Design of an Optimum Single Phase Inverter for a Grid Tie PV System

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Abstract Power converter optimization by genetic algorithm (GA) is used to provide simpler and more reliable converter design for high efficiency, small size and low cost. This paper presents a Computer-Aided Design Optimization Tool based on GA to determine the optimal structure of single-phase voltage source inverter devoted to grid-connected photovoltaic applications. An accurate non-linear averaged model was used to model the power converter. The hysteresis technique was used to control the output sine wave current of the inverter while the Elitist Non-dominated Sorting Genetic Algorithm NSGA-II was used to search the Pareto optimal front and the best design in terms of efficiency, volume and cost under electrical constraints. The converter model and the NSGA-II algorithm are developed in the MATLAB/Simulink environment. The problem formulation was detailed. It was shown that the optimization of a power converter, working in a given application without the need of tedious and expensive experimental tests classically used to build this converter, is possible by mean of simulation. This will decrease time to market phase for manufacturers.

Keywords Genetic Algorithm, DC/AC Converter, Non-Ideal Averaged Model, Hysteresis Control Strategy, NSGA-II

1. Introduction

Due to rising prices and environmental impacts of fossil fuels, renewable energy resources have been considered as one of the most efficient solutions to meet global energy demand [1]-[3]. Photovoltaic (PV) solar technology is the fastest growing energy source for renewable energy production at an annual average rate of 8.3% [4]. Grid integrated PV energy sources have been widely used to

produce electricity, but their performances need to be improved. To access the grid, the power electronic converter is an extremely important element for photovoltaic systems. To maximize performance, an optimized design of the conversion stage becomes the key to achieve the above goal.

A general block scheme of a PV system connected to the grid is shown in Fig. 1. In such a structure, the inverter is a basic component of the grid connected PV systems. Its main task is to convert the direct current to a quasi-sinusoidal form to be injected into electrical grid.

The design of power electronic converter or its components by optimization using metaheuristic methods, such as genetic ones, is an effective and widely used approach to obtain an optimal system with better performance [5]. In [6], the authors proposed an optimal design of a DC/DC cascaded converter dedicated to grid-connected photovoltaic systems to maximize efficiency or minimize volume. The obtained results showed that the best solution is a topology with two boosts converters in cascade. References [7]-[9] set out a design methodology based on the multi-objective genetic algorithm of DC/DC converters for grid-connected PV systems to minimize losses, size and cost. Multi-objective optimization was used to obtain the optimal design of a distributed maximum power point tracking synchronous boost converter in [10]. In detail, the efficiency and reliability of the power converter are maximized while its price is minimized. In [11], a study of modelling approaches of several components for power electronic converter was performed. In [12] and [13], the authors adopted a multi-objective GA-based methodology to design and select the appropriate DC/DC stage for a module-integrated inverter. In [14], a systematic methodology using multi-objective evolutionary algorithm and multi-objective covariance matrix adaptation evolution strategy are used in the extraction of power diode parameters.

Figure 1. Grid-connected power generation scheme

The optimization of a power system itself is the final goal of applying evolutionary algorithm, but this task is also a means of modelling, forecasting, control and simulation. Although previous works have taken into account the characteristics of optimization, they still have some limitations. The used models are simplified and the behavior of the power electronic converter is mistreated. The control strategy is shortened, even limited to a constant duty cycle for DC/DC converters [6]-[9].

This paper presents a modeling and optimization approach to reveal the optimal design of the DC/AC converter in a grid-connected photovoltaic system using the popular and effective multi-objective algorithm NSGA-II. Optimization focuses on fulfilling three objectives: maximizing inverter efficiency, minimizing its size and reducing its cost. To model the power converter, an advanced non-ideal averaged model was used.

