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A Hybrid Optimization Algorithm in Power Filter Design

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Abstract – Clonal Selection Algorithm (CSA) is one of the most widely employed immune-based approaches for handling optimization tasks. Characterized with the similartaxis and dissimilation properties, Mind Evolutionary Computation (MEC) is a new evolutionary computation method. In this paper, we propose a hybrid optimization algorithm based on the principles of the CSA and MEC to search for the optimal parameters (values of inductor and capacitor) of a passive filter in the diode full-bridge rectifier. Simulation results demonstrate that our algorithm can acquire the optimal LC parameters within the given criteria for power filter design.

Keywords: Artificial Immune System (AIS), optimization, Clonal Selection Algorithm (CSA), Mind Evolutionary Computation (MEC), passive filter, harmonic distortion.

I. INTRODUCTION

Artificial Immune System (AIS), based on the natural immune systems, is considered as an emerging kind of biologically inspired computational intelligence methods, which have attracted considerable research interest from different communities over the past decade [1]-[5]. As an important partner of the AIS, Clonal Selection Algorithm (CSA) has been successfully applied to handle challenging optimization problems with superior performances over classical approaches [6] [7] [8]. Alternatively, Evolutionary Computation (EC) is another type of effective methods to deal with optimization tasks. Based on the analysis of human mind thinking principles, Sun proposed the Mind Evolutionary Computation (MEC) in order to overcome the premature drawback of conventional EC [9].

In this paper, we first present a hybrid optimization algorithm combining both the CSA and MEC, which will be described in details in Section II. In Section III, we next discuss the parameter optimization problem of a full-bridge diode rectifier. Computer simulations are made in the following section. The performance comparison among the GA, CSA, and our hybrid optimization method is also made. Finally, in Section V, we conclude this paper with some remarks and conclusions.

II. HYBRID OPTIMIZATION ALGORITHM

A. Clonal Selection Algorithm (CSA)

As aforementioned, the AIS is a new kind of computational intelligence methodologies inspired by the natural immune systems to cope with real-world problems [10]. The CSA is based on the Clonal Selection Principle (CSP), which explains how the immune response is mounted, when a non-self antigenic pattern is recognized by the B cells [11]. It is actually an evolutionary process in the natural immune systems, during which only the antibodies that can recognize intruding antigens (non-self cells) are selected to proliferate by cloning [12].

B. Mind Evolutionary Computation (MEC)

The Mind Evolutionary Computation (MEC) is an evolutionary optimization approach. In the MEC, all the individuals are grouped into either the superior set or temporary set [13]. The former holds the information of winners of global competition, while the later keeps records on the procedure of global competition. At each generation, all the individuals of every group put their competition information on the local billboards. The global billboard, on the other hand, holds the information of every group, and records the winners during the global competition. Especially, similartaxis and dissimilation are the two unique features of the MEC. The similartaxis is an iterative process, in which individuals compete against each other in a local area to search for the local optima. A group is considered matured, if there are no new winners being selected any longer. The dissimilation is another procedure, in which all the groups compete with each other to globally search for new possible candidates in the whole solution space [14]. The similartaxis and dissimilation are two distinguished MEC characteristics during evolution. More information of the MEC can be found in [13].

C. Hybrid Optimization Algorithm

In this paper, we develop a hybrid optimization algorithm based on the ideas of the above CSA and MEC. The basic diagram of our hybrid optimization algorithm is illustrated in Fig. 1, which can be explained as follows:

Step 1: Initialize the candidate pool including *N* groups.

Step 2: Do similartaxis for each group. The best affinity is regarded as the record of the corresponding group, and will be used to compete with other groups. This process is, in fact, carried out by the CSA:

1. Evaluate the fitness of all the individuals in the current population, and select the best candidates according to their fitness.

2. Clone these best antibodies into a temporary pool (C).

3. Generate a mutated antibody pool (C_1). The mutation rate of each individual is inversely proportional to its fitness.

4. Evaluate all the chromosomes in C_1.

5. Re-select the individuals with better fitness from C_1 to compose memory set M. Other improved individuals of C_1 from mutation can replace certain members in the initial population to maintain the antibody diversity.

