Metaheuristic Optimization Methods Applied to Power Converters: A Review

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***Abstract*—Power converters systems aimed at renewable energy applications have become a common option for sustainable electricity and distributed generation, since their performance has improved, and prices have steadily been reduced in the last years. However, there are still several drawbacks that hinder their widespread installation, such as the simultaneous minimization of cost and volume, efficiency maximization, size reduction, etc. Quite often, accomplishing these goals requires dealing with complicated optimization problems, which are difficult to solve by classical methods. Metaheuristic techniques provide a viable alternative to solve complex intricate optimization problems, such as those encountered in the development of power electronics converters. This paper presents a comprehensive coverage of metaheuristic methodologies applied in the area of power converters. The review includes a classification of the methodologies and main objective functions in each paper surveyed. An aim for this paper is to highlight the importance of the optimization tools, and the many benefits they provide to tackle the challenges encountered in the design, operation, and control of power converters.**

***Index Terms*—Evolutionary algorithms, genetic algorithm (GA), metaheuristic, optimization methods, particle swarm optimization (PSO), power converter.**

I. Introduction

OPTIMIZATION is a process that forms an integral part of daily life. In the most basic sense, it can be defined as a process of finding the best way to use available resources, while at the same time not violating any of the constraints that might exist. The optimization process involves several steps: Define a system mathematically, identify its variables and the conditions they must satisfy, define properties of the system, and then seek the state of the system (that is, the values of the variables) that yields the most desirable properties, either maximum or minimum.

Throughout the years, several approaches have been proposed to carry out the optimization. Most of these approaches are based on classical methods, such as the sequential unconstrained minimization technique, the augmented Lagrangian, Newton–Raphson (NR), the successive quadratic programming algorithm, the steepest descent algorithm, dynamic and integer programming, and the stochastic Newton optimization method. Classical methods, such as linear programming and nonlinear programming are efficient approaches that can be used to solve special cases of optimization problem in power system applications. However, a drawback of these techniques is that they are not well suited to solve complex optimization problems. As the complexities of the problem increase, especially with the introduction of uncertainties to the system, more complicated optimization techniques that overcome the limitations of classical approaches have to be used. Metaheuristic methods have been developed with this goal in mind.

Metaheuristic methods imitate the best features in nature, motivated by natural selection and social adaptation. Its fundamental properties and advantages have been described by Alba [1], Blum and Roli [2], Boussaïd *et al.* [3], and Dréo *et al.* [4], among many others.

1) The basic concepts of metaheuristics can be described on an abstract level, unlinked to any specific problem. Metaheuristic algorithms range from simple local search procedures to complex learning processes.
2) Metaheuristics use domain-specific knowledge in the form of heuristics that are controlled by an upper level strategy.
3) Metaheuristics are strategies aimed at "guiding" the search process, in such a way that the search space is efficiently explored.
4) Metaheuristic algorithms are usually nondeterministic (that is, they do not use the gradient or Hessian matrix of the objective function.), thus providing near-optimal solutions.
5) They include several parameters that must be fitted to the problem at hand, and may incorporate mechanisms to avoid getting trapped in confined areas of the search space.
6) More advanced metaheuristic techniques take advantage of the experience gathered from previous searches. This memory is used to guide the current search.

Metaheuristic optimization methods can be broadly divided into two classes: trajectory-based and population-based methods. The main difference between these two classes relies in the number of tentative solutions used in each step of the (iterative) algorithm. A trajectory-based method (e.g., hill climbing, tabu search, simulated annealing, and explorative local search methods) starts with a single initial solution, and at each step of the search, the current solution is replaced by another (often the best) solution found in its neighborhood. It is not uncommon for trajectory-based metaheuristic methods to quickly find a local optimal solution.

In contrast, population-based algorithms use a set of solutions (that is, a population of solutions). The initial population

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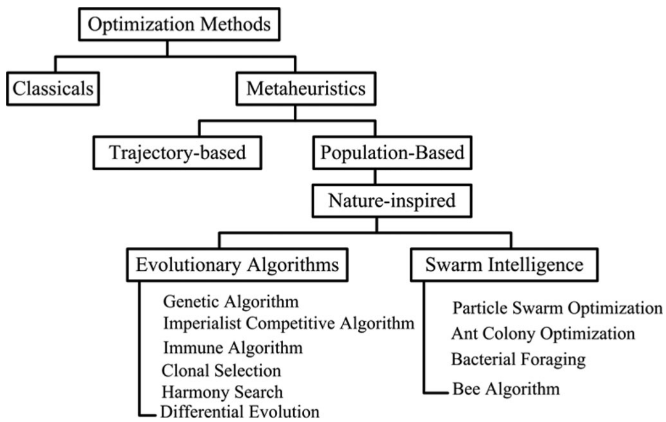

Fig. 1. Metaheuristics optimization methods classification.

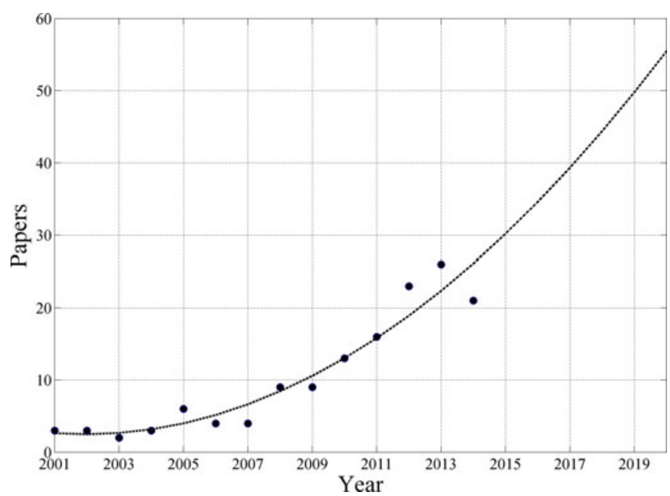

Fig. 2. Number of papers using optimization algorithms in the area of power converters.

