Artificial Intelligence Applications in High-Frequency Magnetic Components Design for Power Electronics Systems: An Overview

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***Abstract*—This article provides an overview of how artificial intelligence (AI) is applied in designing high-frequency magnetic components, primarily high-frequency inductors and transformers, for power electronics systems. Four categories of AI, including expert systems, fuzzy logic, metaheuristic methods, and machine learning techniques, are addressed. First, AI models for estimating losses in high-frequency magnetic components are discussed. Subsequently, AI-based design methods in high-frequency inductors and transformers are observed. Then, AI tools applied to the automatic design of high-frequency magnetic components are introduced and compared. Drawing insights from an analysis of over 200 publications, this article highlights significant advancements: the development of AI-driven models for precise loss estimation in high-frequency magnetic components, the application of AI in optimizing design configurations for the components, and the automation of design processes. These achievements demonstrate AI's capability to enhance the efficiency, performance, and innovation in high-frequency magnetic component design, offering a roadmap for future research in power electronics systems.**

***Index Terms*—Artificial intelligence (AI), high-frequency (HF) inductor design, HF magnetic components, HF transformer design, loss models.**

I. Introduction

HIGH-FREQUENCY (HF) magnetic components, such as HF transformers, HF dc inductors, and HF ac inductors, play a crucial role in a wide range of electronic systems and applications. HF magnetic components are essential for energy conversion, signal conditioning, impedance matching, resonant circuits, switching power supplies, RF communication, wireless systems, and high-speed data transmission [1], [2]. They enable efficient and reliable operation of electronic systems in various industries and applications. However, the miniaturization of magnetic components remains a challenge, as magnetics constitute a large proportion of the volume and weight and are the primary cause of power losses within a power converter [1], [2], [3], [4], [5].

The design of magnetic components for power electronics involves multiple objectives. One primary goal is to maximize the utilization of magnetic capabilities, enabling the achievement of multiple functions within a single component [1]. In addition, this design aims to minimize the size of HF magnetic components by substituting ferrites with soft magnetic materials, which offer lower power losses [6]. These alternative materials, including iron (Fe) and various metallic elements such as silicon (Si), nickel (Ni), chromium (Cr), and cobalt (Co), offer advantages such as higher saturation points, increased permeability, and a range of options, such as Fe-Si alloys, powder cores, amorphous materials, and nanocrystal materials [2], [7], [8].

The key to achieving these objectives lies in the design of HF magnetic components, which heavily relies on factors, such as geometric structure, excitation conditions, and magnetic properties, including power losses. These properties are crucial in determining the suitability of a magnetic core for incorporation into a component [9]. Given their complexity and the intricate interplay between these factors, analytical modeling of these components presents significant challenges. Artificial intelligence (AI) provides an effective framework for tackling these intricate design aspects, by capturing nonlinear relationships and offering insights into variable interactions [10].

AI applications in HF inductor and transformer design share similarities in optimizing materials, geometry, and performance through predictive modeling and automated design processes. However, they differ significantly in their focus: inductor design primarily addresses HF behavior and compactness [11], while transformer design concentrates on efficient energy transfer, complex winding arrangements, and power applications [12]. The role of AI in each is tailored to these specific challenges and objectives.

AI has gained substantial traction in various domains, especially in the field of power electronics [13], [14]. Its applications are already manifesting in optimizing heat sink designs, intelligent control systems, and energy conversion, among others [15], [16], [17], [18], [19], [20]. As a result, the capabilities of AI can also extend to elevating HF magnetic component design through a range of benefits, such as handling design complexities, exploring various design possibilities, and fostering innovation. These advantages collectively contribute to improving the efficiency,

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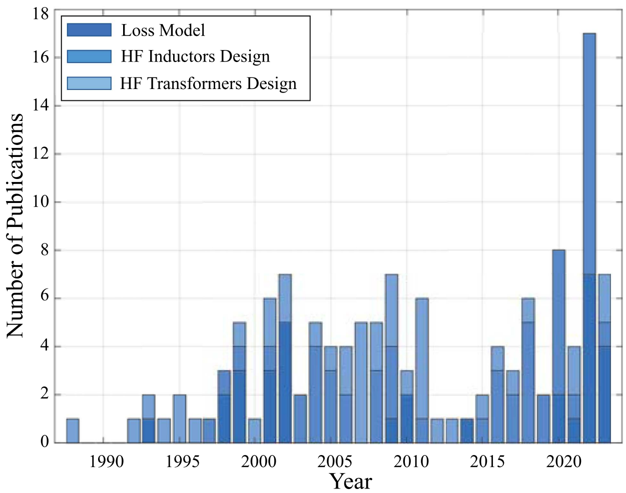

Fig. 1. Publication count of AI-based magnetic components design starting from 1989 to 2023.

effectiveness, and innovation quotient of power electronics and affiliated industries.

Numerous studies on this topic have been available in recent research. Fig. 1 illustrates the yearly publication count about the intersection of AI-based magnetic components design starting from 1989. The statistical information is derived from a search on the IEEE Xplore and Scopus databases. Notably, starting from 2000 and up to October 2023, there has been a noticeable rise in publications related to design applications, with a particularly pronounced trend in the past two years.

A review [10] of AI in power electronics systems was published in 2021. It comprehensively introduces AI algorithms in the whole power electronics systems from the lifecycle perspective, including design, control, and maintenance. For the design part, Zhao et al. [10] provided an introductive level for constructing multiobjective problems and how AI can help from modeling and time reduction parts. For AI in HF magnetic components, it is not mentioned.

Consequently, a gap in the literature exists concerning a comprehensive review of AI algorithms and applications specific to HF magnetic components design. To address this, this article aims to thoroughly review published research in HF magnetic component design that utilizes AI techniques. The primary aim is to consolidate the existing knowledge in this area systematically. The contributions of this article encompass the following aspects.

1) This article systematically investigates AI algorithms in HF magnetic components design for power electronics systems. The focus is on identifying relevant AI algorithms, their essential functions, and the corresponding applications in the HF magnetic components design field.
2) A road map is illustrated with the AI in HF magnetic components design.
3) Comprehensive applications of AI across each category are presented, along with an in-depth discussion of the challenges and future research directions in the field.

This article proposes a comprehensive overview of the use of AI in the design of HF magnetic components. The rest of this article is organized as follows. Section II introduces the key advantages and overarching applications of AI in this field. Sections III and IV delve into the detailed applications of AI, specifically in developing loss models and innovative design methods for HF magnetic components. Section V discusses how current AI tools contribute to the automation and enhancement of the design process for these components. An outlook of AI in HF magnetic components design is given in Section VI. Finally, Section VII concludes this article.

II. Overview of AI Involved in HF Magnetic Components

AI, an interdisciplinary technology, can combine cognition, machine learning (ML), emotion detection, human–computer interaction, data storage, and decision-making [21]. AI has emerged as a transformative tool, particularly in thermal and magnetic design. It improves energy conversion and system control in thermal designs and optimizes combustion processes in engines and boilers [22]. AI-driven genetic algorithms automate the design and optimization of magnetic metamaterials [23]. In addition, they enable efficient cooling solutions that do not compromise on size and weight in electric motors [24]. Furthermore, AI facilitates finite-element (FEM) analysis, leading to more efficient thermal management and automatic heatsink design [15]. These highlight AI's critical role in advancing thermal and magnetic design, offering innovative solutions that enhance performance and efficiency in engineering applications.

As introduced in Zhao et al.'s work [10], AI can be categorized into four main categories as follows. Expert system, fuzzy logic, metaheuristic methods (MMs), as well as ML. Detailed components of these four AI methods are concluded in Fig. 2. The usages of these four main AI categories among the publications analyzed in Fig. 1 are shown in Fig. 3. To be more detailed, AI is valuable in the design of HF magnetic components for several reasons, shown in Fig. 4.

1) *Fast convergence:* AI algorithms can rapidly explore a vast design space and efficiently identify optimal solutions. This saves significant time and effort compared to traditional manual design processes, which are often iterative and time-consuming.
2) *Complex modeling:* HF magnetic components involve intricate electromagnetic phenomena, making their design challenging. AI can handle complex loss modeling, such as core loss models, winding loss models, and simulation tasks. It allows designers to accurately predict the performance of different designs and optimize them accordingly.
3) *Data-driven design:* AI can leverage large datasets of previously designed and tested magnetic components. By analyzing this data, AI algorithms can identify patterns, correlations, and insights that human designers may overlook. This data-driven approach enhances the overall design process and facilitates the development of high-performing components.
4) *Multiobjective optimization:* Designing HF magnetic components often involves balancing conflicting objectives, such as size, efficiency, and power losses. AI can

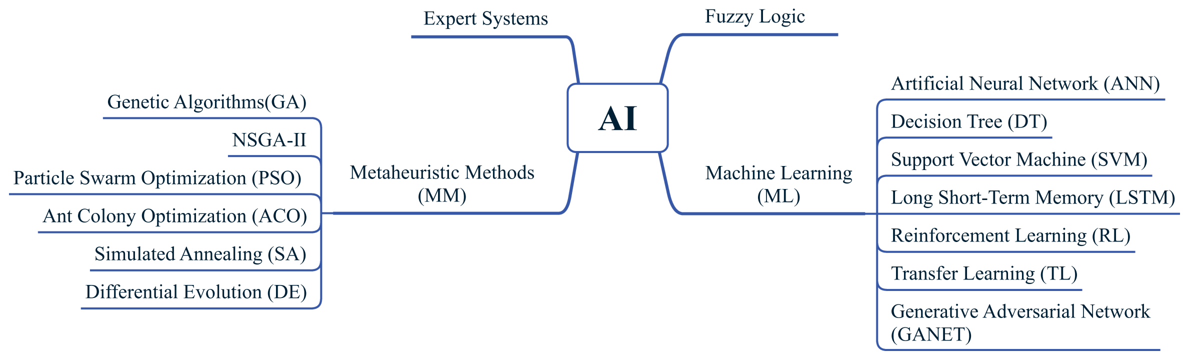

Fig. 2. AI components in the design of HF magnetic components.

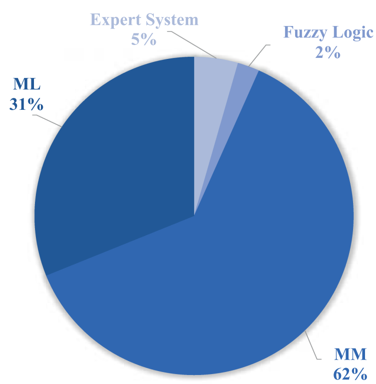

Fig. 3. Proportions of the four main AI categories.

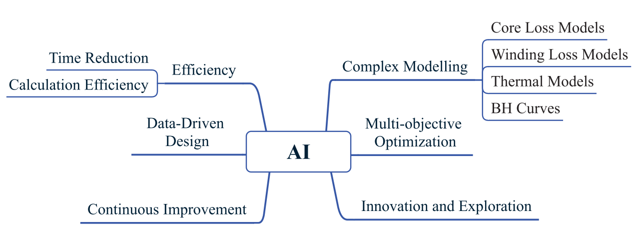

Fig. 4. AI functions in HF magnetic component design.

employ advanced optimization techniques to simultaneously optimize these objectives and find tradeoffs not considered by designers.

Therefore, AI significantly enhances power converters, especially magnetic design, offering advantages in automation, accuracy, and efficiency. AI's applications range from automated circuit parameter design [25] and data extraction for design automation [26] to overall improvements in the design, control, and maintenance of power converters [10]. It particularly excels in optimizing power loss and magnetic design in complex systems, such as hybrid ac–dc microgrids [27], outperforming traditional methods by reducing human dependence and improving operational efficiency in various aspects of power electronics.

In the design of HF magnetic components, AI plays a transformative role in each of the five key steps, as shown in Fig. 5.

1) *Material selection:* AI algorithms organize and analyze data on magnetic materials, enabling faster retrieval and predictive analysis for new material discovery.
2) *Modeling and simulation:* Enhanced by AI, simulation tools can more accurately predict component performance, incorporating advanced core and winding loss models.
3) *Design optimization:* AI applies generative design and optimization algorithms to propose a variety of efficient design solutions within the specified constraints.
4) *Prototyping:* AI-assisted design tools, integrated with software, such as LTspice [28], PLECS [29], and Ansys [30], facilitate seamless data flow and validation tests in prototyping stages.
5) *User interface optimization:* AI personalizes the design tool interfaces, improving user experience and productivity.

Moreover, AI enhances test verification and experimental work by automating and optimizing various processes. It efficiently processes large test datasets, detects and predicts errors, and optimizes experimental parameters through ML models [31], [32]. AI-driven simulations enable testing in varied scenarios without physical prototypes [33]. In quality assurance, AI ensures consistency in standards application and generates detailed analytical reports. Real-time monitoring through AI allows for immediate feedback and dynamic adaptation of test procedures [34]. In addition, AI's predictive maintenance capabilities in prototyping are crucial for preemptive adjustments, making it an indispensable tool in improving accuracy, efficiency, and reliability in testing and experimental designs [10].

AI-based tools especially offer holistic solutions throughout the HF magnetic component design process. From the automated generation of design solutions based on customer specifications to integration with various simulation and design software, AI facilitates a comprehensive and efficient workflow. Its capability to iteratively learn and improve from each design cycle enhances both the speed and quality of the design process. Furthermore, the impact of AI on user experience, through intuitive and tailored interfaces, significantly boosts designer productivity and collaborative efficiency.

