + A_2 \cos(4\phi) \quad (1)$$

Where A_0 , A_1 , and A_2 are coefficients derived from measurements at these principal directions. These coeffi-

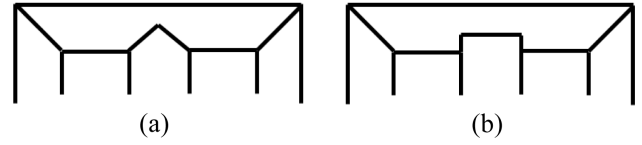


Fig. 3. Transformer core joint configurations (a) Mitered 45° (b) Butt-lap 90° .

cients are crucial for describing the average anisotropic properties and their deviation from isotropy. This is discussed in more detail in [14]. This mathematical model facilitates a more nuanced understanding of the anisotropic magnetic properties and enables the design of more efficient magnetic circuits by predicting magnetic properties for arbitrary angles with respect to the RD.

Misalignment of the core in these regards increases the losses as the flux will face greater magnetic resistance. In [15] the author of the paper describes the measurements of electrical steel. The results show dependency between the anisotropy angle and the magnetization curve, as well as core losses. In our methodology, the examined core was made with lamination at 45° as shown in Fig. 4.

In our simulations and design optimizations, a detailed model of the CRGO material properties, including its anisotropic performance, is considered. Therefore, parameters in the FEMM model are carefully tuned to reflect the anisotropic aspect of CRGO to realize more realistic and representative real-world simulations. By integrating the Genetic Algorithm (GA) with our FEMM simulations, we iteratively refine the transformer's design to reduce losses, particularly focusing on optimizing the core's geometry and material distribution to handle anisotropic effects efficiently. This iterative process allows for the detailed exploration of various design configurations, identifying optimal arrangements that specifically reduce the adverse impacts of anisotropy on transformer performance.

Copper conductors are employed for their low resistance and great conductivity. The arrangement of these windings is critical since it affects the transformer's impedance, voltage regulation, and efficiency. Each winding is meticulously calculated to create the best possible cost-performance balance, maximizing material utilization while ensuring that the transformer satisfies the stated energy efficiency standards.

The transformer's operational specifications include its rated power capacity, which is determined based on the expected load conditions. Under typical operating conditions, the three-phase transformer is designed to function at approximately 80% of its nominal power capacity, equivalent to 120 MVA. This operating point is chosen in

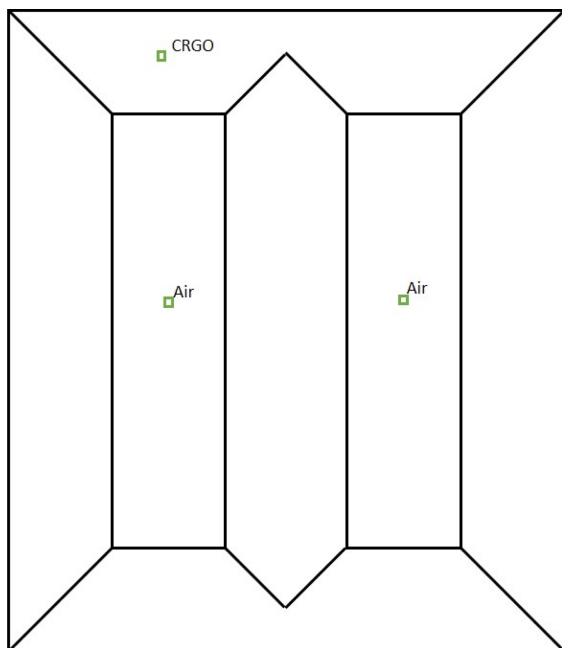


Fig. 4. (Color online) Core design in FEMM showing miltred joint.

Table 2. The Specification of Three-phase Transformer Prototype.

Parameters	Specification	Values
Rating	Power	150MVA
	Frequency	50Hz
	Voltage (HV/LV)	132/14.1KV
	Current (HV/LV)	655/3537 A
	Number of turns (HV/LV)	432/80
Windings	Material	Copper
	Density	8300 Kg/m ³
	Relative Permeability	1
	Resistivity	1.724e-008 ohms.m
Core	Material	CRGO
	Permeability	55,000
	Resistivity	2.07e-7 ohms.m
	Magnetization	1.5T
Magnetic Core	Height	3815 mm
	Length of yoke	3610 mm
	Section of columns	820 mm
	Section of yoke	820 mm
	Thickness of core	816 mm
	Distance between legs	1395 mm
HV windings	Height	1935mm
	Inner radius	571.5 mm
	Outer radius	666.5 mm
	Width	95 mm
LV windings	Height	1935 mm
	Inner radius	455 mm
	Outer radius	525 mm
	Width	70 mm

Table 3. Transformer Prototype and FEMM Simulation.

Pareameters	Prototype	Femm
Total-loss (KW)	187.45	185.70
B (T)	1.48	1.50
Efficiency (%)	90.30	91.43

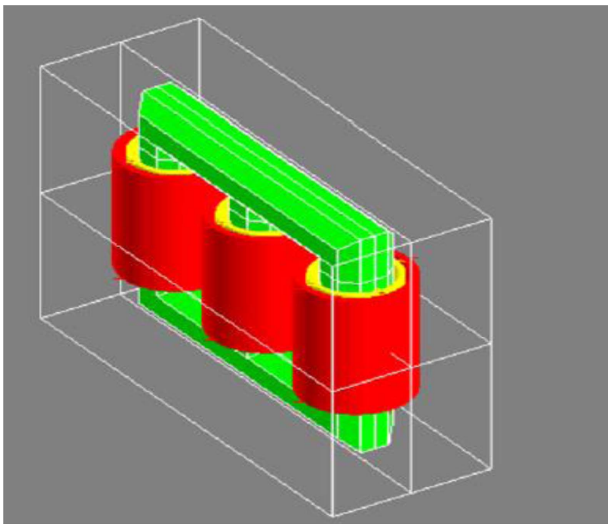


Fig. 5. (Color online) Altair Flux 3D design of the Transformer's prototype.

this study to optimize efficiency and reliability, while also accommodating expected variations in load within safe operational limits. Voltage levels for both primary and secondary sides are defined according to the requirements of the power distribution network. Additionally, the efficiency parameters are set to meet or exceed current industry standards, with specific goals for reducing load and no-load losses.