TABLE I
DECISION VARIABLES

Power Converter	Semiconductor type and configuration (series or parallel)
	Length of heatsink
	Thermal resistance of heatsink
	Duty cycle
	Switching frequency
	Switching angles, in pulse modulated waveforms
	Amplitude of each voltage level, in multilevel inverters
Magnetic Components	Core size
	Core window width
	Magnetic flux density
	Current density
	Number of turns to the windings
	Winding conductor diameter (AWG)
	Winding area
	Cross sectional area of the ferrite core
	Thickness of the copper layers of the winding
Filter	Capacitance
	Inductance

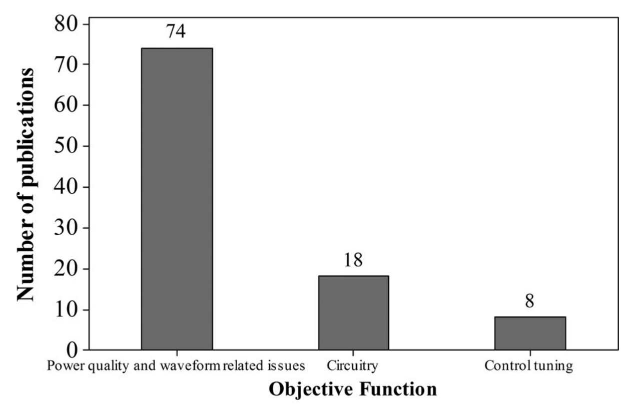

Fig. 3. Optimization topics in the area of power converters.

is randomly generated, and then, enhanced through an iterative process. At each iteration, some members of the population are replaced by newly generated individuals (often those whose characteristics are better suited to the problem at hand), yielding a new generation. These techniques are called exploration-oriented methods, since their main ability resides in the diversification in the search space [1]. Population-based methods have better performance for global optimization. Among these methods are evolutionary algorithms, swarm intelligence, and neural networks, which have received enormous attention in recent years, primarily because of the rapid progress in computer technology and the development of user-friendly software.

A simplified classification of the optimization methods surveyed x in this paper is shown in Fig. 1, synthetized from previous classifications already proposed in the literature.

Fig. 2 shows a histogram of the publications involving optimizing procedures in the area of power converters during the last ten years, and extrapolated for the next five. Prior to 2000, optimized designs were reported now and then. As can be readily appreciated, the number has increased substantially in recent years, and exhibits a growing trend.

From a power electronics point of view, the aim of a design optimization procedure is to completely specify the components which will be employed to build a converter, in such a way that its values, dimensions, operating frequency, etc., will result in the minimization (or maximization, depending on their nature) of a given characteristic previously defined by the designer (e.g., power losses, power density, THD, etc.), while simultaneously satisfying the design specifications [5].

In the majority of papers, the optimization procedure involves only the power converter stage, or some parts of it, such as magnetic components and the output filter. The decision variables regularly employed in power converter optimization are listed in Table I , grouped as those related to power converter, magnetic component, and filters.

Fig. 3 is a histogram of the objective functions reported between 2002 and 2013. Power quality and waveform-related issues account for 74% of the published papers. In contrast, only 18% of the papers deals specifically with circuitry related issues, such as efficiency, physical size (volume, weight and area) and cost, and a scant 8% with control tuning issues.

Numerous power converter topologies aimed at different applications have already been reported, many of them exhibiting good efficiency and power density. Hence, the current focus of research is not to devise new topologies, but to improve the existing ones by taking advantage of the optimization algorithms as tools for obtaining the best possible converter. The design, control, and operational problems encountered in the power electronics area usually involve the simultaneous optimization of multiple objectives, some of them often at odds with others (i.e., simultaneous minimization of design cost and maximization of the system reliability). With the purpose of solving the conflicts, these cases can be formulated as multiobjective optimization problems [6].

Metaheuristic methods have had a slow start in the power electronics area, in spite of the considerable amount of research information already available. Therefore, the paper is focused on population-based methods, such as evolutionary algorithms and swarm intelligence applied to power converters, covering applications reported after 2002 [16]–[115]. The main purpose is to provide an overview about the insights and implementation of the optimization techniques reported, as well as the trends in the applications of metaheuristic methodologies. An aim for this paper is to highlight the importance of the metaheuristic optimization methods, and the many benefits they provide to tackle the challenges encountered in the design, operation, and control of power converters.

II. Optimization Problem

An optimization problem involves three main aspects: decision variables, objective functions, and constraints. Decision variables (also called design variables) are quantities in the design process, which are selected by the designer, although they cannot be chosen arbitrarily because certain specified functional requirements must be satisfied. In the design of a power converter, the decision variables may be the physical dimensions, type and size of the inductor core, conductor diameter, number of turns, etc.

An objective function is the criterion or property to be optimized in the design, expressed as a function of the decision variables. The objective functions to optimize may be based on the weight, cost, volume, efficiency, or on a combination of two or more of the desired attributes. In turn, the constraints are restrictions that must be satisfied to produce an acceptable design. They are imposed by performance specifications, such as input and output voltages, rated power, THD, available electrical components, and thermal and electrical characteristics.

The optimization can be defined as the process of finding the conditions that provide the maximum or minimum value of the objective function [7]. Further, the optimization can be single objective (involving one objective function) or multiobjective (with several objective functions). Let $f(X)$ be a vector of objective functions. A multiobjective optimization problem is mathematically represented by

$$\text{Find } \boldsymbol{X} = \begin{Bmatrix} x_1 \\ x_2 \\ . \\ . \\ . \\ . \\ x_n \end{Bmatrix}, \text{which Min/Max } f(\boldsymbol{X}). \quad (1)$$

Subject to the following constraints:

$$x_l \leq x \leq x_u \quad (2)$$

$$g_j\left(\boldsymbol{X}\right) \leq 0, \quad j = 1, 2, \ldots, m \quad (3)$$

$$h_j\left(\boldsymbol{X}\right) = 0, \quad j = 1, 2, \ldots, p \quad (4)$$

where x is an n-dimensional vector of decision variables, x_l is a vector of lower limits, x_u is a vector of upper limits, $g_j(\boldsymbol{X})$ is a vector of inequality constraints, and $h_j\left(\boldsymbol{X}\right)$ is a vector of equality constraints. Each objective function in $f(\boldsymbol{X})$ can be either minimized or maximized. Unconstrained optimization problems, as the name implies, do not involve any constraints, and can be stated by (1). The problem stated in (1) with the constraints stated in (2)–(4), is a constrained problem, so called because it is subject to constraints that are weighted during the optimization procedure, and the goal is to maximize the weight of satisfied constraints.

