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Optimization approaches in electric machine design: insights from a bibliometric analysis

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Abstract
Optimizing the design of electric machines is a complex task due to the large number of interrelated geometric and physical parameters that influence performance, efficiency, cost, and sustainability. Numerous deterministic and stochastic optimization techniques have been developed to address these challenges, each presenting distinct advantages and limitations. Deterministic approaches, though computationally efficient, often converge to local minima, while stochastic methods provide broader search capabilities at the expense of higher computational effort. Despite the growing application of optimization in electric machine design, a comprehensive bibliometric overview of this research area is lacking. This study aims to fill that gap by conducting a bibliometric analysis of optimization methods applied to electric machine design. Using data retrieved from the Web of Science (WoS) and analyzed through co-citation mapping with VOSviewer, 246 relevant articles were examined, resulting in a focused sample of 73 key studies. The analysis identifies the most frequently optimized machine types, the main optimization objectives, and the predominant methodologies employed in recent years. By addressing these dimensions, this work provides a conceptual reference framework to guide both academic researchers and industry professionals in selecting appropriate optimization strategies. The results also highlight emerging trends and future research opportunities, contributing to a deeper understanding of the evolution and intellectual structure of optimization in electric machine design.

Keywords Optimization methods, Electric machines, Bibliometrics, Co-citation analysis, Deterministic and stochastic techniques.

Introduction
Optimizing the design and performance of electric machines poses significant challenges due to the multitude of variables, geometric and physical, that directly influence their operation. For instance, in the design procedure, the number of parameters and variables is very high and frequently interrelated. The objectives are diverse and numerous: efficiency, performance, size and weight, cost, critical materials, control, environmental impact, reliability, compatibility and customization, all of which must be carefully considered in the development of new design. In addition, various optimization techniques

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are available, adaptable to the specific needs of designers. As a consequence, optimizing an electric machine is recognized as a complex task. As stated by Pyrhönen [1], the optimization design becomes unattainable unless the number of objectives and variables is kept low. The main research efforts in this field aim to enhance optimal solutions while simultaneously reducing computational costs [2].

Most problems deal with multiple design variables and different objectives, leading to multiobjective optimization procedures. These methods aim to identify sets of design points that represent the best trade-off among objectives, without prioritizing any particular objective to globally optimize the objective function [3]. The concept of Pareto optimality is crucial in multiobjective optimization since it helps to focus the efforts only on points that are Pareto optimal, saving time in the search for the best solution.

When it comes to optimizing a machine's design, two main approaches are commonly employed: deterministic and stochastic [4]. The deterministic approach is a widely recognized technique in this field for providing an optimal design or a Pareto front in a short time or with a reduced computational cost when compared to other methods. The deterministic approach is a widely recognized technique in this field, known for its ability to provide an optimal design or a Pareto front within a short time frame or with reduced computational costs compared to other methods. This algorithm relies on linear algebra and consistently produces the same output for a specific input. Typically, it utilizes gradient or Hessian information of the objective function to find the optimal solution. In the deterministic model, variables are defined solely by the model parameters and their previous states [5]. This approach requires fewer iterations to converge, making it computationally efficient. However, its main drawback is the tendency to converge to local minima instead of the global minimum. Examples of deterministic methodologies include Newton's method and Quasi-Newton methods [6].

An alternative to deterministic methods is the use of stochastic methods, which leverage randomness to generate solutions that optimize the model. Most stochastic algorithms are population-based, employing a collection of design points distributed throughout the solution space. This diversity helps the stochastic algorithm avoid getting trapped in local minima, providing a significant advantage [3]. In contrast to deterministic models where parameters are defined by unique values, stochastic models define parameters using random variables or distributions. Consequently, state variables are also defined by probability distributions, enabling the stochastic model to handle various potential solutions and evaluate the inherent uncertainty of the modelled machine [5]. a drawback of stochastic methods is their time-consuming nature [7]. Examples of stochastic methodologies include genetic algorithms, particle swarm optimization, and differential evolutionary algorithms [8].

The increasing popularity of optimization techniques applied to the design of electric machines highlights the relevance of this work. Before delving into the detailed bibliometric analysis presented in Sects. 2 and 3, a comprehensive bibliographic search was conducted to assess previous reviews on this topic. A set of keywords was employed as selection criteria to evaluate the state of the art and identify possible gaps in the existing literature that warrant attention.

The study revealed a gap concerning papers related to bibliometric and systematic analyses in the specific field of design optimization of electric machines. However, there are some bibliographic reviews, and two of them stand out in the database. Omar et al.

[8] provide a review emphasizing the following methods: gradient based algorithm, tabu search, genetic algorithm, differential evolution, particle swarm optimization, multiobjective algorithm and deterministic optimization method. Besides an explanation of the methodologies, the review presents important references that applied those approaches and main results. As for the second article, Lei et al. [9] develop an actual guide for optimizing electric machines. The main techniques are elaborated upon, with mentions of robustness and level-set optimization. Its most significant contribution lies in its conclusive insights regarding future directions in the field.

Building upon the identified gap in the literature within the authors' knowledge, the primary aim of this work is to undertake a bibliometric analysis and highlight the prevailing trends in optimization methods currently employed in electric machines. To accomplish this, the top sources and articles were categorized, key methods were identified, and the evolution of the field was traced. Therefore, the research questions guiding this study are as follows: RQ1, Which machines are the focus of optimization efforts? RQ2, What specific objectives are pursued through optimization? RQ3, Which methods are predominantly utilized? By addressing these questions, a conceptual reference guide can be developed to assist both industry professionals and academic researchers. Such a guide would aid companies in selecting the most appropriate methods and avoiding time wasted in searching for reliable references. For academia, the use of bibliometric analysis in this field holds the potential to inspire further studies employing this approach. Additionally, it can assist researchers in understanding the trajectory of the field and identifying unexplored areas for future investigation.

Therefore, this article aims to facilitate access to the main optimization methods currently in use, as well as popular techniques that can be tailored to specific machine types and objective functions. The methodological approach follows the one outlined in [10]. After performing a selection of 246 relevant articles on the subject under analysis from the Web of Science (WoS), the co-citation bibliometric technique was employed, utilizing VOSviewer software [11], to provide a comprehensive overview of the intellectual structures within the topic, yielding a sample of 73 articles.

The remainder of this article is structured as follows. The following section details the methodology and procedures adopted for the bibliometric analysis. The third section presents and discusses the results of the bibliometric performance analysis, followed by a section which focuses on the findings from the co-citation science mapping. Finally, the main conclusions and potential directions for future research are outlined.

Methodology

The bibliometric analysis employed in this research, as previously outlined, is a method for examining extensive collections of bibliographic materials. It provides a holistic view of the research field, highlighting its emerging trends and most relevant sources [12].

The bibliometric analysis comprises two main complementary insights of the research field: performance analysis and science mapping. The performance analysis assesses the contributions of the scientific agents (authors, institutions, countries, and journals) to a specific area of research [13]. These contributions are evaluated based on metrics such as the number of publications, total of citations, number of contributing authors, etc. The science mapping is primarily utilized to analyse the structural dynamics of a scientific field, generating a spatial representation of the relationships among research agents

[14]. The science mapping technique adopted in this paper is the co-citation analysis. It is used to verify the intellectual structure of a certain research field, and it works within the references of the main database. Therefore, in a co-citation map the publications serve as references for the database studies, and a link between two publications occurs when they are both cited in the reference list of another study [10].