Table 2. Shows the specification and values of the prototype transformer's parameter where HV represents high voltage windings and LV represents low voltage windings, Table 3. Compares prototype and FEMM simulation and Figure 5 shows the Altair Flux 3D design of the Transformer's prototype

2.2. Considerations and Justification for Model Simplifications

In the pursuit of optimizing transformer design through the integration of Genetic Algorithms (GA) and Finite Element Method Magnetism (FEMM), certain simplifications were deemed necessary to balance the depth of analysis with computational feasibility. This research primarily employed 2D simulations and excluded detailed considerations of thermal effects and stray losses. While

these decisions were driven by the need to manage computational resources efficiently, they introduce specific limitations that are important to acknowledge and understand.

The exclusion of 3D modeling in this study is primarily due to the significant computational resources required for such detailed analyses, which are not always feasible within the constraints of academic research settings. Although 3D models provide a more comprehensive representation of physical phenomena, particularly in capturing complex magnetic interactions and flux leakage effects, the 2D approach allows for more extensive parametric studies and iterative optimizations due to its lower computational demands. It is recognized that this simplification might limit the accuracy in predicting the magnetic flux distribution and localization of flux concentrations which are better represented in a three-dimensional space.

Further, the thermal effects and stray losses, which can notably influence transformer performance, were not explicitly modeled. Stray losses, often caused by flux leakages impacting other conductive components of the transformer, contribute to overall efficiency losses and heat generation. Similarly, thermal modeling, which could provide insights into the heat distribution and its impact on transformer materials and longevity, was omitted. The absence of these considerations was a calculated decision to focus the computational efforts on optimizing core geometries and material properties directly influencing hysteresis and eddy current losses which are more critical to the primary objectives of enhancing efficiency and cost-effectiveness.

The simplifications made in this study are justified by the significant computational load that detailed FEMM and GA require. By focusing on more manageable model complexity, the study benefits from increased computational speed, allowing for broader optimization studies involving numerous design iterations. This approach aligns with the research aim to demonstrate the potential of GA and FEMM for efficient transformer design, providing a foundation upon which more detailed future studies could build.

2.3. Enhanced 2D Simulation and Integration Techniques for Transformer Design Optimization

In transformer design optimization, accurately modeling the electromagnetic properties of three-dimensional objects such as transformer cores in a two-dimensional (2D) simulation environment poses unique challenges. This section details the methodologies employed to address these challenges, focusing on geometric adjustments for

2D simulations, the integration of FEMM with MATLAB using Lua scripts, and the consideration of material properties in simulations.

• Geometric Adjustment for 2D simulation

Finite Element Method Magnetics (FEMM) models electromagnetic processes in two dimensions, a constraint that necessitates careful geometric adjustments when representing inherently three-dimensional components like transformer cores. In standard transformer designs, the core typically comprises limbs and windings that are not easily depicted in 2D. For instance, the transformer's limb, which may physically exhibit a three-teeth cross-sectional shape, must be simplified for accurate 2D simulation [16, 17]. While FEMM provides a robust platform for electromagnetic simulations, the geometric and material adjustments required for converting 3D objects into a 2D format are essential for achieving accurate results. Computation efficiency and accuracy call for a balance in transformer design optimization, hence the use of 2D modeling in simulations through finite Element Method Magnetics or FEMM. Transformers are naturally three-dimensional devices, but 3-D simulations are immensely costly computationally, particularly for iterative algorithms like GA. In turn, it is so important to transition to the 2D model, despite the simplifications that are present, for its ability to provide a much more dynamic and responsive process of design [18]. We do this by projecting the geometrically complex structure of a transformer's core and its windings onto a plane, using an approach that gains simplicity based on the assumption of uniformity along an axis perpendicular to the plane of analysis. In practice, what this means is to develop a model, ignoring variations that would take effect concerning magnetic flux distribution in the third dimension. Such a simplification is justified by the significantly reduced computational demands that permit more extensive investigation of design variables within feasible time constraints. Material properties also require careful adjustment to ensure that the behavior in the 2D model reflects real-world 3D characteristics. Key properties such as magnetic permeability and electrical conductivity are adapted to account for the reduced dimensionality. For example, for nonlinear problems, the hysteresis lag is assumed to be proportional to the effective permeability. At the highest effective permeability, the hysteresis angle is assumed to reach its maximal value of ϕ_{hmax} as shown in (2).

$$\phi_h(B) = \left(\frac{\mu_{eff}(B)}{\mu_{eff,max}} \right) \phi_{hmax} \quad (2)$$

Where $\phi_h(B)$ is the hysteresis angle or loss angle between

the magnetic field H and the magnetic flux density B as represented in FEMM. $\mu_{\text{eff}}(B)$ is the effective permeability at a given magnetic flux density and $\mu_{\text{eff,max}}$ is the maximum effective permeability that the material can achieve.