III. AI for Magnetic Component Loss Models

Recent advancements have shifted HF magnetic component loss prediction from traditional physical equation-based methods, which were simple but imprecise [35], to more accurate

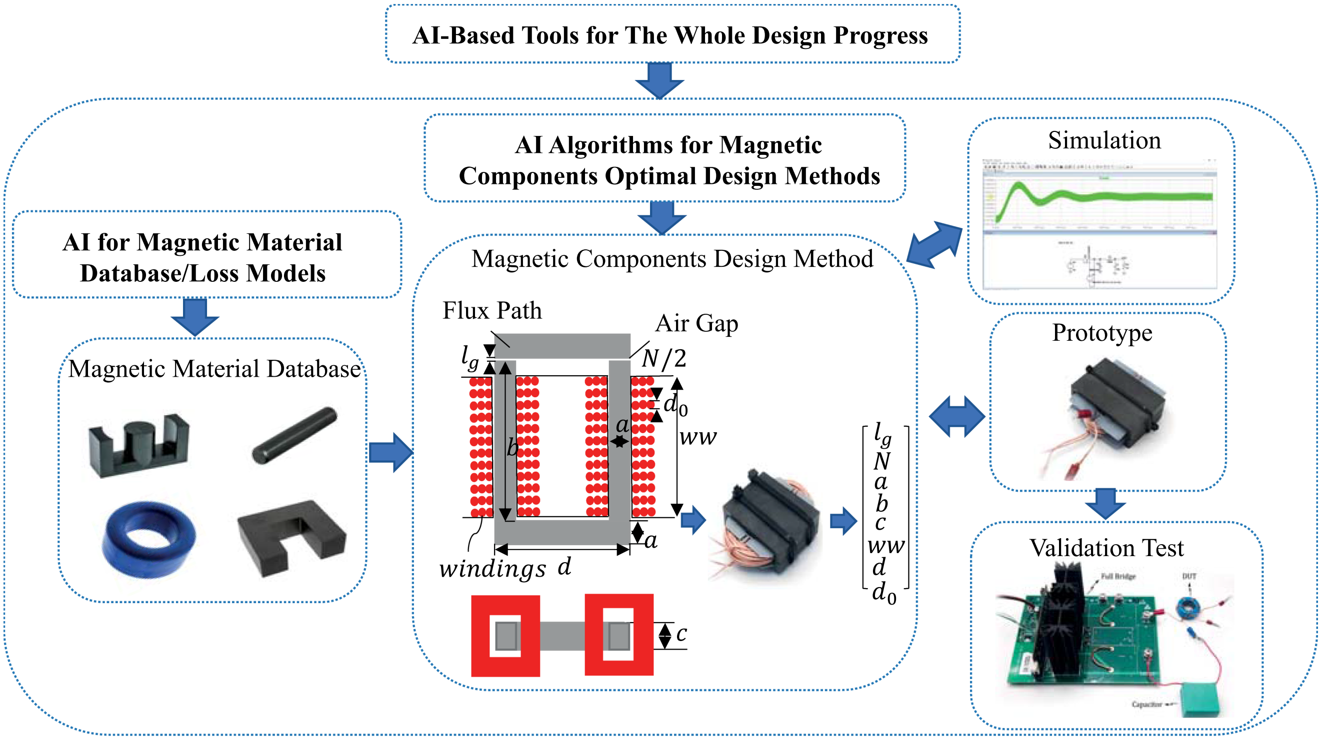

Fig. 5. Overview of the design of HF magnetic component and AI integration.

AI and ML techniques. These modern methods use metaheuristic approaches combined with ANN models, leveraging large datasets for enhanced performance in iron loss prediction. This evolution represents a significant improvement in loss prediction accuracy, a crucial aspect of the design process.

1) ANN-Based Loss Models: Magnet, an open-source dataset of high-quality data, encapsulates information from six varieties of ferrite materials: TDK (N27, N49, N87), Ferroxcube (3C90, 3C94), and Fair-Rite (78). The dataset spans a frequency range of 50–500 kHz and a flux density range of 10–300 mT for sinusoidal, triangular, and trapezoidal waveforms. The creation of magnet aimed to offer a common platform for conducting extensive research on data-driven magnetic core loss models [31], [36]. Similarly, traditional ANNs are applied with different materials, temperatures, sizes, and different operating conditions, etc., to predict core losses [37], [38], [39], [40].

2) TL-Based Loss Model: TL [31], [41] is utilized to leverage knowledge gained from solving one problem and apply it to a related but distinct problem in order to enhance performance on the latter task. The pretrained model is designed to identify shared patterns and characteristics associated with magnetic core loss. Subsequently, TL is employed to facilitate the creation of core loss models for novel materials, excitations, temperatures, or dc-bias conditions. The results demonstrate that as the amount of data for retraining increases, the average relative error of the pretrained neural network decreases from 8% to 5%.

3) LSTM-Based Loss Models: As the input waveform is the time series signal with different excitations such as triangle, pulse, and sinusoidal, LSTM is used to process with the time sequence. Its structure has 32 cells and is to classify, process, and make predictions based on the time series data. The input of

TABLE I
RELATIVE ERROR ON TEST SET FROM DIFFERENT MODELS FOR DIFFERENT MATERIALS

Model	# Params.	N87	N27	N49
iGSE	3	14.56%	14.44%	15.09%
ANN(2,1,3)	21	19.76%	19.24%	25.45%
ANN(5,8,4)	109	9.81%	6.76%	15.52%
ANN(44,57,47)	5515	1.77%	1.63%	4.38%

this model is the time series signals, and its output is aggregated and fed to the ANN. After training, ANN will produce the power loss [42], [43]. Details of average relative error comparisons of ANN predictions with iGSE calculations are shown in Table I [43].

4) GA-Based Loss Model: In the context of [44], the optimization procedure commences by selecting the rotor capacitive reactance (X_c) as the design parameter. This article wants to minimize the stator and rotor copper loss and by adjusting the capacitive reactance to improves the efficiency of the wound rotor induction motor. Therefore, GA is used to find the minimum value of capacitive reactance. The process is displayed as followed. First, the number of genes in a chromosome is set and initialize the objective function. In this article, the number is rotor capacitive reactance. Next, population size and initialize population is the random number of rotor capacitance. Furthermore, the cost function that is related to rotor capacitive is applied to find the minimize copper loss. After the cost function generates the output, the algorithm will test if it is convergence. If it is true, the algorithm will stop, otherwise, it will go back to start reproduction process and new generation.

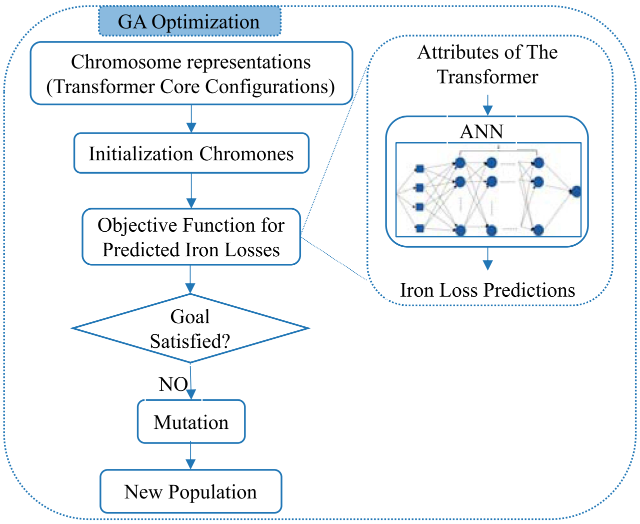

Fig. 6. Workflow of the NN+GA algorithm.

5) PSO-Based Loss Model: Chiarello and Almansa Malagoli's work [45] introduced an objective function designed to minimize copper losses in electromagnetic actuators. This article presents a table that compares the losses before and after optimization for various current values. The results in this article indicate a substantial reduction in losses after applying the PSO technique. This highlights the practical feasibility of utilizing PSO to effectively mitigate copper losses in electromagnetic actuators and support the design process.

6) Differential evolution (DE)-Based Loss Model: The novel approach utilizing DE for optimizing parameters in the dynamic Jiles–Atherton model [46], as presented in Zhang and Fletcher's work [47], offers a significant advancement in the characterization of core losses for Mn-Zn ferrites. By enhancing the accuracy, efficiency, and stability of the parameter extraction process, this method directly contributes to a more precise prediction of core losses across various frequencies and magnetic field strengths. Such improvements are crucial for the design and optimization of magnetic components, such as inductors and transformers, leading to more efficient electrical devices with minimized core losses. This methodology not only streamlines the characterization process but also ensures that material properties are accurately represented, thereby facilitating the development of high-performance magnetic materials tailored for advanced electronic applications.

7) ANN–GA-Based Loss Model: In Doulamis's work [48], a research endeavor is presented that combines ANN and GA as a novel approach, shown in Fig. 6. The approach uses ANN to predict iron loss in transformers based on various attributes, such as supplier data, thickness, and magnetic grade. It then employs GA to optimize core grouping to minimize total iron loss. Different ANNs are used for varying transformer "environments" based on attributes. The GA evaluates performance by aggregating predicted iron losses by the proposed ANN model to form an objective function. This method favors more fit chromosomes for future generations, resulting in improved predictions and reduced total loss as the algorithm iterates.

8) ANN–DT-Based Loss Model: This proposed combination model shares similarities with the ANN+GA model. However, a notable distinction lies in the emphasis on selecting optimal inputs to enhance the ANN's performance, specifically by identifying significant attributes associated with transformers [49]. To achieve this, the DT methodology is applied to select the most relevant attributes from a pool of candidates, thereby reducing the dimensionality of the input space. As documented in Georgilakis et al.'s work [49], DT serves a dual purpose by offering both attribute selection and attribute ranking. Through the assignment of information quality scores to each attribute, DT effectively ranks the attributes based on their predictive usefulness. The resulting table presents the selected attributes of transformers obtained using the DT technique.

IV. AI-Based Design Methods for HF Magnetic Components

The integration of AI algorithms, such as expert systems, fuzzy logic, and MMs, is transforming the design of HF inductors and transformers, crucial magnetic components in power electronics for energy storage, filtering, impedance matching, and optimizing energy transfer. These AI-driven techniques streamline the design process by efficiently analyzing complex datasets, optimizing parameters, and exploring broader design spaces, thereby enhancing the performance, efficiency, and functionality of HF magnetic components in contemporary electronic systems. This innovation marks a pivotal advancement in achieving more efficient, flexible, and high-performing power converters.

A. AI-Based HF Inductor Design

Early works on computer-aided HF inductor design, dating back to the 1970s, transitioned from traditional manual calculations to sophisticated computer-based approaches. They collectively marked a pivotal shift toward leveraging computational power to optimize inductor designs, addressing challenges such as minimizing winding resistance [50], determining optimal air-gap lengths [50], [51], and selecting suitable operating points on magnetization curves under varying dc bias conditions [52], [53]. The methodologies described ranged from algorithms optimizing air-gapped inductors to comprehensive design procedures for electronic power supply inductors, demonstrating an early recognition of the potential for computer algorithms to significantly enhance the design process and pave the way for AI-based design techniques.

1) Expert System-Based Design: Garret and Jain [54] detailed a knowledge-based system developed for the design of HF transformers and inductors, emphasizing computer-aided strategies that transition from traditional manual calculations to more sophisticated, automated methods. It highlights the implementation of algorithms to optimize design parameters, such as air gap lengths, winding resistance, and operating points on magnetization curves under various conditions. This early work signifies a pivotal shift towards leveraging computational power in the field, setting the stage for further advancements

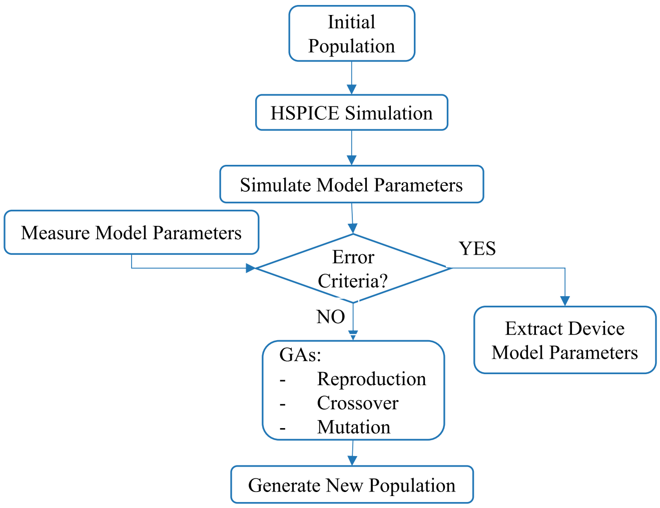

Fig. 7. GA-based extraction of circuit model parameters for passive devices.

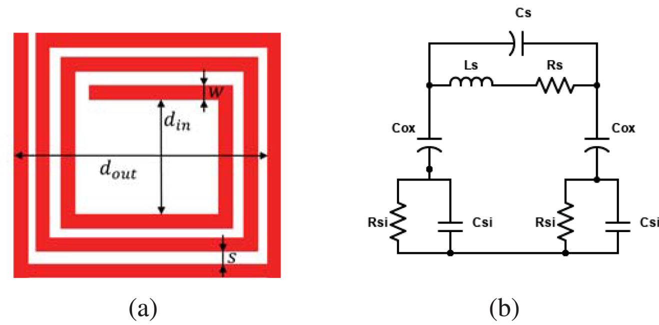

Fig. 8. Spiral inductor-on-substrate. (a) Structure. (b) Physical model.

in AI-based design techniques for HF inductor and transformer design.

