A Comprehensive Optimal Design of Inductors Using Monte Carlo Tree Search

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This paper presents a strategy of optimizing inductors with non-linear properties, using Monte Carlo tree search. Compared with existing optimization tools, the proposed method can simultaneously optimize global configuration such as material, number of turns and winding arrangement, and local geometry. It indicates that the strategy statistically provides a best solution from global and local aspects after iterations with different lengths of chromosomes, which is challenging in conventional optimization techniques. The covariance matrix adaptation evolution strategy is used to solve the parametric optimization. For validation, the optimizations on 2-D inductors are performed. The proposed method is very suitable for optimization of devices with possibly different global configurations. The most notable originality of this work is in the proposal of an inherited search for design targets with different emphases, suggesting that using an inherited search from the previous search history can make it easier to find the optimal solution.

Index Terms—**Optimal strategy, Monte Carlo tree search, non-linear electromagnetic problems, inductors.**

I. Introduction

INDUCTORS are key components in switched-mode power supplies. To select a suitable inductor in the power supplies, many design parameters need to be determined, such as the core material, the core and winding structure and the number of turns. Therefore, for effectively designing an inductor that satisfies given specification, a comprehensive design is expected to be more effective than the conventional design focused on local geometry.

Meanwhile, the artificial intelligence (AI) has been extensively used for modeling and designing inductors in recent years [1]. Among various AI algorithms, Monte Carlo tree search (MCTS) is one of the most widely used methods especially for games [2]. As a search tool, it exploits the actions that are the best at the current station, whilst continuing to explore the alternative actions that may provide a better solution, thus making a trade-off between the exploitation and the exploration during the searching process [3].

Apart from the aforementioned feature, the distinct advantage of MCTS is that it can realize the design optimization of magnetic devices simultaneously considering both their global configurations and local geometries [4, 5]. When we consider the optimal design of inductors, to which we pay attention in this work, device configurations such as materials, turns of coils, etc., core shape and coil arrangement are optimized so that their overall performance is maximized. Compared with conventional optimization techniques, which is challenging for handling different length of chromosomes by the different structures, MCTS-based design can systematically perform comprehensive design optimization.

To date, MCTS has been successfully implemented in the single and multi-objective optimization of electric motors [4] and [6]. In this paper, the potential of MCTS for the design of inductors considering magnetic saturation is verified and discussed. In addition to the different application targets from above, the innovation of the work lies in the following aspects.

First, the selection of non-linear materials of the core is considered, which is not taken into consideration in [4] and [6]. Second, the proposed method can simultaneously deal with different structures represented by chromosomes with different lengths, which is otherwise challenging for alternative optimization algorithms due to the difficulty of crossover among the chromosomes with different lengths. Third, a search based on inheritance of previous search history is implemented to design inductors with different emphases on the electrical performance. Compared to MCTS from an initial blank state, the search with inheritance can reach the best solution more easily, resulting in fewer search iterations. Finally, another originality is that by using MCTS, an alternative configuration path along which the mean reward at each node reaches maximum after iterations is successfully predicted to attain the best performance even if this path does not occur in the search history. This paper investigates for the first time the design based on the statistical results, which provides an alternative optimal solution apart from the best-ever solution.

II. Process for Optimization

We assume that the two-dimensional model of an inductor, consisting of a rectangular core and several turns of windings, as shown in Fig. 1, is to be optimized. In the initial phase of the design, configurations of the inductor have not yet been determined, such as the material applied to the core and its size, the number of turns for windings horizontally and vertically, etc. For each category of configurations, several options are offered as candidates. The design process is based on the optimization strategy involving MCTS to determine the configuration settings of inductors, and to optimize their geometric

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parameters afterwards.

Additionally, having the optimal solutions, and the history of search paths by aforementioned process, more optimizations on inductors behaving different electromagnetic performances can also be explored, introduced in II.*C* for details.

A. Implementation of MCTS

Figure 2 shows the design tree for the inductor. In this work, the material of the core (designated by M_i, i=1, 2, …, 8), the length of the core (l_j, j=1, 2, …, 12), the height of the core (h_k, k=1, 2, …, 6), the number of windings horizontally (m) and vertically (n) are considered. All these configuration settings are arbitrarily arranged from the top to the bottom leaf nodes, only if all nodes have same attributes for each layer of the tree.

