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Review

Review of Soft Computing Models in Design and Control of Rotating Electrical Machines

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Abstract: Rotating electrical machines are electromechanical energy converters with a fundamental impact on the production and conversion of energy. Novelty and advancement in the control and high-performance design of these machines are of interest in energy management. Soft computing methods are known as the essential tools that significantly improve the performance of rotating electrical machines in both aspects of control and design. From this perspective, a wide range of energy conversion systems such as generators, high-performance electric engines, and electric vehicles, are highly reliant on the advancement of soft computing techniques used in rotating electrical machines. This article presents the-state-of-the-art of soft computing techniques and their applications, which have greatly influenced the progression of this significant realm of energy. Through a novel taxonomy of systems and applications, the most critical advancements in the field are reviewed for providing an insight into the future of control and design of rotating electrical machines.

Keywords: soft computing; artificial intelligence; machine learning; rotating electrical machines; energy systems; deep learning; electric vehicles; big data; hybrid models; ensemble models; energy informatics; electrical engineering; computational intelligence; data science; energy management; control; electric motor drives

1. Introduction

In 1831, Michael Faraday invented the disk machine which can be considered as the earliest form of the DC machine. Until 1870 when Thomas Edison started the commercial development of the DC generator, electrical machines were applied and investigated only in laboratories. Edison's pioneering concept of electric power distribution from central generation stations allowed the introduction of the electric grid infrastructure concept, which was the primary condition for widespread the application of electric motors [1]. The patent of the three-phase induction motor by Nikola Tesla in 1888 was an utmost important milestone in the history of the electric machines. After that, the construction of electrification began, which lasted until 1930 in the USA, and then conquered worldwide [2]. Nowadays, it is estimated that more than sixty-five percent of the energy demand of present-day industrialized countries used by electrical drives [3]. Constant or variable speed or servo-motor drives are employed almost everywhere: in households, industry, electric traction, transportation, aerospace, military equipment, medical equipment, agriculture, etc. These sectors are mainly focused on an alternative source for the existing power transfer technologies, where major subsystems would also be controlled and driven electronically [4].

Recently, electromechanical drives for position and speed control play a key role in process control, EVs, factory automation, robotics, autonomous vehicle, mobility and energy conservation [5–15]. Due to the introduction of vector control methods in the 1970s and low price and the high reliability of cage induction motors made induction motor as the most popular rotating electrical machine. The recent advancements of PM materials, solid-state devices and microelectronics have contributed to new energy efficient, high-performance electric drives which use modern PM brushless motors [16–19]. It is entirely possible that these permanent magnet brushless motor drives will become predominant in the next century [20]. Nevertheless, the control, design, and optimization of rotating electrical machines require advanced techniques and modern mathematical models to keep up with the ever-increasing demand for energy [21–25]. In fact, practical solutions to engineering problems involve model-integrated computing [26,27]. Model-based computing approaches or so-called soft computing (SC) provide a challenging way to replace the procedure with a knowledge-based method [28–33]. SC techniques denote a set of computational approaches that are used to approximate mathematical problems which are hard or unable to solve by the traditional time-consuming classical mathematical tools [34–36]. Figure 1 presents the principal SC algorithms widely used in engineering applications.

Furthermore, combining SC, non-conventional and novel data representation techniques is a possible way to overcome this difficulty [37–40]. Over the last decades, the benefits of SC techniques have been widely recognized and have brought several new solutions in the design and control of electrical machines [41,42]. However, there is a gap in the effectiveness of the SC models [43,44]. Thus, identification and evaluation of the SC models would be a practical approach to evaluate the progress and provide an insight into the future application of SC methods [45,46]. Consequently, the intention of the current work is to give a comprehensive overview of the recent state-of-the-art solutions using soft computing techniques in the design and control of rotating electrical machines. The organization of the rest of this article is as follow. In Section 2, the research methodology of the review is presented. Section 3 presents a review of the SC models used in electrical rotating machines. Section 4 presents the discussion followed by Section 5 with a conclusion to the review.

2. Methodology

The primary goal of this survey is to present the state of the art of SC techniques in the design and control of rotating electrical machines. The purpose of the research methodology is to identify, classify, and review the notable peer-reviewed articles concerned in top-level subject fields. In our comprehensive review using the Thomson Reuters Web-of-Science and Elsevier Scopus for implementation of the search queries would assure that any paper in the database would meet the essential quality measures, originality, high impact, and high h-index.

To identify the application of soft computing in design, control, and development of rotating electrical machines, the search queries were carefully chosen to build the initial database. The taxonomy of SC influenced the search queries. Figure 1 presents the principal SC tools and the subsections that we have identified by a slight modification of the classifications given in [27,28]. Accordingly, the keywords of the search queries to identify the SC tools were selected to be “fuzzy” or “neural network” or “evolutionary computation” or “genetic” or “meta-heuristics” or “ant colony” or “particle swarm” or "tabu search" or "cuckoo search" or "simulated annealing" or "Bayesian network" or "Markov logic network" or "rough set".

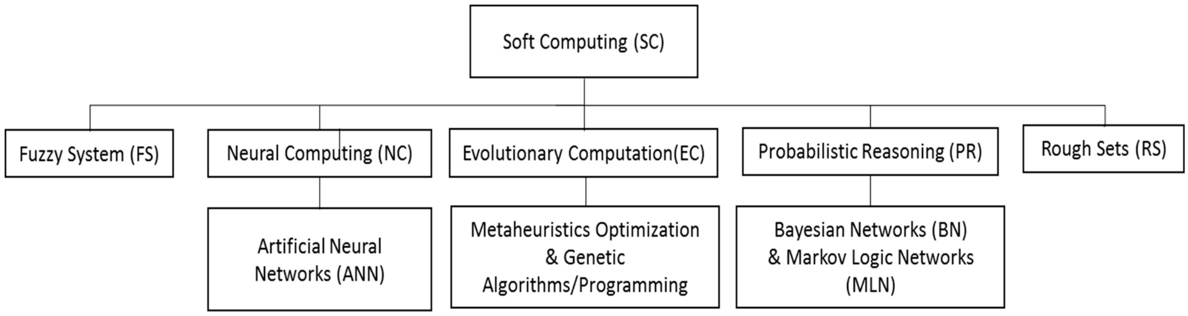

Figure 1. Taxonomy of soft computing methods used in making the initial database [47,48].

On the other hand, the search queries for the applications to rotating electrical machines may include various aspects of design and control, i.e., electric machine, rotating electrical machine, electric motor, electric generator, electromechanical generator, transformer and electrostatic, homopolar, permanent, brushed, magnet, reluctance and induction machines. Consequently, the entire search query is presented as: (TITLE-ABSTRACT-KEYWORDS ("electric machine" or "rotating electrical machine" or "electric motor" or "electric generator" or "electromechanical energy converter" or "generator" or "transformer" or "brushed machine" or "permanent magnet machine" or "induction machine") or TITLE-ABSTRACT-KEYWORDS ("reluctance machine" or "electrostatic machine" or "homopolar machine") and TITLE-ABSTRACT-KEYWORDS ("fuzzy" or "neural network" or "evolutionary computation" or "genetic" or "metaheuristics" or "ant colony" or "particle swarm" or "tabu search" or "cuckoo search" or "simulated annealing" or "Bayesian network" or "Markov logic network" or "rough set")) and PUBLICATION-YEAR > 1986 and PUBLICATION-YEAR < 2018. This query resulted in a total of 24,382 documents. It should be noted that each section contained a brief result and conclusion about the subject to help the authors and researchers make a sustainable and suitable decision about applications of soft-computing techniques.

Furthermore, to present an in-depth review and understanding of each modeling technique and its progress, we aimed at having different categories for the SC models used i.e., simple fuzzy systems, adaptive neuro-fuzzy inference system (ANFIS): neuro-fuzzy, advanced ANFIS/neuro-fuzzy: hybrids, neural computing: artificial neural network (ANN), evolutionary computation (EC) and metaheuristics, ant colony, tabu and cuckoo search, simulated annealing, probabilistic reasoning and Bayesian networks, and hybrid soft computing methods. Furthermore, the research methodology follows a comprehensive and structured workflow based on a systematic database search and cross-reference snowballing. The flowchart of the research methodology is presented in Figure 2.

In the step 1 of the methodology, the initial database of the relevant articles was identified based on the search queries of SC models through exploring the Thomson Reuters Web-of-Science and Elsevier Scopus databases. In step 2 the database was created with the relevant literature. For every SC model, we applied a new search query to suit that search well.

Nevertheless, some articles in the initial database might not be highly suitable for the review. For that matter, step 3 investigated an indent consideration of the literature to pass the irrelevant papers to step 4 to be excluded from the database. Note that the search queries will identify the relevant articles, yet the queries were uncertain as to whether the SC model belonged to a hybrid category. For instance, a hybrid model of SC may include single SC model. Therefore, step 5 is designed to reclassify the literature into one of the categories of SC models.

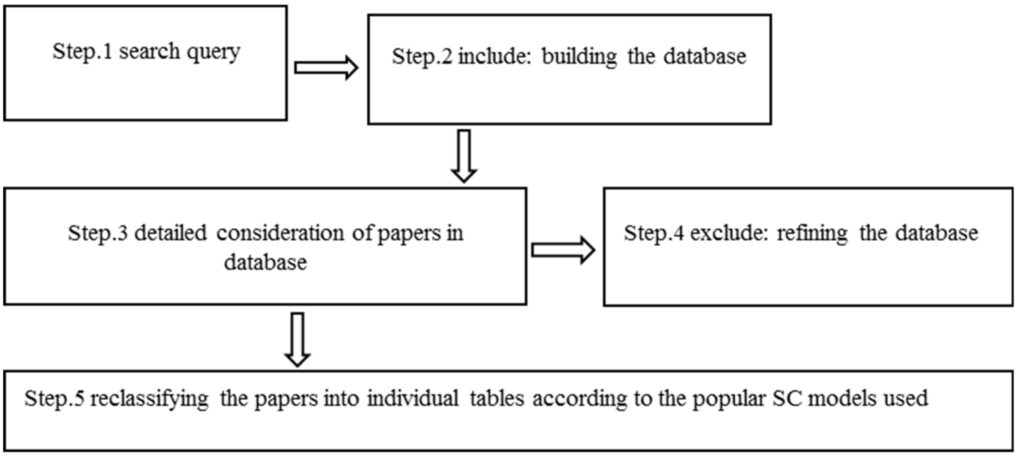

Figure 2. Methodology of research.