III. Metaheuristics Methods

The term metaheuristic was coined by Glover (1986) and combines the prefix *meta-* (meaning "after" or "beyond", in an upper level) with *heuristic* ("to find" or "to discover"). In classical optimization methods, the exact, optimal solution is found in a finite (although often prohibitively large) amount of time. In contrast, metaheuristic methods are aimed at finding a solution that is "good enough" in a computing time that is, "small enough"; therefore providing a better tradeoff between solution quality (i.e., accuracy) and computing time [8].

Many metaheuristic algorithms have been developed in the last decades. Genetic algorithms (GA) and particle swarm optimization (PSO) have been widely applied because they have demonstrated two main advantages over trajectory-based methods: The ability of dealing with complex problems, and parallelism. Further, population-based methods have better performance for global optimization, and can deal with objective functions that are stationary or transient, linear or nonlinear, continuous or discontinuous.

A. Genetic Algorithm

GA was developed by J. H. Holland, in the early 1970s as a class of search techniques inspired by evolutionary biology. A GA optimizer does not operate on the parameters themselves, but rather on a coding of the parameters. It performs the following sequential tasks.

1) *Initialization:* The GA optimizer encodes the solution parameters as genes (according to previously defined rules),

creates a string of genes to form a chromosome, and initializes a starting population (which is merely a set of chromosomes, each chromosome being a solution to the optimization problem). Larger populations provide more genetic diversity, smaller populations yield faster execution, especially when dealing with complicated fitness functions

2) *Fitness Value:* Evaluates and assign fitness values to individuals in the population.
3) *Selection:* Selects pairs of the best-fitted individuals from the population according to a specific selection strategy.
4) *Crossover:* Selected pairs of individuals (parents) are combined to form two members of a new generation (children). Crossover ensures that each child includes a given number of genes from each parent, and is the primary way a GA optimizer searches for new better solutions. High probability crossover provides rapid searching.
5) *Mutation:* Randomly selects and changes a gene in each child; thus, providing a means to explore solutions not represented in the genetic pool of the current population. Mutation introduces solutions that would otherwise be excluded, but at the expense of pushing the population's average fitness away from the optimal value.
6) *Reinsertion:* Some members of the current generation are replaced by children from the new one. In generational replacement, the current generation is completely replaced by the new one. The process is repeated from step 2 until an appropriate stopping criterion is reached [9].

The selection of parameters and problem representation is a task that requires expertize, and has a crucial effect on both computation time and accuracy.

The optimal values for the parameters depend on the problem at hand, and on the amount of time that will be spend in its solution, usually requiring a compromise between accuracy and computational time [10].

There are several issues involved in problem encoding: the size of the initial population, the fitness function, the selection operator, the type of the probability of crossover and mutation, and the stopping criteria. These parameters are interrelated and affect the performance of the GA [11].

General rules are not easy to come by. For instance, in a particular application, the population size will depend on the complexity of the problem; several population sizes are tested and the one that yields the best results is reported. Afterward, similar problems can be solved with a population size close to the one already known to produce good results [12].

It is commonly assumed that decreasing population size provides a shorter execution time. It has been found, however, that beyond a certain point premature convergence slows the optimization speed down [13]. In terms of accuracy, larger populations provide better results, but it should be kept in mind that a very large population requires larger computational resources without substantially improving accuracy [10]. A small population size and a relatively large mutation rate is far superior than a large populations and low mutation rates [14].

TABLE II
OPTIMIZATION METHODOLOGIES APPLIED TO POWER CONVERTERS

Methodology \ Objective Function			Power quality and waveform related issues	Control Tuning	Circuitry
METAHEURISTIC	Evolutionary Algorithms	GA and variants	[16-53]	[90]	[98-100] [101-104] [105-107] [108,109] [111-113]
		Others	[54-59]	[91] [92]	[58]
	Swarm Intelligence	PSO and variants	[16] [39] [52] [60-81]	[93-96]	[98]
		Others	[82-84]	[97]	
	Neural-networks-based methods		[40] [85]		
Classical methods			[86-89]		[102] [107] [110] [114,115]

B. Particle Swarm Optimization

PSO was introduced by Kennedy and Eberhart in 1995. As its name implies, it was inspired by the movement and intelligence of swarms. A particle swarm optimizer is initialized with a set (population) of random potential solutions (particles) to the optimization problem, and each particle is assigned a velocity to move throughout the search space, which includes all possible solutions. The algorithm keeps track of the best individual, global fitness, and positions, iteratively performing four operations until some stopping criterion is satisfied:

1) evaluate the fitness of each particle;
2) update the best individual, global fitness, and positions;
3) for each particle, calculate the new velocity taking into account: a) the actual velocity; b) the actual position; c) the position that corresponds to the best individual fitness value; d) the position that corresponds to the best global fitness value;
4) for each particle, calculate the new position taking into account the new velocity.

The performance of the PSO optimizer depends on the manner in which the new velocities and positions are calculated. In a PSO system, multiple candidate solutions coexist and collaborate simultaneously. PSO system combines local search method (through self-experience) with global search methods (through neighboring experience), attempting to balance exploration and exploitation [15].