Various approaches have been directed toward power loss estimation in semiconductor components. The most widely used approach is the semiconductor refined models. This approach gives accurate results. Unfortunately, the simulation cost of these models is unaffordable especially in converter optimization context. Simplify models of power semiconductor devices are therefore essential for the analysis and the design in different applications. Averaged circuit modeling of switching power converters has been a major topic of research since 1976. The average model of the semiconductor devices is a simplified representation of a switch cell that is common in different converter topologies [15]-[16]. Non-linear effects of the power semiconductor devices are not included in most of averaged models because they use ideal switches instead of semiconductor device models. Considering the unsatisfactory situation in the averaged modeling, an effort was undertaken in the averaged models presented in [17]-[20]. Thus, the authors have proposed an advanced PWM-Switch Model including semiconductor device nonlinearities.

Hence this model has been used in this study to estimate power losses in different semiconductor devices. The main advantage of the average model is that the simulation time is greatly reduced and accuracy is good enough. This is due to the fact that the commutation of the switch and the diode is averaged.

The use of the optimization algorithms requires cheap (in term of time) simulation models, particularly if

multi-objective algorithms are used.

Since the power converter control is a crucial phase to think over the overall function of a grid-connected inverter, the hysteresis current control was used to generate switch gate drives [22]-[24]. This control strategy offer a high current tracking accuracy, robustness and simplicity but it's usually used with models based on electrical scheme of power converters which don't take into consideration the nonlinearities of power semiconductor devices. In this work, we use the hysteresis current control with the non-linear averaged model to combine the benefits of the two adopted methods.

This paper is structured as follows. Section 2 describes the basic idea of the study, including the hysteresis current control strategy and the electrical power converter modelling. Section 3 highlights the principle of the NSGA-II multi-objective genetic algorithm. Section 4 focuses on the formulation of optimization problem under study including the definition of design variables, constraints and objectives. Section 5 describes the results of continuous mono, bi and tri-objective optimization under electrical constraints to achieve higher efficiency, smaller size and/or lower price.

2. Basic Idea for Study

2.1. Inverter Current Control Strategy

The work presented in this paper consists of the study and the optimization of a single phase inverter used in a grid-connected photovoltaic system. The chain is composed by a photovoltaic generator, a power conversion stage (inverter) and the grid. Fig. 2 presents a single phase grid-tied voltage source inverter which is directly connected to a photovoltaic generator via a bias capacitor C_{dc} . The DC/AC converter consists of four transistors (IGBT or MOSFET), four freewheel diodes and a control system. The design of the control system requires a detailed modelling of the converter. The non-linear average model is used to model the actual operation of the converter since it provides a very approximate estimation of the converter's dynamic behavior. In our case, the four switches operate so that the driving signal S_{12} is complementary to S_{11} at fundamental frequency ($f_{grid}=50$ Hz) and S_{22} is complementary to S_{21} at switching frequency (f_s).

The hysteresis control allows an instantaneous adjustment of output current to be maintained below the hysteresis band limited by the upper limit of $(I_{ref} + \Delta I)$ and the lower limit of $(I_{ref} - \Delta I)$ where I_{ref} is the reference current and ΔI is the output current ripple. When using a model with ideal semiconductor devices, the implementation of hysteresis control is simple. However, in case when the non-linear averaged model is used, it appears necessary to develop a method to estimate the duty cycle in order to control the active switches. One way to attend such a target is to estimate the value of the switch on-time (T_{on}) and off-time (T_{off}) and then determine the duty cycle.

Fig. 3 depicts the principle of hysteresis current regulation. As shown in this figure, the T_{on} and T_{off} values depend on the sign of the grid voltage (v_s) and of the

output voltage (v_{out}). Therefore, an estimation of these two values during fundamental period can be expressed as follows [25]

$$\begin{cases} (T_{on})^P = \frac{2L\Delta I}{(E_{on})^P - v_s - L\omega I_{ref} \cos(\omega t)} \\ (T_{off})^P = \frac{-2L\Delta I}{(E_{off})^P - v_s - L\omega I_{ref} \cos(\omega t)} \end{cases} \quad (1)$$

$$\begin{cases} (T_{on})^N = \frac{-2L\Delta I}{(E_{on})^N - v_s - L\omega I_{ref} \cos(\omega t)} \\ (T_{off})^N = \frac{2L\Delta I}{(E_{off})^N - v_s - L\omega I_{ref} \cos(\omega t)} \end{cases} \quad (2)$$