The bibliometric performance analysis was conducted using the Biblioshiny software [15] from the Bibliometrix R v.4.3.0 package [16]. Additionally, the construction of the co-citation map was executed with the VOSviewer v. 1.6.18 software [17].

The bibliographic data was sourced solely from the Web of Science (WoS) database. While using multiple databases can enhance the comprehensiveness of a literature corpus, it also introduces significant challenges: each database has typically distinct features leading to discrepancies in the outputs, variations in indexing criteria and different updating timings, which requires extensive and time-consuming data cleaning and deduplication. The choice of WoS as the sole source represents a strategic trade-off aligned with the study's core objective. To map the dominant thematic structure and key methodological paradigms in electric machine optimization, a consistent, high-quality corpus is prioritized over exhaustive coverage. WoS is particularly suited for this purpose due to its selective indexing of high-impact journals, proving a robust and reliable foundation for science mapping.

The selection process was executed in September 2023, with the search equation: TOPIC ((optimizat* OR "optim* design") AND ("permanent magnet motor" OR "permanent magnet generator" OR "permanent magnet machine" OR "induction motor*" OR "induction generator" OR "induction machine" OR "brushless dc" OR "asynchronous machine" OR "synchronous machine" OR "reluctance motor")) – TOPIC corresponding to the title, abstract and/or keywords.

The initial sample obtained consisted of 7419 objects. Subsequently, to ensure the relevance and cohesion of the analysis, the search was restricted to full articles published exclusively in peer-reviewed journals, as well as review articles within the categories outlined in Table 1. Additionally, the sample was constrained to manuscripts written in English, with no limitation of the time span, resulting in a total of 4305 manuscripts.

The second filtering process involved a manual examination of the titles, abstracts, and keywords of each manuscript after extracting that information from the WoS. While some manuscripts aligned with the research theme, they did not correspond to the objectives of this study. Articles related to control, fault identification, equivalent circuit estimation, and drive/sensor optimization were consequently excluded from the dataset. Despite filtering only regular journal papers in the WoS, some conference papers

Table 1 Taxonomic categorization of the article dataset based on Web of Science subject areas

Taxonomy Categories
Engineering Electrical Electronic; Energy Fuels; Physics Applied; Engineering Multidisciplinary; Automation Control Systems; Instruments Instrumentation; Telecommunications; Computer Science Information Systems; Computer Science Interdisciplinary Applications; Mechanics; Computer Science Artificial Intelligence; Engineering Mechanical; Mathematics Applied; Transportation Science Technology; Green Sustainable Science Technology; Materials Science Multidisciplinary; Thermodynamics; Mathematics Interdisciplinary Applications; Multidisciplinary Sciences; Chemistry Multidisciplinary; Engineering Chemical; Environmental Science; Engineering Multidisciplinary; Computer Science Software Engineering; Environmental Studies; Operations Research Management Science; Mathematics; Computer Science Theory Methods; Electrochemistry; Engineering Industrial; Physics Multidisciplinary; Engineering Aerospace; Nuclear Science Technology; Robotics; Oceanography; Engineering Environmental; Physics Mathematical; Metallurgy Metallurgical Engineering; Materials Science Characterization Testing.

and documents as, for instance, errata type, persisted in the database; hence, they were subsequently filtered out. Following this process, 841 documents remained at this stage.

Finally, to enhance the validity of the sample, a journal-ranking criterion was applied. Specifically, only articles published in journals classified in the first quartile (Q1) of the Scimago impact ranking (https://www.scimagojr.com) were retained, resulting in 246 articles. This refinement prioritizes journal prestige over full field-specific comprehensiveness, and therefore represents a methodological trade-off that focuses the analysis on the most influential literature.

The resulting dataset served as the foundation for the subsequent bibliometric performance analysis, the main results of which are outlined in the following section.

The same subset of 246 articles was subsequently processed in VOSviewer to conduct the science mapping analysis, serving as the citing documents in the co-citation technique. To focus on the most relevant connections and reduce noise, a minimum threshold of 5 citations for a cited reference was set. Consequently, the co-citation analysis yielded a new dataset of 86 manuscripts based on the references cited. After detailed screening, 13 documents were excluded either because they were not journal papers (in a total of 6) or because they did not align with the research field (in a total of 7). This refinement led to a final sample of 73 articles, which were then categorized into seven thematic topics, as elaborated in Sect. 4. Figure 1 illustrates the overall selection process.

Bibliometric performance analysis

Statistical data trends

The database of the 246 articles spans a significant range, beginning with 2 articles in 1979 and extending to 23 articles in 2023.

The main trends regarding the number of publications and the number of citations over the years in the field of electrical machinery optimization are presented in Fig. 2. The last two decades have been pivotal for the field's expansion, with the majority of publications occurring during this period. Notably, 2021 stands out as the year with the highest number of publications, while 2018 recorded the highest number of citations.

Although there have been oscillations in the number of publications and citations over the years, there is a noticeable overall growth in both. Nevertheless, in the last three years, the number of citations has not followed the rising trend of publications; in fact, it has dropped, with a significant decrease in 2022. This trend may be attributed to more recent articles focusing on highly specific research rather than general concepts applicable to other studies. Additionally, it's important to note that the database research was conducted in September 2023, which led to the exclusion of articles published in the last quarter.

A first perception on the evolution of optimization in the field of electric machines can be obtained through an informative look at both the oldest and the most recent articles included in the database. The oldest article, from March 1979, discusses optimizing the active material cost of an induction motor using a non-derivative sequential search method named Rosenbrock's Hill Algorithm [18]. Among the articles published in 2023, the most recent study combines a genetic algorithm (GA) and particle swarm optimization (PSO) to optimize the flux barriers of a permanent magnet (PM) synchronous motor. The key finding of this study was that PSO yielded better results than GA [19].