3. State of the Art of Soft Computing Techniques and Applications

Exploring the literature on rotating electrical machines shows continued progress on the design and advancement of rotating electrical machines. Almost half a million documents in this particular realm show the importance of this topic and the dependent technologies. Figure 3 shows the progress in some literature. It is also apparent that the use of SC models has been started from the late 80s and early 90s and boosted the design advancement.

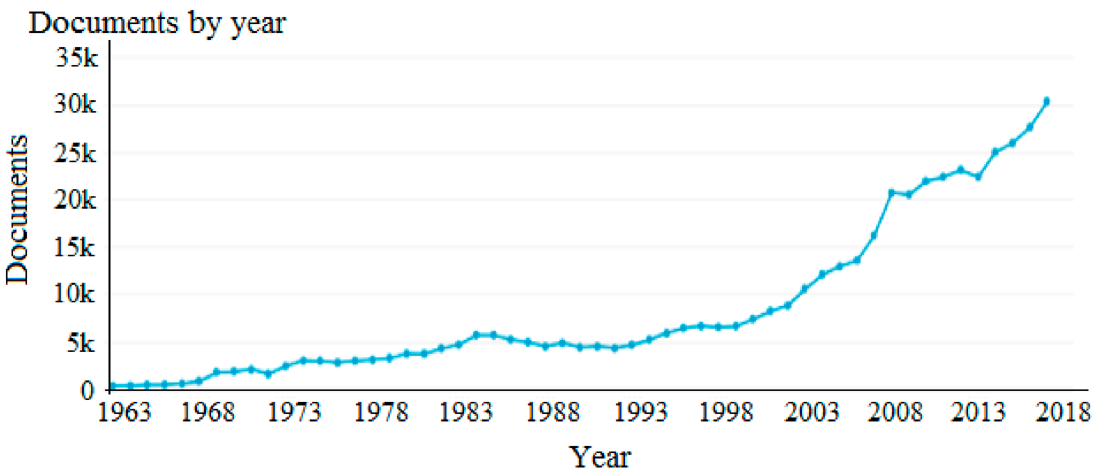

Figure 3. The number of published articles on rotating electrical machines from 1963–2017: 483,320 document results. (Source: Scopus & Web of Science).

Exploring the various SC models in wide applications to design and control the rotating electrical machines results in an extended database. The literature has been progressing since the early 1980s, with a fast-pace of involvement of SC methods in design and control purposes. Figure 4 shows the increasing popularity of SC, especially during the past two decades. It is apparent that statistics on the number of articles in literature change when using soft computing for advancement. Furthermore, the primary analysis of the database of the search shows that some SC methods have been more popular than the others and the usage of many SC methods has been very limited and not worth mentioning in the review. The most popular SC methods can be classified into five categories of fuzzy systems, neural computing: ANN, EC and metaheuristics, probabilistic reasoning and Bayesian Networks, and further hybrid soft computing methods.

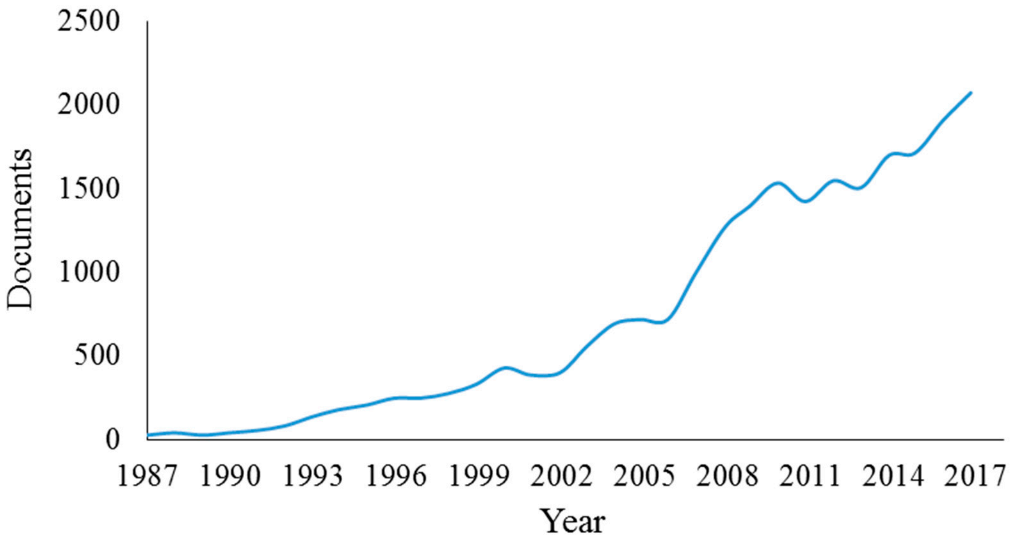

Figure 4. Analysis of the literature on soft computing in design, control, and development of rotating electrical machines from 1987–2017. Total of 30,382 document results. (Source: Scopus & Web of Science).

The analysis of literature type shows a significant number of articles were original papers written on the advancement and development of rotating electrical machines and only a tiny fraction of literature was devoted to reviewing papers (see, Figures 2–5).

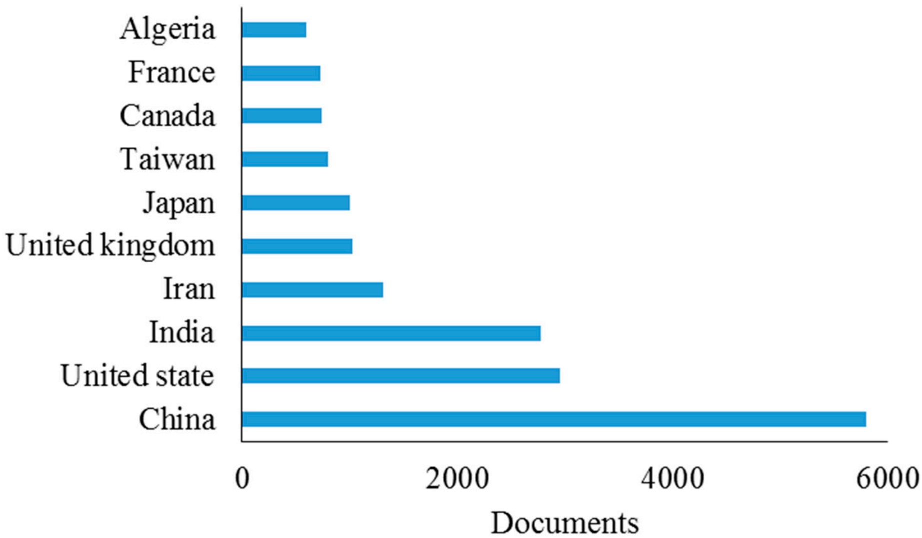

Figure 5. Analysis of the literature by based on countries (Source: Scopus & Web of Science).

Analysis of the literature based on countries showed that China, USA, India, Iran, and the UK are among the top five active regions on the advancement of rotating electrical machines using SC methods (see, Figure 6).

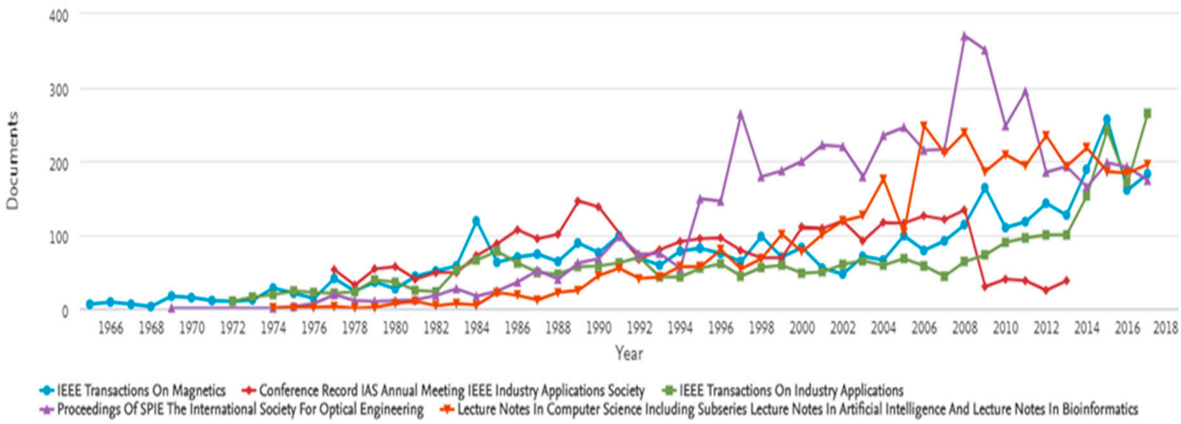

Figure 6. Analysis of the literature based on publishing sources (Source: Scopus & Web of Science).

The top five sources included: proceedings of the International Society for Optical Engineering (SPIE) (with 5841 papers), lecture notes in computer science, including subseries lecture notes in artificial intelligence and lecture notes in bioinformatics (with 4064 papers), Institute of Electrical and Electronics Engineers (IEEE) Transactions on Magnetics (with 3989 papers), and IEEE Transactions on Industry Applications (with 3306 papers), conference record Industry Applications Society IEEE Annual (with 2943 papers), for a total of 24,382 document results (see, Figure 6).

The analysis of literature type shows a significant number of articles are original papers written on the advancement and development of rotating electrical machine and only a tiny fracture of literature is devoted to reviewing papers (see, Figures 7 and 8).

