

Multi-objective Magnetic Design of Powder Core Inductors Based on Deep Reinforcement Learning

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A novel multi-objective optimization approach for the magnetic design of power inductors is proposed based on the deep reinforcement learning (DRL). The optimization problem is modeled using an artificial neural network (ANN) with the encoder-decoder architecture. The encoder processes the design specification, while the encoder indirectly generates the optimal design variables by modeling their probability distributions. Trained via reinforcement learning, the design task can be addressed by the DRL-based method without iterative processes, drastically cutting down computational time. Additionally, the advantages in the convergence and diversity of the proposed approach are demonstrated through a case study on a power inductor for inverters.

Index Terms—Power inductors, deep reinforcement learning, artificial neural networks, multi-objective optimization.

I. INTRODUCTION

WITH the rapid advancement of power electronic technologies, the demand for high-power-density and high-efficiency power conversion systems has dramatically increased across various compact applications, such as the electric vehicles, renewable energy systems, and the consumer electronics. As the crucial components of converters, passive components, especially the magnetic-core power inductors, comprise a substantial proportion of the weight and volume within these systems, posing an obstacle to the overall downsizing [1]. Additionally, the miniaturization of power inductors while maintaining the specified inductance value is constrained by the increased iron and copper losses. Therefore, faced with the multiple optimization objectives, researches on the design method of power inductors have received increasing attention [2], [3], [4].

Compared to the time-consuming brute force grid search [2], some metaheuristic algorithms such as non-dominated sorting genetic algorithms (NSGAs) and multiobjective evolutionary algorithms (MOEAs) have been developed to more rapidly form the Pareto front (PF) [5], [6]. However, all these algorithms inevitably lead to increased computational time due to more iterations required for better converged results.

In this article, a novel multi-objective optimization approach for the magnetic design of inductors is proposed based on the deep reinforcement learning (DRL). The optimization problem is modeled using a generative artificial neural network (ANN) with an encoder-decoder architecture, which is trained by reinforcement learning. Once the model is trained, the task of inductor design with different target weights can be accomplished without iteration and repetitive training, significantly reducing the time consumption compared with classical methods. Moreover, a power inductor used in inverters is taken as a specific test case to demonstrate its effectiveness. The test results show that the DRL-based method exhibit obvious advantages in terms of convergence and diversity.

II. PROPOSED DESIGN APPROACH

The magnetic design of power inductors is formulated as a multi-objective optimization problem. Using the weighted sum

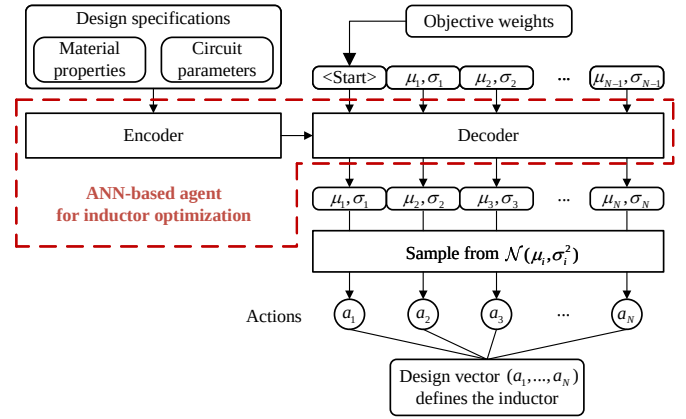


Fig. 1. Illustration of the model structure and the novel inductor design framework based on the agent.

method, The common objective function is shown as follows:

$$\min_{\mathbf{x} \in X} g(\mathbf{x}) = \sum_{i=1}^M \lambda_i f_i(\mathbf{x}) \quad (1)$$

where X is the feasible decision space, $\mathbf{x} = (x_1, \dots, x_N)$ is the design vector with N variables, $g(\mathbf{x})$ is the combined objective function, $f_i(x)$ is the i th cost function, and $\lambda = (\lambda_1, \dots, \lambda_M)$ is the spread weight vector associated with M objectives. The innovative design framework is shown in Fig. 1. And the ANN-based agent for inductor optimization is elaborated as follows.

a) *Encoder*: Some design specifications including circuit parameters and material properties are incorporated into the encoder as inputs. All these raw input data are transformed into dense and high-dimensional vectors. Finally, these high-dimensional vectors are fed into the decoder, where they are processed to participate in the agent's action decisions.

b) *Decoder*: The decoder outputs the distribution probabilities of the designed variables, assuming that every one follows a normal distribution $\mathcal{N}$ characterized by its mean μ and standard deviation σ . The workflow of the decoder begins with an objective weight vector to generate the first

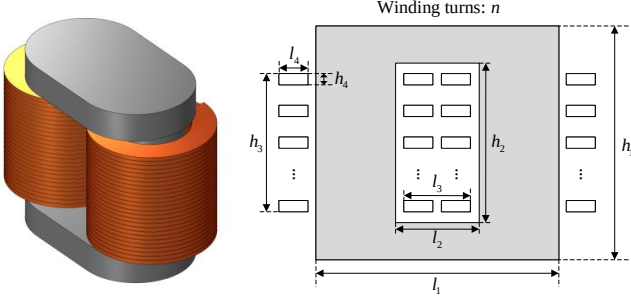


Fig. 2. 3-D model and cross section of the inductor.