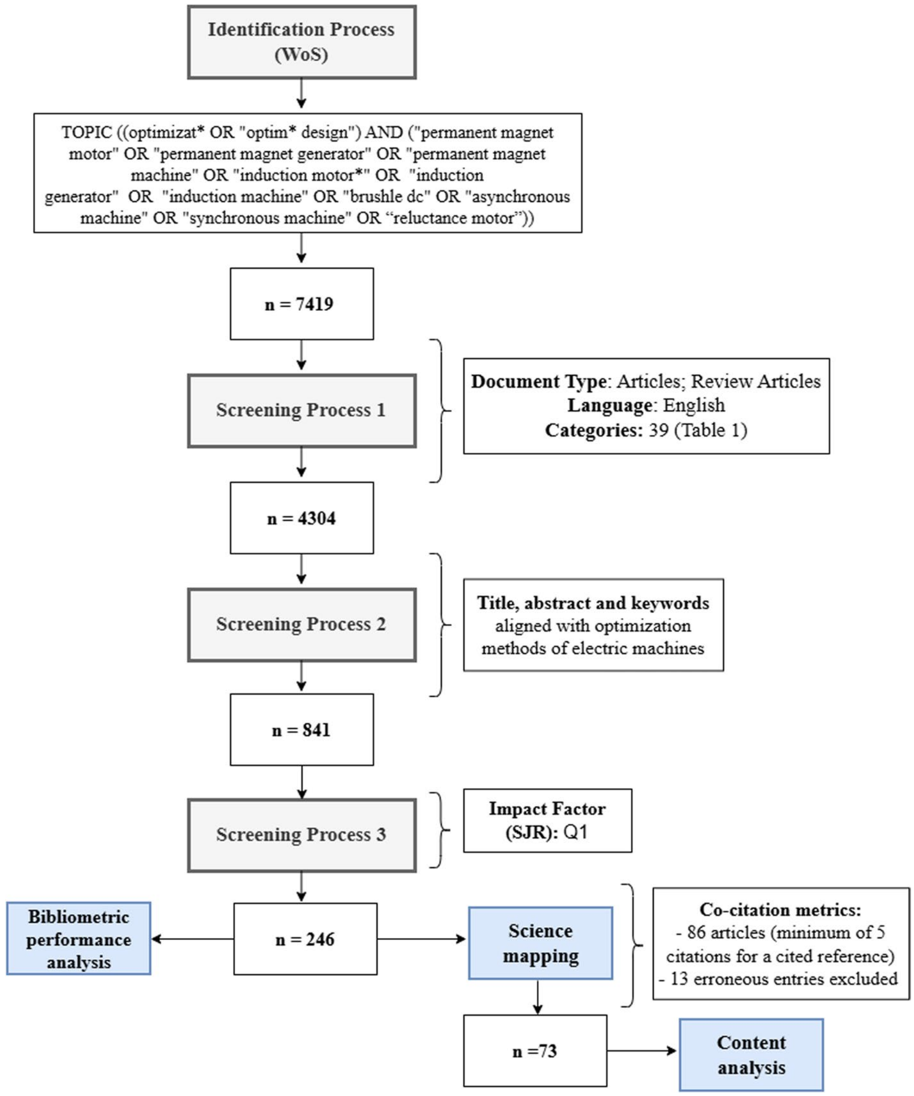

Fig. 1 Systematic identification and screening workflow for bibliometric and science-mapping analyses

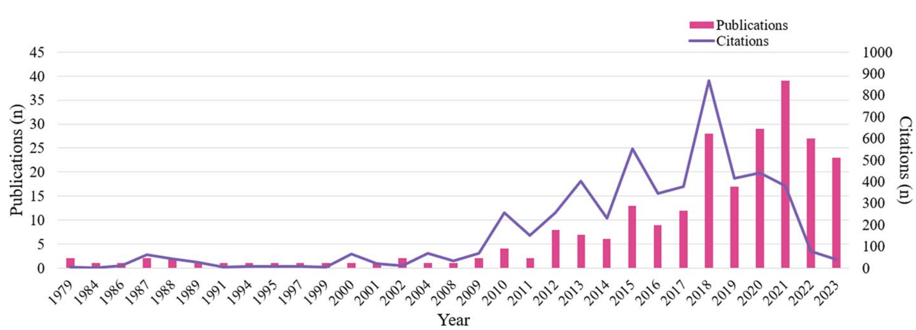

Fig. 2 Temporal trends in the number of publications and total citations in the article dataset

Table 2 Most prolific contributors - Journals

Journal	Publications(*n*)	Citations	JIF[1] 2023
IEEE Transactions on Industrial Electronics	47	1706	7.7
IEEE Access	33	198	3.9
IEEE Transactions on Industry Applications	17	559	4.4
IEEE Transactions on Transportation Electrification	16	102	7.0
IEEE Transactions on Vehicular Technology	10	207	6.8
Structural and Multidisciplinary Optimization	7	33	3.9
Computers & Electrical Engineering	5	28	4.3

[1] Journal impact factor from Clarivate Journal Citation Report 2023

Table 3 Most prolific contributors - Authors

Authors	NP[1]	TC[2]	Affiliation	PY_start[3]
Xiaoyong Zhu	11	466	Jiangsu University	2016
Li Quan	10	464	Jiangsu University	2016
Jianguo Zhu	9	168	University of Sydney	2018
Gang Lei	8	134	University of Technology Sydney	2020
Zixuan Xiang	8	386	Jiangsu University	2016

[1]Number of publications

[2]Total of citations

[3]Year of the first publication in the database

Based on the methodological evolution of these studies, it can be inferred that there is a trend towards using population-based methods for optimization in this field.

Most relevant sources

The journals with five or more publications are displayed in Table 2. It should be mentioned that although IEEE Transactions on Magnetics is not included in this list due to journal-ranking criterion of Q1, this journal boasts an impressive number of 129 publications in the field, nearly twice as many as the identified top journal in the list. Its high publication volume reflects this journal's broad editorial scope, which encompasses tutorial expositions and critical reviews of established and current topics, often without the requirement for prototyping or experimental validation. This broader scope results in classifications across lower quartiles, which, under the applied methodological criteria, led to the journal's exclusion from the analysis.

Most influent authors

The top five authors with the most publications in this field of research are listed in Table 3. Analyzing these authors reveals that their affiliations are primarily from China and Australia. The author with the most publications is Xiaoyong Zhu, with 11 papers. His most cited publication is a 2016 paper on optimizing a brushless double mechanical port flux-switching permanent-magnet motor using multi-level design optimization [20]. Notably, the second author in this list, Li Quan, and the last author, Zixuan Xiang, also contributed to this paper, indicating frequent collaboration among them. Xiaoyong Zhu's most recent article [21], published in 2022, was also a collaboration with Li Quan and Zixuan Xiang. This paper focuses on rare-earth permanent magnet motors in electric vehicles, a highly relevant topic. It employs a deterministic approach to address previous issues with robust optimization, building on the multi-level optimization concepts from Zhu's earlier work.

The third most prolific author in the database is Jianguo Zhu. His most cited publication, with 34 citations, published in 2018 [22], discusses the optimization of a hybrid switched reluctance motor using a genetic algorithm to enhance the motor's torque. Jianguo Zhu's most recent work, published in 2023, focuses on the topology optimization of a synchronous reluctance motor to improve the torque using a gradient-based algorithm [23]. It is worth mentioning that the author Gang Lei, in the fourth position, also collaborates with Jianguo Zhu in two articles of the database regarding robust optimization [24, 25].

Articles with most citations

To provide a comprehensive overview of the subject, Table 4 presents the 10 most cited articles from the database, detailing their objectives and key-findings. These articles, published between 2010 and 2018, align with Fig. 2, which highlights the significance of the last two decades in the development of the field. The papers listed in Table 4 summarize the main optimization methods and the most prominent machine types of the field. Permanent magnet synchronous machines, along with the reluctance and induction motors, are the primary focus of these optimization studies due to their widespread application globally. Most optimization efforts involve multiobjective problems, driven by industry demand for globally optimized machines. Notably, genetic algorithms are widely used in these scenarios due to their proven efficiency and versatility across various machine types. In line with this trend, evolutionary algorithms and multi-level design optimization techniques are gaining popularity, often delivering superior results compared to traditional genetic algorithms.

Co-citation analysis

As a complementary analysis of the original database, the bibliometric technique of co-citation was applied to the corpus of 246 articles. The main objective is to provide a meta-aggregation approach, mapping research field structures. By setting a minimum threshold of five citations for a cited reference from the original dataset, i.e., the citing references, the analysis yielded a refined database of 86 articles. Using VOSviewer software, a bibliometric map of the 86 articles was generated, grouping them into 7 clusters connected by 853 links, as shown in Fig. 3.