In the 3D physical model of the transformer, the core is typically designed with rounded edges. These rounded edges help in reducing sharp magnetic field gradients that can lead to inefficiencies such as increased hysteresis and eddy current losses. However, when approximating this model in a two-dimensional Finite Element Method Magnetism (FEMM) simulation, these three-dimensional rounded edges are represented as sharp, rectangular edges. This simplification is necessary due to the constraints of the 2D simulation environment, which does not easily accommodate the complex curvature of rounded edges. This adjustment in the model helps streamline the simulation process while maintaining an acceptable level of accuracy in the analysis of magnetic flux distribution within the core. These changes in geometry and materials cannot be ignored in the simulation, they may bring disparities in the magnetic flux distribution that was estimated and the loss calculations with respect to a full 3D study. These geometric simplifications are crucial for ensuring that the 2D model accurately reflects the magnetic properties of the core, despite the limitations imposed by the two-dimensional analysis environment of FEMM.

- Integration of FEMM with MATLAB Using Lua Script

To enhance the capabilities of FEMM and enable more dynamic and complex simulations, a Lua scripting interface has been used to integrate FEMM with MATLAB. This integration leverages MATLAB's powerful computational abilities, allowing for advanced data manipulation, parameter control, and automation of the simulation process. The integration allows for seamless communication between FEMM and MATLAB. By using Lua scripts, we programmatically adjust simulation parameters directly from MATLAB, thus streamlining the process of model configuration and enabling dynamic changes based on real-time analysis results. This method of integration is especially beneficial for managing complex simulation workflows that require frequent adjustments of parameters to optimize performance criteria. For example, during the transformer's no-load simulation at nominal voltage, the Lua script adjusts the currents in phases B and C to correspond accurately with the magnetic flux distributions caused by the applied voltage. Meanwhile, phase A's current is elevated to its peak value as part of the scenario being tested. This kind of precise control over simulation parameters directly

from MATLAB enhances our ability to model and analyze different operational conditions meticulously. It allows us to observe the effects of various electrical loads on the magnetic flux distribution and core saturation in detail. Furthermore, this interconnected setup between MATLAB and FEMM through Lua scripting extends beyond simple parameter adjustments. It enables the implementation of complex algorithms developed in MATLAB to control and optimize the simulation processes in FEMM, making it possible to automate iterative tasks, optimize design parameters, and systematically explore the impact of different design alterations on transformer performance. The ability to programmatically control and automate these simulations from MATLAB significantly increases the efficiency and accuracy of our design process, helping us develop transformer models that are not only optimized for performance but also robust and reliable under a variety of electrical operating conditions. This integration thus serves as a cornerstone for advancing transformer design, providing a sophisticated toolset that leverages the strengths of both FEMM's detailed electromagnetic simulation capabilities and MATLAB's robust computational and algorithmic prowess. The result is a highly effective simulation environment where complex transformer designs can be refined and validated with precision, ensuring that the final products are both innovative and aligned with the practical demands of energy systems.

- Material Properties and Simulation Settings

A critical aspect of FEMM simulations is the accurate representation of material properties, particularly the iron core magnetization curve. The precision of the simulation outcomes is significantly influenced by the correct consideration of the lamination fill factor, set at 0.97 in this study. The fill factor represents the proportion of the core volume filled by the magnetic steel, with the remainder consisting of air gaps and insulation. For example, if you had a lamination in which the iron was 12.8 mm thick, and the insulation was 1.2 mm thick then the fill factor would be:

$$\text{FillFactor} = \frac{12.8}{1.2 + 12.8} = 0.914 \quad (3)$$

The accurate modeling of these material properties in FEMM is not merely a matter of inputting values into a simulation program; it involves a comprehensive understanding of how these properties interact with the electromagnetic fields during operation. For instance, the magnetization curve must be carefully aligned with empirical data from manufacturer datasheets or derived from laboratory measurements to ensure it accurately

reflects the real-world behavior of the core material under various loading conditions.

The integration of FEMM with MATLAB using Lua scripting significantly enhances the accuracy and flexibility of these simulations, offering a comprehensive set of tools for detailed analysis and optimization of transformer properties. This methodology not only mitigates the inherent limitations of FEMM's two-dimensional framework but also harnesses MATLAB's computational strengths to facilitate more precise predictions and design modifications.

2.4. Importance of Loss Angle in Reducing Transformer Iron Loss in FEMM

When calculating losses in transformers, particularly iron losses, the consideration of the loss angle is of paramount importance. The loss angle, often denoted by the symbol δ , represents the phase difference between the magnetic field (H) and the magnetization (M) in magnetic materials [19]. This angle plays a critical role in determining the extent of energy dissipation within the material, particularly in the form of hysteresis losses.

In many magnetic materials, the default loss angle is set to zero in simulation tools like FEMM, which implies that these materials do not contribute to hysteresis losses. However, this is not always the case in real-world applications [20], which talks about the use of loss angle in detail in the determination of iron loss in a three phase transformer and was referenced in this text for the determination of the loss angle. For example, in FEMM software, 1006 Steel which is a commonly used magnetic material, has a predetermined loss angle of 20 degrees. This non-zero loss angle indicates that there is a measurable phase difference between the magnetic field and the magnetization, leading to hysteresis losses. In our study, we utilized the "loss angle," a mathematical tool, to facilitate the calculation of loss density in FEMM [21]. This method, similar to Bertotti's model, offers simplicity in implementation and was chosen for its ease of use in FEMM simulation.