Step 3: Select the groups with the best affinity, and randomly generate the supplementary groups to replace the matured ones. Actually, this step is equivalent to the dissimilation in the aforementioned MEC.

Step 4: If the preset performance criteria is met, terminate the optimization procedure. Otherwise, go back to Step 2.

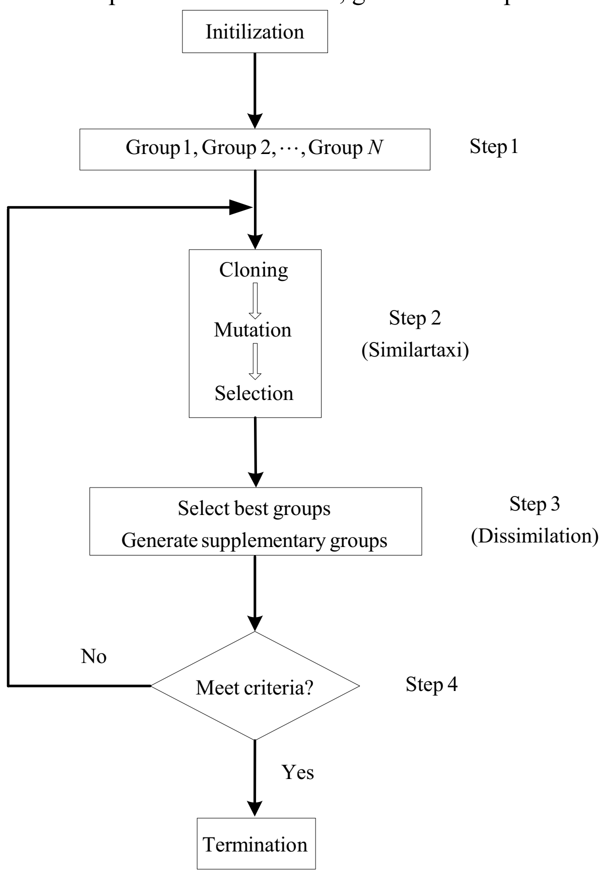


Fig. 1. Basic diagram of hybrid optimization algorithm.

Obviously, our hybrid optimization algorithm takes advantage of both the CSA and MEC. In principle, the dissimilation and similartaxis in the CSA are for the global and local optimal search, respectively. As we know, compared with the GA, the convergence speed of the CSA is relatively slow. However, in our hybrid optimization algorithm, the dissimilation borrowed from the MEC can keep the candidate pool dynamical during iterations as well as explore larger solution space. Therefore, the common premature problem in the classical GA-based approaches can be efficiently handled. In addition, we employ a new mutation operator in Step 2, through which the mutated values of individuals are inversely proportional to their fitness by means of selecting different mutation variations. In other words, the better fitness the individual has, the less it changes by mutation. We should point out that the clone size in Step 2 is generally defined as either a monotonic function of the affinity measure or a constant value [15]. Here, it is a constant. Based on our rules, the candidate pool tends to be more diverse. The hybrid optimization algorithm can, thus, avoid being trapped into local minima, and achieve an improved convergence speed. For the demonstration purpose, we employ this optimization algorithm, CSA, as well as GA to deal with the minimization of the following test function [9], and compare their optimization results:

$$y = 100\left(x_1^2 - x_2^2\right)^2 + \left(x_1^2 + 1\right)^2 . \qquad (1)$$

The simulation results are shown in Fig. 2. Some important parameters used are given in Table 1. Apparently, the convergence speed of our hybrid optimization algorithm is much faster than those of the CSA and GA. Note, this hybrid algorithm begins with a small initial population size. However, due to the embedded dissimilation operation, it can search for the global optimum in the solution space.