2) Fuzzy Logic-Based Design: Dhawan and Davis [55] showed the successful application of fuzzy logic in optimizing inductor design. Optimization can be performed for individual core categories or the entire core database. In addition, this article demonstrates that the decision-making process can be further improved by considering multiple parameters.

However, further research is required to explore the relationships and dependencies among different parameters, enabling the selection of the most appropriate parameters for the optimization process. Constructing an accurate and effective rule base can be a time-consuming and complex task, requiring expertise and extensive knowledge of the system being modeled; therefore, more data structure and parameter selection, fuzzy logic was replaced by GAs and ML algorithms in the future.

3) GA-Based Design: At the beginning of GA application related to HF inductor design, GA was used to implement the passive circuit model parameter extraction for further optimization. Yun and May [56] examined the extraction of circuit model parameters for passive device test structures using GAs, as shown in Fig. 7 and compared it with optimization using the Levenberg–Marquardt (LM) algorithm employed in the HSPICE circuit simulation program.

The findings indicate that GAs generally offer enhanced accuracy and are more adept at finding global optima. In contrast, the LM method is highly sensitive to the initial starting point of the parameter search and is prone to get trapped in local optima. Consequently, GAs demonstrate significant potential in this field.

In Fivaz and Cronje's work [57], GAs are used for a design approach for computer-aided engineering, incorporating an expert system to yield satisfactory results. The chromosome of GA encompasses both design parameters and database indexes. The design parameters encompass numerical values that describe various design aspects, such as sizes. On the other hand, the database indexes indicate the choices available for components within the databases. Each component requiring selection corresponds to a gene within the chromosome.

As electronic devices and integrated circuits become smaller, the operating frequencies tend to increase. Higher frequency on-chip inductors are required to meet the size constraints while maintaining the desired performance. Fig. 8(a) depicts the structure of spiral inductor-on-substrate. In Fig. 8(b), a concise overview of the proposed physical model by Yue et al. [58] is presented.

In Wang et al.'s work [59], based on the physical model and to maximize the quality factor Q, the optimization problem for on-chip inductors falls under the nonlinear combinational optimization category. Similar research was conducted in [60] and [61]. Yang et al. [62] presented an approach for optimizing the design of a transverse flux inductor using a combination of subpopulation competition, data exchange, and GAs. This approach enhances convergence speed and local search capabilities. A coupling procedure is also introduced for electromagnetic-thermal problems, specifically for transverse flux induction heating, which reduces computational time. The optimization in Novac et al.'s work [63] focuses on induction heating using GAs, fmincon, and minimax methods to improve electrical efficiency and temperature distribution uniformity. A novel GA-based design in Ebert et al.'s work [64] proposes determining magnetic induction and current density values for planar magnetic elements via experimental data and GA-based optimization. Finally, Farhat et al. [65] improved GA-based HF inductor design by estimating parameters using empirical formulae and then optimizing performance through GAs or geometric programming, often with tools, such as MATLAB [66].

Regarding multiobjective optimization of HF inductor, an inductor example for a buck converter was shown in Wang et al.'s work [67]. It introduces a comprehensive approach to designing and optimizing inductors, which has been automated into a software tool. The tool consists of five main components: a graphical user interface (GUI), a magnetic equivalent circuit (MEC) solver, databases for EE, EI, UI, and toroid MEC, a database for core material and wire data, and the NSGAII optimizer. This framework offers a generalized solution that can generate a complete set of Pareto-optimal inductor designs. In Stoyka et al.'s work [68], the application of evolutionary algorithms (EAs) allows for the identification of viable and optimal

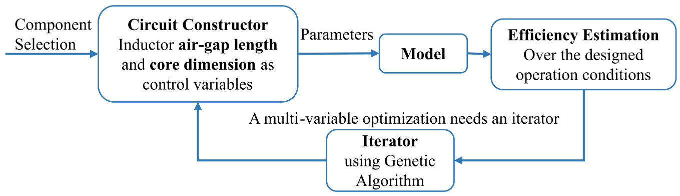

Fig. 9. Optimization with customizable cores.

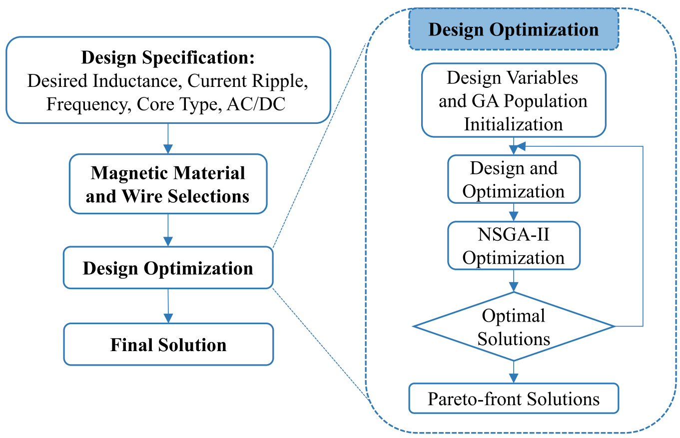

Fig. 10. Design flow of an armed inductor based on NSGA-II [71].

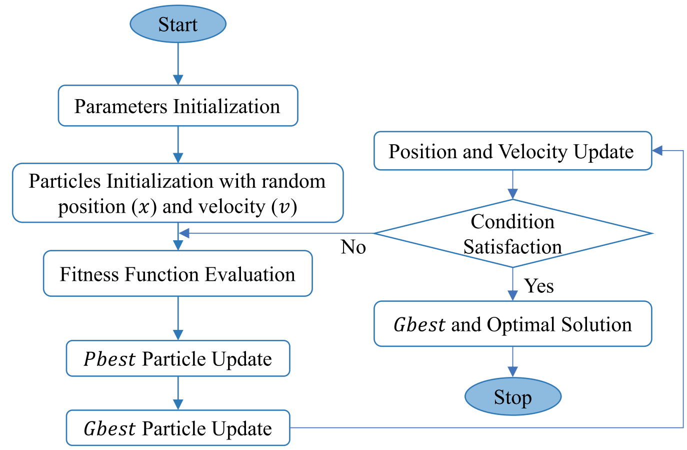

Fig. 11. Design flow of PSO.

solutions that balance efficiency, inductor volume, reliability, and electromagnetic emissions.

In Zhang and Perreault's work [69], a comprehensive design based on GA and commercial cores was proposed. When using commercial cores, the only adjustable parameter is the air-gap length of the inductor, provided that the construction of Litz wire is chosen, as shown in Fig. 9. This approach is especially useful when the design space is more complex and traditional analytical methods become less effective. In the design process of the inductor–capacitor–inductor (LCL) filter, NSGA-II was employed to identify the optimal design parameters [70]. To address the constraints inherent in the design problem, a novel method was proposed. This method involves transforming the constraints into decision variables, allowing the GA to handle them effectively during optimization. By incorporating the constraints as decision variables, the NSGA-II algorithm can explore a wider design space and identify solutions that meet both performance objectives and constraints, leading to more robust and feasible LCL filter designs. NSGA-II is widely adopted for multiobjective optimization due to its high efficiency, accuracy, and effectiveness. The GA-based approach makes it relatively straightforward to handle multiple conflicting objectives simultaneously, allowing for identifying Pareto-optimal solutions. In Wang et al.'s work [71], the core design of the arm inductor is subjected to multiobjective optimization with constraints on area product, maximum magnetic flux density, and window area. This optimization process utilizes NSGA-II, as shown in Fig. 10.

4) PSO-Based Design: The PSO algorithm, known for its simplicity in implementation compared to EAs, such as GAs, is used to synthesize spiral inductors in radio-frequency integrated circuits (RFIC) [72]. PSO randomly assigns positions and velocities to particles, with each particle's initial position marked as its personal best (Pbest). The global best position (Gbest) is determined based on the best fitness among all particles. Particle velocities and positions are updated using specific equations, considering factors, such as personal and global best positions.

The goal of the research [72] is to optimize spiral inductor parameters (N, d, W, S) to achieve a target inductance (L_{des}). The fitness function measures the absolute difference between the desired and calculated inductance. PSO stops when it reaches a maximum iteration count or when the global best value approximates a desired threshold, as shown in Fig. 11.

In RFIC design, achieving high-quality factor (Q) spiral inductors is challenging. With its effective constraint handling via simple feasibility rules, PSO offers a promising solution. This method rapidly identifies optimal spiral inductor layouts with improved quality factors, as evidenced in related research [73].

5) ABC-Based Design: The ABC algorithm mimics honeybee behavior with three groups: employed bees, onlookers, and scouts [74]. Each food source corresponds to a potential solution to an optimization problem; its nectar amount indicates the quality of solution. The number of employed/onlooker bees equals the number of solutions in the population. ABC employs a mechanism to determine if a food source should be abandoned. It involves using trial counters and a predefined limit parameter. If a solution, represented by a food source, fails to improve over a specific number of trials (the limit), the food source is considered abandoned. Consequently, the employed bees associated with that food source become scout bees. These scout bees then randomly create a new food source to replace the abandoned one, hoping to discover better solutions through this process.

In Abi et al.'s work [75], the objective is to design an optimally integrated spiral inductor using two swarm intelligence-based metaheuristics: ABC and ACO. The optimization process involves determining the physical dimensions of the square spiral-integrated inductor as design parameters while adhering to essential constraints, such as the fixed required inductance ($L_s$req), the operating frequency, and the minimum quality factor (Qmin). It turns out ABC has a fast convergence behavior.

Algorithm 1: Differential Evolution Algorithm.

$T \leftarrow 0$
Generate the initial population of individuals N
Evaluate $g(x_j, k)$
for i in Individuals N **do**
  Randomly Choose s_1, s_2, s_3 within $[1, N]$
  for each parameter j **do**
    Generate the mutant vector
    Generate a new vector
  end for
  if $g(u_j, k+1) \leq g(x_j, k)$ **then**
    $x_{j,k+1} = u_{j,k+1}$
  else
    $x_{j,k+1} = x_{j,k}$
  end if
end for
$T = T + 1$

Similar analysis and results were implemented and verified in Abi et al.'s work [76].

Hajjami et al. [77] presented a comparative analysis of convergence, robustness, computing time, and circuit size between GAs and ABC for the optimal sizing of RF-integrated circular inductors. ABC exhibits better convergence compared to GA. Although GA is faster than ABC, both algorithms provide good results regarding the circuit's size. GA provides a more stable value of inductance compared to ABC. The self-resonant frequency (SRF) achieved by GA is approximately 15 GHz, while for ABC, it is around 18 GHz. The error in inductance values for both GA and ABC remains below 5.6% in the frequency range of 2–4 GHz. Regarding the Q-Factor, at a frequency of 3 GHz, the error is 7.6% for GA and 8.45% for ABC.

6) Ant Colony Optimization (ACO)-Based Design: ACO is a metaheuristic technique used for optimization, drawing inspiration from the foraging behavior of real ant colonies. It is based on the collective behavior of ants depositing and monitoring pheromones on paths, which is observed in insect colonies [78]. Abi et al. [75] presented the optimal design of an integrated square spiral inductor, aiming to maximize its quality factor (Q) while considering design requirements and fundamental constraints. The ACO algorithm yielded superior results in terms of circuit size, while the ABC algorithm demonstrated faster convergence. It shows two metaheuristic algorithms that prove effective in designing integrated spiral inductors with higher quality factors.

7) DE-Based Design: The DE algorithm is a type of EA and a stochastic, population-based optimization technique. It was developed by Rainer Storn and Kenneth Price in 1997 [79]. DE is particularly effective for optimizing real-valued multidimensional functions and is known for its simplicity, speed, and robustness [80]. The pseudocode can be examined in Algorithm 1, as referenced in Hajjami et al.'s work [81], to optimize the shape of planar inductors used in RF circuits.

Di Capua et al. [82] introduced the DE experimental measurements processing method for identifying saturation curves of ferrite core inductors (FCIs) in dc–dc power converters, providing more accurate data for predicting FCIs' performance than traditional methods. Elhajjami et al. [83] further demonstrated DE's effectiveness in optimizing RF integrated inductors, achieving high accuracy in maximizing quality factor, Q, minimizing surface area, and optimizing SRF, even under constraints posed by parasitic effects. In addition, Abi et al. [76] explored the use of DE in the optimal sizing of CMOS RF square spiral integrated inductors, comparing it with ACO and ABC techniques. DE was found to be most effective for circuit size optimization, highlighting its potential in HF inductor design for achieving high-quality factors and efficient power density in SMPSs. These studies collectively underscore DE's growing importance in the advanced design and optimization of HF inductors.

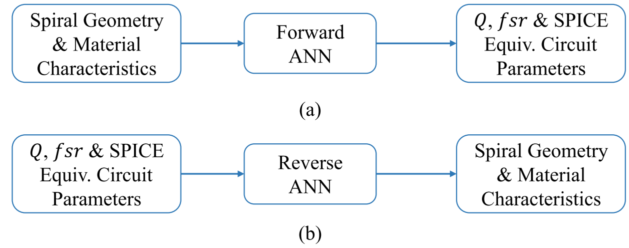

Fig. 12. Forward and reverse ANNs.

8) ANN-Based Design: In the beginning of ANN applications in 1998, it was focused on modeling exploration and data structures; for example, the issue of modeling the behavior of nonlinear hysteretic and parametric inductors has been tackled using an ANN approach [84].