From the refined database, six documents were excluded due to their format (book or conference paper) and an additional seven were removed as their primary focus did not align with the objectives of this study, remaining 73 articles. All these works have been thoroughly analysed using an approach designed to identify recurring patterns and relationships among the articles within each cluster, enabling the detection of trends and supporting them with evidence, as proposed in [35]. The proximity between two articles on the map represents the strength of their relationship based on co-citation links: the closer they are, the stronger their connection. Distinct clusters are represented by different colors, with references serving as the primary unit of analysis.

Based on the identified trends and supporting evidence, the clusters can be categorized as follows: *i*) Theorical and practical concepts involving PM machines (cluster 1-colored in red); *ii*) Optimization of PM and reluctance machines (cluster 2-depicted

Table 4 Highly-cited (top ten) research

Title	Authors	Journal	Objective	Key-findings	Citations[1]
A Review of Recent Developments in Electrical Machine Design Optimization Methods with a Permanent-Magnet Synchronous Motor Benchmark Study	Y. Duan and D. M. Ionel. (2017) [26]	IEEE Transactions on Industry Applications	A review of the most significant developments in the optimization of electrical machines. Covering the surrogate modelling and direct and stochastic search algorithms for single and multiobjective optimizations.	When optimizing the permanent-magnet brushless synchronous machine design, two methods were used, the differential evolutionary algorithm and the response surface technique. In conclusion, the differential evolutionary algorithm proved to have a better performance.	229
Multiobjective Optimization of Switched Reluctance Motors Based on Design of Experiments and Particle Swarm Optimization	C. Ma and L. Qu. (2015) [27]	IEEE Transactions on Energy Conversion	The proposition of a multiobjective design optimization of switched reluctance motors by combining 3rd - order response surface (RS) models and a particle swarm optimizer.	The combination of 3rd-order RS models with the particle swarm optimization proved to have a better accuracy than the usual 2nd – order RS models. And it can also be applied to problems with a larger range of design variables.	156
Modern Electrical Machine Design Optimization: Techniques, Trends, and Best Practices	G. Bramerdorfer et al. (2018) [28]	IEEE Transactions on Industrial Electronics	A guide and a review of techniques and methods to effectively optimize an electric machine.	A state of art and presentation of the main trends in the optimization field. Provides a well explained guide, very useful for beginners, appointing the basic theory of optimization, and includes practical examples from the literature.	128
Multilevel Design Optimization and Operation of a Brushless Double Mechanical Port Flux-Switching Permanent-Magnet Motor	Z. Xiang et al. (2016) [20]	IEEE Transactions on Industrial Electronics	A new systematic optimization design method to enhance the efficiency and accuracy of a Brushless Double Mechanical Port Flux-Switching Permanent-Magnet Motor by using multi-level design optimization.	The proposed design method of using the response surface method in the mild-sensitive level, and the multiobjective genetic algorithm in the strong-level, was proved to be very efficient in the optimization of the of output torque, torque ripple, and magnetic coupling.	124
Application of an imperialist competitive algorithm to the design of a linear induction motor	C. Lucas et al. (2010) [29]	Energy Conversion and Management	The power factor and efficiency optimization of a low-speed single sided linear induction motor by using an imperialist competitive algorithm (ICA).	The ICA is a new evolutionary algorithm and when compared to the genetic algorithm application, it provided better solutions with a shorter convergence time.	117

Table 4 (continued)

Title	Authors	Journal	Objective	Key-findings	Citations[1]
Comprehensive Sensitivity Analysis and Multiobjective Optimization Research of Permanent Magnet Flux-Intensifying Motors	X. Zhu et al. (2018) [30]	IEEE Transactions on Industrial Electronics	Optimize the output torque, reverse saliency ratio, and torque ripple of two permanent magnet flux intensifying motors by the combination of a comprehensive sensitivity analysis and a sequential nonlinear programming algorithm.	Two prototypes of the optimized motors were built and tested. The combination of a comprehensive sensitivity analysis and a sequential nonlinear programming algorithm proved to be very effective and practical to develop complex machine designs.	96
Multiphysic Modeling of a High-Speed Interior Permanent-Magnet Synchronous Machine for a Multiobjective Optimal Design	X. Jannot et al. (2010) [31]	IEEE Transactions on Energy Conversion	Optimize an interior permanent-magnet synchronous machine to maximize its efficiency and minimize its weight by using a genetic algorithm.	The objectives were achieved, and Pareto fronts were used to select the better result. The genetic algorithm coped well with the complex non-liner objective functions. The work also emphasizes the importance of precise thermal and mechanical multiphysics models.	90
Design and Optimization of a Switched Reluctance Motor Driving a Compressor for a PEM Fuel-Cell System for Automotive Applications	T. Raminosoa et al. (2010) [32]	IEEE Transactions on Industrial Electronics	Modify the geometry of a high-speed three-phase switched reluctance motor to optimize the torque and current density by using a genetic algorithm.	The genetic algorithm was able to successfully define the dimensions of the stator and rotor laminations of the motor. A low-cost and robust high-speed solution was provided for automotive applications.	82
Design Optimization and Analysis of Single-Sided Linear Induction Motor, Considering All Phenomena	A. Shiri and A. Shoulaie (2012) [33]	IEEE Transactions on Energy Conversion	A multiobjective optimization based on genetic algorithm to maximize the efficiency and power factor and reduce the primary weight and end effect braking force of a single-sided linear induction motor.	The end effect braking force can be minimized by correctly selecting the motor parameters, especially the number of poles. The 2-D and 3-D finite element simulations confirmed the effectiveness of the optimization method the obtained outputs of the motor.	80
Asymmetric Flux Barrier and Skew Design Optimization of Reluctance Synchronous Machines	E. Howard et al. (2015) [34]	IEEE Transactions on Industry Applications	Maximize the average torque and minimize the torque ripple of a reluctance synchronous motor by using a gradient-base optimization algorithm and a sequential linear programming algorithm.	The objectives were achieved. It was observed that the rotor skew optimum angle depends not only on the stator configuration but also on the rotor topology. The simulated and measured results agreed with each other.	75

[1]The number of citations was sourced from the Web of Science platform (September, 2023)

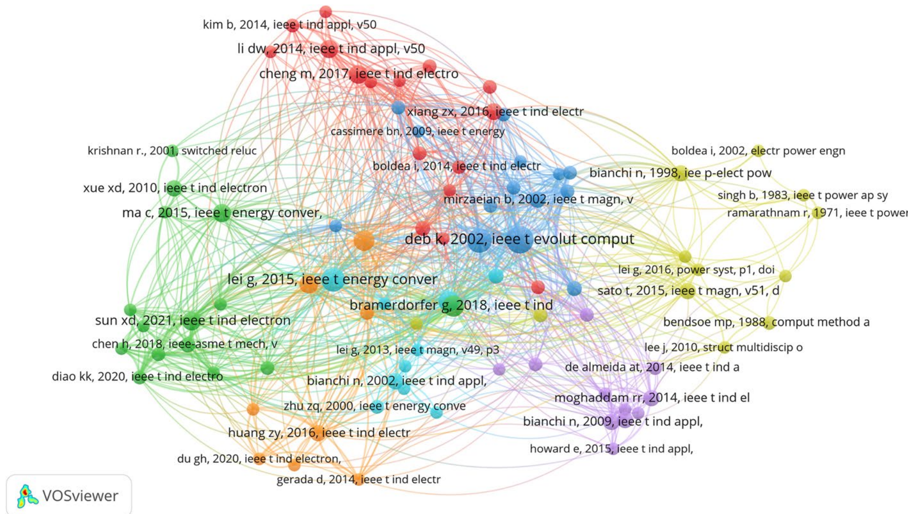

Fig. 3 Conceptual network of co-citation clusters. Cluster 1 (red): Theorical and practical concepts involving PM machines. Cluster 2 (green): Optimization of PM and reluctance machines. Cluster 3 (blue): Genetic algorithm optimization approaches coupled with finite element analysis of electric machines. Cluster 4 (light olive): Optimization of torque characteristics in electrical machines. Cluster 5 (purple): Optimization procedures for synchronous reluctance machines. Cluster 6 (cyan): Non-conventional PM machines and cogging torque studies. Cluster 7 (orange): Optimization strategies and high-speed electrical machines