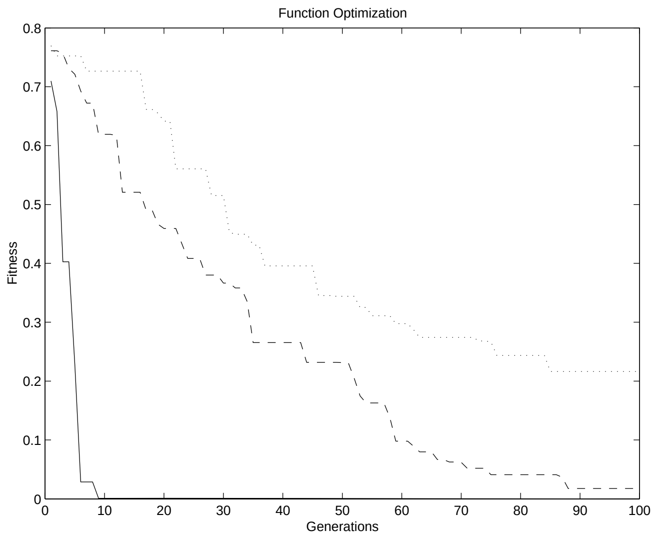


Fig. 2. Evolutionary behaviors of function optimization.
Solid line: hybrid optimization algorithm.
Dashed line: CSA. Dotted line: GA.

Table 1. Parameters in Fig. 2.

Parameter	**Value**
Initial group	3
Clonal size	2
Generations	100
x_1 range	-1 ~ 1
x_2 range	-1 ~ 1
Mutation rate	0.01

III. SINGLE-PHASE DIODE RECTIFIERS

In modern power electronics, it is advantageous to utilize inexpensive rectifiers with diodes to convert AC input into DC output in an uncontrolled manner. These rectifiers are widely applied in the majority of power electronics applications, such as switching DC power supplies and AC/DC motor drives [16]. A large capacitor as a filter at the DC side is used to charge a value close to the peak of the AC input voltage. Unfortunately, the deployment of this electrolytic storage capacitor usually results in a poor Power Factor (PF) as well as highly distorted current of AC side from the utility. Generally, a power filter (active or passive) targets at shaping the input waveforms. It has been proved that by using the active filters, we can improve the PF to be very close to unity with small harmonic currents. However, such an approach increases the control complexity and circuit costs as well. Alternatively, passive filers are more attractive choices, because of their simple configuration, reliability, and easy implementation, especially in case of a specific load power [17]. They have become an effective method for the tasks of PF correction and harmonic current reduction. Figure 3 illustrates a typical LC passive filter circuit topology for full-bridge rectifiers. Conductor L_s and capacitor C_s can be deployed in conjunction with the diode rectifier bridge to improve the current waveforms. Actually, a large inductor has a negative impact on the associated post regulator control strategy caused by the increased DC source voltage regulation. Thus, we have to select as small inductors as possible in our passive filter design [18]. The analysis of the single-phase diode full-bridge rectifier system is based on the following two assumptions.

1. Capacitor C_o is sufficiently large so that the output voltage is ripple free constant DC voltage.
2. AC voltage and diodes D_1, D_2, D_3, and D_4 are ideal components.

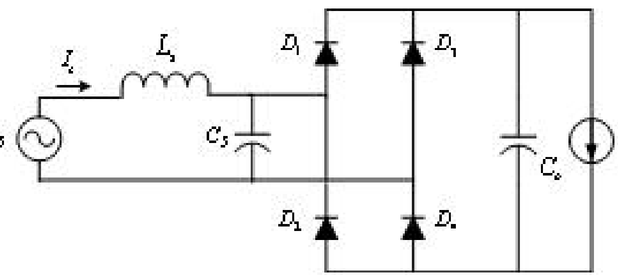


Fig. 3. A typical LC passive filter circuit topology for full-bridge rectifiers.