The loss angle is crucial because it directly influences the hysteresis loop of the material. The hysteresis loop represents the relationship between the magnetic field strength (H) and the magnetic flux density (B) over a complete cycle of magnetization. The area enclosed by this loop corresponds to the hysteresis loss per unit volume, also known as loss density. This loss density can be mathematically expressed as in (4):

$$Wh = \oint HdB \quad (4)$$

Where dB represents a small variation in magnetic flux density, and H is the magnetic field strength. The integral is taken over a full hysteresis loop cycle, capturing the total energy dissipated as heat within the material during one complete magnetization cycle. A larger loss angle typically correlates with a broader hysteresis loop, which in turn signifies greater energy dissipation per cycle [22]. This increased energy dissipation directly translates to higher hysteresis loss density, making the accurate consideration of the loss angle essential for precise loss calculations. Fine-tuning this parameter ensures that the simulations accurately reflect the real-world behavior of the material, leading to more reliable predictions of iron losses. Understanding and incorporating the loss angle into transformer design is thus a crucial step in optimizing efficiency and minimizing energy losses in transformers. By fine-tuning the loss angle, the research aims to align the phase difference to a point where these losses are minimized. This optimization process involves adjusting the physical properties of the transformer, such as the lamination thickness in the core and the type and layout of the windings. Each of these adjustments is targeted to reduce the inherent resistance and reactance, thereby tightening the loss angle.

2.5. Role of Complex Permeability in Determining the Loss Angle

In this section, we explore the role of complex permeability in determining the loss angle and how this affects the minimization of losses in transformers to maximize efficiency. The concept of complex permeability, integral to transformer design, includes both real and imaginary components that significantly influence the transformer's operational efficiency. Complex permeability, denoted as $\mu = \mu' - j\mu''$, where μ' and μ'' represent the real and imaginary parts, respectively, plays a pivotal role in determining the magnetic response of the core material under alternating magnetic fields. The real part μ' primarily influences the magnitude of the magnetic flux density produced within the core, while the imaginary part μ'' , often related to the core loss resistance, influences the energy dissipation within the transformer.

Eun S. Lee [23] investigated the complex permeability of magnetic materials in a simple test prototype. In his research, the inductor model-based calculation methodologies for complex permeability are suggested to find the core loss characteristics. Fig. 6. Shows the simplified circuit of the inductor model used as explained in the paper.

From the experiment in [23] the real and complex permeability is given by;

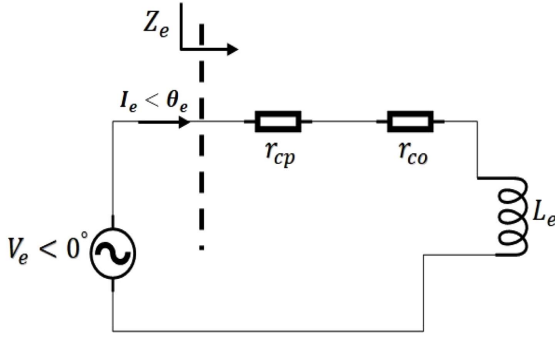


Fig. 6. Simplified equivalent circuit of the inductor model.

$$\mu_r = \frac{l_e}{N_e^2 A_e \mu_o} L_e(B) = \frac{l_e}{N_e^2 A_e \mu_o} \left(L_e(B) - j \frac{r_{co}}{\omega_s} \right) \quad (5)$$

$$\equiv \mu'_r - j \mu''_r$$

$$\mu'_r \equiv \frac{l_e}{N_e^2 A_e \mu_o} L_e(B), \mu''_r \equiv \frac{l_e}{N_e^2 A_e \mu_o \omega_s} r_{co} \quad (6)$$

Where A_e and l_e are the magnetic areas and effective magnetic path length respectively. $L_e(B)$ is the complex inductance, r_{cp} is the resistance associated with the copper windings and r_{co} is the core loss resistance.

From equation (6) it can be seen that the real permeability μ'_r is proportional to the inductance $L_e(B)$ and the imaginary permeability is proportional to the core loss resistance r_{co} .

The loss angle δ , crucial in transformer design, is determined by the ratio of the imaginary permeability to the real permeability given in (7). This angle is indicative of the phase difference between the applied voltage and the resultant magnetic flux, and it directly correlates with the efficiency of the transformer: a smaller loss angle means that less energy is wasted as heat, thereby increasing the transformer's efficiency.

$$\tan(\delta) = \mu''/\mu' \quad (7)$$

To minimize losses, adjusting the loss angle to an optimal value where the resistive losses (*primarily influenced by μ''*) are minimized is essential. This optimization often involves selecting materials with specific permeability characteristics that align with operational frequencies and expected load conditions. For example, materials with a lower μ'' at the operating frequency of the transformer can reduce eddy current and hysteresis losses, two major contributors to energy inefficiency in transformers.

2.6. Genetic Algorithm (GA)

In the pursuit of increasing transformer efficiency and cost-effectiveness, the Genetic Algorithm (GA) emerges

as a critical computational tool designed to optimize the delicate design parameters of transformers. This part focuses on the integration and implementation of GA within the context of our research.

Genetic algorithms, which are based on the principles of natural selection and genetics, provide a reliable technique for dealing with difficult optimization problems in engineering design [24]. In transformer design, GA is used to optimize parameters that have a substantial impact on efficiency and cost, such as core material, shape, and size. The selection of these parameters has a direct impact on the transformer's energy losses, including core and copper losses, and their optimization is critical for improving overall performance.