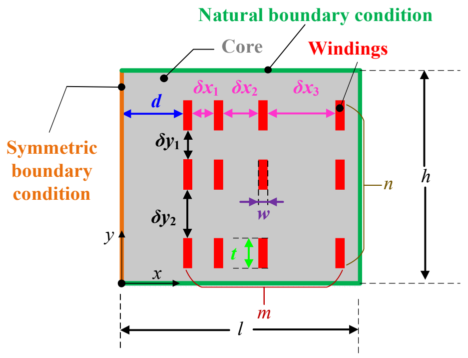


Fig. 1. Cross section of an inductor (1/2 model).

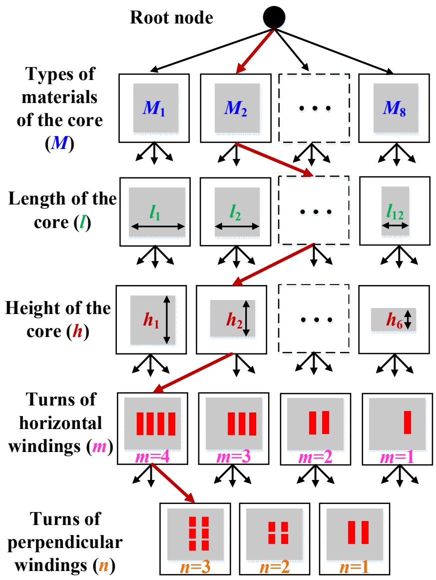


Fig. 2. Configuration settings of the inductor by MCTS.

To start, the number of rounds for the tree search is set. Then for each round, four steps are performed, i.e., Selection, Expansion, Simulation, and Backpropagation for MCTS. Explicitly, they are described below in details.

1. Selection: located at a current node p which is selected from a previous round, the best child of p, designated by p_i, is selected, according to the Upper Confidence Bound applied to trees (UCT), yielding:

$$UCT(p_i, p) = \frac{\sum_1^{N(p_i)} f_{MCTS}(p_i)}{N(p_i)} + c\sqrt{\frac{\ln(N(p))}{N(p_i)}} \qquad (1)$$

where $f_{MCTS}(p_i)$ is the nodal value at p_i which is obtained by Simulation introduced afterwards. In (1), N is the number of visits on a particular node (p or p_i), and c is the constant coefficient. The best child node is selected with the maximum value of UCT. In the initial phase of the search, the root node is set to be p. After the leaf node is reached, p is reset to be the root node to perform a new search.

2. Expansion: the precondition of the selection is that p_i is fully expanded. If the condition is not fulfilled, the child node that hasn't been visited is selected instead of the UCT-based selection.

3. Simulation: the random policy is applied for obtaining a complete path to reach the leaf node from p_i. Then all the configurations of the inductor are set, the optimization of the geometric parameters can be performed, which will be presented in II.*B*.

4. Backpropagation: after obtaining the simulation results, the information with regard to the number of visits N, and the reward f_{MCTS} will be updated from p_i back to the root node. This step is different from [4] and [6], which updates the information of all nodes traversing the path, including those generated by the random policy.

B. Simulation

In the inductor design, we focus on several key characteristics: the inductance L, saturation current I_{sat}, DC resistance R_{dc}, and iron loss of the core P_{loss}. In this work, our target is to design inductors that have the specified value of inductance L_0 and I_{sat}, whilst minimizing R_{dc} and P_{loss}. Mathematically, the objective function can be written as

$$f_{MCTS} = -C_2\left(w_1\left|1-\frac{L(\boldsymbol{x})}{L_0}\right| + w_2\left|1-\frac{I_{sat}(\boldsymbol{x})}{I_0}\right| + w_3\left|\frac{R_{dc}(\boldsymbol{x})}{R_0}\right| + w_4\left|\frac{P_{loss}(\boldsymbol{x})}{P_0}\right|\right) \to \max \qquad (2)$$

where I_0, R_0 and P_0 are corresponding reference value for normalizing; w_1, w_2, w_3, w_4 are weighting coefficients, and chromosome $\boldsymbol{x}$ is a vector composed of the geometric parameters to be optimized, which has variable dimensions according to the configuration, listed in Table I, and all the labels in the table can be found in Fig. 1. Besides, C_2 is a positive weighting constant.