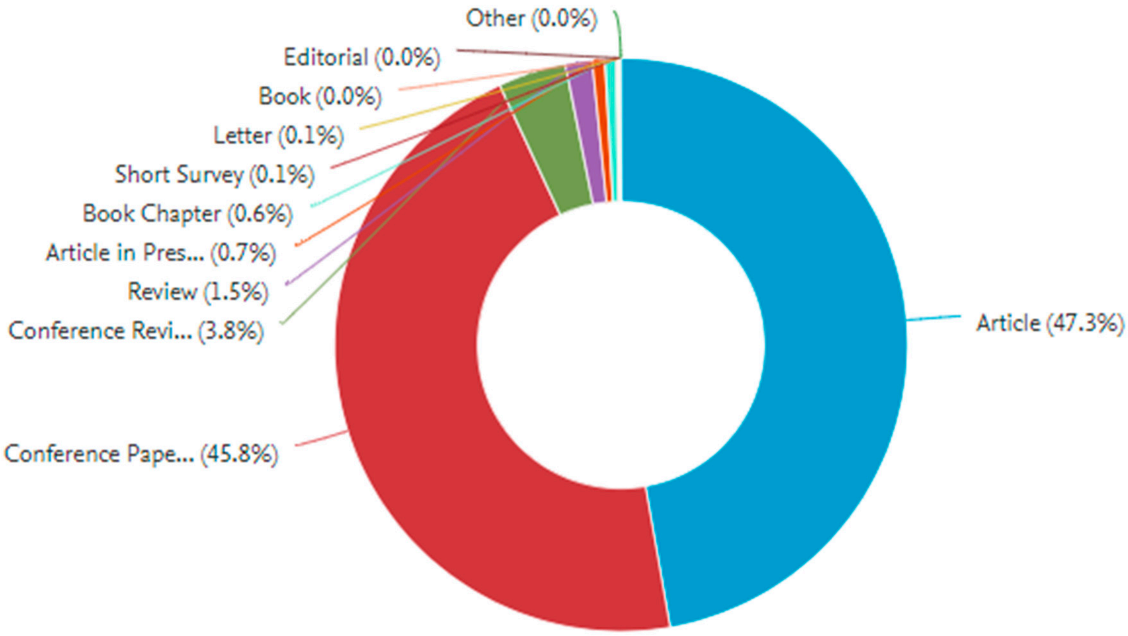

Figure 7. Literature types on the on rotating electrical machines using soft computing, from 1987–2017. (Source: Scopus & Web of Science).

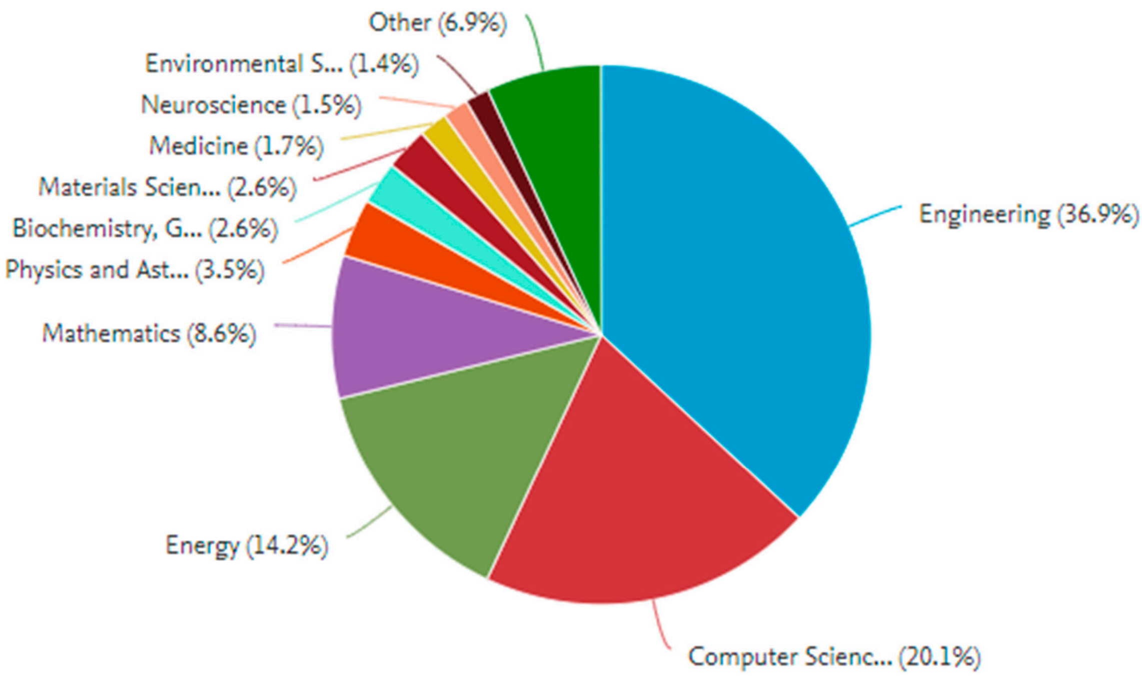

Figure 8. The subject area of rotating electrical machines using soft computing, from 1987–2017. The math, computer science, and energy subject areas had a rise (Source: Scopus & Web of Science).

3.1. Fuzzy Systems

Fuzzy logic is widely used for modeling complex and ill-defined systems. The core concept relies on the application of linguistic variables which are transformed into graded membership functions. Therefore, fuzzy logic is an extension of classical Boolean logic where logical statements are not only true or false but can also range from almost certain to very unlikely. A large number of practical applications apply fuzzy logic due to its excellent approximation properties.

3.1.1. Simple Fuzzy Systems

Fuzzy logic is widely used in nonlinear controllers due to their easy applicability and high performance. These are capable of replacing the most common Lyapunov's second method of nonlinear control, which is a complicated technique from a mathematical point of view and needs very skilled designers. The two most widely known systems are the Mamdani- and Sugeno-type inference systems. The main difference between them is that the latter allows functions as outputs instead of membership functions. Fuzzy logic serves as a useful tool for engineering practice; numerous examples found for the utilization of fuzzy logic in the control and design of electrical machines. Major works from the recent past collected in Table 1 illustrate that this trend is still unbroken.

Table 1. Simple fuzzy systems in rotating the electrical machine.

Reference	Year	SC Method	Application
Aguilar et al. [49]	2017	Fuzzy logic	Brake control
Rao Amulya [50]	2016	Mamdani type inference	Fault detection and vibration
Ben Smida, M.; Sakly, A. [51]	2016	Fuzzy controller	Power regulation
Z. Husain [52]	2018	Fuzzy expert system	Condition monitoring of power transformers via dissolved gas analysis test
Kahla, S.; et al. [53]	2018	Combination of standard on-off strategy with fuzzy logic	Maximize the power point tracking of wind energy

Aguilar [49] used a simple fuzzy logic algorithm for the intelligent brake control of an electric motorcycles engine in order to recover the maximum energy in braking processes while maintaining the vehicle's stability. The success of the employed method is very bold, such that the results of comparing the regenerative system with the ABS in a low adhesion condition have been presented in Figure 9 in terms of mean deceleration (a) and distance (b). Based on the results, the proposed systems could optimize the energy regeneration strategy.

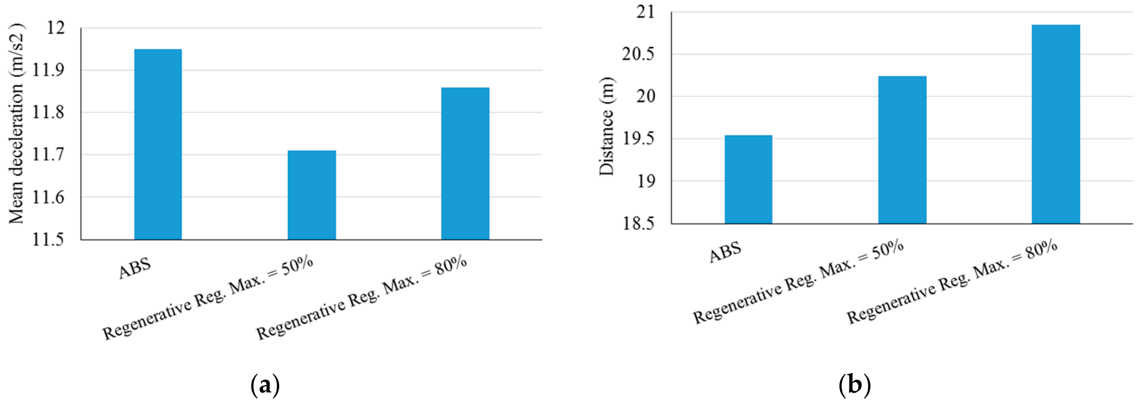

Figure 9. Results of the study by Aguilar [49] in terms of (**a**) mean deceleration and (**b**) distance.

In the paper by Amulya, in 2016 [50] a steam turbo-generator condition assessment problem was considered in which the condition is determined by fuzzy logic-based vibration analysis. Recommendations for improving the performance of the conventional pitch angle control strategy for power regulation in wind turbines are given in Ben Smida (2016) [51] in which the pitch angle is based on fuzzy logic. The study was developed using fuzzy logic and proportional integral derivative PID controllers. The comparison of the performance of the two systems was performed using mean absolute error (MAE) and mean percentage error (MPE). Such that, a fuzzy logic controller with low MAE (29.02%) and MPE (0.0088%) values provided a best-controlling ability compared that for PID controller which can make a smooth controlling process.

Husain (2018) [52] applies a fuzzy expert system for fault diagnosis of power systems which incorporates the information obtained from dissolved gas analysis test. The proposed approach could successfully reduce the issues raised by the conventional fault diagnosis methods. Also, the proposed method by Arumugam 2017 improves dynamic response and the energy saving and by the fast detection ability and removes the errors raised by the dynamic voltage restorer (DVR) response.

Kahla (2018) [53] introduces a fuzzy logic system in the on-off control strategy in case of wind energy conversion. The proposed method allows maximizing the power point tracking of wind energy and reducing the mechanical loads in comparison to the standard on-off control strategy.

