Normalization Group Brain Storm Optimization for Power Electronic Circuit Optimization

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ABSTRACT

This paper proposes a novel normalization group strategy (NGS) to extend brain storm optimization (BSO) for power electronic circuit (PEC) design and optimization. As different variables in different dimensions of the PEC represent different circuit components such as resistor, capacitor, or inductor, they have different physical significances and various search space that are even not in comparable range. Therefore, the traditional group method used in BSO, which is based on the solution position information, is not suitable when solving PEC. In order to overcome this issue, the NGS proposed in this paper normalizes different dimensions of the solution to the same comparable range. This way, the grouping operator of BSO can work when using BSO to solve PEC. The NGS based BSO (NGBSO) approach has been implemented to optimize the design of a buck regulator in PEC. The results are compared with those obtained by using genetic algorithm (GA) and particle swarm optimization (PSO). Results show that the NGBSO algorithm outperforms GA and PSO in our PEC design and optimization study. Moreover, the NGS can be regarded as an efficient method to extend BSO to real-world application problems whose dimensions are with different physical significances and search ranges.

Categories and Subject Descriptors

I.2.8 [**Artificial Intelligence**]: Problem Solving, Control Methods, and Search – *Heuristic methods*; G.1.6 [**Numerical Analysis**]: Optimization – *Global optimization*

Keywords

Brain storm optimization (BSO), normalization group strategy (NGS), power electronic circuit (PEC)

1. INTRODUCTION

Power electronics circuit (PEC) always consists of a number of components such as resistors, capacitors, and inductors that have to be optimally designed to obtain better circuit performance. Several evolutionary computation (EC) algorithms such as the genetic algorithm (GA) [1] and particle swarm optimization (PSO) [2][3] have been reported successfully applied to PEC, showing great promising of using EC algorithms in the PEC problem [4][5].

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Brian storm optimization (BSO) is a new kind of swarm intelligence (SI) algorithm that was first proposed by Shi in 2011 [6]. The BSO algorithm is motivated by the intelligent brainstorming behaviors of human beings in problem solving. Shi has successfully designed a BSO by emulating this brainstorming process in human being solving problem and conducted simulation results on typical benchmark functions to validate the effectiveness of BSO in solving optimization problems [6].

In this paper, we focus on using the modified BSO (MBSO) proposed by Zhan *et al*. [7] to solve the PEC problem. However, we find that the grouping operator in basic BSO or MBSO is not directly suitable for PEC. Traditionally, the grouping operator is based on the position information of the solutions. This can be useful when all the decision variables are within similar search range. For example, in classic real-parameter optimization benchmark, all the variables of different dimensions are within the same search range, e.g., [-100, 100]. In such condition, the cluster or group strategy based on the position information can work. However, in the PEC optimization problem, different variables in different dimensions have different physical significances. For example, some variables represent the resistors while some other variables represent the capacitors. Their search ranges are significantly different. For example, the search range for resistor is [100Ω, 100kΩ] while the search range for the capacitor is [0.1μF, 100μF]. In such condition, clustering or grouping the solutions based on the position information is not a rational strategy. Therefore, we have to re-design the grouping operator to make it suitable for the optimization characteristic of PEC. In this paper, we propose to use a normalization group strategy (NGS). That is, all the dimensions of a solution are firstly normalized to the range of $x^*_{id} = (x_{id} - L_d)/(U_d - L_d)$, so that $x^*_{id} \in [0,1]$. Then the grouping operator is executed based on the normalized position information. Moreover, according to the suggestion in [8] that a simpler creating operator is used, the NGS based BSO (NGBSO) in this paper also uses this simpler creating operator. That is, NGBSO generally uses the following four operators named *grouping*, *replacing*, *creating*, and *updating* the same as the ones in MBSO to evolve new solutions generation by generation to approach the optimal solution [7][8]. We apply NGBSO to solve the PEC problem to show its effectiveness. The PEC problem is the same as the one in [5].

2. RESULTS COMPARISONS

2.1 Comparisons on Fitness Quality

The mean convergence characteristics of 30 runs of GA, PSO, and NGBSO are plotted in Figure 1. The curves show that GA falls into very poor local optima quite early whilst NGBSO is able to obtain very high fitness in early state and to improve the fitness value steadily for a long time. Even though PSO can improve the solutions for long time, the final solution is still much worse than that of NGBSO. The figure shows that NGBSO has strong global search ability to avoid local optima and has significantly improved the fitness value. Moreover, the curves indicate that NGBSO is faster than the other algorithms to optimize the component values. That is, when a fixed fitness is given, NGBSO is observed to use much less FEs to obtain this specific value than other algorithms.