TABLE I
THE VECTOR $\boldsymbol{x}$ AND ITS CONFIGURATION

Configu-ration	Geometric parameters $\boldsymbol{x}$	Configu-ration	Geometric parameters $\boldsymbol{x}$
m= 1, n= 1	[d, w, t]	m= 2, n= 1	[d, w, t, δx_1]
m= 3, n= 1	[d, w, t, δx_1, δx_2]	m= 4, n= 1	[d, w, t, δx_1, δx_2, δx_3]
m= 1, n= 2	[d, w, t, δy_1]	m= 2, n= 2	[d, w, t, δx_1, δy_1]
m= 3, n= 2	[d, w, t, δx_1, δx_2, δy_1]	m= 4, n= 2	[d, w, t, δx_1, δx_2, δx_3, δy_1]
m= 1, n= 3	[d, w, t, δy_1, δy_2]	m= 2, n= 3	[d, w, t, δx_1, δy_1, δy_2]
m= 3, n= 3	[d, w, t, δx_1, δx_2, δy_1, δy_2]	m= 4, n= 3	[d, w, t, δx_1, δx_2, δx_3, δy_1, δy_2]

One can observe that the number of design parameters varies from 3 to 8. With the help of MCTS, the dimension can be determined, then next the covariance matrix adaptation evolution strategy (CMA-ES) [7] searches for optimal solution of $\boldsymbol{x}$. Comparatively, it needs to consider about 7000 different configurations shown in Fig. 2 to each optimization of the local geometry which has to be performed.

For the electromagnetic characteristic parameters in (2), we utilize FEM to compute the 2-dimensional static magnetic field, combined with Newton Raphson method to solve non-linear equations. Boundary conditions are shown in Fig. 1. The *B-H* curves of candidates are shown in Fig. 3.

Subsequently, the $L(\boldsymbol{x})$ is computed from

$$L(\boldsymbol{x}) = \int_V J_z \cdot A_z dV / I^2 \quad (3)$$

in which J_z and A_z are the current density, the magnetic vector potential along the z-direction in Cartesian coordinate system, V is the volume of the inductor, and I is the magnitude of the current flowing in each turn of the coil. $I_{sat}(\boldsymbol{x})$ is determined based on the comparative analysis with the initial design value of inductance L_0. Through multiple FEM calculations, as I is gradually increasing, the inductances are obtained. When L decreases to 0.7 L_0, the magnetic saturation is considered to be reached and the current at present is identified to be $I_{sat}(\boldsymbol{x})$. $R_{dc}(\boldsymbol{x})$ is obtained from Ohm's law, and $P_{loss}(\boldsymbol{x})$ is calculated using the Steinmetz equation, yielding

$$P_{loss}(\boldsymbol{x}) = K f^{\alpha} B^{\beta} \quad (4)$$

where K, α, and β are constant coefficients derived from attributes of materials listed in TABLE II, f and B are the frequency and the magnitude of the magnetic flux density, respectively.

TABLE II
COEFFICIENTS FOR STEINMETZ EQUATION

Material	K	α	β	Material	K	α	β
M_1	36.0	1.96	2.94	M_5	21.2	1.95	2.83
M_2	9.5	1.99	2.75	M_6	18.2	2.00	2.97
M_3	37.0	1.93	2.83	M_7	70.9	1.84	2.78
M_4	14.6	1.98	2.95	M_8	29.4	1.91	2.79

C. Inherited search for multiple targets

Sections *A* and *B* provide a comprehensive strategy for designing an inductor with a specific objective. If other designs of the inductor with different emphases are expected, the inherited search based on the previous stored statistical data is a promising solution. The procedure is described below.

It is assumed that the optimal solution of an inductor design has been obtained by solving (2). Then next we aim to design a new inductor with a focus on its electromagnetic performance on other aspects. In other words, w_1, w_2, w_3, w_4 are replaced by new ones, represented by w_a, w_b, w_c, w_d. We use the symbol f_{MCTS1} and f_{MCTS2} to denote these two objective functions. In this case, since all parameters have been calculated and stored at nodes when f_{MCTS1} was evaluated, f_{MCTS2} can be obtained by querying the stored paths and recalculating based on the known characteristics. Thus, the best solution with a path *Pa* can be derived from the stored data. What follows is to update the initial states of tree nodes for computing f_{MCTS2}. The value of f_{MCTS2} and the first time of visits are recorded in nodes along *Pa*. After completing this step, we will repeat the whole process in II. *A* and II. *B*.