Figure 2. Proposed modular configuration for grid-connected PV systems

Figure 3. Hysteresis current control scheme for single-phase grid-tied inverter ((T_{on})^P: on-time when v_s is positive; (T_{off})^P: off-time when v_s is positive; (T_{off})^N: off-time when v_s is negative; (T_{on})^N: on-time when v_s is negative)

Where (E_{on})^P, (E_{off})^P, (E_{on})^N and (E_{off})^N are respectively the steady states turn-on and turn-off modulated voltages which depend on the inverter output voltage sign and are given by

$$\begin{cases} (E_{on})^P = \begin{cases} V_{in} - 2V_{sw} & \text{if } V_{out} \geq 0 \\ -V_{in} - 2V_d & \text{if } V_{out} < 0 \end{cases} \\ (E_{off})^P = -V_{sw} - V_d \quad \forall V_{out} \end{cases} \quad (3)$$

$$\begin{cases} (E_{on})^N = \begin{cases} V_{in} + 2V_d & \text{if } V_{out} \geq 0 \\ -V_{in} + 2V_{sw} & \text{if } V_{out} < 0 \end{cases} \\ (E_{off})^N = V_{sw} + V_d \quad \forall V_{out} \end{cases} \quad (4)$$

Then, the switching period (T_s) and the duty ratio (ρ) can be defined respectively as follows

$$\begin{cases} (T_s)^P = (T_{on})^P + (T_{off})^P \\ (T_s)^N = (T_{on})^N + (T_{off})^N \end{cases} \quad (5)$$

$$\begin{cases} (\rho)^P = \frac{(T_{on})^P}{(T_s)^P} \\ (\rho)^N = \frac{(T_{on})^N}{(T_s)^N} \end{cases} \quad (6)$$

The switching frequency is determined as the inverse of (5) and it is given by (7).

Fig. 4 shows the effects of the current ripple and duty cycle on the switching frequency variation. It can be seen that the switching frequency admits a maximum value ($f_{s,max}$) that must be controlled to protect semiconductor devices and reduce switching losses. This maximum frequency is sensitive to any variation in current ripple rate and output inductance value. By resolving the derivative of (7) equal to zero, with respect to time t , and by replacing the solution in (7), the maximum switching frequency can be easily determined.

Figure 4. Switching frequency variation over fundamental period (a) for $L=1.5$ mH, (b) for $\Delta I = 0.5A$

2.2. DC/AC Converter Modelling

Modelling a power converter is the first step necessary in order to analyze its dynamic behavior in various applications. The averaging method is the widely used technique since both accuracy and rapidity are required especially for long time simulation and for complicated circuits. In spite of classical averaged model where the converter is assumed to be a linear system using ideal switches [26], the non-linear averaged model uses semiconductor device models where both static and dynamic characteristics of the switch are taken into account. In [17] and [18], the authors proposed an advanced pulse width modulation (PWM) switch model to account for nonlinearities in semiconductor devices.

Fig. 5(a) shows the studied inverter leg with two active switches (IGBTs or MOSFETs) directly controlled by external control signals and two passive switches (DIODES). In Fig. 5(b), the adopted leg circuit based on the used averaged model is presented.