It is well known that the performance of the passive filter is determined not only by its circuit topology but also the values of the inductor and capacitor involved. Numerous passive filter design methods have been introduced to optimize these LC parameters in order to obtain the best input current waveform. For example, two interesting schemes are advocated by Moo and Chen. Moo developed a computer program to create the contour maps of the PF, Total Harmonic Distortion (THD), and DC voltage in dimensioning the LC passive filter [17]. The optimal operation point can be selected under the practical considerations as well as required specifications. However, drawing such contour maps is always time-consuming, and different loads require different maps to be drawn. On the other hand, instead of the traditional gradient descent-based methods, some promising optimization approaches have emerged during recent years, Chen introduced the GA to design the passive filter [19]. As discussed above, compared with the GA, our CSA can achieve both local and global search. In the next section, we investigate a new CSA-based scheme to optimize the LC parameters of the diode full-bridge rectifier (as shown in Fig. 3) within the following three criteria:

1. small inductor for LC input filter;
2. large PF;
3. low THD.

Our hybrid optimization algorithm will also be used in this optimal LC filter design system, and its performance is compared with that of the GA and CSA.

IV. SIMULATIONS

The GA, CSA, and proposed hybrid optimization algorithm are applied here to optimize the parameters of the passive filter. Four kinds of software, i.e., MATLAB, SIMULINK, SimPowerSystems, and Piece-wise Linear Electrical Circuit Simulation (PLECS), are utilized in our computer simulations.

A. Simulation parameters

Since both L_s and C_s of the passive filter are supposed to be optimized by the CSA, every antibody, in form of float numbers, includes two sub-segments that represent the values of L_s and C_s, respectively. Their search ranges should be initially chosen in the CSA. Based on certain prior knowledge, we set $L_s \in [0, 200\text{mH}]$ and $C_s \in [0, 20\mu\text{F}]$ [17]. The fitness (affinity) function has to be defined beforehand as well. According to the principles of the passive filter and other practical appreciations, two issues are considered here.

1. Maximal PF.
2. As small L_s as possible.

Obviously, a better fitness would lead to a larger PF and smaller inductor. The objective of employing the passive filter in the AC/DC rectifier is to obtain the maximal PF as well as minimal THD. As aforementioned, the higher the internal source L_s, the greater the voltage distortion. A small inductor is always desired, although this is not our major optimization goal. In other words, a smaller value of L_s is preferred, if it can achieve a slightly lower but acceptable PF.

Therefore, the fitness of antibodies should be written as a weighted combination of L_s and PF [19]:

$$fitness = PF - k \log_{10} L_s \ . \qquad (2)$$

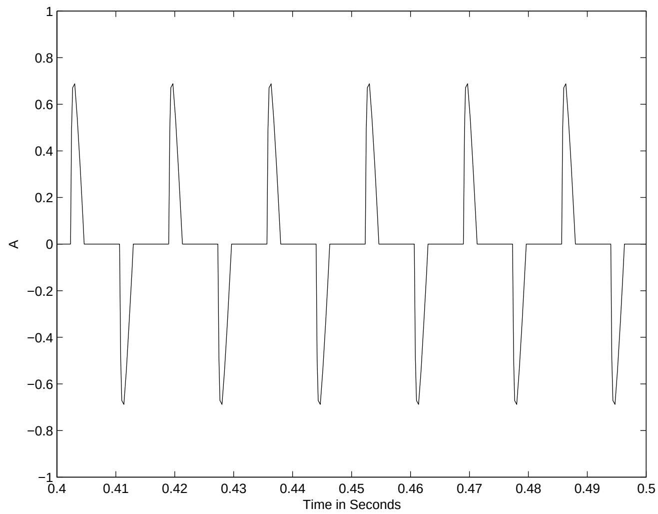
The user-defined coefficient k provides the degree of freedom to adjust the impact of L_s on the fitness and PF of the AC side. The memory set M in the CSA acts as a pool to accommodate the antibodies (possible L_s and C_s) with high affinity. In summary, all the parameters of our simulations are given in Table 2. It should be emphasized that to accelerate the convergence of the CSA, the mutated value of antibodies is inversely proportional to each individual's affinity.

Table 2. Parameters of CSA-based LC filter optimal design.