III. NUMERICAL RESULTS

A numerical experiment is conducted to validate the proposed method for designing inductors. The tree depicted in Fig. 2 is employed to design two inductors. For a material selection of the core, *B-H* curves of eight candidate soft magnetic composites are shown in Fig. 3. In addition, in Fig. 2, l_i represents the length to be 2.3 mm to 1.2 mm with a step of -0.1 mm; h_j denotes the height to be 1.2 mm to 0.7 mm with a step size of -0.1 mm; candidates of m are 4, 3, 2, and 1; for n, they are 3, 2, and 1.

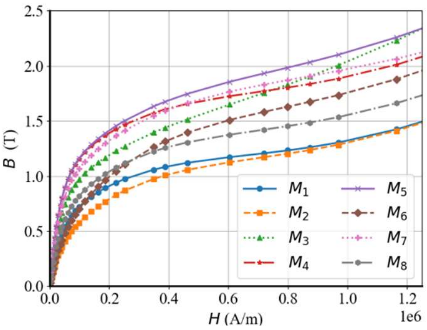


Fig. 3. *B-H* curves of candidate materials.

The two designs of inductors, represented by target 1 and target 2, have the same expected inductance being 250 nH and saturated current being 15 A. For the first inductor design, our objective is to ensure the specified values of the inductance and saturated current. For a second one, we focus on ensuring $L(\boldsymbol{x})$ and $I_{sat}(\boldsymbol{x})$, and minimizing $R_{dc}(\boldsymbol{x})$ and $P_{loss}(\boldsymbol{x})$. Expressed using mathematical modeling, f_{MCTS1} and f_{MCTS2} are with corresponding weighting coefficients [w_1, w_2, w_3, w_4]=[1, 1, 0, 0] and [w_a, w_b, w_c, w_d]=[1, 1, 0.5, 0.5].

Objective function f_{MCTS1} is searched from an initial blank state and f_{MCTS2} is optimized by an inherited search by using the stored search history of f_{MCTS1}. The iteration stops at 100 for f_{MCTS1}, and 50 for f_{MCTS2}, respectively. The reason for setting in such a way is that initially, we need an exhaustive search for achieving optimization for target 1, hence a relatively large number of iterations is needed. Then using the results of target 1 in combination with the search process, the optimization for target 2 is expected to be completed in fewer iterations. In addition, in the simulation of each round, 25 iterations are used for CMA-ES to achieve the optimization of the geometric parameters at the leaf nodes. On average, every 50 iterations of searching take approximately eight and a half hours to complete, with using a PC of Intel(R) Core (TM) i7-12700K CPU (3.60 GHz), and 32 GB RAM.

After the process of searching and optimizing, results for f_{MCTS1} and f_{MCTS2} reach maximum values, and their convergence histories are shown in Fig. 4. It depicts the iterative process of both objectives continuously, f_{MCTS1} from the 1st to 100th iteration, and f_{MCTS2} from the 101st to the 150th iteration. It indicates that both targets get maximum values after the comprehensive optimal design. Besides, a comparative convergency history of target 2 without using results of inheritance is also shown. It is evident that for optimizing target 2, the trend of convergence is relatively gradual. This is consistent with expectations, since in the second optimization, its initial state inherits an optimal solution and path from the first optimization. Simultaneously, it also continues to explore the possibility of a better solution by integrating the benefits of the MCTS.

The results of the optimization are shown in TABLE III. The CMA-ES convergence histories and the optimal structures of both best-ever solutions are illustrated in Fig. 5 and Fig. 6.

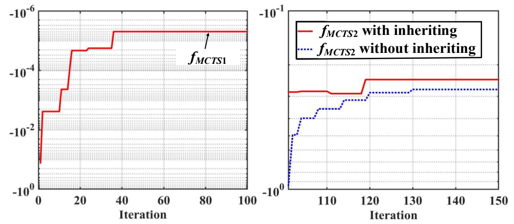


Fig. 4. Convergence history of MCTS for f_{MCTS1} and f_{MCTS2}.