in green); *iii*) Genetic algorithm optimization approaches coupled with finite element simulations (cluster 3-colored in blue); *iv*) Optimization of torque characteristics in electrical machines (cluster 4-light olive label); *v*) Optimization procedures for synchronous reluctance machines (cluster 5-colored in purple); *vi*) Non-conventional PM machines proposals and cogging torque studies (cluster 6-cyan label), and, finally, *vii*) Optimization strategies and high-speed electrical machines (cluster 7-represented in orange).

A cross-analysis of the top-cited articles from the performance analysis, listed in Table 4, and their placement within the co-citation network, depicted in Fig. 3, reveals that five of the ten most-cited papers are represented in the network, yet with uncharacteristic roles within the thematic clusters. The multilevel design optimization study by Z. Xiang et al. [20] is positioned in Cluster 1, although it does not act as a central node within that network. Two scholarly works [27] and [32], , are located in Cluster 2, focusing on the optimization of reluctance machines, with article [32] assuming a structural central role in this thematic group. The remaining two articles [26] and [31], , appear in Cluster 3. It is noteworthy that, despite being the most-cited work in the dataset, the study by Y. Duan and D. M. Ionel [26] is not structurally central within its cluster. This cross-mapping underscores that high citation metrics do not necessarily translate into structural influence in the co-citation network, whose main objective is revealing the thematic structure of the knowledge field.

The following analysis explores the citation patterns and research scope of each cluster. It is important to note that co-citation analysis can be prone to bias, often resulting in the identification of "outliers" [35]. These outliers may represent peripheral studies that, while not fully aligned with the cluster, remain relevant and influential within the broader cluster pattern. Alternatively, they could be foundational works that do not fit neatly into current categorizations. For this reason, these potential outliers have been retained in the analysis to provide a more comprehensive understanding of the citation dynamics.

Cluster 1: Theorical and practical concepts involving PM machines

This cluster encompasses 14 articles, ($n = 14$), on both theoretical and practical optimization approaches regarding PM machines. This cluster is further divided into two sub-clusters: Sub-cluster 1A focuses on different topologies and electromagnetic performance of PM machines, while Sub-cluster 1B addresses the optimization of PM motors for electric vehicle (EV) applications.

Sub-Cluster 1A: Topologies and electromagnetic performance of PM machines

This sub-cluster comprises 8 articles focusing on the operational principles and underlying different configurations of PM machines, with a recurring emphasis on their optimization. Boldea et al. [36] provide a comprehensive review of techniques adopted aimed at reducing the amount of rare-earth material while maintaining the high performance and torque density characteristic of rare-earth PM machines.

Cheng et al. [37] offer an overview focusing on the concepts, operational principles, machine topology, torque ripple mitigation, and electromagnetic performance of PM brushless machines. Meanwhile, the work presented in [38] makes a significant contribution by formulating a general theory for field modulation applicable to a wide range of electric machines, including PM machines. This theory plays a crucial role in design optimization, particularly the ones addressing topological challenges.

Hua et al. [39] investigate the impact of various magnet and field winding configurations on the electromagnetic performance of a hybrid-excited flux-switching machine.

The work performed by Kim and Lipo [40] provides formulations for the back electromotive force and the output power of a PM Vernier motor, a design that has garnered significant attention in recent decades due to its high torque capabilities enabled by the magnetic gearing effect. Their study offers valuable insights into the key geometric parameters influencing motor torque and provides guidance for determining optimal slot and pole combinations for future advancements. Still in the topic of PM Vernier machines [41], delves into the trade-off between their high torque density and low power factor. The study not only investigates this limitation but also proposes a novel design for a high-power factor PM Vernier machine, offering valuable theoretical insights and design propositions. Additionally [42], presents a generic design methodology for surface PM Vernier machines aimed at maximizing output torque.

Finally, the research presented in [43] on interior PM synchronous machines is particularly noteworthy. It offers a comparative analysis of this configuration with various rotor topologies, evaluating their electromagnetic performance. This study serves as an excellent reference for future research focused on designing this type of machine.

Sub-Cluster 1B: Optimization of PM motors for electric vehicles

This sub-cluster comprises 6 articles focused on the optimization of PM motors for EV applications. The study in [44] explores the optimization of a permanent magnet synchronous reluctance machine tailored for electric vehicles. This work substitutes high-cost rare-earth magnets in the rotor with more affordable ferrite PMs, aiming to achieve two primary objectives: enhancing torque production and reducing torque ripple. Fatemi et al. [45] a multiobjective optimization approach leveraging a differential evolution algorithm (DEA) to minimize both the weight and losses of PM motors. Similarly, the study in [46] employs a differential evolution algorithm, but with a distinct focus on optimization objectives, prioritizing the maximization of efficiency and the reduction of production costs.

A combination of response surface (RS) with the genetic algorithm is used in [20], to improve the motor's efficiency, the output torque and minimize the torque ripple.

Still focusing on the EV applications, Wang et al. [47] optimize a surface-mounted PM motor with concentrated windings by evaluating factors such as the slot-pole number combination, machine inductance, axial length, and number of turns, aiming to minimize total energy losses over the driving cycle. Lastly, the work presented in [48] optimizes the output torque, torque ripple and the core loss of the PM motor by using the RS method with the novelty of performing a sensitivity analysis, assigning weights to each design variable based on its contribution to the objectives, resulting in a significant reduction in computational time during the optimization process.

Cluster 2: Optimization of PM and reluctance machines

Given the complementary nature of the subjects covered by this group, this cluster ($n = 12$) has been divided into two sub-clusters: sub-cluster 2A, focusing on theoretical proposals for optimization, and sub-cluster 2B, dedicated to the optimal design of reluctance machines.

Sub-Cluster 2A: Theorical proposals for optimization

This sub-cluster comprises 5 articles focusing on theoretical proposals related to electrical machines and their optimization potential.

The work by Staton and Cavagnino [49] serves as a cornerstone in understanding heat transfer and flow analysis. It provides a comprehensive collection of heat transfer and flow formulations that are highly applicable to the thermal analysis of electrical machines. While it may be classified as an outlier due to its broader scope, this foundational paper is critical to the thermal design of electrical machines, offering significant implications for their optimization.

Core loss of a switched reluctance motor is extensively analyzed in [50], by using a non-linear lumped parameter equivalent circuit model. Meanwhile, Shi et al. [51] address computational cost reduction in optimization by employing a fuzzy-based sequential Taguchi robust optimization method. This technique is thoroughly detailed in the paper and can be effectively applied to various configurations of electrical machines, beyond PM motors. Another innovative approach is presented in [52], where multilevel optimization combined with the Nondominated Sorting Genetic Algorithm II (NSGA-II) is demonstrated to be highly efficient for optimizing high-dimensional machines. Finally, Zhao et al. [53] introduce a novel method that integrates sensitivity analysis with a multiobjective differential evolutionary algorithm featuring a ranking-based mutation operator. This approach optimizes thrust force, thrust ripple, and power factor in a double-sided linear PM Vernier motor by assigning varying weights to design variables throughout the process.