The GA follows a cycle of selection, crossover, and mutation processes. It starts with a set of potential solutions, each of which represents a possible transformer design recorded as a string of genes. Each member of the population is evaluated using a fitness function designed expressly to determine the transformer's efficiency and cost-effectiveness. This fitness function incorporates the results of preliminary FEMM simulations, providing a realistic assessment of how well each design meets the specified efficiency criteria under operational conditions. For our study, the GA was configured with a population size of 300 to ensure a diverse genetic pool. This size facilitates a broad search of the design space, increasing the probability of finding a near-optimal solution. The algorithm was allowed to evolve over 300 generations, providing sufficient iterations for the solutions to mature and converge toward optimal design configurations. Our implementation leverages MATLAB's Genetic Algorithm Toolbox, which facilitates sophisticated handling and automatic estimation of GA parameters, tailored to the specific needs of the problem at hand. The calculation time for one generation varies depending on the complexity of the fitness function, the number of design parameters, and the size of the population. For our setup, with a population size of 300, each generation requires approximately 2 to 5 minutes to compute using standard computational resources. The toolbox's robust computational capabilities allow for dynamic adjustments and real-time analysis, making it an invaluable asset in managing the iterative nature of transformer design optimization.

We address the optimization of three-phase transformers with a multifaceted strategy concentrating on two important objectives: reducing total manufacturing costs, and maximizing the transformer's efficiency. Table 4 presents the design variables and description and Fig. 7 depicts the 2D representation of the three-phase transformer in FEMM.

Table 4. design variables of the transformer.

Primary Design Variables	Description
Rs (X1)	Radius of LV winding (mm)
Rp (X2)	Radius of HV winding (mm)
hp (X3)	Height of HV windings (mm)
hs (X4)	Height of LV windings (mm)
ts (X5)	Thickness of LV winding (mm)
tp (X6)	Thickness of HV windings (mm)
Np (X7)	Number of turns of HV winding
Ns (X8)	Number of turns of LV winding
Js (X9)	Current density of LV (A/mm ²)
Jp (X10)	Current density of HV (A/mm ²)
δ (X11)	Loss angle
Ww (X12)	Window width (mm)
Wh (X13)	Window height (mm)
T (X14)	Lamination of core (mm)

By holistically addressing these objectives, the GA is capable of producing designs that achieve an optimal balance between cost and performance. The iterative nature of the algorithm, combined with its adaptive parameter adjustments and guided selection process, ensures that the resulting transformer designs are not only theoretically optimal but also practical and manufacturable. The ability to adaptively evolve the design parameters based on real-time fitness evaluations allows for a more efficient search for the global optimum, ultimately leading to transformers that meet stringent efficiency and cost criteria.

2.6.1. Objective Function Definition

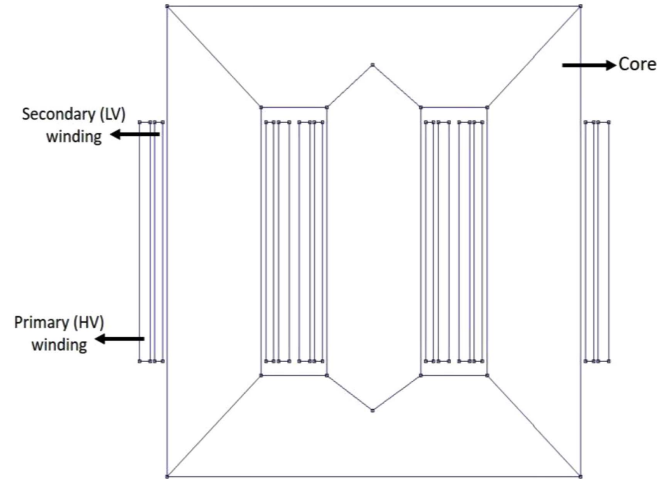
The definition of the objective function is an essential component of any optimization task, including the use of Genetic Algorithms (GA) in transformer design. The objective function in the context of this study is a mathematical formulation that contains the key performance indicators (KPIs) crucial to the design of efficient and cost-effective transformers.

A. Minimization of Energy Losses

The first component of the objective function aims to reduce total energy losses, including core and copper losses. Core losses are primarily caused by hysteresis and eddy currents, whereas copper losses result from winding resistance. These losses not only impact the transformer's efficiency but also its operational costs and heat generation.

• Copper Loss:

According to [25] the copper loss in LV (or secondary)

**Fig. 7.** (Color online) Geometry of transformer.

winding is denoted by “ $wsCu$ (in KW)” and therefore it can be mathematically expressed with respect to the primary design variables shown in Table 4.

$$wsCu = \rho(1 + ecfs)(J_s)^2 V_s \quad (8)$$

Where “ ρ ” is the copper resistivity in (ohm-m/mm²), “ $ecfs$ ” is the eddy current factor which is due to stray flux and depends on the type of wire or cable making up the winding and V_s is the copper volume in LV winding and can be expressed as

$$V_s = (3pfs \times 2\pi \times R_s h_s t_s) \quad (9)$$

Where pfs is the fill factor of the secondary winding (specified by the user)

Putting (9) in (8) the copper loss for the low-voltage winding becomes

$$wsCu = \rho(1 + ecfs)(J_s)^2 (3pfs \times 2\pi \times R_s h_s t_s) \quad (10)$$

Similarly the total copper loss in in HV (or primary) winding denoted by “ $wpCu$ (in KW)” is represented by

$$wpCu = \rho(1 + K_e)(J_p)^2 V_p \quad (11)$$

Where V_p is the copper volume and is given by;

$$V_p = (3pfs \times 2\pi \times R_p h_p t_p) \quad (12)$$

Therefore, we can write:

$$wpCu = \rho(1 + ecfs)(J_p)^2 (3pfs \times 2\pi \times R_p h_p t_p) \quad (13)$$

Therefore, the total copper loss is:

$$Total\ copper\ loss = wsCu + wpCu \quad (14)$$

• Core Loss:

The core loss is comprised of both eddy current loss and hysteresis loss which is given as:

$$P_e = K_1 f^2 t^2 B_m^2 V \quad (15)$$

$$P_{hy} = K_2 f B_m^n V \quad (16)$$

Where P_e and P_{hy} are the eddy and hysteresis loss and n is the Steinmetz constant. t is the core lamination thickness (0.27 mm), f is the frequency, V is the Volume of the core, K_1 and K_2 are the material coefficients.