In this developed model, the leg switches are replaced by a controlled voltage source V_1 in series with a controlled current source I_1 given by

$$V_1 = \langle U_{as} \rangle \quad (7)$$

$$I_1 = \langle i_{e2} \rangle \quad (8)$$

With $\langle U_{as} \rangle$ and $\langle i_{e2} \rangle$ are the time averaged values of the instantaneous terminal waveforms of $U_{as}(t)$ and $i_{e2}(t)$ respectively over one cycle T_s (switching period of the controlled switches).

$$\left\{ \begin{aligned} (f_s)^P &= \frac{I}{(T_s)^P} = \frac{\left[(E_{on})^P - v_s - L\omega I_{ref} \cos(\omega t) \right] \left[(E_{off})^P - v_s - L\omega I_{ref} \cos(\omega t) \right]}{2L\Delta I \left[(E_{off})^P - (E_{on})^P \right]} \\ (f_s)^N &= \frac{I}{(T_s)^N} = \frac{\left[(E_{on})^N - v_s - L\omega I_{ref} \cos(\omega t) \right] \left[(E_{off})^N - v_s - L\omega I_{ref} \cos(\omega t) \right]}{2L\Delta I \left[(E_{on})^N - (E_{off})^N \right]} \end{aligned} \right. \quad (9)$$

Figure 5. (a) The PWM-switch; (b) The corresponding averaged model, [18]

Figure 6. Adopted switching characteristics of the switch and diode components in the PWM-switch, [19]

Fig. 6 shows the adopted switching waveforms of the active switch ($U_{as}(t)$, $i_{e1}(t)$) and the passive switch ($U_{bs}(t)$, $i_{e2}(t)$) during T_s . e_{g1} and e_{g2} are the control signals of T_1 and T_2 respectively.

Based on this analytical representation of the switching characteristics and the study developed in [18], the power losses of semiconductors (P_{switch} and P_{diode}) including both conduction and switching losses and considering the various conduction and switching times can be given by (10) and (11).

$$P_{switch} = \frac{I_L V_t}{T_s} (\rho T_s - t_{don} - t_r - t_{rr} + t_{doff}) + \left(\frac{V_b - E - V_d}{3T_s} + \frac{E + V_d}{2T_s} \right) (I_L + I_{RM}) (t_r + t_{IRM}) + \left(\left(\frac{V_b - V_t}{3T_s} - \frac{V_b}{2T_s} \right) I_{RM} + \left(\frac{V_t - V_b}{2T_s} + \frac{V_b}{T_s} \right) (I_{RM} + I_L) \right) (t_{rr} - t_{IRM}) + \frac{E + V_d - V_t}{2T_s} I_L t_{rv} + \frac{V_t}{T_s} I_L t_{rv} + \frac{E + V_d + V_L}{2T_s} I_L t_{fi} \quad (10)$$

$$P_{diode} = \frac{I_L V_d}{T_s} (T_s - \rho T_s + t_{don} - t_{doff} - t_{fi} - t_{rv} + t_{don}) + \frac{I_{RM}}{2T_s} (V_L + V_{L1} - V_d) (t_{rr} - t_{IRM}) + \frac{I_{RM}}{6T_s} (V_b - V_t) (t_{rr} - t_{IRM}) + \frac{I_L V_d}{2T_s} t_{fi} - \frac{I_{RM}}{2T_s} V_d t_{IRM} \quad (11)$$

3. Multi-Objective Optimization

Over the last few years, stochastic optimization techniques using evolutionary algorithms have received attention in power electronic optimization. Contrary to the conventional methods, genetic algorithms are considered to be an effective way of finding solutions close to the global optimum without being trapped in local minima and they are less dependent upon the initial starting point of the search.

The genetic algorithm is a well-known metaheuristic research method derived from the natural evolution process. It successively executes three genetic operators (selection, crossover and mutation) to give birth to an offspring population. Quite often, optimization problems such as those associated with the development of power electronic converters require a multi-objective approach since at least two conflicting objectives, under certain constraints, must be satisfied simultaneously.