Sub-Cluster 2B: Design optimization of reluctance machines

This set comprises 7 papers, primarily focusing on the optimization of reluctance machines. These machines are considered a cost-effective and structurally simple alternative to PM machines, particularly for use in electric mobility due to the absence of permanent magnets.

Chen et al. [54] utilize a Taguchi-Chicken Swarm Optimization algorithm for robust-oriented optimization of a switched reluctance motor, taking manufacturing constraints into account. Another approach is presented in [55], which combines sensitivity analysis, surrogate models, and genetic algorithms to enhance motor efficiency. This method is further applied by the same authors in [56] with a broader scope, optimizing both a switched reluctance motor and a switched reluctance generator.

An interesting contribution is found in [57], which reviews key optimization methods for reluctance machines, highlighting the prevalent use of stochastic algorithms such as genetic algorithms (GA), differential evolution algorithms (DEA), and particle swarm optimization (PSO). Departing from stochastic methods [58], employs an analytical approach to optimize the average torque, losses, and lamination volume of a switched reluctance motor.

As mentioned earlier in this document, Ma and Lu [27] apply PSO to tackle two conflicted objectives: maximizing efficiency and minimizing torque ripple. Finally, the design and optimization of a switched reluctance motor for automotive applications are explored in [32], which also employs a genetic algorithm in its optimization procedure.

Cluster 3: Genetic algorithm optimization approaches coupled with finite element analysis of electric machines

Within this cluster ($n = 13$), it is possible to discern two sub-sets: sub-cluster 3A – Genetic algorithm optimization applications and sub-cluster 3B – Design and optimization analysis supported by finite element method (FEM) analysis.

Sub-Cluster 3A: Genetic algorithm optimization applications

This sub-cluster contains 10 articles, primarily focused on the application of genetic algorithm methods in the design of electric machines.

A comprehensive literature review on the optimal design of surface PM synchronous machines using PSO and GA techniques highlights the superior robustness of GA compared to PSO [59]. Deb et al. [60] introduce and evaluate the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) across various optimization problems, demonstrating its effectiveness in achieving convergence and identifying diverse solution sets. NSGA-II is employed in [61] to optimize an induction machine, aiming to reduce material costs and noise levels while simultaneously enhancing the machine's efficiency.

A different perspective on the efficiency of GA is presented in [26], where DEA aproach outperforms GA when optimizing a PM synchronous motor. In another study, the GA is combined with the Response Surface (RS) methodology, successfully reducing the weight of a transverse flux linear motor while enhancing its performance during the optimization process [62]. This hybrid approach is also applied in [63] to achieve the largest constant power speed range for a PM motor.

To optimize the efficiency and power factor of a single-sided linear induction motor, GA is utilized in [64]. In a similar context of efficiency maximization, GA is applied to optimize a PM synchronous machine while simultaneously minimizing its weight [31]. Wrobel and Mellor [65] employ GA to maximize the torque density of a brushless PM motor by optimizing its magnetic circuit. Finally, in [66], GA is used to improve the efficiency and reduce torque ripple in a switched reluctance motor.

Sub-Cluster 3B: Design and optimization analysis supported by finite element method

This sub-cluster is smaller and includes only 3 articles, focusing on the integration of FEM simulations in the design and optimization of electric machines.

Ionel and Popescu [67] introduce a more efficient method for simulating and modulating brushless PM motor drives by using a reduced number of FEM simulations with space-time transformations, which is particularly useful for initial machine sizing and optimization. The concept of computational efficient finite-element method (CE-FEM) analysis and its application in an interior PM machine is also explored in [68], highlighting its advantages in optimization tasks. Building on this concept, [69] presents the development of an automated design tool that combines the CE-FEM analysis with a differential evolution (DE) optimizer to PM machines design.

Cluster 4: Optimization of torque characteristics in electrical machines

This cluster comprises 7 publications addressing the optimization of torque characteristics in electrical machines through diverse computational strategies and across different machine types. Despite heterogeneity in modelling approaches and motor configurations, the cluster reflects common thread on improving torque performance indicators, particularly average torque, torque ripple, and associated performance outcomes.

The optimization of torque, efficiency, and active material cost in a PM motor is explored in an early work [70], where two techniques are compared, the Genetic Algorithm (GA) and the hill-climbing direct search method. This work demonstrates the value of evolutionary search methods in identifying global optima for torque and efficiency without becoming trapped in local minima. This is strategically important because smoother torque profiles typically exist in narrow, non-obvious design spaces; GA-based exploration therefore supports not only higher average torque but also reduced torque ripple, helping machines operate with fewer vibrations, lower acoustic noise, and reduced wear.

Surrogate models employed in [71] further enhances these outcomes. By enabling rapid estimations of design variants, surrogate models make it feasible to simultaneously target cogging torque, torque ripple, efficiency and material cost. Minimizing cogging torque and torque ripple directly contributes to better controllability and smoother rotation, while material cost optimization target encourage reduced copper and iron losses, translating into lower energy consumption for a given torque output.

The optimization of induction machines in [72] and [73] highlights a similar progression. A level-set equation combined with a Lagrangian method are exploited to maximize torque by adjusting slot geometry, reinforcing the well-established link between geometric decisions, torque production, and slip characteristics. Attaining higher torque per unit input results in improved conversion efficiency, while shape optimization also helps minimize losses emerging from irregular flux distribution. The non-linear programming approach in [73], constrained by pull-out and starting torque requirements, confirms that optimizing material cost can be undertaken without compromising motor stability and robustness across operating conditions.

The optimization of switched reluctance motors in [74] and interior PM machines in [75] pushes the cluster toward multidimensional design spaces, where torque ripple, mass, and magnetic topology are co-optimized. In [74], the output torque, torque ripple and motor's mass of a switched reluctance motor are optimized using the sequential linear programming method. Reducing torque ripple is particularly beneficial in reluctance machines, where inherent torque pulsations often degrade smoothness.

On the other hand [75], proposes a topology optimization method for multi material models based on the normalized Gaussian network applied to the average torque of an interior PM motor to determine the distributions of magnetic core, flux barriers and magnets. Lower motor weight and optimized magnetic distribution reduce inertial loads and core losses, contributing to lighter, more energy-efficient drive systems.

Finally [76], introduces a novel bionic intelligent optimization algorithm, the gray wolf optimizer (GWO), capable of balancing conflicting torque objectives across multiple speed conditions. The algorithm's capacity to simultaneously maximize average torque, minimize torque ripple, and reduce harmonic distortion promotes electromechanical smoothness and reduced energy losses in PM synchronous machines. Harmonic reduction, in particular, mitigates eddy current and hysteresis losses, further contributing to overall system efficiency.

Cluster 5: Optimization procedures for synchronous reluctance machines

This cluster consists of 9 articles, primarily focusing on optimization techniques for rotor design in synchronous reluctance and PM-assisted reluctance motors. It is worth mentioning that two articles deviate slightly from this central theme but are still included for their methodological relevance and the potential cross-disciplinary insights they offer into optimization practices for electrical machines.