In Kowaltschuk et al.'s work [85], the relationship of on-chip inductor geometry parameters and operation scenarios with the inductor inductance was also learned by ANN. Liu et al. [86] used a similar structure with S-parameter formulation of the quality factor for a spiral inductor to achieve improved speed and accuracy performance despite significantly reducing the training data size.

Ilumoka and Park [87] proposed an ANN and a reversed ANN for the modeling and geometry re-design of on-chip spiral inductors, as shown in Fig. 12. The approach involves the use of neural networks to create mappings for multilevel spiral inductors, performing two distinct tasks.

A novel scalable model called the space mapping neural network (SMNN) in [88] has been introduced to characterize the radio-frequency behaviors of on-chip spiral inductors. The model combines the advantages of a compact model and a neural network. The proposed SMNN model uses a physics-based T equivalent circuit model, and the values of T model elements are efficiently and accurately extracted using mathematical formulations derived from resonant responses analysis.

ANN can function as surrogate models in the design of HF magnetic components. Surrogate models, also known as metamodels or response surface models, are mathematical models that approximate the behavior of complex and computationally expensive simulations or experiments. In the HF magnetic

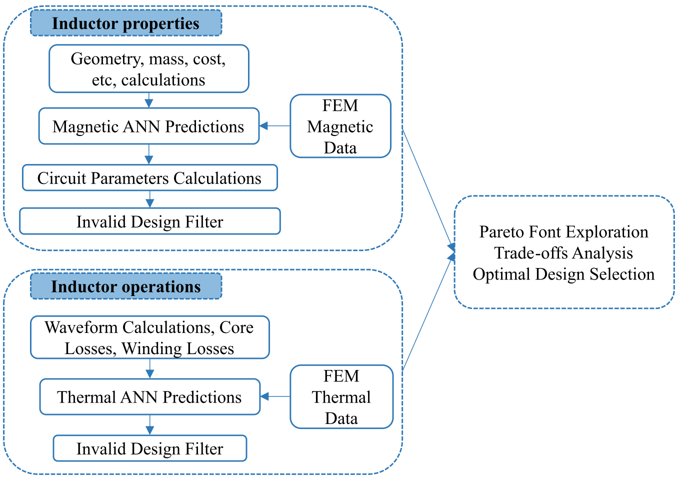

Fig. 13. Workflow for the design of an inductor using ANNs for thermal and magnetic models [11].

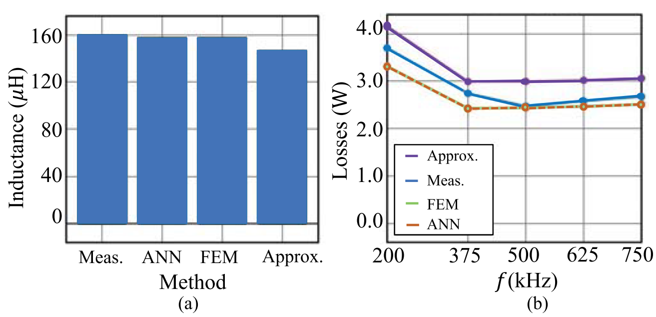

Fig. 14. Comparing measured values: ANN workflow versus 3-D FEM simulations and analytical approximations for inductance and losses [11].

components design context, the simulations or calculations required to characterize their behavior can be time-consuming and resource-intensive.

Guillod et al. [11] highlighted the integration of ANNs with FEM for optimizing HF inductor designs. It showcases a hybrid model that combines the accuracy of the finite element method (FEM) and ANNs' computational efficiency, covering extensive variables and effects, such as magnetic and thermal fields. In this approach, the FEM primarily provides the detailed and accurate training data needed for training ANNs. These data, reflective of various inductor designs and conditions, enable the ANNs to simulate and optimize inductors efficiently while maintaining high accuracy compared to comprehensive FEM simulations.

Fig. 13 depicts a streamlined process for computing inductor designs with reduced computational costs and a parallelized workflow. It involves two main steps: computing basic inductor properties and evaluating various operating points and waveforms. During the optimization process of the ANN-based workflow, five million designs were evaluated, out of which 700 000 met the validity criteria (such as saturation and thermal limits). The entire computation for these designs was completed in 40 s.

Fig. 14 demonstrates that the ANN-based workflow closely matches 3-D FEM simulations with minimal deviation (under 0.6%) for inductance and losses. In contrast, analytical approximations show larger errors, 8.6% for inductance and 21.2% for losses. However, using the ANN-based approach reduces these discrepancies to 1.4% and 11.5%, respectively, which enhances ML techniques applications in power electronic models, particularly for magnetic components.

Similarly, Cajander et al. [89] demonstrated that the example of inductance topology clearly shows that using FEM-supervised trained ANNs dimensioning models is a highly efficient alternative, striking a good balance between precision and computing time in optimal inductor design. The incorporation of dimensionless form factors as input variables in the supervised ANN model further enhances the training process by providing inherent preliminary scaling, leading to improved convergence during training.

In Li et al.'s work [90], an ANN model is introduced to enhance training performance by utilizing Gaussian error linear unit (GELU) and Huber functions for constructing parameterized TSV models. The DNN-TSVs model was built using the GELU activation function and the Huber loss function, which were chosen after comparing different activation and loss functions for enhanced robustness.

Wang et al. [91] introduced an efficient synthesis–analysis machine for on-chip inductor synthesis and modeling, along with an automatic dataset generation topology to create training datasets for ANNs.

In Zhou and Preindl's work [92], the proposed ANN is created to examine the ac losses of the proposed solid/litz-printed circuit board (PCB) winding. By optimizing the parameters of the PCB winding, it is possible to minimize the losses in the inductor. A 3-D routing method for PCB winding is developed to minimize HF copper losses. The method involves analyzing the parameters of the litz PCB, such as strand number, trace width, thickness, and layout, in detail. Different coil types, including solid/litz types of PCB/wire windings, are compared and analyzed based on their ability to reduce HF copper losses and optimize space utilization.

9) SVM-Based Design: Wang and Franzon [93] employed the Nu-SVM regressor as the model method and integrate it into a surrogate-based optimization design flow, automating the tedious inductor redesign process. The core idea behind SVM is to find a set of hyperplanes that maximize the geometric margins between the training dataset and these hyperplanes. This approach allows for efficient optimization and automatic adjustment of inductor designs, leading to improved accuracy and faster design cycles.

10) GANET-Based Design: In Baldan and Barba's work [94], a combination of a GANET and a forward neural network (FNN) is employed to generate additional Pareto optimal solutions based on the outcomes of a genetic algorithm used as the training set. The GANET and FNN work together, with the FNN cascade connected to the GANET generator, as shown in Fig. 15. This approach ensures accurate prediction of the objectives of the generated solutions, eliminating the need for further field analyses. By leveraging the GANET and FNN in this manner, the study aims to offer improved diversity and a more comprehensive set of nondominated solutions to support decision-making in coil design for induction hardening applications.

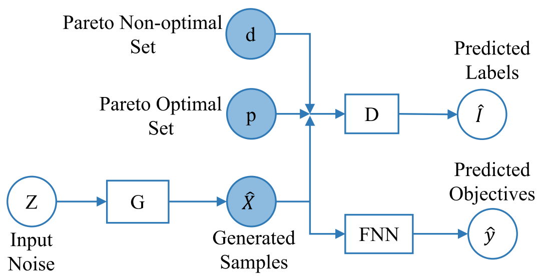

Fig. 15. GANET-based approach in Baldan and Barba's work [94].

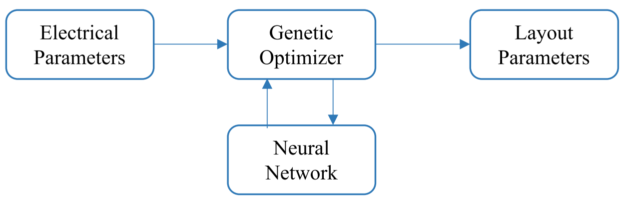

Fig. 16. GA-ANN optimization workflow.

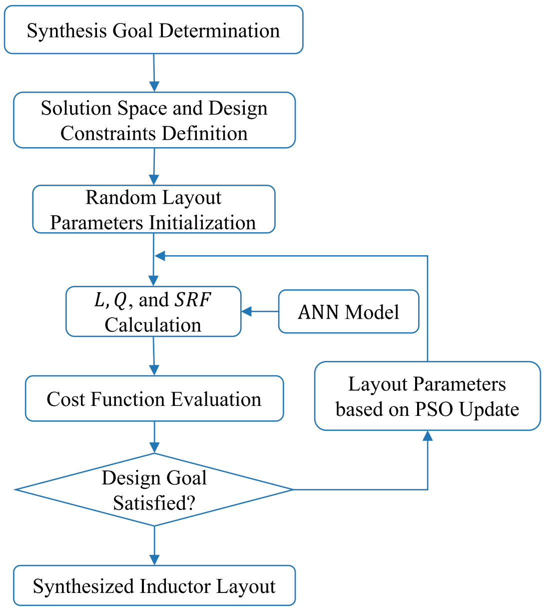

Fig. 17. PSO-ANN optimization workflow.

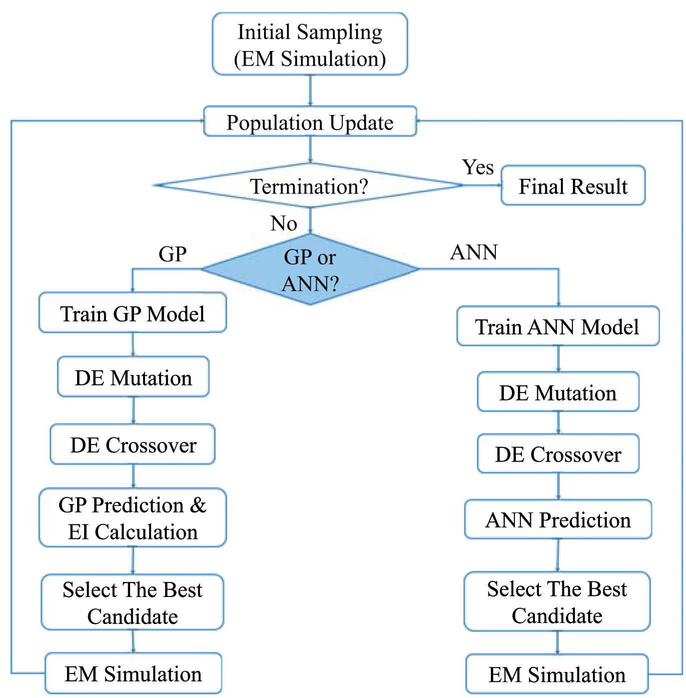

Fig. 18. MMLDE proposed in Liu et al.'s work [97].

11) ANN–GA-Based Design: The first integration of ANN and GA was proposed in Pratap et al.'s work [95] for on-chip inductor design. ANN works as the surrogate model, and GA implements the optimization process. The design of multilayer RF passives involved the integration of neural network modeling and genetic optimization. This combined approach leveraged the strengths of neural networks for accurate modeling and genetic algorithms for efficient optimization. The optimization process is illustrated in Fig. 16.

In the initial step, a precise ANN model was developed. A genetic optimizer was employed to retrieve output values from this neural network model. The genetic optimizer was given the desired electrical characteristics and began with an initial population of layout parameters. It computed the response of this population using the neural network model and selected the best-performing samples. These samples then underwent genetic manipulation to yield improved results. The process continued iteratively until the remaining samples achieved the desired electrical characteristics.

12) ANN-PSO-Based Design: In Mandal et al.'s work [96], a spiral inductor is characterized using artificial neural networks, where the layout design parameters, such as the spiral outer diameter, number of turns, width of metal traces, and metal spacing, serve as inputs. The neural model generates outputs for inductance (L), quality factor (Q), and self-resonance frequency (SRF). To achieve a specified target inductance while adhering to the constraints on SRF and other factors, PSO optimization is employed to explore the layout space and find the optimal set of design parameters for the spiral inductor with the whole procedure in Fig. 17. This approach allows for efficient and effective tuning of the inductor's layout to meet the desired performance criteria.

13) GP-ANN-Based Design: An approach in Liu et al.'s work [97] called memetic machine learning-based differential evolution (MMLDE) is introduced. MMLDE combines the advantages of a memetic evolutionary optimization mechanism and online surrogate modeling. The key idea of MMLDE as shown in Fig. 18, is to generate training data adaptively during the optimization process using the DE algorithm as the optimization kernel and EM simulation as the performance evaluation method, leading to high-quality solutions. By incorporating the Gaussian process (GP) and ANN in the search mechanism, online surrogate models are constructed to predict performances, significantly reducing the need for expensive EM simulations.