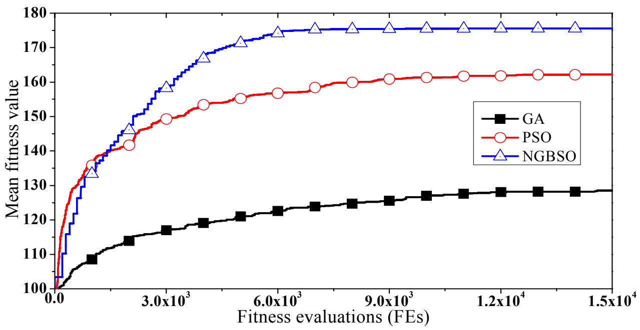


Figure 1. Mean convergence characteristics of different approaches in optimizing the PEC.

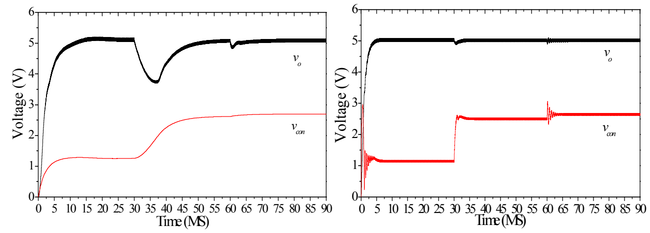
2.2 Comparisons on Simulation Result

Simulations are conducted in this sub-section. The component values of the PEC are set as the optimized results of different approaches. In order to make the comparisons clearer, the median solution obtained by each approach is used. The simulation results are plotted and compared in Figure 2 to show the voltage results of GA and NGBSO.

The simulation lasts for 90 milliseconds (ms). The input voltage v_{in} is 40 V and the output load R_L is 10 Ω. The simulated startup transients can be compared in the first 30 ms of the figures. It is observed that the circuit with NGBSO-optimized component values has better performance, giving faster settling time. The buck with component values optimized by NGBSO uses only about 5 ms to reach the steady state, while the circuit with component values optimized by GA uses about 10 ms.

Figure 2 also shows the simulated transient responses under large signal disturbances. On the 30 ms, when the regulator is in steady state, the input voltage is suddenly changed from 40 V to 20 V, with the load still fixed as 10 Ω. As the responses to this change, the output voltage v_o, and the control voltage v_{con} are both disturbed. However, the circuit optimized by NGBSO has much smaller disturbance and shorter response time (less than 5 ms) than the one optimized by GA (more than 10 ms), confirming the advantages of the NGBSO algorithm. Moreover, the overshoot of v_o of the GA-optimized circuit is much larger than that of the NGBSO-optimized circuit.

Similar tests on load disturbances are also studied when the system has reverted a steady state with v_{in} equals 20 V and R_L equals 5 Ω. In this disturbance, R_L is suddenly changed from 10 Ω to 5 Ω on the 60 ms, with the v_{in} being still fixed as 20 V. The simulation results in the figures also show that the NGBSO-optimized circuit has a smaller disturbance response to the change and a shorter time to revert the steady state when compared with GA. Therefore, the proposed NGBSO algorithm can optimize the circuit component values and make the circuit exhibit better dynamic performance.



(a) GA (b) NGBSO

Figure 2. Simulated voltage responses from 0 ms to 90 ms. From 0 ms to 30 ms, v_{in} is 40 V and R_L is 10 Ω; on the 30 ms, v_{in} is suddenly changed from 40 V to 20 V while R_L is still 10 Ω; on the 60 ms, R_L is suddenly changed from 10 Ω to 5 Ω while v_{in} is still 20 V.

3. CONCLUSION

This paper presents a BSO based algorithm for optimizing the component values in designing PEC. The challenge of using BSO in PEC optimization is that different dimensions have different physical significances to represent different kinds of components, and therefore with significantly different search ranges. This makes the grouping operator that is based on the solution position information not suitable for PEC optimization. To overcome this problem, the NGBSO that uses the normalization group strategy is proposed. The effectiveness and efficiency of the NGBSO algorithm in optimally designing PEC have been evaluated with the design of a buck regulator with overcurrent protection. The results compared with the ones obtained by GA and PSO show the advantages of NGBSO.

4. ACKNOWLEDGMENTS

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