IV. SURVEY RESULTS

Table II lists the methodologies applied, sorted by number of occurrences and including all methodologies. A meager 9% of the reviewed papers used classical optimization methods, in contrast with 91% that use metaheuristic methods. It can be observed that, from the papers surveyed, the most common algorithms are PSO and GA. In the evolutionary algorithms

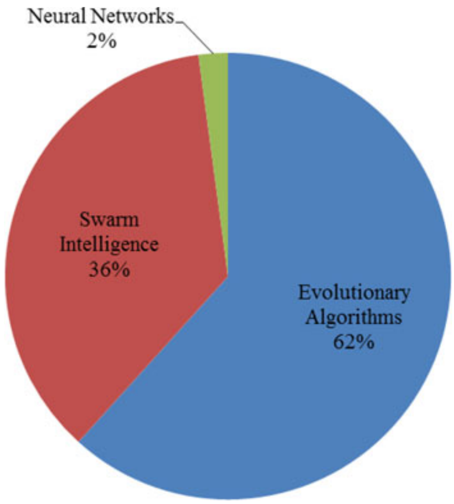

Fig. 4. Distribution of the metaheuristic methods applied to power converter optimization.

section, the row labeled "others" refers to methodologies, such as imperialist competitive algorithm, immune algorithm, clonal selection, harmony search, and differential evolution. In the swarm intelligence section, the row "others" includes ant colony optimization (ACO), bacterial foraging optimization (BFO), and bee algorithm (BA).

Fig. 4 shows the distribution of publications, where metaheuristic methods were applied to solve optimization problems in power converters. Fig. 5 shows the distribution of publications that use GA and PSO, within its respective category.

Regarding the objective function, Fig. 6 shows that most of the problems are formulated with just one objective function to optimize. Furthermore, the majority of the problems formulated with more than one objective function are converted into single-objective optimization problems.

A. Power Quality and Waveform-Related Issues

A problem frequently discussed is related to the waveform generated by an inverter. The distortion at the output affects the type of filter required, and the components values which must be selected in order to meet the constraints of the maximum THD allowed by the regulatory bodies of the electric grid [16]–[89].

The harmonic content can be improved using the selective harmonic elimination SHE technique. The challenge in this case is to solve a system of nonlinear equations in order to find the switching angles required to eliminate a given set of harmonics. In this application, it has been found that metaheuristic methods are more effective than conventional techniques [39]–[89].

In a general SHE case, there are more than two voltage sources and five output levels. Let $\theta_1, \theta_2, \ldots, \theta_{\mathrm{m}}$ be the m switching angles. According to Fourier analysis, the fundamental component is given as

$$a_1 = \left(\frac{4V_{\mathrm{dc}}}{\pi}\right) \sum\nolimits_{k=1}^{m} \cos(\theta_k) = M \tag{5}$$

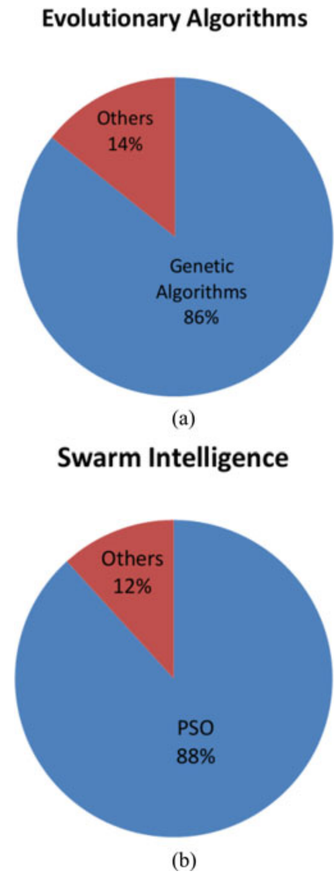

Fig. 5. Publications distribution within its respective category. (a) Evolutionary algorithms, and (b) swarm Intelligence.

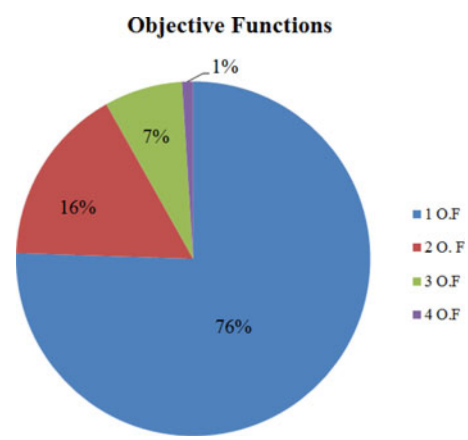

Fig. 6. Distribution of the number of objective functions in the optimization problem formulation in power converters.

where M is the desired amplitude. The harmonics to eliminate at the output are given by

$$a_n = \left(\frac{4V_{\mathrm{dc}}}{n\pi}\right) \sum_{k=1}^{m} \cos(n\theta_k) = 0 \tag{6}$$

where $n = 6i \pm 1 \ (i = 1, 2, 3, \ldots)$. Nonlinear transcendental equations are thus formed for the n harmonics to eliminate, keeping in mind that it is not necessary to include triple harmonics because they are automatically cancelled in a three-phase balanced system. After solving these equations, θ_1 through $\theta_{\rm m}$ is computed. It is clear that m – 1 harmonics can be eliminated with m switching angles. The THD of the output voltage waveform can be computed using

$$\mathrm{THD}(\%) = \left[\frac{1}{a_1^2}\sum_{n=5}^{\infty}(a_n)^2\right]^{\frac{1}{2}} \times 100. \tag{7}$$

To reduce the overall THD in the output voltage waveform, the objective function $F(\theta)$ expressed in (6) has to be minimized with the constraints of SHE. Mathematically, the problem can be formulated as follows:

$$\text{Minimize}\, F(\theta) = (\theta_1, \theta_2, \ldots, \theta_m)$$
$$\text{Subject to} : 0 < \theta_1 < \theta_2 < \ldots \theta_m < \frac{\pi}{2}; a_1 = M ... a_n \le \varepsilon_n$$

where $\varepsilon_{\rm n}$ represents the allowable limits of individual harmonics.