Table II presents an overview of the AI algorithms employed in the design of HF inductors. The application scenarios of the

TABLE II
ANALYSIS FOR AI-BASED HF INDUCTOR DESIGN

AI algorithms	Type of inductor	Objective	Advantages	Disadvantages
Expert System [55]	DC bias Inductors	Magnetic Saturation/ Core Window Fill Factor	1. Speeding up the design process without extensive prior knowledge 2. Helps GAs to select optimal components from databases	1. Limitation of understanding decision basis 2. Dependency on Expert Knowledge
Fuzzy Logic [56]	DC bias Inductors	Magnetic Saturation/ Core Window Fill Factor	1. Expert Knowledge and core database incorporation 2. Multi-criteria optimization for trade-offs between parameters	1. The complexity of design process and time-consuming 2. Challenging Knowledge Acquisition
GA [59] [60] [63] [78]	Spiral Inductors	Quality Factor/ Geometric Parameters	1. Well-suited for finding global optimal solutions 2. Identifying trade-offs 3. Adapbilities to changes in the design space and objective functions	1. Struggling with scalability 2. No guaranteed global optimum 3. Slower convergence speed
NSGA-II [70] [71] [72] [95]	LCL Filters/ Arm Inductors	Filter Parameters/ Magnetic Saturation/ Core Window Fill Factor	1. Pareto front exploration 2. Identify globally optimal or near-optimal solutions 3. Adaptability of changes	1. High computational costs and 2. Lack of interpretability
PSO [73] [74]	Spiral(on-chip) Inductors	Desired Inductance Value/ Quality Factor	1. Design space exploration 2. Independent from gradient 3. Easy implementation and adaptability to changes	1. Premature convergence and lack of guaranteed global optimum 2. Limited exploration in high dimensions
ABC [75] [76] [77] [78]	Spiral Inductors	Geometric Parameters/ Quality Factor	1. Finding global optima 2. Easy implementation and adapability to changes	1. Slow convergence speed 2. Parameter sensitivity and limited exploration
ACO [76]	Spiral Inductors	Geometric Parameters	1. Capability of whole design space and global optima 2. Easy implementation and adaptability	1. Slow convergence speed 2. Parameter sensitivity and limited exploration
DE [77], [83], [84]	DC Inductors/ On-chip Spiral Inductors	BH/Current Ripple curves/ Geometric Parameters & Quality Factor	1. Simple and Flexible 2. Flexible Good Convergence Handling Non-linearities	1. Parameter Sensitivity 2. Risk of Premature Convergence to a suboptimal solution 3. Limited Local Search Capability
ANN [93] [11], [85]–[92]	DC bias Inductors/ On-chip Spiral Inductors	BH curves/Inductance/ Loss&Thermal surrogate models	1. Capability of capturing and modelling complex nonlinear relationships between design parameters and performance metrics 2. Data-driven Design and parallel processing	1. Data dependency and overfitting 2. Complexity and challenging interpretability of ANN as 'black-box' models 3. Limited data extrapolation and training complexity
SVM [94]	Spiral Inductors	Geometric Parameters	1. Outlier robustness and margin maximization 2. Kernel trick to map data into higher-dimensional spaces	1. Computinally intensive for larger datasets 2. High-quality dependency for trianing
GANET [95]	HF Inductors	Pareto Optimal Solutions	1. Additional Solutions generation and Pareto Front solutions production 2. Diversity enhancement and ANN integration	1. Complexity and time-consuming 2. Limited direct applicability into generating synthetic responses of HF magnetic components
ANN-GA [96]	On-chip inductor	Geometric Parameters	1. Time and cost minimization 2. Great accuracy	1. Data dependency 2. Model validity on quality and representativeness
ANN-PSO [97]	On-chip inductor	Inductance/ Quality Factor	1. Cycle Time Reduction 2. Improving accuracy and efficiency	1. Data dependency 2. Limited to trained scenarios
GP-ANN [98]	Spiral Inductors	Synthesis of Passive Components	1. Computational efficiency and speed-up 2. Improved efficiency and solution quality	1. Data dependency and generalization issues 2. Trade-off between accuracy and efficiency

algorithms are listed. The advantages and disadvantages are discussed in detail.

B. AI-Based HF Transformer Design

1) Expert System-Based HF Transformer Design: The TRANSEX expert system, introduced in Dhawan et al.'s work [98], streamlines HF transformer design by integrating decisions on core geometry, operational conditions, and transformer losses using manufacturer datasheet data.

Complementing this, core geometry selection aid, a fuzzy logic-based expert system detailed in Dhawan et al.'s work [99], aids in selecting appropriate core geometries. It combines expert system and fuzzy logic approaches, addressing factors such as power, cost, shielding, heating, and power density through IF-THEN logic to manage the inherent uncertainties.

A sophisticated expert system for transformer design is detailed in Hernandez and Arjona' work [100] and illustrated in Fig. 19. This system mimics professional-level designs using user-specified parameters, such as winding current densities, core dimensions, and flux density. It then computes critical aspects such as turn count, insulation clearances, conductor sizes, cooling mechanisms, and electrical characteristics, such as impedance and efficiency.

2) MM-Based HF Transformer Design: GA is employed as a powerful instrument for addressing multiobjective optimization

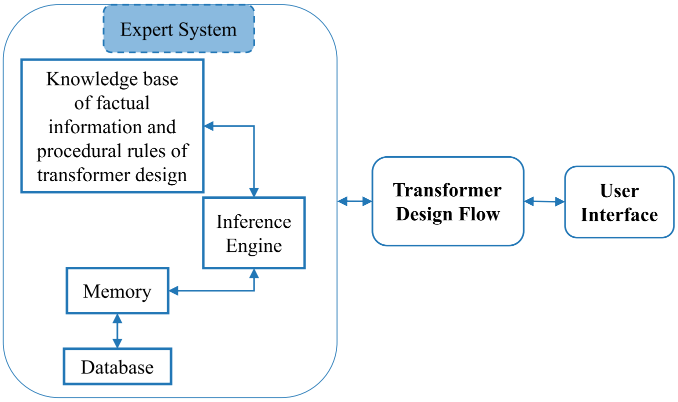

Fig. 19. Expert system-based HF transformer design.

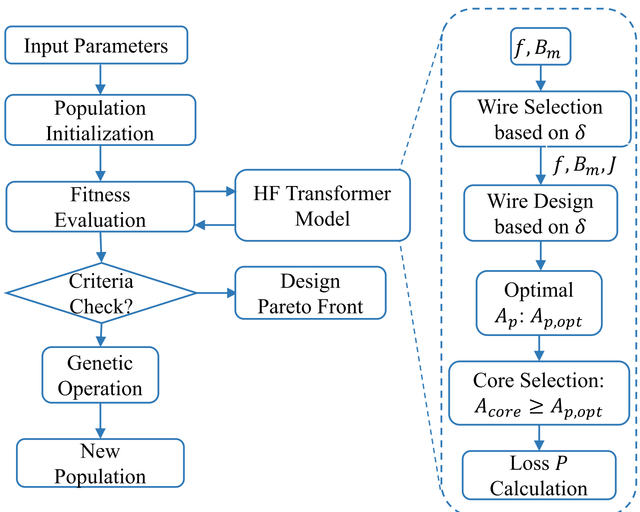

Fig. 20. GA-based HF transformer design flow.

challenges. In Tutkun and Moses's work [101], the GA approach has been applied to enhance the design of a strip-wound toroidal core. The primary objectives are the mitigation of power loss and the reduction in building material expenses.

NSGA-II [102] is employed to execute the search and optimization processes. The metrics utilized for optimization are the area product A_p, defined as the multiplication of the core's cross-sectional area and the winding area, and the power loss. Simultaneously, the design variables include the operational frequency f and the maximum flux density B_m within the core's cross-sectional area. It is noteworthy that the preference was given to minimizing the area product rather than the weight or volume of the transformer. This choice is justified by the fact that weight and volume can be conveniently represented in terms of the area product [103], thereby streamlining the objective functions and enhancing efficiency.

The comprehensive optimization procedure in Versele et al.'s work [104] has been encoded in MATLAB [66], as depicted in Fig. 20. The process is initiated by creating an initial population through randomization. Subsequently, the defined objective functions are computed based on this initial population and the previously outlined HF transformer model. To assess convergence, a termination criterion is tested. If this criterion is not met, the genetic operations-driven reproduction process commences. A fresh population is generated, and the preceding steps are iterated until the termination criterion is met. Alternatively, if the termination criterion is satisfied, the Pareto front, comprising nondominated solutions spanning the entire search space, is visualized. This step concludes the optimization process.

Similarly, the optimization challenge associated with transformer design revolves around the task of minimizing the overall mass (or cost) of both the core and wire materials. The focal point of design optimization is to achieve a solution with the lowest feasible mass (or cost), with the constraints. This is achieved by tactically configuring the transformer's geometric parameters and aligning them with the required magnetic properties. Yadav et al. [105] addressed this design problem through the utilization of GA and SA techniques. The outcomes obtained using the geometric programming technique are juxtaposed with the results derived from applying GA and SA methods.

The intended approach in Garcia-Bediaga et al.'s work [106] seeks to achieve the optimal HF transformer design tailored to a specific power converter topology. This study is focused on achieving the optimal medium-frequency transformer suitable for a specific power converter topology. This is achieved through the optimization of the transformer's weight (W_t) and efficiency (η), while simultaneously minimizing the disparity between the realized and anticipated values of leakage and magnetizing inductances.

Coelho et al. [107] introduced a novel DE variant, NDE, incorporating a truncated gamma probability distribution for enhanced multiobjective optimization, notably in transformer design. This variant outperforms traditional DE algorithms in solution spread and convergence to the Pareto front. Separately, Tria et al. [108] assessed DE for parameterizing HF planar transformers, finding it more suitable for postdesign validation compared to 1-D and 3-D electromagnetic analyses. While DE accurately predicts magnetizing inductance, it tends to overestimate other parameters, such as series resistance and leakage inductance.

In Qin et al.'s work [109], a blend of PSO and DE is introduced as a solution strategy for addressing a multiobjective problem for HF transformer, which holds paramount significance as a pivotal element within a dual active bridge converter employed in power electronics-driven solid-state transformers. Moreover, the permissible window area sets boundaries on the potential winding configurations for the transformer. By incorporating DE, diversity is infused into each particle's personal best (Pbest), a facet absent in conventional PSO approaches. The workflow of DE-PSO design is shown in Fig. 21.

Jafari et al. [110] outlined an optimized design procedure for a multiwinding HF toroidal transformer aimed at integration within a modular multilevel inverter connected to photovoltaic systems. The transformer's design targets specific inductance values and optimal efficiency. This process involves utilizing the lumped parameter model as the initial phase, the PSO-based reduced Newton method for iterative optimization, and FEM for precise design analysis.

3) ML-Based HF Transformer Design: Nussbaum et al. [111] proposed the concept of ANN-cascades as a solution to a

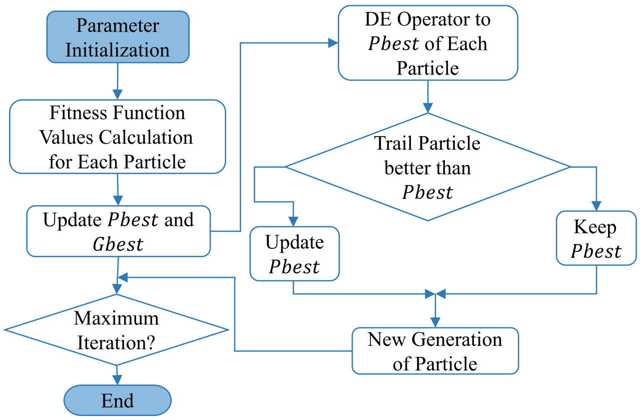

Fig. 21. Flowchart of DE-PSO-based HF transformer design.

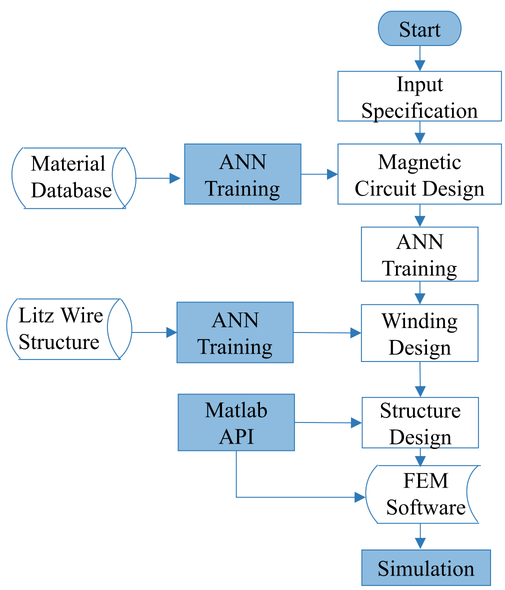

Fig. 22. ANN-FEM-based design structure [112].

primary issue arising from the fact that an increase in input parameters results in a significant rise in training batches, which are established through time-consuming model core experiments. To reduce the required training data, a combination of ANN1 trained on linearized joint data and ANN2 trained on mitred cores of different sizes has been attempted. To address larger cores, an ANN cascade structure has been tested, incorporating a second ANN that considers the indirect effects of joint designs on the overall distribution of losses. The primary challenge faced by an ANN-based prediction system lies in the establishment of representative training data. Modified versions of the ANN method can be utilized for various tasks, including the prediction of losses and noises in full-sized cores.

Li et al. [112] focused on a refined computer-based design environment for transformers. This platform aids engineers in automated modeling, simulation, and optimization of transformer designs through the implementation of an ANN and the FEM, as shown in Fig. 22.

A letter [113], published in 2023, introduces an innovative forward-converter transformer (FCT) design methodology

TABLE III
COMPARISON OF FEM AND KNN-GRU-DNN DESIGNS FOR FCT

Metrics	FEM-design	KNN-GRU-DNN design
Complexity	$O(n^2)$	$O(n)$
Process time	2.9h	132s
Iteration epochs	–	1450
Used memory	1084.6 MB	849 MB
Flux saturation	Occurred	Not occurred

leveraging AI, specifically through a K-nearest neighbor (KNN), gated recurrent unit (GRU), and DNN model to enhance design efficiency and accuracy. The approach significantly reduces the need for repetitive design processes, achieving over 91% estimation accuracy and meeting design requirements within 1450 epochs without requiring further training. Validations through FEM simulations and hardware-in-the-loop experiments confirm the AI-based model's capability to satisfy design specifications, outperforming traditional methods in terms of complexity, processing time, and efficiency, as shown in Table III. This advancement represents a significant leap forward in the field of power electronics, offering a more streamlined and effective approach to transformer design.