According to [27] and [28], the multi-objective optimization problem can be defined as the problematic of finding a vector of decision parameters that meets the constraints and optimizes a vector of criteria whose elements are objective functions. Thus, the result is not a single solution, but rather a set of optimal compromise solutions. This front is obtained by the Pareto optimality theory. Proposed by Deb et al. [29]-[30], the NSGA-II is used to find a family of solutions that best satisfies the established requirements (objectives). It is equipped with a sorting procedure based on Pareto's optimal approach, which is an elitist method that preserves the diversity of populations and keeps the best solutions found in previous generations. It is supplied also with a comparison operator based on a crowding distance calculation to manage diversity in Pareto front [31]. The pseudocode for NSGA-II is shown in the flowchart in Fig. 7.

After drawing the Pareto front, it is necessary to

determine the point adopted as the optimal design. The decision maker can pick an individual, among the individuals contained in the Pareto front, depending on the application and regarding the importance of the different criteria, a more difficult task for more complex applications. That is why a method to determine the best solution is required. The ideal is to have a solution that includes the optimum for each objective considered independently reached at the same specifications, variables and optimization constraints that is called the ideal objective vector. In general, this vector corresponds to a non-existent solution. One way to overcome this problem is to identify the closest solution to this ideal point. To do this, the distance between the ideal solution and each optimal Pareto solution is calculated as follows

$$d_i = \sqrt{\left(\frac{F_{i_1} - F_1^{\min}}{F_1^{\min}}\right)^2 + \left(\frac{F_{i_2} - F_2^{\min}}{F_2^{\min}}\right)^2 + \dots + \left(\frac{F_{i_m} - F_m^{\min}}{F_m^{\min}}\right)^2} \quad (12)$$

Where d_i ($i = 1 \dots N$; N : population size) is the distance between the ideal point and the i_{th} individual, $\{F_{i_1}, F_{i_2}, \dots, F_{i_m}\}$ ($m \geq 2$) are the problem objectives for the i_{th} Pareto optimal individual, and $[F_1^{\min}, F_2^{\min}, \dots, F_m^{\min}]^T$ is the ideal objective vector.

Power converters are often optimized for minimal losses, size and cost. The appropriate optimization process is illustrated in the flowchart in Fig. 8. As presented, the NSGA-II identifies the design parameters that are used in the simulation model to calculate the constraints of the problem and determine the values of the objective functions that are then returned to the genetic algorithm for evaluation. This will be repeated for each individual in the population until the maximum number of generations is reached.

Figure 7. Flowchart of NSGA-II genetic algorithm, then, the minimum distance from the N calculated distances is determined and the closest individual to the ideal point is chosen as the optimal solution

Figure 8. Optimization process for the DC/AC converter, where R_{DC} is the inductor DC resistance and $I_{L,rms}$ is the rms value of the output current

4. Problem Formulation

4.1. Design Parameters

Design parameters are the numerical quantities that can be modified to achieve the objectives while respecting the constraints. Before starting any optimization study, it is crucial to define the problem parameters and their limits. The design variables of the system under investigation are the output current ripple (ΔI) and the output inductance (L). Note that the bias capacitor is not considered as an optimization parameter. It is designed to insure an input voltage ripple of approximately 5V.

4.2. Problem Constraints

Constraints are restrictions imposed by the particular characteristics or nature of the problem under study. These limits must be fulfilled to obtain acceptable solutions. For the current problem, two electrical constraints are taken into account which are the total harmonic distortion (THD) and the maximum switching frequency of semiconductor devices ($f_{s,max}$). The THD for the injected grid current should not exceed 5% in normal operation in order to meet the grid harmonic requirements and to avoid negative effects on other equipment connected to it. The $f_{s,max}$ should be lower than a selected value (fixed here to 50 KHz) to operate the power converter in a given switching frequency range. This is due to the dependence of the switching losses on this frequency and the limitation of the maximum switching frequency of power semiconductors since any over-increase in the switching frequency leads to an increase in the temperature of the semiconductor and, consequently, the failure of the device.