TABLE I
DESIGN SPECIFICATIONS

The circuit parameters					
I_p [A]	175	P [kW]	55	L_{targ} [μ H]	170
The material properties					
Type	Fe-Ni alloy	B_{sat} [T]	1.5	μ	60
k [W/m ³]	917.3	a	1	b	2.17

pair (μ_1, σ_1) for the first design variable. Then, the generated pairs $\{(\mu_i, \sigma_i), i = 1, \dots, t\}$ will be input to the decoder along with the initial weights, sequentially providing the next pair $(\mu_{t+1}, \sigma_{t+1})$. During the training process, the actions $a = \{a_1, \dots, a_N\}$ are then randomly sampled from these distributions. Each action represents one of the selected values for various design parameters. The corresponding probability chain rule is defined as

$$P(a|s) = \prod_{i=0}^n P(a_{t+1}|a_1, \dots, a_t, s) \quad (2)$$

$$P(a_{t+1}|a_1, \dots, a_t, s) = \frac{1}{\sqrt{2\pi}\sigma_{t+1}} e^{-\frac{(a_{t+1} - \mu_{t+1})^2}{2\sigma_{t+1}^2}} \quad (3)$$

where the state s is the combination of the input design specifications and the weight vector for the inductor design. Upon completion of the training phase, the mean sequence with the highest probability density is selected as the action sequence without further random sampling.

The agent model is trained using the Actor-Critic method, a well-known algorithm for DRL. The loss function of actor network is defined as

$$Loss = \frac{1}{T} \sum_{j=1}^T (Q(s^j) - R^j) \log P(a^j|s^j) \quad (4)$$

where R^j is the real reward, $Q(s^j)$ is the value function, and T is the number of the instances. The network parameters are updated based on the gradient descent (GD).

III. NUMERICAL RESULTS

To valid the performance of the DRL-based approach, the power inductor consisting of combined cores and flat wires is taken as a study case. As presented in Fig. 2, nine design variables $(l_1, \dots, l_4, h_1, \dots, h_4, n)$ have been selected to define the geometry of an inductor. Table I summarizes a set

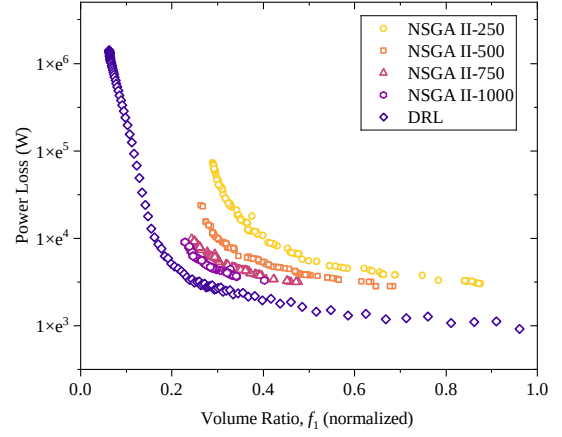


Fig. 3. The solutions obtained by the DRL-based method and NSGA II with the population size 100.

of specifications for the inductor design. The parameters k , a and b are the steinmetz coefficients.

Two design objectives, volume V and power loss P_{loss} , are considered. The objective functions are described as follows

$$f_1(\mathbf{x}) = V/V_{max} \quad (5)$$

$$f_2(\mathbf{x}) = \ln(P_{loss}) \quad (6)$$

where V_{max} is evaluated by the upper of variables.

With the population size 100, four sets of solutions are obtained by non-dominated sorting genetic algorithm II (NSGA-II) after 250, 500, 750 and 1000 generations, respectively. Besides, the same number of solutions is generated by the DRL-based method. The solutions are shown in Fig. 3. The DRL-based method achieves the desired convergence in just 11.8 s. In contrast, NSGA-II requires increasing the number of iterations for a similar level of convergence, leading to a time consumption from 26.2 s to 104.2 s. Furthermore, the DRL-based method outperforms NSGA in terms of solution diversity, which solutions do not tend to concentrate in a narrow region.

REFERENCES

- [1] E. Asahina, M. Fukuoka, I. Masuda, A. Nagai, K. Maeda, and M. Ishitobi, "Structure of air-core power inductor with high energy density and low copper loss," *IEEE Transactions on Magnetics*, vol. 59, no. 11, pp. 1–5, 2023.
- [2] T. Guillod, P. Papamanolis, and J. W. Kolar, "Artificial neural network (ann) based fast and accurate inductor modeling and design," *IEEE Open Journal of Power Electronics*, vol. 1, pp. 284–299, 2020.
- [3] S. Yin, H. Sato, and H. Igarashi, "A comprehensive optimal design of inductors using monte carlo tree search," *IEEE Transactions on Magnetics*, vol. 60, no. 3, pp. 1–4, 2024.
- [4] L. Solimene, D. Cittanti, F. Mandrile, S. Musumeci, and R. Bojoi, "Optimal air gap length design in powder core inductors," *IEEE Transactions on Magnetics*, vol. 59, no. 11, pp. 1–5, 2023.
- [5] B. Liu, D. Zhao, P. Reynaert, and G. G. E. Gielen, "Synthesis of integrated passive components for high-frequency RF ICs based on evolutionary computation and machine learning techniques," *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems*, vol. 30, no. 10, pp. 1458–1468, 2011.
- [6] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan, "A fast and elitist multi-objective genetic algorithm: Nsga-ii," *IEEE Transactions on Evolutionary Computation*, vol. 6, no. 2, pp. 182–197, 2002.