The minimization of torque ripple in synchronous reluctance machines, including PM-assisted designs, is explored in [77]. The study focuses on adjusting the position of the flux-barrier ends, a factor that significantly impacts the torque waveform. The analysis combines an analytical model with finite element simulations to enhance accuracy and reliability.

Howard et al. [78], investigate an alternative flux-barrier topology for synchronous reluctance rotors aimed at maximizing average torque while minimizing torque ripple. The study employs two optimization algorithms: a gradient-based method, specifically the modified method of feasible directions, for achieving the first objective, and sequential linear programming for the second. Both optimization procedures are supported by FEM simulations to ensure precise and reliable analysis.

The work developed by Pellegrino et al. [79] utilizes multiobjective genetic optimization algorithms combined with FEM analysis to improve the performance of a synchronous reluctance motor. Their work focuses on enhancing efficiency and torque while minimizing material costs and torque ripple. Similarly [80], emphasizes efficiency optimization, exploring technological trends in synchronous and asynchronous machines.

The work described in [81] analyses the rotor slot pitch, insulation ratio, and controller angle to optimize a synchronous reluctance machine, aiming to maximize torque and minimize torque ripple. Similarly [82], focuses on torque ripple minimization for this machine type, presenting three experimental results featuring distinct inner rotor designs. Building on this theme [83], investigates torque ripple reduction by comparing various rotor geometries, offering a comprehensive collection of experimental results with diverse rotor designs.

Finally, two works with distinct focus of the research field have been included. The first one employs the Taguchi robust design method to optimize an interior PM synchronous motor, using FEM to validate the optimization results [84]. Meanwhile, article [85] explores the differential evolution method, a widely used stochastic direct search technique known for delivering excellent optimization outcomes.

Cluster 6: Non-conventional PM machines and cogging torque studies

Due to the different focus within this cluster ($n = 10$), it is further divided in two sub-clusters: sub-cluster 6A - Non-conventional PM machine design optimization and sub-cluster 6B - Cogging torque minimization.

Sub-Cluster 6A: Non-conventional PM machine design optimization

Similar to Cluster 1, which emphasizes research on PM machines, this sub-cluster, comprising 6 articles, also focuses on optimizing PM machines, including novel configurations as axial flux machines. However, it distinguishes itself by exploring a diverse range of optimization techniques that differ from those previously discussed.

A robust design optimization method based on Design for Six Sigma (DFSS) is employed in [86] to enhance the reliability of a PM motor and reduce manufacturing costs. The optimization focuses on a PM motor with soft magnetic composite material cores, aiming to improve performance while addressing cost and reliability challenges.

The work present in [87] discusses multilevel design optimization techniques for PM motors, in a framework design including, the sizing equation, local sensitivity analysis, global sensitivity analysis, and design of experiments techniques. Stochastic methods are utilized to minimize material costs and maximize output torque, offering a comprehensive approach to optimization.

Mahmoudi et al. [88] implement a genetic algorithm in combination with FEM analysis to optimize the power density and reduce cogging torque of an axial flux PM motor, achieving improved motor performance.

The optimization of efficiency, motor cost, and torque ripple of a double-stator hybrid-excited flux-switching PM machine is presented in [89]. The authors employ an archive-based multiobjective genetic algorithm and sensitivity analysis to balance multiple design objectives and enhance the machine's performance.

The fractional-slot concentrated-windings synchronous PM machine is presented in [90]. The article emphasizes the theory and design of these machines, highlighting their high efficiency and low cogging torque as key advantages.

Lastly [91], presents the optimization of a less-rare-earth PM brushless motor using RS, sequential nonlinear programming, and sensitivity analysis. The study aims to achieve higher output torque, improved efficiency, and reduced PM cost, alongside minimizing cogging torque, contributing to the development of more sustainable and cost-effective motor designs.

Sub-Cluster 6B: Cogging torque minimization

This sub-cluster comprises 4 articles, all of which focus on efforts to minimize cogging torque in PM machines. A review of various techniques aimed at reducing both cogging and ripple torques in PM motors is provided in [92].

Zhu and Howe [93] explore the relationship between specific design variables of PM machines and their corresponding cogging torque. A novel contribution of their work is the introduction of a factor to evaluate the effectiveness of slot and pole combinations in terms of their impact on cogging torque.

In [94], the reduction of cogging torque is analyzed by controlling the air-gap performance function and flux density function, offering an alternative approach to address this issue.

Finally, Bianchi and Bolognani [95] present a comprehensive overview of both classical and innovative methods for minimizing cogging torque in surface-mounted PM motors. This work includes multiple experimental results and discusses the advantages and disadvantages of each technique, such as skewing, pole arc width, and shifting of the permanent magnets.

Cluster 7: Optimization strategies and high-speed electrical machines

Given the multiple pivotal fields within this group, cluster 7 ($n=8$) is divided into two sub-clusters: sub-cluster 7A, which addresses optimization strategies aimed at increasing robustness and reducing computational costs, and sub-cluster 7B, a peripherical one, which focuses on aspects of high-speed electrical machines, highlighting a specialized domain that do not heavily rely on the other, suggesting a niche area.

Sub-Cluster 7A: Optimization strategies for computational efficiency

This sub-cluster is composed of 3 articles that share a common focus on using optimization strategies to reduce computational burden.

The first two studies [96] and [97], , are developed by the same authors, with the second as a continuation of the first. The authors first utilize a deterministic approach for multilevel design optimization to a PM transverse flux machine with the goal of minimizing material cost and maximizing output torque. This method is compared to single-level optimization, showing that it provides better solutions while significantly reducing computational cost. The sequel to this work [97], , uses a robust approach based on DFSS optimization implemented for the same problem. The multilevel design optimization approach involves allocating design variables at distinct levels based on their significance.

The optimal design of a double-rotor flux-switching PM machine is explored in [98] including the output torque, torque ripple, and magnetic coupling. Besides the use of the response surface (RS) method to fit for the optimized region in the multiobjetive optimization problem, a sequential nonlinear programming (SNP) is also used to reduce the computational cost for the multiobjective optimization problem.

Sub-Cluster 7B: Aspects of high-speed electrical machines

This sub-cluster includes 5 articles that address various aspects and optimal designs of high-speed electrical machines.

Table 5 Synthesis of key research dimensions per thematic cluster

Cluster	Prominent Machine Types	Dominant Optimization Objectives	Characteristic Methodologies
#1	PM machines (topological designs and EV applications).	Electromagnetic performance (torque density, torque ripple), cost reduction (rare-earth materials), efficiency.	Combination of theoretical electromagnetic analysis and metaheuristics (DEA, GA&RS)
#2	PM machines and switched/synchronous reluctance machines.	Thermal management, core loss reduction, efficiency, multiphysics performance.	Theoretical formulations, sensitivity analysis, surrogate models, Taguchi methods, NSGA-II, PSO, multiobjective optimization.
#3	(Broad) PM machines, induction machines, switched/synchronous reluctance machines.	Cost reduction, weight minimization, efficiency, torque density, noise reduction.	Genetic Algorithms (GA, NSGA-II) coupled with FEM and hybrid approaches.
#4	(Broad) PM motors, induction motors, switched reluctance motors.	Torque characteristics (average torque, torque ripple, cogging torque), efficiency, cost reduction.	(Diverse) GA, surrogate models, level-set/Lagrangian, nonlinear/sequential linear programming, novel algorithms (GWO).
#5	Synchronous reluctance machines and PM-assisted reluctance motors.	Torque ripple minimization, average torque maximization.	FEM and analytical models, gradient-based and linear programming.
#6	Non-conventional PM machines (axial flux, flux-switching).	General performance, cost, power density, cogging torque minimization.	DFSS, multilevel/sensitivity analysis, archive-based GA; analytical/skewing techniques.
#7	High-speed PM machines	Computational cost reduction, robust design, multiphysics and multilevel design.	Multiobjective and multimode optimization, response surface (RS), SNP, DFSS.