4.3. Objectives Functions

4.3.1. Inverter Losses Models

Power losses calculation is necessary in the design of power converters, since it characterizes their energy efficiency, which should be maximized. The converter losses are mainly caused by conductive and switching losses in semiconductor devices (P_{switch} and P_{diode}) as well as core and copper losses in the load inductor. The losses in DC capacitor P_{Cap} are neglected because its value is too low compared to the semiconductor losses P_{SC} and the inductor losses P_L . Semiconductor power losses are derived from (10) and (11). The iron losses of the load inductor are supposed to be given by the well-known Steinmetz equation [32]-[34]

$$P_{core} = KF^\alpha \hat{B}^\beta \quad (13)$$

Where $\hat{B}$ is the peak induction of sinusoidal excitation with frequency F , P_{core} is the time-average power losses per unit volume, and K , α , β are Steinmetz

parameters,

And the inductor winding losses are obtained by

$$P_{cu} = R_{DC} I_{L,rms}^2 \quad (14)$$

Then, the total losses are given by

$$P_{Total} = \underbrace{P_{cu} + V_L P_{core}}_{P_L} + \underbrace{4(P_{switch} + P_{diode})}_{P_{SC}} \quad (15)$$

With V_L and P_L are respectively the inductor volume and losses.

4.3.2. Inverter Volume Models

The volume of the DC/AC converter when the studied optimization problem is purely electrical is mainly due to the inductor volume V_L and the DC capacitor volume V_{Cap}

$$V_{Inverter} = V_L + V_{Cap} \quad (16)$$

Where V_L is defined as

$$V_L \approx V_{core} = K_L (A_W A_C)^{3/4} \quad (17)$$

$$A_W A_C = \frac{L I_{L,max} I_{L,rms}}{K_W J_{rms} \hat{B}} \quad (18)$$

With A_W is the winding area, A_C is the core section, $I_{L,max}$ is the peak value of the inductor current, J_{rms} is the rms value of the current density, K_L and K_W are the geometrical parameters of the magnetic circuit.

And V_{Cap} is given by

$$V_{Cap} = A_{Cap} + B_{Cap} C_{dc} \quad (19)$$

For example, $A_{Cap} = 12.632 \text{ cm}^3$ and $B_{Cap} = 90794 \text{ cm}^3/\text{F}$ for an EVOX RIFA electrolyte capacitor [35].

4.3.3. Inverter Cost Models

When designing a power converter, its price must be taken into consideration to provide a more economical solution.

In our case, the inverter cost is defined as

$$C_{Inverter} = C_{Cap} + C_L + 4(C_{switch} + C_{diode}) \quad (20)$$

The cost of DC Bus capacitor is expressed as

$$C_{Cap} = A_{C_{dc}} + B_{C_{dc}} E \quad (21)$$

With $A_{C_{dc}} = 15.015 \text{ €}$, $B_{C_{dc}} = 0.025 \text{ €/V}$ and $E = ? C_{dc} (U_{C_{dc}})^2$ is the capacitor stored energy ($U_{C_{dc}}$ is the capacitor rated voltage) [35].

The cost of the load inductor depends on its volume and can be defined by

$$C_L = A_{Ind} + B_{Ind} V_L + C_{Ind} V_L^2 \quad (22)$$

With $A_{Ind} = 0.07008 \text{ €}$, $B_{Ind} = 0.3904 \text{ €/cm}^3$ and $C_{Ind} = 2.16 \times 10^{-4} \text{ €/cm}^6$ [35].

In addition, semiconductor devices costs should be taken into account. Thus, the devices that meet the studied system requirement are selected (IGBT SGP15N60 (15A, 600V) and PIN diode 15ETH06PbF (15A, 600V)) in our application.

5. Pure Electrical Optimization Results

5.1. Mono-objective Optimization

Fig. 9 shows the convergence of single-objective optimization of losses, volume and cost by number of iterations, while Table 1 summarizes the results obtained from this work. The converter losses decrease from 71.23 W (A1) to 63.45 W (B1) (Fig. 9 (a)). Based on (7), the switching frequency is inversely proportional to the product $L\Delta I$. In fact, this product is lower in point A1 ($L=10.68$ mH, $\Delta I \approx 0.56$ A) than in point B1 ($L=13.49$ mH, $\Delta I \approx 0.6$ A), which results in the diminution of the switching frequency from A1 to B1 and, consequently, the reduction of power losses.