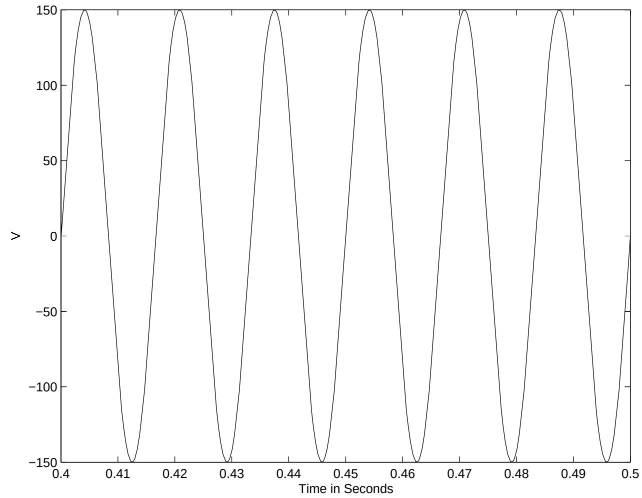
Parameter	**Value**
Population size	6
Clone size	2
Weight k	0.001
C_s (μF) range	0 ~ 20
L_s (mH) range	0 ~ 200

B. Simulation results

For the diode full-bridge rectifier in Fig. 3 without the LC passive filter, the simulated input current I_s and source voltage v_s are illustrated in Figs. 4 (a) and (b) respectively. Without the passive LC filter, the PF of the AC mains is 0.62, and the input current THD is 115% for the load current $I_o = 0.4\text{A}$ with output capacitor $C_o = 220\mu\text{F}$.



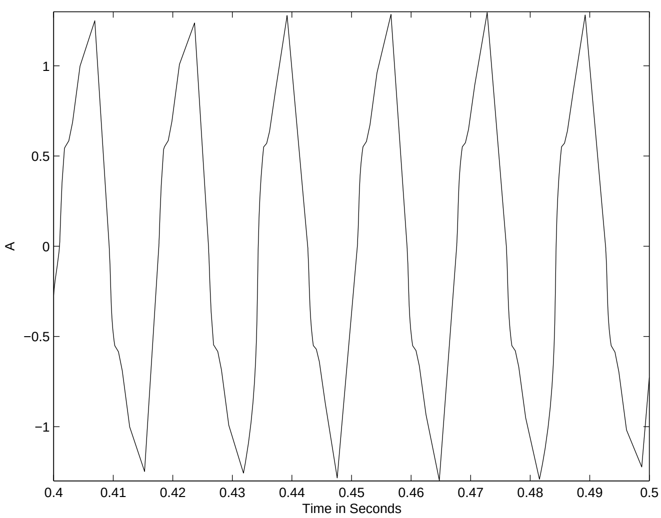
(a)



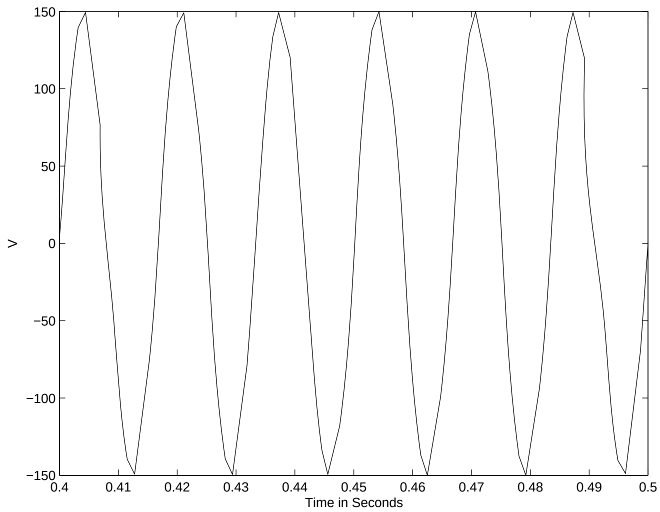
(b)

Fig. 4. Waveforms of I_s and v_s in Fig. 3 without LC passive filter: (a) I_s, and (b) v_s .