V. AI DESIGN TOOLS FOR HF MAGNETIC COMPONENTS

As discussed previously, designing HF magnetic components requires an advanced understanding of electromagnetic fields, materials science, circuit design, and often complex computational methods. Several online tools and software platforms integrate AI to assist engineers in this domain. These tools, varying in complexity and specificity, include the following.

1) *MagNet Princeton [31], [32], [114]:* It is designed to aid researchers in using ML for simulating magnetic core loss, thereby accelerating power electronics design. It contains extensive voltage and current data from various magnetic components. These datasets serve as excitation-response pairs for developing analytical magnetic models or calculating core loss for static models.
2) *M2Spice Princeton [115], [123]:* This open-source software models planar magnetics, converting device geometries into SPICE netlists. It is designed for 1-D multiwinding, multilayer planar magnetics in HF ranges, focusing on skin and proximity effects. Its primary function is to generate netlists for SPICE simulations.
3) *CoupL Princeton [116]:* Developed by Princeton's Power Electronics Research Lab, CoupL is a sophisticated simulation tool for inductors and transformers. It supports various design parameters and uses advanced models to optimize design traits, proving essential for HF magnetic component research and engineering.
4) *Frenetic.AI [33]:* Starting with user specifications, such as voltage levels, ripple requirements, and current limitations, Frenetic.AI introduces Core Optimizer™. This feature accelerates the core selection process, allowing quick comparison of different shapes and materials. The

SUZUKA CIRCUIT SIMULATOR™, issued by Frenetic.AI, is a high-efficiency tool for modeling converters and their controllers, enabling simulation of custom topologies directly within a browser. At the validation and prototype stages, it provides a comprehensive file including product bills, 3-D FEM simulations, and PDF version drawings.

5) *PowerBrain.AI [26], [117]:* As an AI tool for HF magnetic components design, PowerBrain.AI significantly enhances the design process. The semiconductor data extractor stands out, extracting dynamic data from semiconductor datasheets and converting them into machine-readable formats. The magnetic core loss tool enables comprehensive analysis of core losses for various materials and configurations, integrating measurement data, Steinmetz equation, and a DNN model for accurate predictions.
6) *AI-Mag [118]:* This tool combines ANNs with the FEM for rapid and precise inductor modeling. AI-mag's capability to rapidly generate thousands of designs, backed by accurate 3-D simulations, revolutionizes the optimization process for various inductor types, such as buck, boost, and resonant. Its GUI facilitates exploration of tradeoffs, such as power density, cost, and efficiency, enabling the selection of optimally designed components.
7) *Open Magnetics [119]:* Open Magnetics provides a collection of online tools tailored for the design and simulation of magnetic components, operating on a fully open-source basis. This approach ensures that any code instrumental in the models or computations is accessible to the community, promoting an environment of collaborative development and innovation.
8) *Magnetec [120]:* Magnetec offers innovative tools for the design and simulation of HF magnetic components, particularly emphasizing nanocrystalline cores. The "Simtool" is a software application enabling the simulation of nanocrystalline magnet cores, aiding in the creation of customized designs. In addition, Magnetec provides a comprehensive calculation tool for determining saturation current in nanocrystalline ring cores, aiding in the precise analysis and design of magnetic components.
9) *AI-Power [121]:* Although its primary focus is on general power electronic applications, the platform's approach to integrating AI for enhancing efficiency and reducing lifecycle costs is highly pertinent to the design of HF magnetic components. AI-Power exemplifies how physics-informed AI can bridge the gap between academic research and industry applications, providing a template for similar advancements in HF magnetic component design. Moreover, as the world's first power electronics data platform, AI-Power underscores the growing trend of leveraging big data and advanced algorithms to optimize electronic component design, a methodology that could significantly impact the future of HF magnetic component design strategies.
10) *ChatGPT [122]:* As an advanced AI language model, ChatGPT offers a transformative approach to the design and optimization of HF magnetic components. It acts as an intelligent assistant, assimilating and analyzing technical literature and research, thus enabling designers to stay abreast of the latest advancements in HF magnetic component design. ChatGPT facilitates innovative design brainstorming, suggesting alternative materials or geometries based on its extensive knowledge base. It can also aid in the preliminary assessment of design feasibility, providing quick insights into potential challenges or performance limitations.

Table IV presents an overview of the current AI tools related to HF magnetic components design. It showcases a comprehensive range of AI and computational tools that have significantly impacted the design and optimization of HF magnetic components. These tools, from MagNet Princeton to ChatGPT, represent a diverse spectrum of applications, from core loss simulation and SPICE model generation to the integration of complex algorithms for design optimization. Each tool offers unique capabilities, such as Frenetic. AI's Core Optimizer™ and PowerBrain. AI's magnetic core loss tool, catering to specific aspects of HF magnetic component design.

In conclusion, the landscape of HF magnetic component design is being profoundly reshaped by these AI-driven tools. They not only streamline and enhance the design process but also open up new possibilities for innovation and efficiency. This convergence of AI and advanced computational methods is indicative of a significant technological advancement in the field, paving the way for more sophisticated, efficient, and effective power electronic systems. The tools listed each with its specialized focus and advanced capabilities, collectively represent a leap forward in meeting the complex demands of modern electronic systems design. This evolution underscores the growing importance of AI in driving future developments in this area.

VI. Potential, Challenges, and Future on AI in HF Magnetic Components Design

The utilization of AI in HF magnetic components design heralds a new era of innovation, offering substantial opportunities to overcome longstanding design challenges. However, this journey is not without its hurdles. This section delves into the promising prospects AI introduces to the field, such as comprehensive database integration and advanced loss models, while also confronting the critical issues that persist, including data integration challenges and the need for multidisciplinary approaches. A detailed exploration of both the transformative impact of AI and the bottlenecks that must be navigated illuminates the evolving landscape of magnetic component design as follows.

1) *Comprehensive database integration:* One critical challenge is the absence of a comprehensive database that integrates simulations, experimental data, and historical design examples. Such a database could serve as a valuable resource to inform and guide the development of innovative solutions. Initiatives such as Powerbrain.AI [117], and Magnet [124], have begun collecting

TABLE IV
COMPARISON OF AI DESIGN TOOLS FOR HF MAGNETIC COMPONENTS

Tool name	Primary function	Unique features	Target users	Application scope
MagNet Princeton [115]	Simulating Magnetic Core Loss	Extensive Voltage and Current Data, ML Models	Researchers, Power Electronics Design	Core Loss Simulation
M2Spice Princeton [116]	Modeling Planar Magnetics, Generating SPICE Netlists	1-D Multi-Winding, Multi-Layer Focus, Skin/Proximity Effects	Circuit Designers	Planar Magnetics Simulation
CoupL Princeton [117]	Simulation Tool for Inductors and Transformers	Advanced Models for Design Optimization	Engineers, HF Component Researchers	Inductor and Transformer Design
Frenetic.AI [34]	Core Selection and Converter Modeling	Core Optimizer™, Suzuka Circuit Simulator™	Engineers, Designers	Core Selection, Converter Modeling
PowerBrain.AI [27], [118]	HF Magnetic Components Design	Semiconductor Data Extractor, Magnetic Core Loss Tool	Engineers, Data Analysts	Magnetic Component Design
AI-Mag [119]	Rapid Inductor Modeling	ANN Combined with FEM, Extensive Design Generation	Engineers, Academics	Inductor Optimization
Open Magnetics [120]	Design and Simulation of Magnetic Components	Open-Source Platform, Community Collaboration	Researchers, Open-Source Community	General Magnetic Component Design
Magnetec [121]	Design and Simulation of a Wide Range of Magnetic Components	Comprehensive Product Range Including Nanoperm®, CoolBlue®, EMV Chokes, and More	Engineers, Designers, Researchers in Magnetic Technology	Diverse Magnetic Component Applications Including EMC, Power Electronics, etc.
AI-Power [122]	General Power Electronic Applications	Physics-Informed AI, Emphasis on Efficiency and Cost	Industry Professionals	Power Electronics, HF Components
ChatGPT [123]	AI-Assisted Design and Optimization	Intelligent Assistance, Technical Literature Analysis	Designers, Engineers	Design Brainstorming, Feasibility Assessment

data, but AI techniques, such as generative adversarial networks (GANETs), can enhance these efforts. GANETs can assist engineers in data extraction, feature extraction, data augmentation, and anomaly detection, thereby contributing to a richer database.

2) *AI-assisted loss models:* Current AI-based loss models for HF magnetic components are often limited to specific sizes or topologies. To advance this field, a comprehensive database encompassing magnetic components of varying shapes, sizes, and materials is required. AI can play a pivotal role in creating an integrated model capable of accurately predicting losses for different geometries and materials. This holistic approach will provide engineers with more precise insights into magnetic component performance.
3) *Thermal design advancements:* There are few references related to thermal management for HF magnetic components design. AI holds great promise in analyzing thermal behavior, predicting areas of heat build-up, and guiding the development of efficient heat dissipation solutions, such as heat sinks and advanced thermal materials. AI can optimize material selection by balancing electrical and thermal performance through extensive database analysis and simulations.
4) *Comprehensive optimization design:* While various AI algorithms have shown promise in enhancing the design process, they often target specific scenarios at the research level. The future of AI-based design lies in comprehensive optimization. By leveraging AI's ability to analyze extensive and intricate datasets alongside advanced optimization algorithms, engineers can revolutionize the design process across industries. Collaborative efforts among AI algorithms can generate, analyze, and refine design options, fostering innovation in HF magnetic component design.
5) *Automatic AI tools:* Efforts such as Frenetic [33] and AI-mag [118] aim to develop automated AI-driven design platforms that encompass the entirety of the magnetic component design process. While existing platforms offer a two-step approach to design and simulation, there is room for expanding the repository of prototypes, specifications, and data. The envisioned future entails integrating more comprehensive design methodologies into these platforms, covering the complete design journey from core/winding selection to prototype realization and specification simulation.

Challenges and future directions lie in addressing data quality, design complexity, and integration hurdles is paramount. Future research should focus on developing unified, high-quality databases, multidisciplinary AI models, and strategies for seamless workflow integration. Enhancing AI's scalability and generalization across different designs will be key to overcoming current limitations.

Moreover, future market time efficiency can be enhanced by facilitating rapid prototyping, automated design verification, and supply chain optimization. AI can significantly reduce the time from design to market. Adopting digital twin technology and integrating AI in manufacturing processes promise to improve procedural efficiencies, making the design process more agile and responsive to market demands.

VII. Conclusion

A comprehensive review is addressed for present AI applications in HF magnetic component design for power electronics systems. AI has made significant contributions to the field of HF magnetic components design, offering innovative approaches and solutions to enhance efficiency, performance, and accuracy across various stages of the design process. The following key conclusions can be drawn from our review.

1) AI can predict and quantify core and winding losses in magnetic components. This information can guide designers to select materials and geometries that minimize energy dissipation and improve overall efficiency, especially in HF applications with significant losses. As introduced previously, ML models can predict material performance and behavior under different conditions, aiding designers in making informed choices.
2) AI-driven design techniques can assist in finding optimal magnetic core shapes and winding geometries. GA, ANN, and other optimization methods can explore a vast design space to identify configurations that minimize losses, improve coupling, and enhance efficiency.
3) AI can analyze historical design data and outcomes to provide insights into trends, correlations, and patterns. This information guides designers in making informed decisions based on past experiences.
4) When it comes to ML, it is essential to understand that GA, PSO, ABC, and ACO are optimization algorithms, not ML algorithms. They are used for solving optimization problems, particularly in continuous and combinatorial optimization. However, ML and optimization algorithms are not mutually exclusive. ML techniques can be combined with these optimization algorithms in various ways to enhance their performance and adaptability.
5) Future opportunities and challenges are addressed for this specific field. The promising blueprints we have identified hold the potential to revolutionize HF magnetic component design further.

References

[1] A. J. Hanson and D. J. Perreault, "Modeling the magnetic behavior of n-winding components: Approaches for unshackling switching superheroes," *IEEE Power Electron. Mag.*, vol. 7, no. 1, pp. 35–45, Mar. 2020.

[2] K. M. Krishnan, *Fundamentals and Applications of Magnetic Materials*. London, U.K.: Oxford Univ. Press, 2016.

[3] A. Bahmani, "Core loss evaluation of high-frequency transformers in high-power dc-dc converters," in *Proc. 13th Int. Conf. Ecological Veh. Renewable Energies*, 2018, pp. 1–7.

[4] M. Hossain et al., "Recent progress and development on power DC-DC converter topology, control, design and applications: A review," *Renewable Sustain. Energy Rev.*, vol. 81, pp. 205–230, 2018.

[5] W. Martinez, S. Odawara, and K. Fujisaki, "Iron loss characteristics evaluation using a high-frequency GAN inverter excitation," *IEEE Trans. Magn.*, vol. 53, no. 11, Nov. 2017, Art. no. 1000607.

[6] J. M. Silveyra et al., "Soft magnetic materials for a sustainable and electrified world," *Science*, vol. 362, 2018, Art. no. 6413.