3.1.2. ANFIS: Neuro-Fuzzy

Artificial neural systems represent systems acting as parallel distributed computing networks. Neural systems can find new associations, new functional dependencies and new patterns through learning. Therefore their primary advantage is their additivity. Consequently, combining neural networks with fuzzy logic techniques is evidently useful [54]. Thus, the excellent approximation properties are complemented with higher additivity and parallelism [40,55,56]. Such composed system is called fuzzy neural, neural fuzzy, neuro-fuzzy or fuzzy-neuro network, or ANFIS in which for instance neural networks can be used to tune membership functions of fuzzy systems. A vast amount of published papers supports its applicability [57–59]. However, in electrical machine design issues, only a few examples are found (see Table 2).

Table 2. Adaptive neuro-fuzzy systems in electrical machines.

Reference	Year	Method	Application
Arumugom [60]	2017	ANFIS based MIC controller	Dynamic Voltage Restorer Controller
Aruna [61]	2016	MWT and Accommodative ANFIS with ABC algorithmic rule.	IPMSM control
Bentouhami [62]	2016	Neuro-fuzzy combined method	Control of DSIM
Haritha [63]	2017	Q learning and ANFIS	Optimal relationship of rotor speed of the PMSG
Thankachan and Singh [64]	2016	Neuro-fuzzy	Speed and torque control of IM drive

An interesting application of neuro-fuzzy systems is described in Arumugom (2017) [60] where the authors attempt to design a DVR with energy conservation using a MIC and vibration energy harvester (VEH). Aruna [61] proposed in 2016 a hybrid method using ANFIS for the speed control of interior permanent magnet synchronous motor (IPMSM). Their results demonstrate that their solution enables better disturbance rejection compared to the classic PID controller. The settling, arising and overshooting times of the proposed controlling method has been compared with PID, MR-PID, and MWNN-particle swarm optimization (PSO) controlling algorithms. Figure 10 indicates the time values for each term. The related results indicate that the proposed controlling method is the best technique to eliminate the nonlinearity with high reliability, and sustainable performance compared with that for the other techniques.

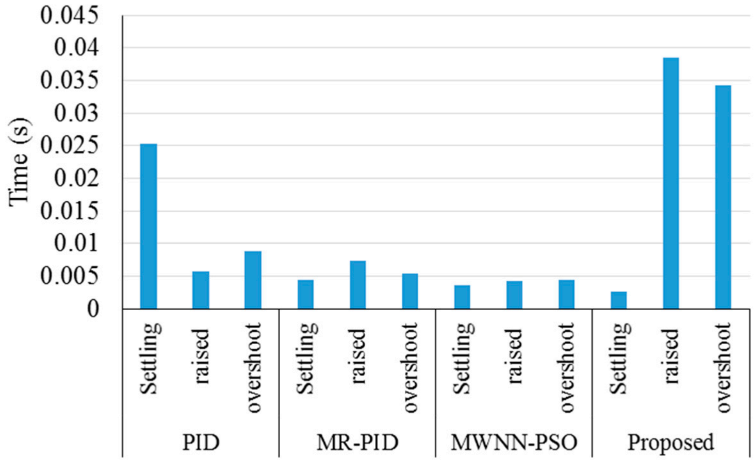

Figure 10. Comparing the time values for the study by Aruna (2016) [61].

Advanced method for the control of dual star induction machine (DSIM) supplied by Five-Level Inverter is shown by Bentouhami (2016) [62] who apply an ANFIS controller composed of an online learning algorithm with a neuro-fuzzy network. Haritha (2017) [63] introduced a neuro-fuzzy and Q learning-based technique for the maximum power point tracking control for improving learning efficiency of permanent magnet synchronous generator (PMSG) wind energy conversion system (WECS).

3.1.3. Advanced ANFIS/Neuro-Fuzzy: Hybrids

Adaptive neuro-fuzzy inference systems can be supported or combined further mathematical tools if the problem requires. The resulted systems are called hybrid fuzzy-neuro systems. In advanced ANFIS systems, the capabilities of the neural network are higher due to better learning algorithms (e.g., trust region reflective), so they can learn various parameters. These techniques are especially useful in highly nonlinear control problems of electrical machines or condition assessment issues (see Table 3).

Table 3. Hybrid techniques applied in electrical machine design and control.

Reference	Year	Technique	Application
Li et al. (2005) [65]	2005	Robust model reference fuzzy controller	DC servo motor system
Fatih Kececioglu [66]	2017	NFC	hybrid passive filter configuration proposed for PWM rectifiers
Gnanaprakasam [67]	2015	S-transform algorithm & ANFIS	detecting and classifying the vibration signal of IM
Hossain [68]	2015	FLC, SNC & ANFIS	Nonlinear controllers augment of a large-scale hybrid power system
Dehghani et al. [40]		ANFIS and GW	Hydropower generator performance

A vast amount of literature on nonlinear control solutions have been publishing in recent years. For instance, Li et al. (2005) [65] propose a control technique using a robust model reference controller with the combination of the hybrid fuzzy controller. The core of the control strategy is based on the classical Lyapunov technique which is a complicated technique, but the control signal includes fuzzy, classic and robust terms. The fuzzy logic controller was compared with the hybrid-fuzzy controller using root mean squared error (RMSE) values in terms of output tracking for DC servo motor and inverted pendulum. The results have been presented in Figure 11. Based on results, the hybrid controlling method had the best performance in both terms.

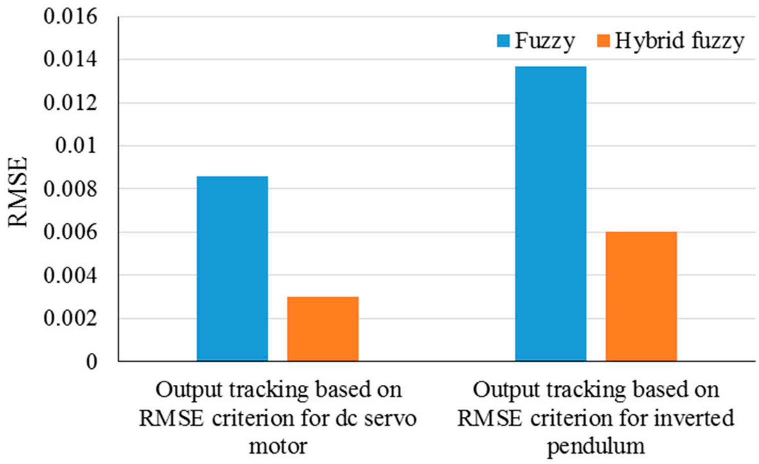

Figure 11. Results for the study by Li et al. (2005) [65].

In order to limit the current and voltage harmonics, and to improve total harmonic distortion and true power factor in Fatih Kececioglu, (2017) [66], a neuro-fuzzy controller is applied in a hybrid passive filter for PWM rectifiers. Gnanaprakasam (2015) [67] proposed a hybrid approach for the detection and classification of the vibration signal of an induction motor in which the fault detection process including the extraction of significant features of vibration signals is carried out by using the S-transformation algorithm. After, the ANFIS classification technique was employed to classify the signal into its faulty or the normal state. S-transform-ANFIS, S-transform- radial basis function neural network (RBFNN), S-transform-FFNN, and DWT-RBFNN were compared in terms of accuracy, sensitivity and specificity for IR faulty condition, centered or fault, opposite or fault, orthogonal or fault, and BB fault conditions. The general results have been presented in Figure 12. In all conditions, S-transform-ANFIS has the highest accuracy, sensitivity, and specificity compared with those for the other methods.

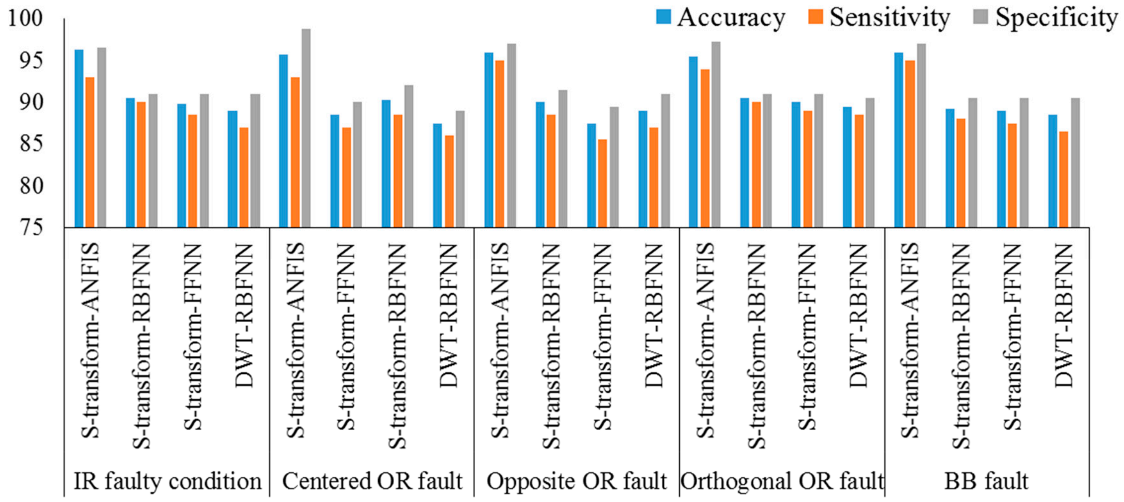

Figure 12. Results for the study by Gnanaprakasam (2015) [67].

In the paper by Hossain (2015) [68] three nonlinear control strategies are compared, namely the fuzzy logic controller, SNC, and ANFIS-based controller. Their results show that the proposed fuzzy logic controller-, SNC-, or ANFIS-based VR-FCL are effective in improving the transient stability of a large-scale hybrid power system consisting of a doubly-fed wind power generator (DFIG)-based wind farm, a PV plant, and SG.

In general, in all cases mentioning fuzzy systems, the fuzzy controller has a robust and smooth controlling process, which improves the control process and causes less damage to the hardware used and reduces the cost of servicing and maintaining of the systems. On the other hand, this would have a direct impact on the energy consumption of the control system and would lead to more sustainable control in the control system. This conclusion has also been confirmed in a study by Ardabili et al. (2016) [69] to design a fuzzy control system in a mushroom growing hall. Also, the operator's dominance and focus also increase with the use of fuzzy systems. Hyphenation hybrid systems can also optimize the system with the benefits of both fuzzy and neural systems in parallel with the creation of a fuzzy control sustainable system.