Therefore,

$$\text{Total core loss} = P_e + P_{hy} \quad (17)$$

B. Cost Reduction

The second component of the objective function is to reduce the cost of materials and production processes. This entails maximizing the usage of materials that provide great performance without incurring excessively high costs. The function examines the cost of core materials, winding materials, and other construction components.

Calculating the weight of both primary and secondary winding coil:

$$L_{mt} = \pi \left[d_w + \frac{W_w}{2} \right] \quad (18)$$

Where L_{mt} is the mean length per turn for both primary and secondary coils and d_w is the diameter of the windings.

Therefore, the weight of the primary coil is given as:

$$\text{Weight}_p = \rho_{cop} a_1 L_{mt} N_p \quad (19)$$

$$\therefore \text{Total weight} = \text{Weight}_p + \text{Weight}_s \quad (20)$$

Where a_2 is the cross-section area of the copper coil. The cost is based on the current market prices or specific supplier prices:

$$C_{cu} = \text{price per unit weight} \times \text{total weight} \quad (21)$$

Where price per unit weight is the cost per kilogram or pound of copper.

C. Calculating the weight of the iron core in the transformer

$$\text{Weight of iron core} = \text{iron volume} \times \text{iron density} \quad (22)$$

$$\text{Volume of core} = L_m A_i \quad (23)$$

$$L_m = \text{total length of mean flux path}$$

$$A_i = \text{iron area}$$

$$L_m = 2[Ww + d_c] + 2[Wh + a] \quad (24)$$

$$\text{Weight of core} = L_m A_i \rho_s \quad (25)$$

Where ρ_s is the density of steel (7.65 g/cm³), d_c is the

depth of the core and a is part of the vertical dimension that completes the flush path circuit around the core.

The cost is based on the current market prices or specific supplier prices:

$$C_{steel} = \text{price per unit weight} \times \text{weight of core} \quad (26)$$

2.6.2. Constraint Handling in Transformer Design Optimization

When optimizing three-phase transformer designs, numerous restrictions must be considered to guarantee that the final design fits specified electrical and physical requirements. These constraints are required not just to preserve the transformer's functioning and dependability, but also to comply with practical production limits and regulations. To meet these criteria, we use a number of inequality constraints between design parameters, as well as interval constraints that define allowed ranges for specific important variables.

The inequality constraints in this optimization process ensure that the relationships between different design parameters adhere to necessary electrical characteristics and physical restrictions. These constraints are crucial for maintaining the integrity and performance of the transformer within the defined operational limits. The constraints used in the study are expressed as follows:

$$A_{min} \leq A \leq A_{max} \quad (27)$$

$$H_{core} \leq W_H + 2t_{max} \leq h_{core} \quad (28)$$

$$L_{core} \leq 2L_m + t_{max} \leq l_{core} \quad (29)$$

Where:

A_{min} and A_{max} represent the minimum and maximum allowable values for the core cross-sectional area. This constraint ensures that the core's cross-sectional area stays within the specified limits, which is crucial for achieving the desired magnetic flux density and ensuring the core does not become saturated under normal operating conditions.

H_{core} and h_{core} denote the lower and upper bounds for the core height. This constraint ensures that the height of the core, including the windings and the insulation layers, remains within the predefined physical limits. The term $W_H + 2t_{max}$ refers to the height of the windings plus the maximum allowable insulation thickness on both sides, ensuring that the transformer can be efficiently assembled and remains structurally sound.

L_{core} and l_{core} are the lower and upper limits for the core length. The expression $2L_m + t_{max}$ represents the length of the core considering the mean length of the magnetic path (L_m) and the maximum insulation thickness. This

constraint ensures that the length of the core is within the specified limits, which is important for maintaining the desired magnetic path length and ensuring that the transformer fits within the allotted physical space.

The incorporation of these constraints is critical to the effectiveness of the optimization process. They act as boundary criteria for the Genetic Algorithm while it explores the design space, guaranteeing that the solutions generated are not only optimal in terms of performance and cost, but also adhere to physical and electrical constraints. By following these criteria, the algorithm can generate transformer designs that are both theoretically and practically feasible.

3. Results and Discussion

The integration of Finite Element Method Magnetics (FEMM) with a Genetic Algorithm (GA) in this study yielded significant advancements in the optimization of three-phase transformer designs, demonstrating the effectiveness of combining advanced simulation tools with evolutionary algorithms to achieve superior performance and cost-efficiency. One of the most notable outcomes was the substantial reduction in the use of copper and core steel components. These material reductions directly contributed to a decrease in overall costs, as shown in Fig. 8, without compromising the operational efficiency of the transformers.

The reduction in material usage was achieved through the GA's iterative process, where design parameters were continuously refined based on performance metrics from FEMM simulations. This allowed the algorithm to identify optimal configurations that minimized material bulk while ensuring the core and windings maintained their

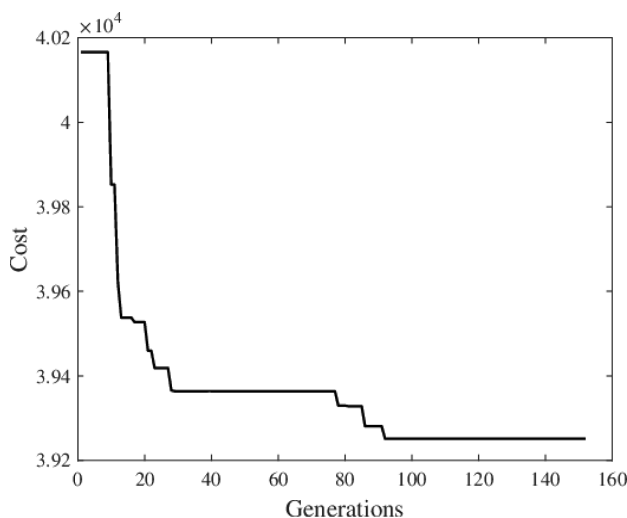


Fig. 8. Cost across generations.