The inverter volume drops by 33.3% from 671.3 cm³ (A2) to 447.9 cm³ (B2) when the number of iterations increases (Fig. 9 (b)). This can be explained essentially by the diminution of the inductance value since the inductor is the bulkiest component of the converter. Another reason of this decrease is the increase of the switching frequency

which yields to the power losses rise and respectively the size reduction.

The cost function decreases from 255.3 €(A3) to 137.2 €(B3) with a profit of 118.1 €(Fig. 9 (c)). This advantage is obtained by reducing the inductance value and increasing the switching frequency which reduce the size of the inverter and therefore its price.

The main disadvantage of the above study is that mono-objective optimization deals with one criterion while neglecting the others. A large size implies a heavy inverter with a large occupied space, even if it is more efficient. In addition, high losses considerably reduce the efficiency of the converter, although it becomes smaller and cheaper. On the other hand, the cost must be kept at a reasonable level even if the converter's capacity is reduced. Indeed, improving one goal often means degrading others. This is why the concept of compromise is often mentioned in optimization where there is not only one objective function to optimize but multiple. Before studying the tri-objective optimization, it is necessary to solve the bi-objective problem in order to determine the optimal designs closest to the ideal vectors for Volume vs. Losses and Cost vs. Losses optimization, which are defined respectively by

$$V_{ideal} (\text{Volume vs. Losses}) = [63.45 \text{ W } 447.9 \text{ cm}^3]^T$$

$$V_{ideal} (\text{Cost vs. Losses}) = [63.45 \text{ W } 137.2 \text{ €}]^T$$

(a)

Figure 9. Convergence of the single objective function as a function of the number of iteration under electrical constraints (a) Objective function losses, (b) Objective function volume, (c) Objective function cost

Table 1. Electrical single objective optimization results

Optimized converter	Objective			Variables		Constraints	
Objectives	Losses (W)	Volume (cm³)	Cost (€)	L (mH)	ΔI (A)	THD	$f_{s,max}$ (KHz)
Losses	63.45	1163.4	591.48	13.49	0.597	0.0499	6.21
Volume	142.86	447.9	137.2	1.85	0.542	0.0497	49.84
Cost	142.87	447.9	137.2	1.85	0.542	0.0497	49.84

5.2. Bi-Objective Optimization

The bi-objective optimization has been carried out and the Pareto optimal solutions are shown in Fig. 10. The Fig. 10 (a) represent the Volume vs. Losses curve, it is clear here that the reduction in volume leads to an increase in energy losses and vice-versa. The curve is limited by the two point A4 and B4 where the point A4 corresponds to the minimum losses while the point B4 represents the minimum size. Moving along the Pareto front from A4 to B4, a diminution of both the inductance value and the current ripple can be recorded. This decrease will leads to the increase of switching frequency and thus, the losses augmentation and the size reduction.

The optimal solution for Volume vs. Losses optimization is chosen according to the method presented in Section III. The minimum distance between the ideal and optimum point is equal to 0.6889 and the best design is obtained for an inductance value of 4.48 mH and a

current ripple of 0.581 A. This design represents the best compromise between the efficiency of the inverter and its volume with losses in the order of 93 W and a size of 643.9 cm³.