Gerada et al. [99] elaborate an extensive research on high-speed machines, reviewing application segments and describing recent developments in material technology (as of 2014).

In [100], strategies for the rotor design of high-speed PM machines are explored, along with their limitations. A finite element comparison is presented, evaluating surface-mounted versus buried magnets using identical motor data.

Scholary works [101, 102] bring into focus the calculation of power losses and thermal distributions in high-speed PM machines, comparing different cooling systems using FEM analysis. Finally, Huang and Fang [103] present the optimization of a high-speed PM machine, with a particular insight on rotor structure to ensure a more robust assembly. The optimization goal is to minimize sleeve thickness, utilizing the RS method for the process.

Synthesis of thematic clusters

With the aim of consolidating the findings of the preceding analysis into a structured overview, directly addressing the guiding research questions previously introduced, Table 5 presents a synthesis of the clusters' core patterns, identifying for each one, (RQ1) the most prominent types of electric machines under investigation, (RQ2) the dominant optimization objectives driving the research withing each thematic group, and (RQ3) the characteristic methodologies and algorithms that define the cluster's analytical approach.

The distinct foci of the performed analysis enable the recognition of research paradigms, providing a clear map of the research landscape, connecting the detailed content of the clusters to their broader significance within the field of electrical machine optimization. Drawing upon these findings, several paradigms emerge, occasionally overlapping, but defining a consistent alignment of machine type, objective and methodological approach.

First, PM machines arise as the most dominant technological platform for advancing performance (clusters 1, 6 and 7), focused on enhancing key electromagnetic metrics, while actively managing materials costs, particularly of rare-earth elements. Likely driven by the non-sustainable sourcing and supply chain challenges of PM materials, reluctance machines (switched or synchronous) are also of significant interest (clusters 2 and 5).

Branching from this core, a multiobjective design paradigm centred on improving the efficiency of the optimization process itself characterizes clusters 2, 3 and 7 A. The defining feature is the strategic integration of advanced algorithms (e.g., NSGA-II, multilevel schemes) with FEM analysis and surrogate modelling, explicitly to make complex, multiobjective optimization and multilevel designs computationally tractable. It is also worth highlighting a complementary paradigm focused on operational reliability and robustness, emerging from the integration of multiphysics analysis framework (electromagnetic, thermal and structural) and multilevel design approaches, evident in cluster 7 A. Elements of robust design for manufacturability also appear in parts of cluster 6 A, where design methodologies address variability and production constraints.

Complementing these are specialized design-focused paradigms, which are characterized by a specific technological or performance niche. Clusters 4 and 5 delve into the torque quality, with the later focusing on the synchronous reluctance machine design, heavily reliant on FEM and targeted algorithms for torque ripple minimization. The cogging torque mitigation paradigm (cluster 6B) focuses on a singular PM machine performance issue, relying on analytical and specialized geometric techniques.

This landscape shows a mature field with a dominant central paradigm (PM machine optimization) and several adjacent or supporting paradigms that address specific methodological, technological, or application-driven challenges.

Conclusions

The study implemented a bibliometric analysis, reporting on performance analysis and science mapping, to explore the optimization methods applied to electric machines. In terms of performance analysis, this analysis traced the evolution of the literature, identified the most cited articles, and highlighted influential authors in the field. With regard to science mapping, a co-citation network was also created to reveal the major themes and topics in the field, revealing clusters generated with the rationale of cited documents that frequently appear together.

The literature on the optimization of electric machines is continuously evolving and has been expanding significantly over the past two decades. A key trend observed in the publications is a shift from deterministic methods towards stochastic strategies, reflecting the growing complexity of the optimization problems being addressed. Among the stochastic techniques, bio-inspired algorithms, particularly genetic algorithms, have gained considerable impact due to their ability to find global optima across a wide range of machine types and optimization objectives.

Multiobjective optimization has become a common practice, as single-objective optimization is increasingly seen as insufficient. The use of Pareto fronts enables the simultaneous optimization of multiple goals, leading to more robust and well-rounded solutions. This reflects the growing recognition that trade-offs between different objectives must be carefully considered in machine design.

A notable concern in recent studies is the reduction of computational time during the optimization process. One promising solution to this challenge is the application of sensitivity analysis, a technique that has emerged in recent years. Sensitivity analysis helps prioritize design variables that have the most significant impact on the optimization objectives, thereby streamlining the search for optimal solutions.

The future of the field appears to lie in the combination of optimization techniques. For instance, combining stochastic algorithms, such as genetic algorithms with particle swarm optimization (PSO), or integrating response surface methods with stochastic algorithms, has shown potential for yielding better results. Similarly, the application of robust optimization alongside nonlinear programming algorithms is gaining momentum. These hybrid approaches leverage the strengths of individual methods, enhancing the likelihood of finding superior solutions.

Ultimately, the field of optimization for electric machines remains vast, with significant room for further exploration and development. The trend toward more efficient, multiobjective, and hybrid optimization techniques signals a promising future, where faster and more effective methods will continue to emerge, driving progress in this important area of engineering.

The co-citation network identified patterns of influence, thematic connections and structures in the body of literature based on how documents frequently are cited together in other work. Through this network, the most influential publications have been identified, and the developmental trends in the field were highlighted, which explicitly answers the research questions. PM machines emerge as a central focus of the publications, likely driven by the rapid growth of the EV market. The primary objectives pursued in the studies include improving torque performance, enhancing efficiency, and reducing the cost of electric machines. Methodological signatures arise from the conducted analysis such as genetic algorithms and FEM paradigm and computational cost reduction strategies.

In essence, this study serves as a valuable reference guide, showcasing key optimization methods and their specific applications across various types of machines. It also sheds light on emerging trends in the optimization field and promotes the use of bibliometric analysis in this area of research. From an industrial perspective, this guide can streamline the selection of appropriate optimization techniques tailored to specific problems.

However, this article acknowledges certain limitations. The exclusive use of the Web of Science database may have excluded relevant works indexed only in other databases, such as Scopus or IEEE Xplore. This limitation was discussed, and studies seeking a fully comprehensive review could benefit from a multi-database strategy. The reliance on source impact factor filtering might have omitted significant papers, and the choice of co-citation analysis as the sole science mapping technique narrows the scope of analysis. Future studies can address these limitations by incorporating additional databases, broadening the range of source inclusion criteria, and exploring alternative science mapping techniques, such as bibliographic coupling or keyword co-occurrence analysis. These steps would further enrich the understanding of optimization methods in the context of electric machinery design.

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Authors' contributions
CPN was responsible for data curation, formal analysis, and writing the original draft. ACS designed the methodology, participated in the formal analysis, and contributed to the output validation. BB and JAC contributed to the conceptualization and resources provision. TB contributed to conceptualization and formal analysis. AF contributed to formal analysis, project administration, funding acquisition, review and editing. All authors read and approved the final manuscript.

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Data availability
The datasets generated and/or analysed during this study are available from the corresponding author on reasonable request.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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