Expert Knowledge Benefits on Discrete Optimization Algorithm

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Abstract — This paper shows the benefits of using expert knowledge within branch-and-bound algorithm in order to solve a discrete optimization problem of electromagnetic converters. Knowledge allows testing the partial solutions (nodes) found in each level of the algorithm in a very short time. The test avoids the evaluation of some nodes that cannot give a possible optimal solution. This reduces the computing time of the optimization algorithm without changing the accuracy of the results.

I. Introduction

Discrete optimization problems of electromagnetic converters are frequently met in industrial applications. The big difficulty in such optimization problems is to find the optimal solution due to the large number of possible combinations.

The branch-and-bound BB method [1] is an efficient algorithm to solve NP-difficult optimization problems. The disadvantage of BB algorithms is its long computing time when the number of evaluated nodes explodes.

The use of expert knowledge is a recent interest in modeling and optimization of electromagnetic converters [2-3]. Knowledge is used in order to achieve satisfactory results in a short time without resorting to conventional design and optimization methods. Indeed, conventional design methods achieve no satisfactory results in a short time but do not require powerful computing systems. In contrast, optimization methods achieve satisfactory results but require powerful computing systems and their computing time depends on the optimization problems size.

In this paper expert knowledge is used within a BB algorithm in order to achieve satisfactory results in a short time. The application employs BB optimization method combined with Output Space Mapping technique [4] using coarse (analytical) and fine (3D-finite elements) models of a safety single phase transformer.

II. Optimization problem

The transformer optimization problem [4] contains 7 design variables: four variables for the transformer iron core geometry *[a, b, c, d]*, two for the section of enameled wires $[S_1, S_2]$, and one for the number of primary turns n_1. The objective of the optimization is to minimize the mass of iron and copper materials with respect to seven nonlinear constraints: the copper and iron temperatures T_{copper}, T_{iron} should be less than 120°C and 100°C, respectively. The efficiency η must be greater than 80%. The magnetizing current I_{10} and the voltage drop DV_2 should be less than 10% of the primary current I_1 and of the secondary voltage V_2, respectively. Finally, the filling factors f_1, f_2 of both coils should be lower than 0.5.

The optimization problem is expressed as:

$$\begin{array}{lllll}
\min\limits_{a,b,c,d,n_1,S_1,S_2} & f(a,b,c,d,n_1,S_1,S_2) = mass & & & \\
\text{with} & \{a,b,c,d\} \subset \Omega_1 & S_1 \in \Omega_2 & & \\
 & S_2 \in \Omega_2 & n_1 \in \Omega_3 & & \\
 & T_{copper} \le 120°C & T_{iron} \le 100°C & \eta \ge 0.8 & \\
s.t. & \dfrac{I_{10}}{I_1} \le 0.1 & \dfrac{DV_2}{V_2} \le 0.1 & f_1 \le 0.5 & f_2 \le 0.5
\end{array}$$

The seven design variables of the transformer are discrete. Indeed, Ω_1 represent 62 possible configurations of *[a, b, c, d]*, Ω_2 is a set of 62 types of enameled wire and Ω_3 contains 1000 possible values of n_1; this leads to 246,078,000 possible values of $\mathbf{X} = [a,b,c,d,n_1,S_1,S_2]$.

The large number of possible combinations makes the optimization problem difficult. Thus, expert knowledge in transformer design is explored within BB algorithm in order to avoid evaluation of some partial solutions.

III. Branch-and-bound algorithm

BB algorithm [1] is based on a tree structure. At each level *i* of the algorithm, one design variable *k* takes discrete values presented in the catalogue and the other ones are free. The node (partial solution) which presents the minimum mass M_{level_i} is chosen to pass to the next level and the design variable *k* is fixed to the discrete value which allowed finding this node. Nodes of the previous level that presented a mass greater than M_{level_i} are eliminated without evaluation. Thus, only parts of combinations are evaluated.

IV. Explored expert knowledge

Knowledge of Pichon and McLyman on transformer design is capitalized in [5] and [6], respectively.

