# Shape Optimization of Power Inductors Using Actor Critic Method

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**Abstract**

This paper presents a shape optimization of power inductor using actor-critic approach which is one of the reinforcement learning. The performance of the actor-critic (AC) approach is compared with that of the genetic algorithm. Comparing to GA, AC is more stably converged to an optimal solution with lower computational cost.

## 1 Introduction

Magnetic components such as inductors and transformers play important roles in power electronics circuits. Shape optimization of these magnetic components has been successfully performed to enhance their efficiency as shown in [1][2]. In this optimization process, the genetic algorithm (GA) is widely used to efficiently find optimal solutions. However, GA evaluates numerous magnetic components with different design parameters using finite element analysis. Therefore, it is required that the optimization time needs to be reduced.

Recently, reinforcement leaning (RL) [3][4] has gained attention across various fields for the ability to efficiently learn and search optimal actions and solutions. For instance, RL techniques such as deep-Q-network and normalized advantage function have been successfully applied to achieve stable control of buck converter [3]. Despite the successful application in the other fields, there are few studies focusing on the shape optimization of the magnetic components.

In this paper, shape optimization of inductors using RL is proposed. In this approach, actor-critic (AC) method [4] is employed as an RL method to optimize the power inductor. Finally, we compare the performance and computational cost of the AC with those for GA.

## 2 Shape optimization of inductor using Actor Critic

In this study, the coil shape of the power inductor (1.6x0.8x0.8mm$^3$) is optimized as shown in Fig. 1. In this inductor, there are 5 design parameters $\boldsymbol{d}$=[$r$, $l$, $w$, $t$, $n$], where $r$, $l$, $w$, $t$ and $n$ are the inner radius, length of the major axis, coil width, coil thickness, and number of coils, respectively. The objective function is defined as follows:

$$f(\boldsymbol{d}) = \left|\frac{L_{target} - L(\boldsymbol{d})}{L_{target}}\right| + kR_{dc}(\boldsymbol{d}) \to \text{min.} \tag{1}$$

where $L_{target}$ is the target inductance which is set to 240nH in this study, and $L(\boldsymbol{d})$ and $R_{dc}(\boldsymbol{d})$ are the inductance and DC resistance with the design parameter $\boldsymbol{d}$ which are computed by FEA. $k$ is a normalized parameter, which is set to 1 in this study.

The AC approach is based on the policy gradient method, in which the policy $\pi(a_d|s_d)$ is updated with the gradient method to minimize (1), where $s_d$ and $a_d$ denote the design parameter and action direction for $s_d$, respectively. In this study, the policy $\pi(a_d|s_d)$ is defined as the normal distribution:

$$\pi(a_d|s_d, \boldsymbol{\theta}) = \frac{1}{\sqrt{2}\pi\sigma(s_d, \boldsymbol{\theta})} \exp\left(-\frac{\left(a_d - \mu(s_d, \boldsymbol{\theta})\right)^2}{2\sigma(s_d, \boldsymbol{\theta})}\right) \tag{2}$$

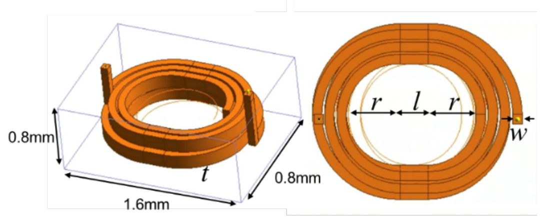



Fig. 1 Power inductor for the optimization

Table I Comparison between actor critic and GA

| | Actor-Critic | GA |
|---|---|---|
| seed | 5 | 5 |
| $N$ | 5 | 5 |
| length(mm) | 0.134 | 0.143 |
| radius(mm) | 0.157 | 0.172 |
| thickness(mm) | 0.263 | 0.255 |
| width(mm) | 0.072 | 0.070 |
| $L$ (nH) | 239.9 | 240.1 |
| $R_{dc}$ (mΩ) | 20.9 | 21.9 |

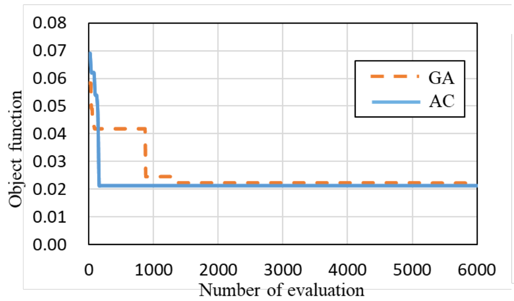
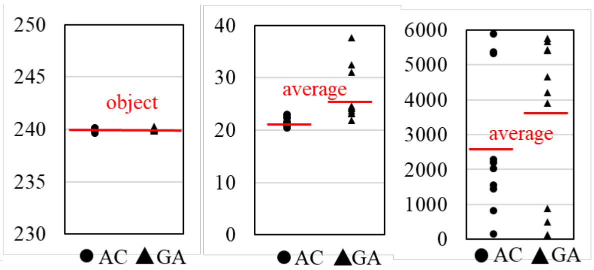



Fig. 2 Convergence history of the GA and AC




(a). inductance. (b) DC resistance (c) # of FE computations

Fig. 3 Comparison of the optimizations for 10 trials

where $\mu$, σ and $\boldsymbol{\theta}$ are the mean, standard deviation, and updated parameter, respectively. $\boldsymbol{\theta}$ is iteratively updated by the policy gradient method [4] to find an optimal policy and action.

## 3 Optimization results

The shape optimization of the inductor shown in Fig. 1 was performed by both the GA and AC approaches. Table I summarizes the optimization results. You can see that we obtained the inductors of 240nH while $R_{dc}$ of AC solution is better than that of GA solution. Moreover, the convergence history of the objective function is plotted in Fig. 2, where the AC approach is quickly converged toward the optimal solution.

To further evaluate the optimization methods, we performed 10 trials with different random seeds. Fig. 3 shows the optimization results for the 10 trials where (a) inductance, (b) $R_{dc}$ and (c) the number of FEA required for the convergence to the optimal solution. In both methods, the inductance is converged to 240nH across the 10 trials. However, for the resistance, the AC method could stably achieve smaller $R_{dc}$. For the number of FEA, AC averagely requires 2500 FE computations while GA averagely needs 3500 FE computations for convergence to the optimal solution. These results show the superior stability and effectiveness of the AC method over GA.

In the full paper, the proposed method will be applied to other inductors, and we will compare them with another optimization approach.

## References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