[7] S. Zurek, *Characterisation of Soft Magnetic Materials Under Rotational Magnetisation*. Boca Raton, FL, USA: CRC Press, 2017.

[8] B. Cullity and C. Graham, "Soft magnetic materials," in *Introduction to Magnetic Materials*. Hoboken, NJ, USA: Wiley, 2008, ch. 13, pp. 439–476.

[9] M. R. Islam, M. A. Rahman, P. C. Sarker, K. M. Muttaqi, and D. Sutanto, "Investigation of the magnetic response of a nanocrystalline high-frequency magnetic link with multi-input excitations," *IEEE Trans. Appl. Supercond.*, vol. 29, no. 2, Mar. 2019, Art. no. 0602205.

[10] S. Zhao, F. Blaabjerg, and H. Wang, "An overview of artificial intelligence applications for power electronics," *IEEE Trans. Power Electron.*, vol. 36, no. 4, pp. 4633–4658, Apr. 2021.

[11] T. Guillod, P. Papamanolis, and J. W. Kolar, "Artificial neural network (ANN) based fast and accurate inductor modeling and design," *IEEE Open J. Power Electron.*, vol. 1, pp. 284–299, 2020.

[12] O. Omorogiuwa Eseosa, "A review of intelligent based optimization techniques in power transformer design," *Appl. Res. J.*, vol. 1, no. 2, pp. 79–88, 2015.

[13] C. M. Bishop, *Pattern Recognition and Machine Learning (Information Science and Statistics)*, 1st ed. New York, NY, USA: Springer, 2007.

[14] I. Goodfellow, Y. Bengio, and A. Courville, *Deep Learning*. Cambridge, MA, USA: MIT Press, 2016. [Online]. Available: http://www.deeplearningbook.org

[15] T. Wu, Z. Wang, B. Ozpineci, M. Chinthavali, and S. Campbell, "Automated heatsink optimization for air-cooled power semiconductor modules," *IEEE Trans. Power Electron.*, vol. 34, no. 6, pp. 5027–5031, Jun. 2019.

[16] X. Zhan, W. Wang, and H. Chung, "A neural-network-based color control method for multi-color led systems," *IEEE Trans. Power Electron.*, vol. 34, no. 8, pp. 7900–7913, Aug. 2019.

[17] C. Wei, Z. Zhang, W. Qiao, and L. Qu, "Reinforcement-learning-based intelligent maximum power point tracking control for wind energy conversion systems," *IEEE Trans. Ind. Electron.*, vol. 62, no. 10, pp. 6360–6370, Oct. 2015.

[18] C. Wei, Z. Zhang, W. Qiao, and L. Qu, "An adaptive network-based reinforcement learning method for MPPT control of PMSG wind energy conversion systems," *IEEE Trans. Power Electron.*, vol. 31, no. 11, pp. 7837–7848, Nov. 2016.

[19] I. Bandyopadhyay, P. Purkait, and C. Koley, "Performance of a classifier based on time-domain features for incipient fault detection in inverter drives," *IEEE Trans. Ind. Inform.*, vol. 15, no. 1, pp. 3–14, Jan. 2019.

[20] E. Mejdoubi, H. Chaoui, J. Sabor, and H. Gualous, "Remaining useful life prognosis of supercapacitors under temperature and voltage aging conditions," *IEEE Trans. Ind. Electron.*, vol. 65, no. 5, pp. 4357–4367, May 2018.

[21] Y. Lu, "Artificial intelligence: A survey on evolution, models, applications and future trends," *J. Manage. Analytics*, vol. 6, no. 1, pp. 1–29, 2019.

[22] B. Paoletti and E. Sciubba, "Artificial intelligence in thermal systems design: Concepts and applications," in *Developments in the Design of Thermal Systems*. Cambridge, U.K.: Cambridge Univ. Press, 1997.

[23] P. Chen et al., "Synthesis design of artificial magnetic metamaterials using a genetic algorithm," *Opt. Exp.*, vol. 16, no. 17, pp. 12806–12818, 2008.

[24] A. F. Akawung and Y. Fujimoto, "Design and thermal analysis of cooling system for high-power density motor based on air-flow," in *Proc. IEEE 28th Int. Symp. Ind. Electron.*, 2019, pp. 273–278.

[25] X. Li, X. Zhang, F. Lin, and F. Blaabjerg, "Artificial-intelligence-based design for circuit parameters of power converters," *IEEE Trans. Ind. Electron.*, vol. 69, no. 11, pp. 11144–11155, Nov. 2022.

[26] F. Tian, D. B. Cobaleda, and W. Martinez, "Automatic data extraction based on semiconductor datasheet for design automation of power converters," in *Proc. Int. Power Electron. Conf.*, 2022, pp. 922–927.

[27] B. Zhao, X. Zhang, and J. Huang, "AI algorithm-based two-stage optimal design methodology of high-efficiency cllc resonant converters for the hybrid AC–DC microgrid applications," *IEEE Trans. Ind. Electron.*, vol. 66, no. 12, pp. 9756–9767, Dec. 2019.

[28] Analog Devices, Inc., "LTspice IV," 2023. [Online]. Available: https://www.analog.com/en/design-center/design-tools-and-calculators/ltspice-simulator.html

[29] Plexim GmbH, "PLECS: Piecewise linear electrical circuit simulation for simulink and MATLAB," 2023. [Online]. Available: https://www.plexim.com

[30] Inc ANSYS, "ANSYS simulation software, 0.23." [Online]. Available: https://www.ansys.com

[31] H. Li et al., "How magnet: Machine learning framework for modeling power magnetic material characteristics," *IEEE Trans. Power Electron.*, vol. 38, no. 12, pp. 15829–15853, Dec. 2023.

[32] D. Serrano et al., "Why magnet: Quantifying the complexity of modeling power magnetic material characteristics," *IEEE Trans. Power Electron.*, vol. 38, no. 11, pp. 14292–14316, Nov. 2023.

[33] "Frenetic. AI." Accessed: 2023. [Online]. Available: https://frenetic.ai/

[34] S. Kiranyaz, A. Gastli, L. Ben-Brahim, N. Al-Emadi, and M. Gabbouj, "Real-time fault detection and identification for MMC using 1-D convolutional neural networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 11, pp. 8760–8771, Nov. 2019.

[35] A. de Souza, I. N. da Silva, C. F. L. N. de Souza, and M. G. Zago, "Using artificial neural networks for identification of electrical losses in transformers during the manufacturing phase," in *Proc. Int. Joint Conf. Neural Netw.*, 2002, vol. 2, pp. 1346–1350.

[36] H. Li et al., "MagNet: An open-source database for data-driven magnetic core loss modeling," in *Proc. IEEE Appl. Power Electron. Conf. Expo.*, 2022, pp. 588–595.

[37] N. Rasekh, J. Wang, and X. Yuan, "Artificial neural network aided loss maps for inductors and transformers," *IEEE Open J. Power Electron.*, vol. 3, pp. 886–898, 2022.

[38] X. Shen, H. Wouters, and W. Martinez, "Deep neural network for magnetic core loss estimation using the magnet experimental database," in *Proc. 24th Eur. Conf. Power Electron. Appl.*, 2022, pp. 1–8.

[39] X. Shen and W. Martinez, "Machine learning model for high-frequency magnetic loss predictions based on loss map by a measurement kit," in *Proc. 25th Eur. Conf. Power Electron. Appl.*, 2023, pp. 1–8.

[40] X. Shen et al., "Multilayer perceptron-based inductor iron loss predictions with loss map by a measurement kit," in *Proc. 12th Int. Conf. Power Electron., Mach. Drives*, 2023, pp. 365–372.

[41] E. Dogariu, H. Li, D. Serrano López, S. Wang, M. Luo, and M. Chen, "Transfer learning methods for magnetic core loss modeling," in *Proc. IEEE 22nd Workshop Control Modelling Power Electron.*, 2021, pp. 1–6.

[42] D. Serrano et al., "Neural network as datasheet: Modeling B-H loops of power magnetics with sequence-to-sequence LSTM encoder-decoder architecture," in *Proc. IEEE 23rd Workshop Control Model. Power Electron.*, 2022, pp. 1–8.

[43] H. Li, D. Serrano, S. Wang, and M. Chen, "MagNet-AI: Neural network as datasheet for magnetics modeling and material recommendation," *IEEE Trans. Power Electron.*, vol. 38, no. 12, pp. 15854–15869, Dec. 2023.

[44] R. K. Kailasan et al., "Genetic algorithm application for efficiency optimization of wound rotor induction motor by rotor capacitive reactance control," *Int. Rev. Modelling Simul.*, vol. 5, no. 1, 2012, Art. no. 239.

[45] E. Chiarello and J. Almansa Malagoli, "Optimal coil design of an electromagnetic actuator using particle swarm optimization," *J. Eur. des Systèmes Automatisés*, vol. 53, no. 6, pp. 755–761, 2020.

[46] D. C. Jiles, J. B. Thoelke, and M. K. Devine, "Numerical determination of hysteresis parameters for the modeling of magnetic properties using the theory of ferromagnetic hysteresis," *IEEE Trans. Magn.*, vol. 28, no. 1, pp. 27–35, Jan. 1992.

[47] D. Zhang and J. E. Fletcher, "Double-frequency method using differential evolution for identifying parameters in the dynamic jiles–atherton model of MN–ZN ferrites," *IEEE Trans. Instrum. Meas.*, vol. 62, no. 2, pp. 460–466, Feb. 2013.

[48] A. Doulamis and N. Doulamis, "A neural network-genetic algorithm scheme for optimal grouping of individual cores in three-phase distributed transformers," in *Proc. 14th Int. Conf. Digit. Signal Process.*, 2002, pp. 1061–1064.

[49] P. Georgilakis, N. D. Hatziargyriou, A. D. Doulamis, N. D. Doulamis, and S. D. Kollias, "A neural network framework for predicting transformer core losses," in *Proc. 21st Int. Conf. Power Ind. Comput. Appl.*, 1999, pp. 301–308.

[50] S. Szuba, "Computer-aided design of air-gapped magnetic core inductors with minimum DC winding resistance," *IEEE Trans. Magn.*, vol. 15, no. 3, pp. 1085–1096, May 1979.

[51] A. Ohri, T. Wilson, and H. Owen, "Design of air-gapped magnetic-core inductors for superimposed direct and alternating currents," *IEEE Trans. Magn.*, vol. 12, no. 5, pp. 564–574, Sep. 1976.

[52] R. Ray and E. Sartori, "Computer design of an inductor carrying direct current," *IEEE Trans. Magn.*, vol. 7, no. 3, pp. 453–455, Sep. 1971.

[53] D. Y. Chen, H. A. Owen, and T. G. Wilson, "Computer-aided design and graphics applied to the study of inductor-energy-storage dc-to-dc electronic power converters," in *Proc. IEEE Power Process. Electron. Specialists Conf.*, 1972, pp. 59–70.

[54] J. Garret and A. Jain, "A knowledge-based system for designing transformers and inductors," in *Proc. 4th Conf. Artif. Intell. Appl.*, 1988, pp. 96–101.

[55] R. Dhawan and P. Davis, "Fuzzy logic based inductor design program," in *Proc. Appl. Power Electron. Conf.*, 1997, vol. 2, pp. 579–584.

[56] I. Yun and G. May, "Passive circuit model parameter extraction using genetic algorithms," in *Proc. 49th Electron. Compon. Technol. Conf.*, 1999, pp. 1021–1024.

[57] J. Fivaz and W. Cronje, "Inductor design aid employing genetic algorithms," *Int. J. Comput. Math. Elect. Electron. Eng.*, vol. 20, no. 1, pp. 167–176, 2001.

[58] C. Yue, C. Ryu, J. Lau, T. H. Lee, and S. S. Wong, "A physical model for planar spiral inductors on silicon," in *Proc. Int. Electron Devices Meeting. Tech. Dig.*, 1996, pp. 155–158.

[59] T. Wang, Y. Wang, and K. Chen, "A global genetic algorithm based optimization technique for spiral inductor on silicon design," in *Proc. IEEE 5th World Congr. Intell. Control Automat.*, 2004, pp. 2095–2098.

[60] E. Gadjeva, V. P. Durev, M. H. Hristov, and D. I. Pukneva, "Optimization of geometric parameters of spiral inductors using genetic algorithms," in *Proc. Int. Conf. Mixed Des. Integr. Circuits Syst.*, 2006, pp. 518–521.

[61] J. Yeo and R. Mittra, "A GA-based optimization scheme for extracting the equivalent-circuit models of spiral inductors embedded in a multilayer structure," *Int. J. RF Microw. Comput.-Aided Eng.*, vol. 15, no. 1, pp. 92–101, 2005.

[62] X. Yang, Y. Wang, L. Zhang, and S. Liu, "Improved genetic algorithm for optimal design of transverse flux inductor," in *Proc. Int. Conf. Elect. Mach. Syst.*, 2005, vol. 3, pp. 2339–2342.

[63] M. Novac et al., "Aspects regarding the optimization of the induction heating process using differential evolution," *J. Elect. Electron. Eng.*, vol. 5, no. 1, 2012, Art. no. 145.

[64] C. L. Ebert et al., "Determination of magnetic induction and current density values for planar cores to operate with minimal magnetic losses," *J. Microw., Optoelectron. Electromagn. Appl.*, vol. 8, pp. 122–134, 2009.

[65] E. O. Farhat et al., "Optimization of RF on-chip inductors using genetic algorithms," in *Computational Intelligence in Analog and Mixed-Signal and Radio-Frequency Circuit Design*. Berlin, Germany: Springer, 2015, pp. 331–361.