Pichon indicates that to obtain an optimal design of a power transformer having a greater efficiency and a small mass, the current density *J* within its conductors must be between 1e6 and 5e6 A/m² as shown in (1).

$$10^6\ A/m^2 \le J \le 5.10^6\ A/m^2 \qquad (1)$$

McLyman stated that the power capability of a transformer core is related to its area product A_p as in (2).

$$A_p = \frac{P_o(1+\frac{1}{\eta})}{K_f\, K_u\, B_m\, J\, f} \quad (2)$$

where K_f is the waveform coefficient (K_f =4 if square wave and K_f =4.44 if sine wave); $K_u = 0.5$ is the window utilization factor; $B_m = 1.5T$ is the maximum flux density; f the frequency (50 Hz in this case) and P_o is the transformer output power.

McLyman stated also that the transformer volume can be related to A_p. Indeed, the relationship is derived according to the following reasoning: volume varies in accordance with the cube of any linear dimension, whereas A_p varies as the fourth power, then the relationship between the volume and A_p can be expressed as:

$$volume = K_{vol}\,(A_p)^{0.75} \quad (3)$$

In (3) K_{vol} is a constant related to core configuration which is obtained by averaging the value of data recorded on several transformers.

V. APPLICATION

Based on (1), (2), constraint on η, and transformer specifications, the maximum and minimum values of A_p are calculated. Then, the volume of the optimal solution can be bounded:

$$K_{vol}\,(A_{p\_\min})^{0.75} \le volume \le K_{vol}\,(A_{p\_\max})^{0.75} \quad (4)$$

The volume of the studied transformer depends on its core dimensions. So, each node in level one of BB algorithm that does not respect (4) is eliminated before its evaluation. From the 62 nodes at level one, only 14 are kept.

In the transformer specifications, the secondary winding must be able to withstand a current of 8A. Using transformer equations and constraint on voltage drop is easy to deduce that the primary current module cannot exceed 0.98 A. So, in levels 2 and 3 of the optimization algorithm each section wire presented in the catalogue and that did not check (1) is eliminated before the node evaluation. Filtering nodes in both second and third levels leaves 19 and 14 nodes, respectively, instead of 62 in each level.

The thousand nodes generated in the last level of BB algorithm are filtered before their evaluation using the constraint on primary fill factor, the window area of the core and the primary wire section selected by the algorithm in the first and the second levels, respectively. 698 nodes are eliminated in this level using expert knowledge.

244,953,352 combinations in total were eliminated using expert knowledge. This represents 99.54% of the initial number of combinations.

The BB algorithm after exploiting expert knowledge is shown in fig. 1.

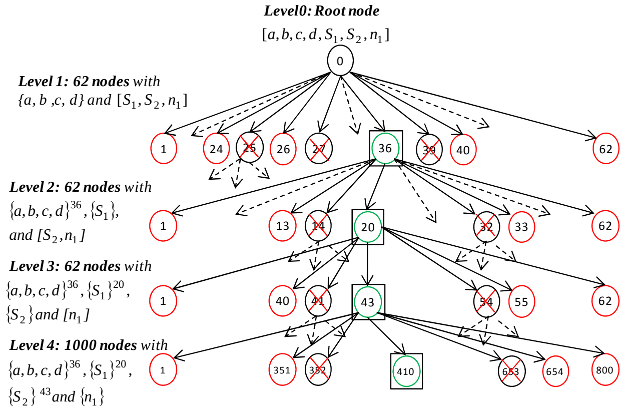

Fig. 1. Branches and nodes of BB algorithm tree. The circular nodes are eliminated by expert knowledge and the crossed ones are eliminated by BB algorithm. Circular nodes within squares are selected by BB algorithm as the optimal design variable configurations.

VI. OUTPUT SPACE MAPPING

Each iteration of the output space mapping technique (OSM) starts with a BB algorithm to find the optimal solution with the coarse model. Then, one 3D FE evaluation is used to compute the outputs of the fine model. Correctors are calculated to align the coarse model's outputs on the fine model's ones. OSM algorithm stops when the discrepancy between the fine and corrected coarse models is small enough.

VII. RESULTS

Table 1 shows results found with and without using the expert knowledge within BB algorithm.

TABLE I
OPTIMIZATION RESULTS

	evaluated nodes	mass (kg)	time (s)	3D FE evaluations
with expert knowledge	26	2.63	158	6
w/o expert knowledge	218	2.63	1230	6

VIII. CONCLUSION

Exploiting the expert knowledge has a great impact in reducing the computing time of BB algorithm. Indeed, knowledge is used to avoid the evaluation of some nodes in each level of BB algorithm. Excluded nodes cannot present a possible optimal solution.

IX. REFERENCES

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