3.2. Neural Computing

The concept of neural networks is usually employed in itself. As the literature review reveals (see, Table 4). ANNs are a common tool of control tasks of electrical machines as other engineering applications [70,71]. However, it seems that the abilities of the nets have not yet been exploited in the field of machine design.

Table 4. Artificial neural networks.

Reference	Year	Technique	Application
Bouchiba [72]	2017	ANN-SMC	Control of multi-motor system coupled induction motors
Çelik et al. [73]	2017	multi-layer feedforward ANN	estimate the output power and efficiency of AFP SG
Zammit et al. [74]	2016	ANN controller	Direct torque control of DFIM
Zouggar et al. [75]	2018	ANN	Voltage and frequency control of a self-excited induction generator

Considering the ANNs–based solutions in the field of electrical machines the study of Bouchiba (2017) [72] provides a fresh example of the NN sliding mode controller for the control for multi-machine web winding systems. The advantage of this technique is that it can significantly reduce the chattering phenomenon and improve the error performance. In this study, the simulation and evaluation processes were performed by employing MATLAB/SIMULINK software. Based on the results, ANN-SMC controller has ignored the effect of disturbance. On the other hand, it is clear that the application of a hybrid PI-SMC controller is easy, but the performance of ANN-SMC controller is better than that for the PI-SMC. Detailed results indicate that the net performance improvement and the robustness of ANN-SMC controller are also strong superiority points compared with PI controller. Çelik et al. (2017) [73] designed a feed-forward multilayer NN in order to predict the efficiency and output power of an axial flux permanent magnet SG. Their tests have shown that the NN is highly suitable for this purpose according to the obtained 3% and 4% error percentages. The efficiency and power of a magnet generator were estimated using a neural network method. Based on results, the best structure was 2–18–12–2 which generated a maximum error of 3.587% for power and −3.909 for efficiencies value. Also, NN controller could estimate the power values higher than that for the experimental limits, and it can be a suitable technique. Some modification and improvements proposed for the classical direct torque controller, e.g., Zemmit et al. (2016) [75] designed an ANN- Direct Torque Control in which the IP and switching table have been replaced by a new artificial neural network. This strategy can reduce the high torque and flux ripples. The paper of Zidani (2018) presents a voltage and frequency control technique of self-excited induction generators that applies a NN-based inverse dynamic model of the system. Results indicate that the proposed technique can significantly increase the performance and stabilize the terminal voltage. This can be an economical and efficient way for stabilizing the voltage, and also it can be used by field programmable gate arrays controller cards on a real-time benchmark system.

In general, according to the results of the papers developed by NN techniques, it can be seen that this method has the most predictive effect on simulations and can, therefore, affect the performance of the system. Therefore, this system can be modeled from empirical data and based on the behavior of the predictive functional system, and the user's tastes can have the least interference, unlike the fuzzy system. Also, all studies have been conducted in order to improve existing conditions and offer the proposed system the best performance compared to previous systems.

3.3. EC and Metaheuristics

Metaheuristics are computational methods which optimize problems by iteratively making efforts to refine the function of a possible solution(s) to achieve a measurement value while guaranteeing polynomial time despite brute force optimization methods. The set of metaheuristics contain various algorithms, such as ant colony, evolutionary optimization, genetic algorithms, etc. EC is a subset of metaheuristics which involve algorithms or global optimization inspired by biological evolution. EC methods are stochastic optimization methods in which the initial set of candidate solutions are generated randomly. After, the new generations (new sets of possible solutions) are iteratively updated while mitigation the natural selection, mutation, etc. The fitting of a candidate solution is determined by a measure defined for the task under examination (see Table 5).

Table 5. Evolutionary computing and metaheuristics.

Reference	Year	Technique	Application
Mamede [76]	2018	GA and DE	Optimum design of SPSRM
Tamilselvi [77]	2018	Adaptive DE with FE	Design of PMMs for EV
Vanchinathan [78]	2018	BA	PID controller
Virtic [79]	2016	GA and analytical evaluation	Axial flux permanent magnet design

Optimization problems, especially ill-posed or multi-objective optimization tasks are common in control and design problems in most of the engineering problems, including electrical machine and drive systems. Most of the applications found in the latest paper employ the evolutionary computing techniques in nonlinear control tasks. There is only a limited number discussing the application or novelty of EC in rotating electrical machine design.

Design issues of electrical machines are usually raising complicated or multi-objective, ill-defined optimization problems. The application of Evolutionary-based solution or stochastic optimization methods can handle these problems by reducing the computational costs and simultaneously providing near-optimal solutions. For instance, Mamede (2018) [76] presents the combination of genetic algorithm (GA) and differential evolution (DE) techniques that allows maximizing the average torque and torque density and minimizing copper loss of single-phase switched reluctance machine (SPSRM). S. B. Tamilselvi, S. (2018) [77] proposes an evolutionary optimization procedure for the design of two, namely the surface-mounted and interior mounted permanent-magnet motor (PMMs) configurations using DE algorithm. Optimization tasks are the core of most control problems also. The metaheuristic optimization methods are effective alternatives in such cases, especially in sensorless drives. Vanchinathan (2018) [78] introduce the bat algorithm (BA) in the parameter tuning issue of a fractional–order PID controller for speed control of sensorless control of brushless DC electric motors. Modified genetic algorithm (MGA), ABC, and BA methods were employed in FOPID controller in three loads (0, 50 and 100% of full load) and the simulation was performed using MATLAB/Simulink software. Based on results, the proposed BA method, have the lowest steady-state error (%), peak time (s), rise time (s) and settling time(s) compared with those for the other methods in each load, separately (Figure 13). It seems that BA method has the best performance at 100% in case of settling, rise and peak times but in case of steady-state error, the condition of 0% provides the best performance for BA technique. The detailed results have been presented in Figure 13.

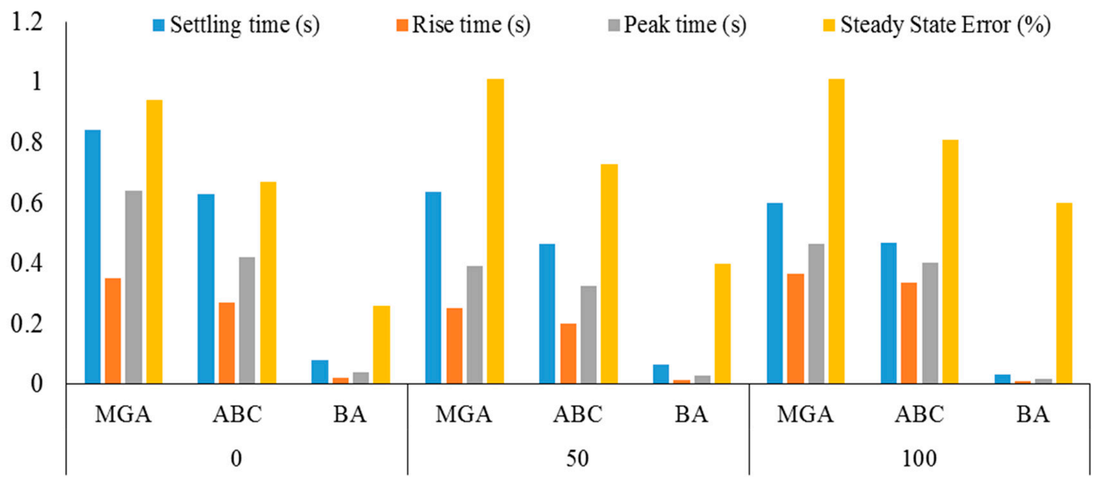

Figure 13. Results for the study by Vanchinathan (2018) [78].

The finding of Virtic (2016) [79] also supports that the evolutionary optimization with the analytical evaluation of objective functions significantly shortens the computational time required for design optimization in comparison with the finite element methods (FEM).

Considering the reasonable and suitable capabilities of the proposed method, it can be concluded that this method is considered as a process optimizer and according to its performance, it is suggested that the hybrid methods in this field can also be developed by researchers.

3.3.1. Ant colony

The ant colony system is a search metaheuristic which concept is based on the imitation of ants seeking nutrition. Ants can communicate with each other by a sophisticated way since they mark the different pathways from the anthill to the food sources and back by pheromone hormone respectively. The pheromone paths are perceived by another ant, and most likely followed. Pathways to foods can be very different, as well as obstacles between them. Ants tend to collect as much food as possible.

The characteristics of some individuals are different, but the unity of the colony is very effective. Each ant moves in an isolated and random way, but recognizing its pathways marked with pheromone is also likely to follow them. Meanwhile, an increase in their pheromone concentration by pheromone emissions, thereby increases the concentration of the pheromone attractiveness. Thus, the frequencies of frequently used routes increase the pheromone's level while being neglected paths. The pheromone emitted by the ants continuously vaporizes, that is, confirmation on the given route (releasing a new pheromone dose) without decreasing the pheromone level (until contains pheromone). If there are two paths leading to food, the shorter route is more likely to turn the ants (as they arrive sooner and later back). Thus, they often reinforce the pheromone level, thereby providing higher "attractiveness" for the route. However, this will attract more ants to the shorter journey. After a while, the shorter way will be taken by most ants, while the longer path for pheromone levels will decrease to a minimum level. The ant colony metaheuristic shares the search task between the ant agents. These agents have very basic subtleties and, to a certain extent, simulate the behavior of true ants. "Artificial ants" (agents) build on solutions based on appropriate problem-specific constructive heuristics. A pheromone matrix determines the order of the building blocks of the solution used to construct good solutions. The values stored in the pheromone matrix are taken into account by the other agents on a probability basis when constructing his solutions. The first ant colony algorithm was applied for the traveling salesman problem (TSP). Since then, it has been widespread in engineering practice. Table 6 includes application of ant colony in rotating electrical machines.

Table 6. Application of ant colony in electrical machines.