For instance, in [18], the GA optimization technique is applied to a seven-levels inverter. The goal is to determine the optimum switching angles that reduce several higher order harmonics while maintaining the required fundamental voltage. The solution is evaluated through simulations in MATLAB/Simulink, and the results are compared with the NR technique. The THD obtained with GA is 24.52%, while the one obtained using NR is 53.08%.

Hosseini *et al.* [21] present a comparison between the sinusoidal pulse width modulation (SPWM) and the SHE technique using GA, and applied to a multicell dc/ac converter. The power circuit includes a dc–dc isolation stage based on a high-frequency resonant mode converter, followed by interleaved dc–ac cells connected in series on the ac output. For each required harmonic profile, the GA finds the optimal set of switching angles. The THD in the voltage waveform obtained with the SPWM technique ($fS = 1.9$ kHz), is almost 13%, and around 10% with the optimized SHE technique.

Dahidah and Agelidis [38] present a methodology using PSO for harmonic elimination in multilevel inverters with nonequal dc sources. To demonstrate the effectiveness and robustness of the proposed methodology, several case studies involving different number of levels and harmonic profiles are carried out. A comparison between the conventional NR technique and the proposed PSO method is also performed. The results are summarized in Fig. 7, including the computational time and the corresponding THD.

It is clear that the proposed PSO is much faster and provides better results than NR. It should be pointed out, however, that although PSO converges to a suitable solution within a couple of seconds, this time may not be fast enough in highly dynamic and online applications, where inverters must respond in a fraction of seconds. In these cases, optimal switching angles can be calculated offline, and implemented by means of a look-up table or a well-trained neural network.

Debnath and Ray [39] present a comparison between GA and PSO techniques applied to the SHE problem. Two multilevel converters are considered, one with seven levels, and the second with 11 levels. The results summarized in Fig. 8 show that GA yields better performance in THD minimization and takes less computational time than PSO.

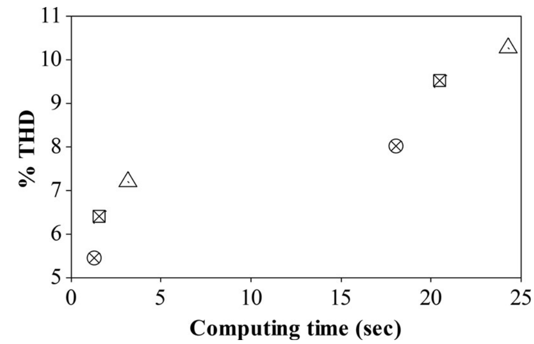

Fig. 7. Comparison between the NR method and PSO.

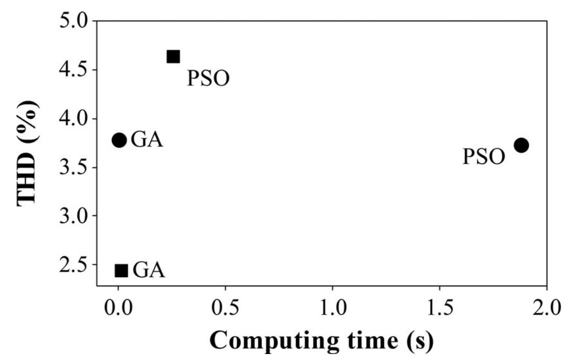

Fig. 8. Comparison between GA and PSO performance in THD minimization.

TABLE III
COMPARISON BETWEEN NR AND GA TO CALCULATE THE OPTIMAL SWITCHING ANGLES

Decision variables	NR	GA
$\theta 1$	6.39°	5.48°
$\theta 2$	18.9°	16.8°
$\theta 3$	26.8°	28.98°
$\theta 4$	44.78°	42.1°
$\theta 5$	62.08°	60.7°
THD (%)	6.83	6.08

Observing Figs. 7 and 8, it can be deduced that increasing the number of levels of the converter increases the number of decision variables (switching angles) in the optimization problem, causing an increase in the computational time.

Salami and Bayat [53] describe a GA approach to minimize the THD for the whole range of the modulation index in a three-phase 11-level inverter, taking the switching angles as decision variables. For comparison purposes, the switching angles were first calculated using a NR based method. Table III shows a comparison between these two approaches. The GA technique provided an 11% improvement over the NR technique, thus demonstrating its efficiency.

In the application described in [69], the binary particle swarm optimization algorithm (BPSO) is used to calculate the optimum switching angles for a single-phase full-bridge inverter. Simulation results demonstrate that low-order harmonics in the output current waveform are eliminated while, at the same time, keeping switching losses low. The results are compared with those obtained from a fixed-time algorithm. The BPSO algorithm provides a better performance ($THD = 0.76\%$, 176 commutations/cycle) compared with the fixed-time algorithm ($THD = 1.57\%$, 224 commutations/cycle).

Kaviani *et al.* [73] describe an advanced variation of the PSO technique applied to multilevel inverters (from 7 and up to 17 levels). The optimization is aimed at low-order harmonic elimination, and the results are compared with those obtained with a continuous genetic algorithm (CGA), a well-known metaheuristic method, and with those obtained with Sequential Quadratic Programming (SQP), one of the most successful numerical methods. The comparison confirms that PSO completely outperforms both CGA and SQP for all cases tested. Its implementation is much simpler than GA, and it converges to global optima with higher probability.

Compared to classical methods, it is clear that metaheuristic methods offer advantages, such as shorter time to convergence, higher accuracy, and better performance and efficiency. As a disadvantage, it is difficult to discern which one is the best methodology for the minimization of THD. PSO and GA have proved themselves to be effective solutions to optimization problems. However, these techniques do not provide suitable solutions for all the problems, despite their apparent robustness. There are adjustment parameters involved in these methodologies, and appropriate setting of these parameters is a key point for success. Additionally, for both approaches the major issue in implementation lies in the selection of an appropriate objective function.