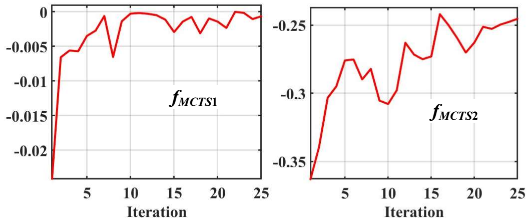
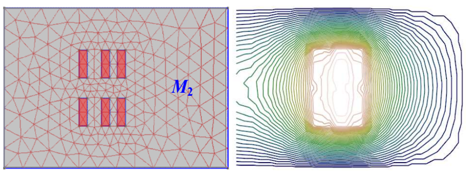


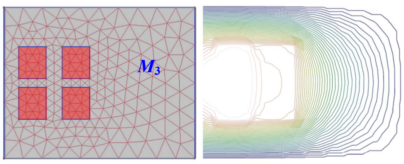
Fig. 5. Convergence history of best ever solutions for f_{MCTS1} and f_{MCTS2} by CMA-ES.

TABLE III
OPTIMAL RESULTS

Results	Target 1	Target 2
Configuration	M_2, l_7, h_2, (m= 3), (n= 2)	M_3, l_{10}, h_2, (m= 2), (n= 2)
$L(\boldsymbol{x})$	250 nH	249.3 nH
$I_{sat}(\boldsymbol{x})$	15 A	15 A
$R_{dc}(\boldsymbol{x})$	32.1 m Ω	5.40 m Ω
$P_{loss}(\boldsymbol{x})$	5.8 μW	6.64 μW
$\boldsymbol{x}$ (mm)	[0.06, 0.19, 0.57, 0.11, 0.06, 0.13]	[0.20, 0.23, 0.11, 0.11, 0.06]



(a)



(b)

Fig. 6. Optimal designs of inductors and their magnetic flux lines. (a) Target 1. (b) Target 2.

Another originality of this paper is that, as a heuristic algorithm, MCTS can not only find the optimal solution, but can also yield its good approximation. For instance, for the target 1, the best-ever solution is found after 100 iterations (Fig. 4). Moreover, along $M_5 \rightarrow l_{12} \rightarrow h_3 \rightarrow (m= 3) \rightarrow (n= 2)$, the mean rewards at nodes with respect to number of visits, reach maximum, while the path has not been visited in the history. Then the configuration along this path is optimized by CMA-ES for a test, and excellent outcomes can also be obtained finally. Specifically, they are: $L(\boldsymbol{x}) \approx 250.3$ nH, $I_{sat}(\boldsymbol{x}) = 15$ A, $R_{dc}(\text{x}) \approx 7.87$ m Ω, $P_{loss}(\boldsymbol{x}) \approx 8.00$ μW with $\boldsymbol{x} \approx$ [0.15, 0.33, 0.35, 0.12, 0.13, 0.07] mm. The predicted optimal design is shown in Fig. 7. Consequently, excepting from obtaining a best-ever solution, MCTS can also predict the best solution pathway based on the statistical results. Therefore, when applying MCTS, both the best-ever solution and the solution with maximum mean rewards on nodes need to be considered comprehensively for designing inductors.

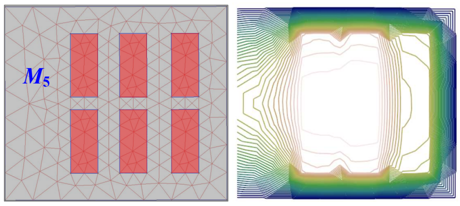


Fig. 7. Predicted optimal designs of Target 1 and its magnetic flux lines.

IV. CONCLUSION

This paper proposed a method for the comprehensive optimal design of inductors with non-linear characteristics. MCTS is implemented for the determination of configurations, and CMA-ES is used for the optimization of geometric parameters. This method is applicable to parameter optimization involving analysis of varying dimensions due to different configurations. Moreover, based on the existing search history, targets with different emphases can also be obtained easily by an inheritance. MCTS can also predict the best solution pathway based on the statistical results even if the path has not been visited in the history. More cases for inductors based on MCTS with an inheritance will be investigated in the further work.

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