Reference	Year	Technique	Application
Ameli et al. [80]	2017	Ant colony	Simultaneous dynamic scheduling of feeder reconfiguration of DG units having uncertain and variant generations
Batista et al. [81]	2014	AS and ant colony algorithm on the graph	Interior permanent magnet motor design

Ameli (2017) [80] applies the ant colony algorithm in distribution systems. The purpose of their study is to minimize the total operational cost of the grid and to reduce the costs and losses. Based on Figure 14, the proposed method strongly reduces the network power losses for both total voltage profile index (TVPI) and total power loss index (TPLI) of the DG units.

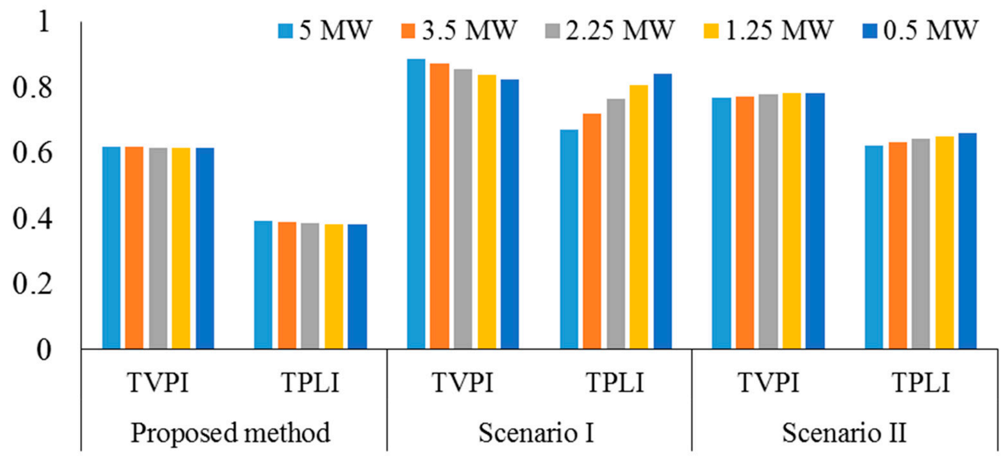

Figure 14. Results for the study by Ameli (2017) [80].

Batista (2014) [81] gives a novel solution where the permanent interior magnet motor design domain is discretized into a suitable equivalent graph representation and an ant system (AS) algorithm is employed to achieve an efficient distribution of materials into this graph. Ant systems have successfully applied also to control problems. The proposed method provided sustainable torque and suitable shapes for designed problems. The results show that the mechanism of optimization of the multi-dimensional topology of electromagnetic devices was successfully performed by the proposed method.

3.3.2. Tabu and Cuckoo Search

The tabu search proposed by Glover (1986) [82] is based entirely on the methods described above and their direct development. In the immediate environment of our current solution, we are investigating new, better solutions. In the tabu search method we are always trying to keep moving, so we always look for the best solution in the environment, even if it is worse than the solution being tested. Since this method has a lot to explore, we have to keep in mind that we need to select the direction in which the search was going and in which direction it was not yet. This so-called taboo lists that are marked by taboo tabs. Limitations on taboo tabs helping to get through the roads already gone by, increasing the search effectiveness. The cuckoo method [83] is a similar optimization method inspired by the breeding behavior of cuckoo species. In this approach, the eggs represent the possible solutions and the search is performed by the quality of the eggs, which leads to finding the best solution. The main differences and advantages of the discussed approaches can be found in some of the most interesting publications collected in Table 7.

Table 7. Tabu and cuckoo search techniques.

Reference	Year	Technique	Application
Chen et al. [84]	2017	The best-guided cuckoo search algorithm	Optimization of power systems
Wang et al. [85]	2018	Improved tabu search algorithm	Optimize a hybrid excited generator
Yang et al. [86]	2015	Improved tabu search algorithm	Performance evaluation of PM motors

The gbest-guided cuckoo search algorithm with the feedback control strategy and constraint domination rule for the security and economic operation of the power system is discussed in Chen et al. (2017) [84]. Results of the proposed method were compared with the results of another method developed by researchers in this field. The comparison results indicate that the proposed approach could provide high-quality, feasible solutions for different problems.

The paper by Wang et al. (2018) [85] proposes a hybrid excited generator for variable-speed wind power generation systems. The excitation sources are PMs on the rotor and the field windings on the stator. The proposed generator can achieve constant voltage control and maximum power point tracking control by controlling the field current while the optimization is carried out by a modified tabu search method. In Yang et al. (2015) [86] a new topological design of PM motor is investigated via five different types of permanent magnet arrangements. An improved tabu search algorithm and finite element method are proposed for the evaluation of the performance of these motors.

3.3.3. Simulated Annealing (SA)

The simulated annealing (SA) method was proposed by Kirkpatrick, Gelatt, and Vecchi in 1983 [87]. The SA searches for a new solution in the vicinity of a randomly chosen initial solution. However, if certain probability conditions are met, it also allows the solution to deteriorating. Therefore, it can escape from a local optimum that a gradient-based or a hill climbing type algorithm cannot. In the vertically improving methods, a series of random points is generated while in the target function improvement can be observed. To apply the SA strategy, it is necessary to define the following four main elements for each optimization problem; (a) solution space, (b) transition (i.e., how to generate a new random point), (c) fitness function, d) annealing schedule (i.e., determination of the number of iterations to be performed in the internal cycle and the method used to reduce the control parameter in the outer cycle). One of the advantages of the algorithm is that it can be easily implemented.

Furthermore, the SA algorithm with proper parameterization does not stick in a local optimum (see Table 8).

Table 8. Simulated annealing.

Reference	Year	Technique	Application
Chiu et al. [88]	2016	SA	Optimization space-constrained base-vibration system excited with a specific frequency
Farhani et al. [89]	2017	SA	Real-time efficiency optimization of the direct vector-controlled induction motor drives
Torrent–Fontbonne and López [90]	2016	SA	DGs

SA is an efficient tool for various optimization problems. It is shown by Chiu et al. (2016) [88]; that SA can be applied in the optimization task of space-constrained base-vibration systems. Based on the results, in the case of increasing the base-vibrating frequency, the extracted electrical energy will increase. Consequently, based on the buckling and fatigue analysis, the employed approach for an optimal designed one-mass vibration-based electromagnetic energy harvester is quite efficient in maximizing the energy.

Simulated annealing algorithm is used for finding a global optimal rotor flux while the suboptimal operating point is determined by a fast, analytical method using the induction machine's model in work of Farhani et al. (2017) [89]. The paper by Torrent–Fontbona and López (2016) [90] reviews the problem and provides a new solution for supporting grid planning with an optimized number DGs. A particle swarm optimization method is found to be the tool for finding the optimal number of DGs which allows for maximizing the profit of the generators, minimizing the system losses, and improving the voltage profile.

3.4. Probabilistic Reasoning and Bayesian Networks

The core of the theory of Bayesian interpretation of probability is based on a concept that probability is a measure of a rational agent's degree of belief in a proposition Ramsey (1926) [91], and de Finetti (1937) [92]. Probabilistic reasoning with graphical models, known as Bayesian networks or belief networks, has become an active field of research and practice in artificial intelligence, operations research, and statistics in the last two decades. In order to reduce the computational needs, an asymptotic approximation could be applied, but it reduces the precision level. Therefore, Bayesian-type methods are mostly applied in power system and network analysis as can be seen from Table 9. Few examples can be found for diagnostics problems or parameter estimation problems of power systems using Bayesian techniques.

Table 9. Application of probabilistic reasoning in the field of electrical machines and power systems.

Reference	Year	Technique	Application
Kari et al. [93]	2018	ANFIS and Dempster–Schafer	Fault detection of power transformers
Kazemdehdashti et al. [94]	2018	Density estimator based on generalized cross-entropy method	Optimal power flow problem in networks containing renewable energy resources, nonstationary loads
Torrent–Fontbona, F. and B. López [70]	2017	Probability theory methods and neuro-fuzzy modeling	Networks containing renewable energy sources

The dissolved gas analysis (DGA) approach is the basic tool for fault detection of power transformers. Kari (2018) [93] introduces an ANFIS system for these purposes. The outputs of the ANFIS model are evaluated by the Dempster–Schafer method which is originally developed for medical reasoning problems. The results of consistency, accuracy, and reliability have been presented in Figure 15. As is clear, the proposed method has the highest average consistency, accuracy, and reliability.

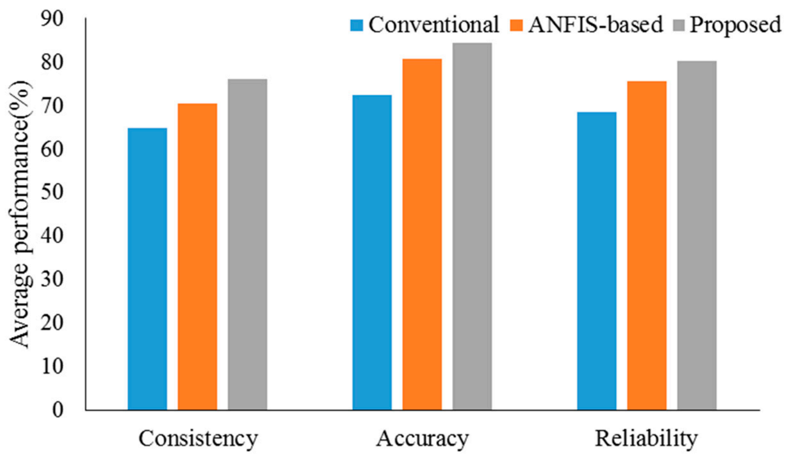

Figure 15. Results for the study by Kari (2018) [93].

Kazemdehdashti (2018) [94] introduces a new density estimator for optimal power flow problem of networks containing renewable energy sources, etc., using generalized cross-entropy method. Figure 16 presents the results of the study in terms of RMSE (a) and time (b) for comparing the proposed method for 14-bus. As is it shown, the RMSE of the proposed method is lower than that for the other methods, but this has increased the processing time. The two-point estimation method (TPEM) has a lower processing time and lowers accuracy.