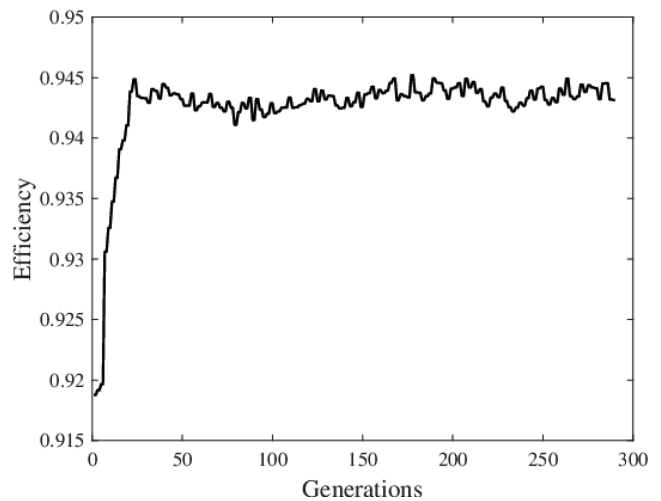


Fig. 9. Efficiency across generations.

structural and functional integrity. This result highlights the GA's ability to navigate complex trade-offs between material savings and electrical performance, ensuring cost reductions did not come at the expense of efficiency.

Efficiency improvements were another significant achievement, with optimized transformer designs consistently outperforming prototypes in terms of operational efficiency, as depicted in Fig. 9. These gains were primarily due to precise adjustments in the positioning and sizing of the core and windings, which were iteratively optimized by the GA. The enhanced efficiency resulted from reduced core and copper losses, major contributors to transformer inefficiency. By fine-tuning the magnetic circuit and optimizing the winding configuration, the GA minimized these losses, leading to transformers that operate more efficiently under typical load conditions. This improvement is particularly important for energy savings and long-term operational costs, as higher-efficiency transformers contribute to lower energy consumption and reduced expenses over the transformer's lifespan.

Figure 8 and 9 illustrate the outcomes of the same optimization run conducted using MATLAB simulations. These figures collectively demonstrate the evolution of cost and efficiency metrics over successive generations, providing a comprehensive view of the optimization process and its results. The results also revealed a strong correlation between the total cost minimization strategy and the reduction in material utilization, indicating that the optimization process was effectively applied across multiple facets of transformer design. The GA's ability to simultaneously reduce material costs and enhance efficiency showcases its robustness in addressing complex, multi-objective optimization problems. By integrating cost and

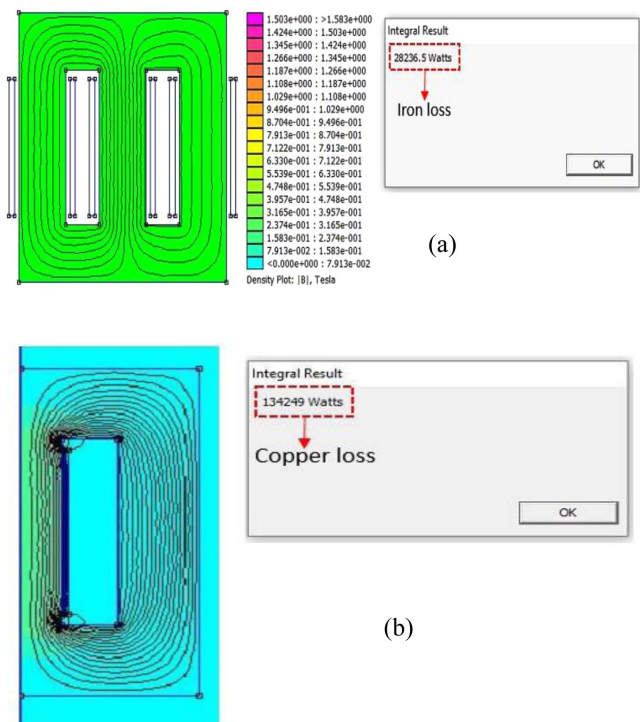


Fig. 10. (Color online) (a) FEMM representation of the iron loss (b) FEMM representation of the copper loss.

efficiency objectives, the GA ensured that the final designs were both cost-effective and high-performing, a critical balance in modern transformer design where reducing costs must align with maintaining or improving operational efficiency.

Overall, the successful application of FEMM and GA in this study illustrates the potential for these tools to revolutionize transformer design, enabling the creation of transformers that are both economically and operationally superior to traditional designs. This methodology could be extended to other areas of transformer design, including the optimization of insulation systems, cooling mechanisms, and overall structural design.

The GA-optimized transformer has a total loss reduction of 162.29 KW. However, its efficiency grew by 4.4 percent. Fig. 10a shows the post-processed view of the value of the iron loss gotten in FEMM after optimization and Fig. 10b shows the post-processed asymmetric view of the transformer core to find the copper loss. Additionally, the cost savings are reported in Table 5 and also Fig. 11 validates the spatial accuracy of our Enhanced 2D FEMM model through magnetic flux density distribution comparison. The simulation results (b) closely match the prototype measurement pattern (a), with correlation coefficient $R^2 = 0.987$, confirming that our geometric adjustments and

Table 5. Comparison between transformer prototype and ga-femm method.