B. Control Tuning

The estimation of self-tuning parameters for inverter controllers can be formulated as a constrained optimization problem, which has been solved using methods based on evolutionary computation algorithms. These methods can provide real-time response, an important feature that improves the power quality in grid-connected systems [90]–[97].

Lexuan *et al.* [90] propose an optimization method for improving operation efficiency of a paralleled dc–dc converter system; the system load current is equally shared among converters and the system efficiency is low especially at low- and medium-load conditions.

The objective function is the minimization of system total conversion losses, and the virtual resistances of the system are decision variables. A virtual resistance shifting method is proposed to adjust the power sharing proportion among converters. Hierarchical control conception is adopted so that droop method is employed on top of the primary control level; voltage secondary control takes charge of voltage deviation restoration, while smoothing higher level regulation, and a GA is implemented in tertiary level for searching the optimal sharing ratio so as to improve system efficiency. The bandwidth of optimization control is usually much narrower than inner loops and droop controller; therefore, the optimal adjustment of virtual resistances can be performed online.

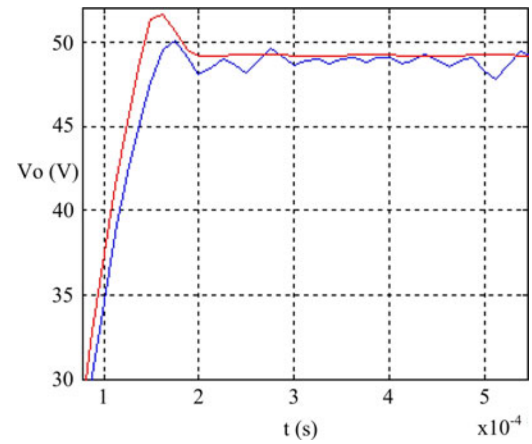

Fig. 9. Comparison of the buck converter to step response. Blue: before tuning. Red: after tuning [91].

Sanabria and Garzon [91] describe the multiobjective optimization of a fuzzy controller in a buck converter. The objective functions are the steady-state error e_{ss}, and the ripple factor F_{r}. The goals is to achieve a step response satisfying the constraints $e_{ss} < 3\%$ and $F_r < 3\%$. The controller architecture is aimed at determining the duty cycle, treated as decision variable. The fuzzy controller adjusts the duty cycle looking that the buck converter is established in a desired value, or a near value of the set point. The optimization was carried out using the nondominated sorting genetic algorithm II, which requires less computational resources, and is suitable for online applications. Fig. 9 shows the step response of the converter, before and after tuning (with $e_{ss} = 2.0684\%$ and $F_r = 1.784\%$).

A grid-connected inverter must present minimal frequency oscillations that might affect the active power transferred, changing the equilibrium point of the control system and altering the power flow equilibrium. The dynamic response of the system can be greatly improved by applying an optimization procedure using differential evolution, as described in [92]. The slopes of the *P*–ω and *Q*–*V* curves are adjusted in such a way that the stability of the system with a minimum settling time can be guaranteed. The decision variables are *kv* and *kp*, which define the slope of the curves *Q*–*V* and *P*–ω, respectively. Differential Evolution meets a set of requirements that make it an attractive method. First, the solutions converge to a global maximum independently of the choice of initial population. Second, the convergence speed is such that the algorithm can be used in online applications.

The PSO methodology has also been employed to obtain the optimal controller parameters, as described in [93]–[96]. Further, the proposed control strategies compensate current harmonic distortion effectively, providing THD values well below the 5% limit set by standard IEEE 1547, for grid connected inverters.

Hassan and Abido [93] describe the optimization of a PI voltage controller (decision variable being the proportional and integral gains k_{pv} and k_i respectively), and of a PI current controller (with k_{pc} and k_{ic} as decision variables) in a microgrid application. The optimization is treated as a constrained problem

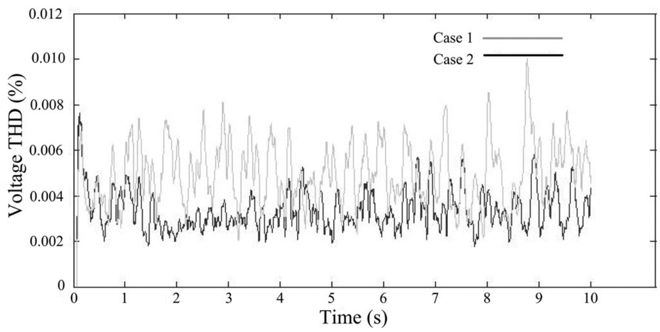

Fig. 10. Voltage THD obtained. Case 1: Based on trial and error method, and case 2: based on the BFO algorithm [97].

with upper and lower bounds for the decision variables. To assess the robustness of the proposed controllers under different conditions, several runs were carried out in autonomous and grid-connected modes. Different disturbances were applied to demonstrate the effectiveness of the proposed design approach. In the grid-connected mode, the step change in the reference power was used to test the system capability to follow this reference power. System stability was analyzed using both nonlinear time-domain simulations and eigenvalue analysis. In the autonomous mode, step change and fault disturbances were used to verify the system stability. The results confirm the effectiveness of the proposed PSO-based approach for optimizing the parameters of PI controllers. The robustness of the proposed PSO technique with respect to its initial guess was confirmed.

Al-Saedi *et al.* [94], [95] present a current control strategy, which is both robust and optimal, applied to a PI controller, using the integral time absolute error as objective function to be minimized. In both cases, the decision variables are the proportional and integrals gains. The controllers provided excellent dynamic responses.

The tuning problem of a nonlinear voltage controller is presented in [96]. The objective function to minimize is the quadratic performance index J, the decision variables are the proportional and integrals gains of the controller, and the physical constraint of the optimization problem is the maximum allowable reactive current component, which depends on the inverter rating. The voltage regulation performance is so fast that voltage-quality problems such as voltage flicker, sags, and swells can be mitigated.