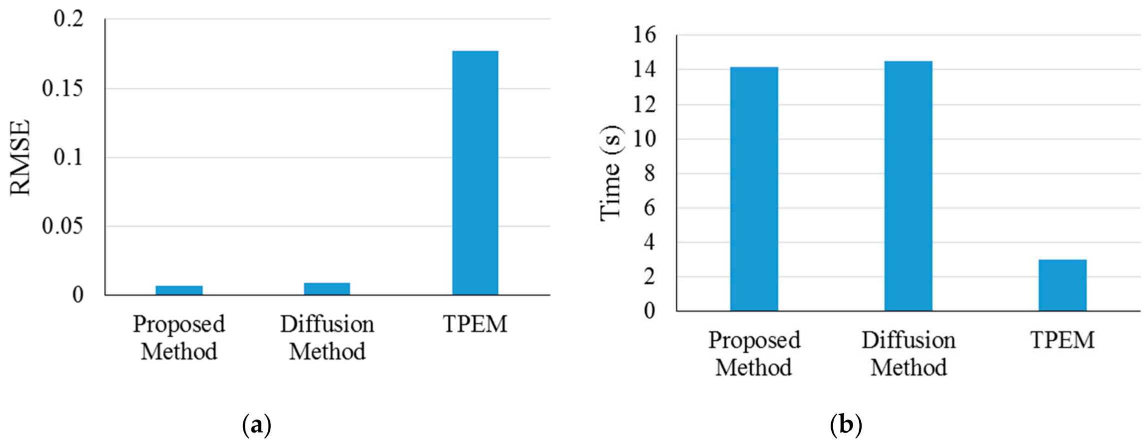

Figure 16. Results for the study by Kazemdehdashti (2018) [94] in terms of (**a**) root mean squared error (RMSE) and (**b**) time.

The paper by Jiang et al. (2015) [95] presents an integrated Bayesian probabilistic method for precise power splitting and the degradation diagnostics of a single-shaft combined cycle plant, accounting for uncertainties in the measured data. Lakehal et al. (2017) [96] introduces a Bayesian network based on the Duval triangle method in the dissolved gas analysis which is the primary technique for identifying faults in transformers. The proposed model makes a quantitative estimation analysis of transformer faults, which supported the IEEE C57.104 standard (see Table 10).

Table 10. Application of Bayesian methods in the field of electrical machines and power systems.

Reference	Year	Technique	Application
Jiang et al. [95]	2015	Bayesian inference method	Diagnostics of a CCGT power plant
Lakehal et al. [96]	2017	Bayesian network based on the Duval triangle method	Transformer condition monitoring via Dissolved gas analysis
Mansouri et al. [97]	2015	Bayesian methods	State and parameter estimation of IMs

Mansouri et al. (2015) [97] applies the Bayes method in a nonlinear time-varying state and parameter estimation task of induction machines (Ims). Based on results, the Bayes method has higher accuracy. Based on the results of the second comparative study, for all methods, estimation accuracy depends on estimating the model parameters as well as the convergence of the estimated parameters and states.

3.5. Hybrid Soft Computing Methods

Single SC techniques are found to be efficient due to their robustness and easy interpretability. At the same time, though their usage can be so advantageous, it is still limited by their exponentially increasing computational complexity. The combination of different techniques offers the synergy of their beneficial properties. Consequently, hybrid soft computing techniques have gained popularity (see Table 11).

Table 11. Application of hybrid methods in the field of electrical machines and power systems.

Reference	Year	Technique	Application
Dai et al. [98]	2016	Quantum-behaved PSO for parameter identification with SA	Ensure the accuracy of the DFIG for control performance of the generator
McDonald [99]	2017	Hybrid GA and pattern search process	Magnet SGs for offshore direct drive wind turbines
Meo et al. [100]	2016	Combining a multi-objective PWO and ANN	Design optimization of a direct-drive permanent magnet flux switching generators

Dai et al (2016) [98] propose a new hybrid quantum-behaved particle swarm optimization-based solution for improving the precision of parameter identification (five parameters including stator resistance, stator inductance, rotor resistance, rotor inductance, and mutual inductance of stator and rotor) of the DFIG. Results indicated that the proposed algorithm accelerated the computing process by reducing the processing time. For the optimization of direct-drive permanent magnet synchronous generators, McDonald, (2017) [99] used a hybrid genetic algorithm and pattern search process and has found that the surface-mounted permanent magnet generator produces the lower cost of energy.

With the purpose of reducing the costs and weight of the machine while maximizing the amplitude of the induced voltage as well as minimizing its total harmonic distortion Meo et al. (2016) [100] has presented a new hybrid approach for the design optimization of a direct-drive permanent magnet flux switching generators. Figure 17 presents the results of hybrid model, non-dominated sorting genetic algorithm (NSGA-II), abyss and proposed ANN-multi-objective particle swarm optimization (SMPSO) in terms of cost (a), total harmonic distortions of voltage (THD) (b), weight (c) and rated line voltage; em (d). As is clear from Figure 17, the proposed method reduces the cost ($) by about 23.85%, reduces the THD by about 17%, reduces the weight by about 44.73% and increases em by about 2.6%. These values claim that the proposed hybrid method improves the condition compared with that for the other techniques.

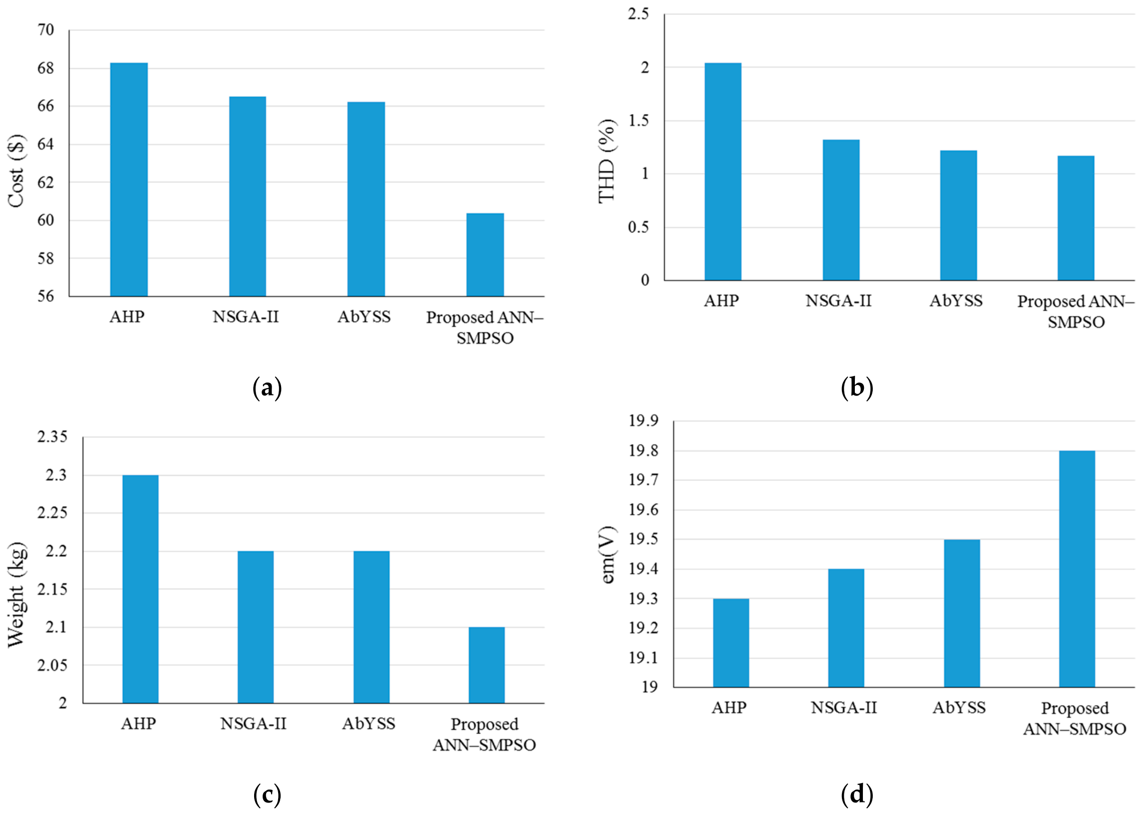

Figure 17. Results for the study by Meo et al. (2016) [100] in terms of (**a**) cost; (**b**) THD; (**c**) weight and (**d**) em.

In general, it can be claimed that hybrid methods can be the most successful methods than single methods because these methods can take advantage of several methods simultaneously and reduce the defects in each method. With the advancement of artificial intelligence and soft computing methods, the trend towards hybrid methods increases for the reasons given. There are still many hybrid methods that have not been used, which suggests that exploration of these methods be increased which can clarify the dark points in this and increase the orientation and usage by the researchers.

4. Discussions

The trend of recent years suggests that the greatest flexibility of design may be ensured by soft computing tools. In this paper, we explore the latest techniques of intelligent algorithmic methods for design and control of electrical machines and investigate how the reviewed methods affect the solution.

The great majority of automated control tasks needs the existence of the system model on some level. General practice of the simple feedback control applies the a priori knowledge, i.e., the system is regulated by the variation of the measured output. However, in practice, the system under control is highly nonlinear, only a few variables are measurable external disturbances degrade the performance, and also the technological processes generate further constraints in the desired control of the system dynamics [101]. Also, adaptive and advanced control methods usually apply the mathematically complicated Lyapunov method [102,103]. It is clear that the system modeling and mathematically easy manageability provided by advanced methods are the key factors in a successful control method design [23]. The choice of the proper control law in case of a specific electric machine and drive system raises many questions. Below we attempt to highlight how the replacement of conventional techniques with the various ”soft” approaches collected in this paper may allow the greatest benefits.