[66] "Matlab-mathworks." Accessed: May 9, 2023. [Online]. Available: https://mathworks.com/products/matlab.html

[67] X. Wang, H. Zeng, D. Gunasekaran, and F. Z. Peng, "Multi-objective design and optimization of inductors: A generalized software-driven approach," in *Proc. IEEE 17th Workshop Control Model. Power Electron.*, 2016, pp. 1–7.

[68] K. Stoyka, N. Femia, and G. Di Capua, "Optimizing power converters with partially saturated inductors by evolutionary algorithms," in *Proc. Int. Conf. Synth., Model., Anal. Simul. Methods Appl. Circuit Des*, 2017, pp. 1–4.

[69] C. Zhang and D. J. Perreault, "An optimization approach for high-efficiency high-power-density boost converters," in *Proc. IEEE 19th Workshop Control Model. Power Electron.*, 2018, pp. 1–8.

[70] S. Huang et al., "Switching harmonic suppression design based on multi-objective optimization algorithm with constraint processing," *Int. J. Comput. Math. Elect. Electron. Eng.*, vol. 39, no. 4, pp. 899–913, 2020.

[71] Y. Wang, S. Chakraborty, D. D. Tran, T. Geury, and O. Hegazy, "Design and optimization of the arm inductor for modular multilevel converter," in *Proc. Int. Symp. Power Electronics, Elect. Drives, Automat. Motion*, 2022, pp. 354–359.

[72] N. Dib and J. Ababneh, "Physical modelling and particle swarm design of coplanar waveguide square spiral inductor," *Int. J. Modelling Simul.*, vol. 28, no. 2, pp. 219–225, 2008.

[73] S. K. Mandal, A. Goyel, and A. Gupta, "Swarm optimization based on-chip inductor optimization," in *Proc. 4th Int. Conf. Comput. Devices Commun.*, 2009, pp. 1–4.

[74] B. Benhala, H. Bouyghf, A. Lachhab, and B. Bouchikhi, "Optimal design of second generation current conveyors by the artificial bee colony technique," in *Proc. Intell. Syst. Comput. Vis.*, 2015, pp. 1–5.

[75] S. Abi, H. Bouyghf, A. Raihani, and B. Benhala, "Swarm intelligence optimization techniques for an optimal RF integrated spiral inductor design," in *Proc. Int. Conf. Electron., Control, Optim. Comput. Sci.*, 2018, pp. 1–7.

[76] S. Abi et al., "An optimal design of square spiral integrated inductor using metaheuristic techniques," *Indonesian J. Elect. Eng. Comput. Sci.*, vol. 20, no. 2, pp. 680–689, 2020.

[77] I. E. Hajjami, B. Benhala, and H. Bouyghf, "Comparative study between the genetic algorithm and the artificial bee colony technique: RF circuits application," in *Proc. 2nd Int. Conf. Electron., Control, Optim. Comput. Sci.*, 2020, pp. 1–5.

[78] M. Dorigo, V. Maniezzo, and A. Colorni, "The ant system: Optimization by a colony of cooperating agents," *IEEE Trans. Syst., Man, Cybern.-Part B*, vol. 26, no. 1, pp. 29–41, Feb. 1996.
[79] R. Storn and K. Price, "Differential evolution–A simple and efficient heuristic for global optimization over continuous spaces," *J. Glob. Optim.*, vol. 11, pp. 341–359, 1997.
[80] S. Das and P. N. Suganthan, "Differential evolution: A survey of the state-of-the-art," *IEEE Trans. Evol. Comput.*, vol. 15, no. 1, pp. 4–31, Feb. 2011.
[81] I. Hajjami et al., "Shape optimization of planar inductors for RF circuits using a metaheuristic technique based on evolutionary approach," *Adv. Sci., Technol. Eng. Syst. J.*, vol. 5, no. 5, pp. 426–433, 2020.
[82] G. Di Capua, N. Femia, and K. Stoyka, "Differential evolution algorithm-based identification of ferrite core inductors saturation curves," in *Proc. Int. Conf. Ind. Inform.*, 2015, pp. 1636–1641.
[83] I. Elhajjami, B. Benhala, and H. Bouyghf, "Optimal design of RF integrated inductors via differential evolution algorithm," in *Proc. 1st Int. Conf. Innov. Res. Appl. Sci., Eng. Technol.*, 2020, pp. 1–6.
[84] S. Cincotti, M. Marchesi, and A. Serri, "A neural network model of parametric nonlinear hysteretic inductors," *IEEE Trans. Magn.*, vol. 34, no. 5, pp. 3040–3043, Sep. 1998.
[85] R. Kowaltschuk, W. A. Artuzi, and O. C. Gouveia Filho, "Design of integrated inductors through selection from a database created using electromagnetic simulation and neural networks," in *Proc. IEEE/SBMO MTT-S Int. Microw. Optoelectron. Conf.*, 2003, pp. 425–430.
[86] T. Liu, W. Zhang, and Z. Yu, "Modeling of spiral inductors using artificial neural network," in *Proc. IEEE Int. Joint Conf. Neural Netw.*, 2005, pp. 2353–2358.
[87] A. Ilumoka and Y. Park, "Neural network-based modeling and design of on-chip spiral inductors," in *Proc. 36th Southeastern Symp. Syst. Theory*, 2004, pp. 561–564.
[88] E. Akso et al., "Surrogate modeling and variability analysis of on-chip spiral inductors," *Int. J. Numer. Modelling: Electron. Netw., Devices Fields*, vol. 31, no. 5, 2018, Art. no. e2313.
[89] D. Cajander, I. Viarouge, P. Viarouge, and D. Aguglia, "Inductor design optimization using FEA supervised machine learning," in *Proc. 24th Eur. Conf. Power Electron. Appl.*, 2022, pp. 1–11.
[90] X. Li, P. Zhao, S. Chen, K. Xu, and G. Wang, "A deep-learning approach for wideband design of 3D TSV-based inductors," *IEEE Access*, vol. 10, pp. 133673–133681, 2022.
[91] Z. Wang, F. Yan, S. Ma, T. Yang, H. Shao, and Y. Wang, "A synthesis-analysis machine with self-inspection mechanism for automatic design of on-chip inductors based on artificial neural networks," *IEEE Trans. Circuits Syst. I: Reg. Papers*, vol. 69, no. 10, pp. 4154–4167, Oct. 2022.
[92] L. Zhou and M. Preindl, "Inductor design for nonisolated critical soft switching converters using solid and litz PCB and wire windings leveraging neural network model," *IEEE Trans. Power Electron.*, vol. 37, no. 3, pp. 3357–3373, Mar. 2022.
[93] Y. Wang and P. D. Franzon, "RFIC IP redesign and reuse through surrogate based machine learning method," in *Proc. IEEE MTT-S Int. Conf. Numer. Electromagn. Multiphys. Model. Optim.*, 2018, pp. 1–4.
[94] M. Baldan and P. Di Barba, "Discovering pareto-optimal magnetic-design solutions via a generative adversarial network," *IEEE Trans. Magn.*, vol. 58, no. 9, Sep. 2022, Art. no. 7200704.
[95] R. J. Pratap, S. Sarkar, S. Pinel, J. Laskar, and G. S. May, "Modelling and optimization of multilayer RF passives using coupled neural networks and genetic algorithms," in *Proc. IEEE MTTS Int. Microw. Symp.*, 2004, pp. 1557–1560.
[96] S. K. Mandal, S. Sural, and A. Patra, "ANN-and PSO-based synthesis of on-chip spiral inductors for RF ICs," *IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst.*, vol. 27, no. 1, pp. 188–192, Jan. 2008.
[97] B. Liu, D. Zhao, P. Reynaert, and G. G. E. Gielen, "Synthesis of integrated passive components for high-frequency RF ICs based on evolutionary computation and machine learning techniques," *IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst.*, vol. 30, no. 10, pp. 1458–1468, Oct. 2011.
[98] R. K. Dhawan, N. Mohan, R. Nilssen, and P. Davis, "Applying expert systems for designing high frequency power transformers," in *Proc. IEEE Appl. Power Electron. Conf. Expo.*, 1994, pp. 318–325.
[99] R. K. Dhawan, P. Davis, and R. Naik, "Applying expert systems and fuzzy logic for core selection for high frequency power transformers," in *Proc. IEEE Appl. Power Electron. Conf. Expo.*, 1995, pp. 342–347.
[100] C. Hernandez and M. Arjona, "Design of an efficient distribution transformer based on an expert system and FE," in *Proc. 19th Int. Conf. Elect. Mach.*, 2010, pp. 1–5.
[101] N. Tutkun and A. J. Moses, "Design optimisation of a typical strip-wound toroidal core using genetic algorithms," *J. Magnetism Magn. Mater.*, vol. 277, no. 1–2, pp. 216–220, 2004.
[102] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multiobjective genetic algorithm: NSGA-II," *IEEE Trans. Evol. Comput.*, vol. 6, no. 2, pp. 182–197, Apr. 2002.
[103] W. T. McLynam, *Transformer and Inductor Design Handbook*. New York, NY, USA: Marcel Dekker, 2011.
[104] C. Versele, O. Deblecker, and J. Lobry, "Multiobjective optimal design of high frequency transformers using genetic algorithm," in *Proc. 13th Eur. Conf. Power Electron. Appl.*, 2009, pp. 1–10.
[105] A. K. Yadav et al., "Design optimization of high-frequency power transformer by genetic algorithm and simulated annealing," *Int. J. Elect. Comput. Eng.*, vol. 1, no. 2, pp. 102–109, 2011.
[106] A. Garcia-Bediaga, I. Villar, A. Rujas, L. Mir, and A. Rufer, "Multiobjective optimization of medium-frequency transformers for isolated soft-switching converters using a genetic algorithm," *IEEE Trans. Power Electron.*, vol. 32, no. 4, pp. 2995–3006, Apr. 2017.
[107] L. dos Santos Coelho, V. C. Mariani, M. V. Ferreira da Luz, and J. V. Leite, "Novel gamma differential evolution approach for multiobjective transformer design optimization," *IEEE Trans. Magn.*, vol. 49, no. 5, pp. 2121–2124, May 2013.
[108] L. A. R. Tria, D. Zhang, and J. E. Fletcher, "High-frequency planar transformer parameter estimation," *IEEE Trans. Magn.*, vol. 51, no. 11, Nov. 2015, Art. no. 8402604.
[109] H. Qin, J. W. Kimball, and G. K. Venayagamoorthy, "Particle swarm optimization of high-frequency transformer," in *Proc. 36th Annu. Conf. IEEE Ind. Electron. Soc.*, 2010, pp. 2914–2919.
[110] M. Jafari, Z. Malekjamshidi, and M. R. Islam, "Optimal design of a multiwinding high-frequency transformer using reluctance network modeling and particle swarm optimization techniques for the application of PV-linked grid-connected modular multilevel inverters," *IEEE J. Em Sel. Topics Power Electron.*, vol. 9, no. 4, pp. 5083–5096, Aug. 2021.
[111] C. Nussbaum, H. Pfutzner, T. Booth, N. Baumgartinger, A. Ilo, and M. Clabian, "Neural networks for the prediction of magnetic transformer core characteristics," *IEEE Trans. Magn.*, vol. 36, no. 1, pp. 313–329, Jan. 2000.
[112] J. Li, W. Water, B. Zhu, and J. Lu, "Integrated high-frequency coaxial transformer design platform using artificial neural network optimization and FEM simulation," *IEEE Trans. Magn.*, vol. 51, no. 3, Mar. 2015, Art. no. 8500204.
[113] G. S. Lee, S. Kim, and S. Bae, "Efficient design method for a forward-converter transformer based on a KNN-GRU-DNN model," *IEEE Trans. Power Electron.*, vol. 38, no. 1, pp. 73–78, Jan. 2023.
[114] P. University, "Magnetism and magnetic materials." Accessed: Oct. 2023. [Online]. Available: https://www.princeton.edu/minjie/magnet.html
[115] P. University, "M2spice." Accessed: Oct. 2023. [Online]. Available: https://www.princeton.edu/minjie/m2spice.html
[116] P. University, "Coupl." Accessed: 2023. [Online]. Available: https://www.princeton.edu/minjie/coupL/coupL.html
[117] KU Leuven, "Powerbrain AI." Accessed: 2023. [Online]. Available: https://powerbrain.ai/
[118] ETH, "Eth AI-MAG." Accessed: 2023. [Online]. Available: https://ai-mag.github.io/
[119] Open Magnetics, "Open magnetics." Accessed: 2023. [Online]. Available: https://openmagnetics.com/
[120] MAGNETEC GmbH, "Magnetec - specialist in inductive components." Accessed: 2023. [Online]. Available: https://www.magnetec.de/en/
[121] AI-Power, "Physics-informed ai for next-generation power electronics." Accessed: 2023. [Online]. Available: https://www.ipower.ai/
[122] OpenAI, "ChatGPT - conversational AI model." Accessed: 2023. [Online]. Available: https://www.openai.com/chatgpt/
[123] M. Chen, M. Araghchini, K. K. Afridi, J. H. Lang, C. R. Sullivan, and D. J. Perreault, "A systematic approach to modeling impedances and current distribution in planar magnetics," *IEEE Trans. Power Electron.*, vol. 31, no. 1, pp. 560–580, Jan. 2016.
[124] P. University, "Magnetism and magnetic materials." Accessed: 2023. [Online]. Available: https://www.princeton.edu/minjie/magnet.html

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