In [97], the tuning of controllers is accomplished using a BFO algorithm to reduce voltage and current harmonic distortions, and complying with the grid interconnection requirements. According to the comparison between a trial-and-error tuning method and the BFO algorithm, the latter one provides a lower voltage THD as shown in Fig. 10.

With the computing power of today's computers, a metaheuristic algorithm will have problems, in most cases, to converge to an appropriate value in a relatively short time. In the case of a controller, the metaheuristic algorithm must provide an acceptable control signal for each control instant. If evolution has occurred only in a small number of generations, the behavior of the population may be poor yet. To overcome these complications, a very useful tool is the parallel computing.

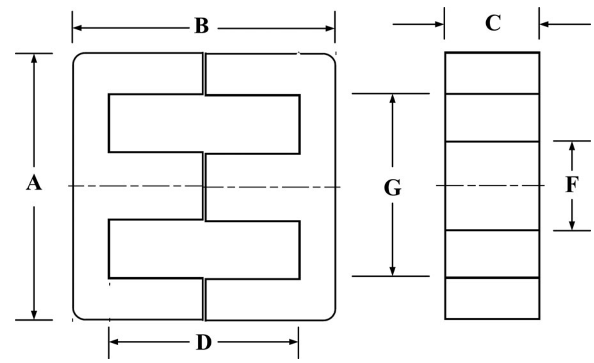

Fig. 11. EE core millimetric dimensions (mm).

TABLE IV
DECISION VARIABLES, CONSTRAINTS, AND THE OPTIMUM DESIGN

Decision variable	Constraints		Optimum design
	Min.	Max.	
f_S (kHz)	1	100	47.1
B (mm)	10	100	19.2
C (mm)	10	100	10
D (mm)	10	100	14
g (mm)	0	1	0
CI	1	70	70

C. Circuitry

Design optimization methodologies for power converters must include both the optimization of the converter configuration, and the circuitry itself at component level.

GA have been applied to the design of isolated dc–dc converters, formulated as multiobjective problems, taking into account requirements, such as minimum weight, losses, and cost, while ensuring the satisfaction of a number of constraints [98], [99]. Other examples are the simultaneous minimization of the heat sink and bus capacitors volumes [100], or the selection of capacitor and inductor values, which yield the best performance in terms of output power, system size, power loss, and reliability [101].

Numerous proposal aimed at the optimization of power converter circuitry have been published. The most common objective functions to minimize are weight [98], [99], [102]–[104], cost [32], [99], [102], [104]–[108], volume [102], [108]–[110], emitted radiations and thermal resistance of a heat sink [111], area [104], [105], and power losses. Alternatively, the optimization can be achieved through efficiency maximization [57], [69], [98], [99], [101], [103]–[105], [108]–[110], [112]–[115]. The optimal values for the decision variables were calculated so that the volume, area, weight, cost, and power losses are minimized, while simultaneously meeting the specifications of the power converter and the limitations imposed by the codes or international standards (e.g., IEEE 1547, IEC 61727, etc.).

Mirjafari and Balog [103] present an approach using PSO to minimize the volume of an inductor using EE core geometry, as shown in Fig. 11. The decision variables, constraints, and the optimum design obtained are listed in Table IV, where f_S is the

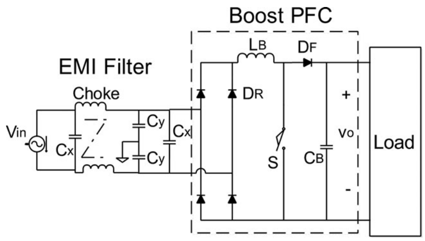

Fig. 12. EMI filter and boost PFC stage schematic.

TABLE V
COMPARISON BETWEEN MANUAL AND OPTIMUM DESIGN

	Decision variables	Manual design	Optimum design
EMI filter	*Lcm* (mH)	1.5	0.97
	Cx (μF)	2.8	2.23
	Cy (μF)	0.005	0.00758
Boost inductor	*OD* (cm)	4.45	4.62
	ID (cm)	2.72	2.33
	Ht (cm)	1.65	1.62
	Aw (cm^2)	11.2×10^{-3}	11.4×10^{-3}
	n	122	88
Frequency	f_S (kHz)	40	29.78
Thermal resistance	R_{sa} (°C/W)	2.2	2.38
Objective function = Cost[a]		100%	90.64%

Cost[a] percentage with respect to the manual design cost.

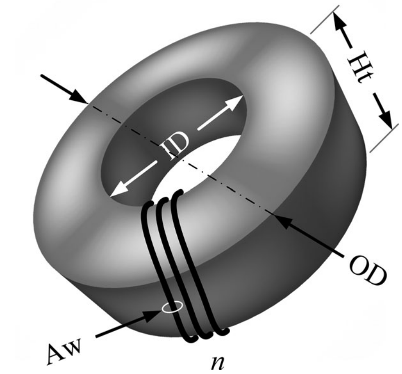

Fig. 13. Boost inductor decision variables.

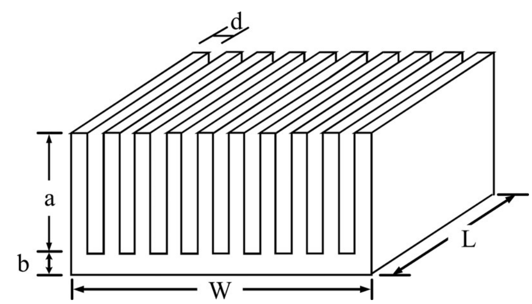

Fig. 14. Heat sink dimensions.

switching frequency in kHz; *B*, *C*, and *D* are core dimensions, *g* represents the core air gap and CI is the magnetic core index.

It is interesting to notice that volume reduction in [103] was obtained at a lower switching frequency $f_S = 47.1$ kHz, which seems to contradict the usual recommendation of using higher frequencies to reduce magnetic components volume.