The algorithmic approaches rely on the physical system equations of motion described by mathematical equations. Such techniques calculate analytically, for example, the controller’s parameters. In such cases when information may be incomplete, or the system model is not fully available, fuzzy logic can be applied as a universal approximator due to the linguistic terms. It is suitable for modeling the system behavior, deducing the control law by fuzzy reasoning built on implications or tuning the parameters by applying the suitable membership functions. Furthermore, the various fuzzy operators allow the flexible fitting of the model behavior to the real scenario. Engineers usually face regression tasks during the control design process. The regression in practice is related to measured data. For each measurement, an error value should be assigned so that the classical regression cannot be handled in common models. Despite this, the fuzzy regression assigns the error values to the measurement error and if the regression line is within this error range that line is accepted. However, an infinite number of lines with such properties may exist within the error range. Therefore, by applying a fuzzy membership function which follows the error probability's distribution and setting a rule basis could easily solve this problem without large computational burdens.

A potential advantage of fuzzy logic-based approximation is that they allow us to optimize multiple variants and configurations and reduce complexity so that the problem may have limited to a smaller number of parameters. Furthermore, the linguistic variables ensure great flexibility context-sensitive machine modeling. This will allow the system to learn by example. We can construct rules whose results are as close as possible for the expected results.

Additionally, the classical control methods require the immediate response of the system in various situation depending on the environment's reactions. Fuzzy control allows taking into account not just the physical properties but also the rules that cannot be exactly mathematically described. A real situation would require a large number of parameters that cannot be totally measured under the operation conditions, for instance, if we wish to teach an electric car how to behave in specific traffic situations. Such cases demand immediate responses, and we cannot wait minutes while the onboard computer solves complicated differential equations since the application of fuzzy logic and other soft computing tools allow the system to learn from examples. After the proper rule system is set up, the system can give the nearly ideal responses.

It is obvious when the only the approximate system model is available, heuristic or cognitive techniques can be applied which describe the context- or situation-dependent behavior of the system. The neural networks emerging from statistical methods are capable of approximating a regular function [104]. This property is highly advantageous in nonlinear control problems where analytically unknow nonlinear functions are required to be found using only a few (measurement) data. Today a significant number of the NN variants are known, therefore specific and highly nonlinear cases can be efficiently handled. We should emphasize that both NN and fuzzy methods can be adapted in most of the conventional control and system modeling techniques.

The estimation of the physical parameters which characterize the model of the machine is also essential for the efficient control of electrical machines. Parameter estimation is particularly fundamental in condition monitoring tasks. Here, the parameter estimation techniques are similar to the methods applied in the control law synthetization and state observations. Such tasks mainly result in nonlinear programming problems where the previous knowledge may become crucial. Since the Bayesian statistic may enhance the estimation performance in contrast to classical probabilistic solutions, examples can be found, e.g., in [105] and in the publications mentioned in Section 3.4. Furthermore, an important step of the estimation is its convergence. Resulted optimization problems may have many constraints. At this point, the evolutionary computing techniques, for instance the heuristic search methods, are applicable, such as genetic algorithms, taboo search, cuckoo method, etc.

Optimization issues arise in most engineering disciplines, and we encounter them in our everyday life. The optimization task aims to achieve the best possible solution according to some objective function by setting the appropriate values of the decision variables. Finding the optimal solution is typically a difficult task because, in practice, the target function is nonlinear, different constraints may occur, etc., and often the algorithm stuck into local extrema of the search space. In case of electrical machine design, although the general practice gives the main directions [4], all of the modeling assumptions are necessary to be satisfied from the beginning of the design process [106] since design optimization may dispute further questions. Constrained multivariate optimization problems usually arise during machine design issues from which it follows that the mathematical models become more complicated.

The classical design practice can describe the problems only with complicated differential equations. Of course, the parameters must be known to solve the equations. Usually, it would take many parameters to describe a real system, or it would take a too long time to solve the problem. The parameters in most cases otherwise cannot be measured. It is, therefore, necessary to estimate them. Another solution is soft computing, especially fuzzy logic.

The general feature of designing technical systems is that the same task can be solved in several ways [107]. Comparison of individual solutions is rather subjective, weighing the advantages and disadvantages relative to each other basically influences the assessment. The solution that is considered to be optimal can only be selected by a pre-formulated criteria system. The subjectivity of judgment is carried by the accepted criteria system. Since its adoption, the optimum system selection has become a specific task. We should be aware that one solution that is considered to be optimal by one of the criteria systems, using another set of criteria, is no longer optimal. Fuzzy logic is proven to be suitable in such assessments. The optimal solution may depend on the applied model parameters. Therefore, once the optimal model has been set up a post-optimality analysis should be performed, usually referred to as parametric study. The role of sensitivity analysis is revealing the sensitive parameters. Classical techniques of sensitivity analyses are observing the influence of the perturbation of the parameters. Soft computing tools could also support this step of the process by providing soft boundaries of the sets.

We see that finding a single optimum solution can be a major challenge. However, finding several optimal solutions at once may result in a more complex task. The so-called multi-modal optimization (MMO) approach serves as a solution to these latter optimization problems [108] during the machine design process. Multimodal optimization could benefit from the various evolutionary-based methods, for instance in founding the basin of attraction of the optimum, or reducing the search domain. Also, the above chapters give insight into modern heuristics which may speed up the design process with a combination of classical optimization because they allow easy parallelization and system-level optimization. Similarly, the fulfillment of the various conditions of the model configurations at the same time is problematic and requires skillful designers. MMO performs the design process by optimizing multiple models having some shared variables. The multi-model optimization approach uses different representations, including coarser and more detailed models, and allows multiple configurations [108]. Therefore, in these cases, stochastic searching methods play a prominent role. Many studies suggest various evolutionary algorithms to multimodal problems (see, e.g., [109]).

However, the expected improvement depends on many conditions, of which the most prominent may be the performance. Most of the suggested algorithmic techniques are only partially effective or applicable to a specific class of problems without the capability of simultaneously satisfying all the different requirements. Further investigations are needed to achieve more reliable and general methods. The theory of fuzzy logic has been elaborated and well established by today, but its introduction into new areas is still ongoing. From the above presented general panorama of the literature, it is obvious that there are only a few results on the global optimization solutions of evolutionary techniques and there is still limited contribution for its fundamental theory. Altogether, these observations suggest that by transferring the approaches between intelligent computational methods in the direction of MMO approaches could be an excellent step toward new and effective algorithmic techniques and plausible theory.

5. Conclusions

Electrical machines and drive systems account for more than half of the global electricity used, and most of it is consumed by electric motors. Thus, there is a great demand for efficient designs to satisfy the competitive requirements. Furthermore, due to the trend of automation, demonstrated in the review, the control and drive systems of electrical rotating machines are expected to continue to grow. Having mentioned that, the control systems and design methodologies and techniques will be evolved to achieve higher performance.

Several SC models reviewed that dramatically improved the efficiency of rotating electrical machines through improvement of parameters for finite element analysis, and nonlinear time-domain finite element analysis. It was observed that most of the issues of each design and control steps are covered by advanced methods. A wide range of intelligent computational techniques serves for the designers, and all of them has advantages and disadvantages. Choosing the optimal method of SC shown to be not an easy task. Such a selection task requires the user to understand the differences among the computation algorithms. This brief literature survey indicates that the fundamental issue is finding the trade-off among model complexity, accuracy, and computing time. Designers could use a combination of various soft computing techniques as the optimal solution to obtain the required machine performances as hybrid techniques.

Recent studies have provided, from a theoretical point of view, how modern heuristics and soft computing techniques may improve the efficiency of engineering practice in the field of electrical machine design and control. Due to the problem-specific nature of SC methods, new effective algorithmic techniques are necessary to be designed for implementing them in any stage of the process. Potential advantages of SC relying on the capabilities to deal with context-sensitivity, high flexibility despite classical methods based on sharp borders. Additionally, without complex mathematical operations, sorting can be automatically performed on alternatives. Also, the relationships between categories can be easily examined.

At present, there is still no general theory or methodology for designing such heuristics, e.g., ANN, GA, etc. The primary intention of the designer should be the specification of the structure of the neural network or the fuzzy reasoning system, etc. After, the key parameters must be identified. Experimental results may help in training these systems.

Our review supports that the hybrid methods outperform the standard ones. Considerable progress in the field could be achieved by the synergetic utilization of the heuristic algorithmic and MMO methods. Our research could support designers in finding enhanced methods.

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Acronyms

ABC	Artificial bee colony
AS	Ant system
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial neural network
ANN-SMC	Artificial neural networks - sliding mode control
ANN-SMPSO	ANN-multi-objective particle swarm optimization
BA	Bat algorithm
CCGT	Combined cycle gas turbine
DC	Direct current
DFIG	Doubly fed induction generator
DL	Deep learning

DGA	Dissolved gas analysis
DSIM	Dual star induction machine
DG	Distributed generation
DE	Differential evolution
EC	Evolutionary computation
FE	Finite-element
EV	Electric vehicle
FR	Feeder reconfiguration
IM	Induction machine
MLP	Multi-layered perceptron
SA	Simulated annealing
IM	Induction machine
SPSRM	Single-phase switched reluctance machine
PMSG	Permanent magnet synchronous generator
PMMs	Permanent-magnet motors
PID	Proportional integral derivative
TPLI	Total power loss index
NSGA-II	Non-dominated sorting genetic algorithm
PV	Photovoltaic
DFIM	Double fed induction machine
GA	Genetic algorithm
NFC	Neuro-fuzzy controller
MAE	Mean absolute error
MPE	Mean percentage error
DWT	Discrete wavelet transform
SVM	Support vector machine
PM	Permanent magnet
MIC	Multi-functional intelligent controller
IPMSM	Interior permanent magnet synchronous motor
MMO	Multi-model or multi-modal optimization
MWT	Multi ripple remodel
PSO	Particle swarm optimization
MGA	Modified genetic algorithm
SC	Soft computing
RBF	Radial basis function
TPEM	Two-point estimation method
ML	Machine learning
VEH	Vibration energy harvester
SG	Synchronous generator
RMSE	Root mean squared error
SNC	Static nonlinear controller
GRNN	Generalized regression neural networks
RBFNN	Radial basis function neural network
TVPI	Total voltage profile index
GW	Grey wolf
AFPMSG	Axial flux permanent magnet synchronous generator

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