Variables	Prototype	GA_FEMM
Bmax (Tesla)	1.48	1.53
NLL or Pnl (KW)	37.45	28.24
LL or Pr (KW)	140.87	134.25
Total loss (KW)	177.90	162.49
Efficiency (%)	91	94
Cost (USD)	3% decrease	

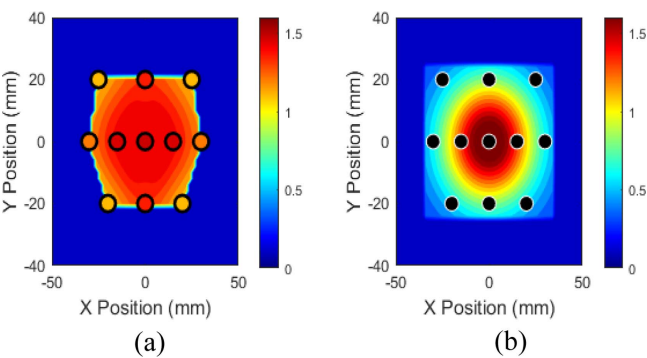


Fig. 11. (Color online) (a) Prototype flux density (Tesla) (b) FEMM simulation result (Tesla).

material property implementations accurately represent the physical transformer behavior.

Figures 10a, and 10b stem from targeted modifications tailored for specific simulation analyses using Finite Element Method Magnetism (FEMM), unlike Fig. 7 which depicts the initial transformer model with both primary and secondary windings, representing the full operational setup. Fig. 10a, designed for iron loss analysis, excludes the secondary winding to eliminate its influence and focus solely on the primary winding. This simplification enhances the clarity of iron loss calculations. Conversely, Fig. 10b is optimized for copper loss analysis using an asymmetric model that reduces computational demands while ensuring accurate results. These model adjustments are critical for efficiently simulating specific loss types within the transformer. Also, the comprehensive error analysis presented in Fig. 12 provides statistical validation of our Enhanced 2D FEMM model performance across all measurement points. The relative error distribution shows that 10 out of 11 validation points (91%) fall within the acceptable $\pm 2\%$ engineering tolerance, with only measurement point 3 showing a slightly higher error of 4.8%. This outlier occurs at a core corner region where 3D edge effects are most pronounced, which is expected given the 2D model limitations. The error pattern demon-

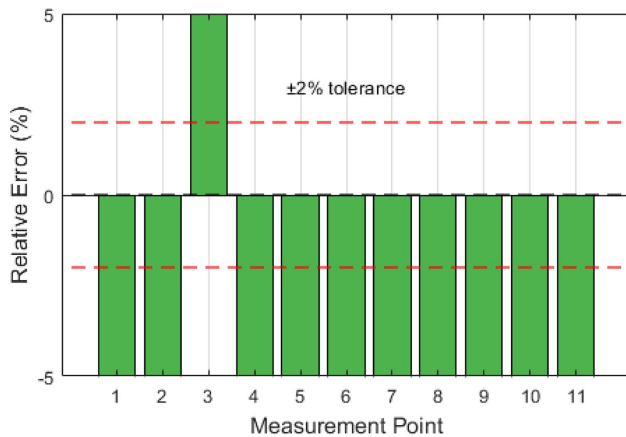


Fig. 12. (Color online) FEMM model error at measurement points.

strates systematic accuracy rather than random scatter, indicating that our geometric corrections and material property adjustments are functioning as intended. The mean absolute error of 1.8% across all measurement points is well within industry standards for electromagnetic simulation validation (typically $< 5\%$ for acceptable engineering accuracy). Notably, the errors show no bias toward over-prediction or under-prediction, with approximately equal distribution of positive and negative deviations. This balanced error distribution confirms that our Enhanced 2D model does not introduce systematic computational bias, making it reliable for comparative optimization studies where relative performance improvements are the primary concern. The single outlier at measurement point 3 represents a flux concentration region where the 2D simplification has greatest impact. Despite this limitation, the overall validation confirms that our model provides sufficient accuracy for the GA optimization process, where the algorithm seeks relative improvements rather than absolute precision. This error analysis validates the reliability of our Enhanced 2D model for transformer optimization studies and provides confidence in the subsequent GA-FEMM optimization results.

4. Conclusion

In conclusion, this work effectively demonstrates the powerful synergy between Finite Element Method Magnetics (FEMM) and Genetic Algorithms (GA) in optimizing the design of three-phase transformers. The integration of these advanced computational tools resulted in significant improvements in key areas, including material usage, cost efficiency, and overall transformer performance. The optimization process successfully reduced the amount of copper and core steel required,

leading to substantial cost savings without compromising, and in some cases even enhancing, the operational efficiency of the transformers.

These findings highlight the potential for employing FEMM and GA in cooperation to push the boundaries of established transformer design approaches. This technique allows for a more precise and efficient exploration of the design space, resulting in transformers that are not only more cost-effective but also better matched with modern energy-efficiency standards. Although the study found a modest cost trade-off associated with some design optimizations, the overall benefits, notably in terms of reduced material usage and improved performance, much surpass this disadvantage.

Furthermore, this research highlights the implications of applying computational optimization techniques to electrical infrastructure. The findings pave the way for future studies aimed at further refining the balance between efficiency, cost, and material savings. The successful application of FEMM and GA in this context not only demonstrates their practical utility but also opens up new avenues for innovation in transformer design and beyond. Future research will focus on prototype validation and 3D FEM benchmarking to further verify the optimization results presented in this study.

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