This approach, however, does not provide a truly optimized converter because only a limited number of solutions to the optimization problem are feasible, the reason being the granularity of commercial components, which are available in discrete values and so limits the ability to find a global optimum solution may require advances in technology component facing off the necessity of components with new characteristics [103], [108].

A solution reported in [103], employed a database containing the different characteristics of the components, which were selected using metaheuristic methods in order of minimize power losses and weight of the power converter.

An approach to optimize a boost power factor correction front-end converter is described in [107]. The optimization includes the input electromagnetic interference filter, as shown in Fig. 12. The objective function to minimize is the total system component cost given practical constraints on the decision variables listed in Table V, where *L*cm is the common-mode choke inductance (mH), *Cx* and *Cy* are the differential-mode and common-mode capacitances (μF); *OD*, *ID*, and *Ht* are core dimensions (cm) as shown in Fig. 13; *Aw* is the area of the copper wire (cm^2), *n* represents the number of turns, f_S is the switching frequency (kHz), and R_{sa} is the heat sink-to-ambient thermal resistance (°C/W).

Table V lists the values obtained from a manual design, and after optimization. As can be seen, a 10% improvement in the objective function was achieved. Again, the improvement is obtained at a lower switching frequency. This is interesting to notice because, while switching capabilities are being extended by semiconductor manufacturers, it is not completely clear weather using a higher switching frequency will produce a reduction in total volume, weight, and cost.

Manivannan *et al.* [111] present an approach for modeling and optimization of the geometry of a flat plate heat sink using GA. The heat sink geometry is shown in Fig. 14.

The GA objective functions are the thermal resistance and the emitted radiation. The decision variables, constraints, and the optimum design obtained are listed in Table VI, where *a*, *b*, *d*, *L*, and *W* are heat sink dimensions (mm), and *N* is the number of fins. The results obtained using GA show the desired output design can be achieved efficiently and accurately.

V. CONCLUSION

This survey has introduced the metaheuristic algorithms that are of interest for research in the development of power converters, and highlight its advantages over classical methods. The survey, in terms of number of citations, represents only a subset of the available literature. Nevertheless, the optimization examples addressed in this paper are indicative of the large number of power converter related topics in which metaheuristic algorithms have proved its profitability and efficiency.

From the review of the literature about power converters optimization, it can be concluded that the topics that have received more attention are THD reduction, harmonics elimination, and efficiency maximization. In spite of its relevance, other topics,

TABLE VI
DECISION VARIABLES, CONSTRAINTS, AND THE OPTIMUM DESIGN OF THE HEAT SINK

Decision variable	Constraints		Desired output design	Optimum design predicted
	Min.	Max.		
a (mm)	10	30	30	21.4
b (mm)	4	8	4	4.16
d (mm)	0.8	1.2	0.8	1.13
L (mm)	70	90	80	70.03
N	10	30	20	27
W (mm)	70	90	80	78.05
Objective Function	Thermal resistance (°K/W)		0.27109	0.263
	Emitted Radiations (dBmV/m)		12.626	12.61

such as reliability optimization has not been exhaustively explored.

The majority of publications describes offline optimization procedures, and yield satisfactory results. Online optimization using metaheuristic algorithms tend to be quite rare to date, due to the high computational effort that is often required to guarantee that the parameters are available when needed.

The advantages of metaheuristic optimization methods (i.e., GA, PSO, ACO, BFO, BA, etc.) over classical optimization techniques have been clearly demonstrated in many applications of power electronics. It should be pointed out, however, that identifying the best metaheuristic method is not a simple task, because the results depends on the objective function selected and the particular requirements of the application.

In power electronics many optimization problems are intrinsically complex, and its solutions require a large computing effort. Optimal solutions can be obtained through classical optimization methods, such as the augmented Lagrangian, dynamic programming, linear and integer programming, and so forth. These methods, however, are often useless in practice as they are extremely time-consuming when solving complex and dynamic problems (i.e., search spaces of large dimension, hardly constrained problems, multimodal and time-varying problems). In contrast, metaheuristic optimization methods allow the computing of suboptimal or optimal solutions in a reasonable execution time; therefore, providing numerical precision of the results and computational efficiency.

Metaheuristic methods have the additional advantage of being generics, thus not requiring a complex tuning for each problem, and can be used as a kind of "black boxes."

VI. Future Perspectives

The trend to use metaheuristic algorithms in power electronics is tied fundamentally to general advances in the research of metaheuristic algorithm theory and applications. Due to the generic nature of metaheuristic, developments that arise in fields, such as finance engineering, logistics or transportation, have been tested providing fruitful results in power electronics applications. However, the research domain of metaheuristic algorithms applied to power converter design is still relatively young but, as Fig. 2 demonstrates, is a growing area of research.

A key point to fully exploit the potential of these algorithms is the availability of low cost high-performance computer architectures, which will increase the effectiveness and quality of the solutions obtained for offline optimization, and overcome the drawbacks of online applications that involve short-term decisions (e.g., fractions of a second). High computational cost has been a major impediment to the widespread use of metaheuristics optimization methods in online optimization. While the computational time for optimization using the GA can be reduced by parallelization, the computational cost can only be improved by reducing the number of function evaluations, as proposed in [116].

Another key point is the challenge that represents the reliability optimization in power converters that has been carried out for decades and now is moving from a solely statistical approach that has been proven to be unsatisfactory in the automotive industry, to a more physical-based approach which involves not only the statistics but also the investigation and modeling of the root cause behind the failures. Moreover, the trend is focusing in the mission profiles for applications under harsh environment and long operation hours, taking into account the failure mechanisms related to excessive temperature (thermal cycling) [117,] [118].

In power electronics, many optimization problems tend to be multiobjective, requiring complex models to accurately represent the real conditions of the case of study. Hence, a popular approach to solve them is the hybridization of metaheuristic algorithms which combines the desirable properties of different algorithms to mitigate their individual weaknesses. The hybridization of metaheuristic algorithms is a growing area for future development.

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