For Cost vs. Losses optimization, shown in Fig. 10 (b), the Pareto front is bounded by points A5 and B5. Solution A5 is the best of all optimal Pareto solutions in terms of efficiency but it is the most expensive, while B5 is the least efficient but the most economical solution. By moving along the Cost vs. Losses curve from A5 to B5, the inductance value and current ripple are reduced, resulting in an increase of switching frequency and thus an increase of losses and a decrease of price. The best design for this bi-objective optimization is obtained at a minimum distance of 0.857 for which the inductance value is approximately 3.6 mH and the output current ripple is about 0.57 A. A trade-off between cost and losses targets can be found in this optimal point with a losses of 102.6 W for an inverter priced at nearly 206.7 €

(a)

Figure 10. Pareto front for continuous bi-objective optimization of (a) Volume vs. Losses (b) Cost vs. Losses

Table 2. Optimal solutions for electrical bi-objective optimization

Optimized converter	Objective			Variables		Constraints	
Objectives	Losses (W)	Volume (cm ³)	Cost (€)	L (mH)	ΔI (A)	THD	$f_{s,\max}$ (KHz)
Volume/Losses	93.24	643.9	-	4.48	0.581	0.0497	19.2
Cost/Losses	102.6	-	206.7	3.62	0.571	0.0497	24.17

Table 2 contains the optimal designs obtained from bi-objective Volume vs. Losses and Cost vs. Losses optimization.

A more efficient solution can be achieved by optimizing the converter design not only by meeting two objectives (Volume vs. Losses or Cost vs. Losses) but by satisfying all three objectives at once, this is the subject of the next section.

5.3. Tri-Objective Optimization

Fig. 11 shows the Pareto front of the continuous tri-objective optimization for the DC/AC converter. The choice of one individual or another among this front depends on the designer preference. If a high efficiency of the inverter is desired despite its size and price, the solution A6 is the most suitable one; however, if the volume or cost minimization is preferred independently to efficiency, the solution B6 is the most appropriate. Sliding

from A6 to B6 along the Pareto front, there is a simultaneous diminution of the inductance and current ripple values. These decreases will lead to a rise of the switching frequency and subsequently an increase of converter losses. On the other hand, they have a direct effect on the reduction of converter size and its cost. The ideal objective vector for tri-objective optimization is defined as follows:

$$V_{\text{ideal}} (\text{Cost vs. Volume vs. Losses}) = [61.09 \text{ W } 447.9 \text{ cm}^3 \text{ } 137.2 \text{ €}]^T$$

The minimum distance between this point and the optimal Pareto solution is then evaluated to about 0.8836 and the optimal structure is obtained for an inductance of 3.36 mH and a current ripple of 0.573 A. This design results in losses around 105.4 W, a size of approximately 565 cm³ and a price of about 196.4 €, as presented in Table 3.

Figure 11. Pareto front for continuous tri-objective optimization of Cost vs. Volume vs. Losses

Table 3. Optimal solution for electrical tri-objective optimization

Optimized converter	Objective			Variables		Constraints	
Objectives	Losses (W)	Volume (cm ³)	Cost (€)	L (mH)	ΔI (A)	THD	$f_{s\max}$ (KHz)
Cost/Volume/Losses	105.41	565	196.4	3.36	0.573	0.0497	26

6. Conclusions

Grid-connected photovoltaic systems are becoming an increasingly active player in the power generation systems of the future, which are connected by a wide range of electronic power converters. In order to improve the specifications of these systems, high requirements have been imposed on the entire photovoltaic installation, in particular for the power conversion stage. The design of power converters often involves a high level of technical and scientific knowledge in several technical fields. Thus, the electrical, thermal, mechanical, volume, control and cost constraints imposed by manufacturers require a design approach under multi-physical constraints. This approach should take into account the different aspects that affect the efficient operation of converters and their integration into a real environment. This approach was well described in this paper.

This paper proposes a methodology for the pre-design of single-phase DC/AC power converters in photovoltaic systems in terms of efficiency, volume and cost based on genetic algorithm. The non-linear average model associated with the hysteresis current regulator is used for the inverter modeling and the multi-objective algorithm NSGA-II is used to reveal the trade-off curves. The results

obtained are very useful for easily design an optimal power converter structure according to the specifications and constraints of the desired system. Multi objective optimization of a power converter working in a given application without the need of tedious and expensive experimental tests is possible if an accurate model of the converter is used. This decrease time to market phase for manufacturers.

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