The waveforms of I_s and v_s with our CSA-optimized LC passive filter are shown in Figs. 5 (a) and (b), respectively. The corresponding parameters are provided in Table 3. The new L_s and C_s are 184 mH and $1.56\mu\text{F}$, respectively. It is clearly visible the CSA can optimize both L_s and C_s to achieve the desired power factor. Meanwhile, the THD has also been reduced to 21.9%. However, we should stress that all the optimization results are obtained only under ideal conditions, i.e., the four diodes are assumed ideal, and values of inductor and capacitor are 100% accurate.



(a)



(b)

Fig. 5. Waveforms of I_s and v_s with CSA-optimized LC passive filter: (a) I_s, (b) v_s.

Table 3. CSA-optimized C_o, L_s, C_s, PF, and THD.

Parameter	Value
I_o (A)	0.4
C_o (μF)	220
L_s (mH)	184
C_s (μF)	1.56
PF	0.96
THD (%)	21.9

To further demonstrate the optimization characteristics of our hybrid algorithm, we compare its evolutionary behaviors with those of the CSA and GA, as depicted in Fig. 6. For the hybrid optimization algorithm, after 50 generations, the PF has been improved to 0.958, and the THD reduced to 21.9%.

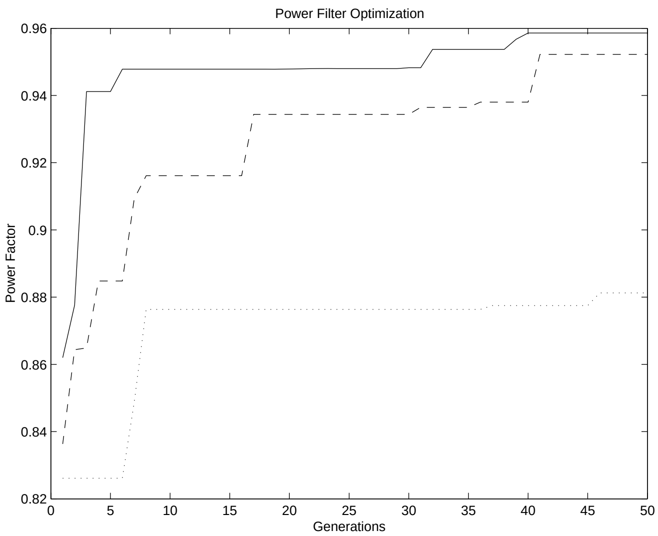


Fig. 6. Evolutionary behaviors in PF optimization of LC passive filter. Solid line: hybrid optimization algorithm. Dashed line: CSA. Dotted line: GA.

We conclude that although initialized with a relatively small population, the proposed hybrid optimization algorithm can still overcome the harmful premature problem, and obtain satisfactory optimization results. Due to the integration of the CSA, another essential advantage of our method over other optimization approaches is that it takes the affinities of antibodies into account during evolution, which can provide a group of different antibodies with the best affinity. Table 4 illustrates such a pool accommodating various appropriate candidates with low self-affinity among themselves. All of the LC combinations in the table can improve the PF to be 0.95 (I_o=0.4A). The diversity of these candidates offers more flexible design choices. This distinguished property has significant potentials in engineering

Table 4. Hybrid optimization algorithm-optimized LC parameters with PF=0.95.

L_s (mH)	C_s (μF)	THD (%)
198.60	3.47	28.4%
194.59	2.58	34.3%
189.51	3.09	31.1%
192.85	1.70	29.6%
196.34	2.98	31.4%
193.59	3.25	30.0%
178.84	1.33	19.9%
197.85	1.48	20.4%
196.71	2.49	34.1%
197.52	1.73	28.9%
197.22	1.54	23.9%

V. CONCLUSIONS

In this paper, a new hybrid optimization method inspired by the principles of the CSA and MEC is first discussed, and further employed to design the LC passive filter. Simulations demonstrate that the proposed approach can acquire the optimal LC parameters within certain given criteria, such as the desired PF and THD. The antibody diversity feature of the CSA as well as anti-premature function of the MEC are fully utilized in this algorithm so that it can be initialized with smaller size of population, and still achieve better optimization performances. Our hybrid algorithm is not only an effective but also flexible optimization method for coping with various real-world problems.

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