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Yunpeng Zhang, Siu-lau Ho, and Weinong Fu

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A dynamic multi-level optimal design method with embedded finite-element modeling for power transformers

Yunpeng Zhang, Siu-lau Ho, and Weinong Fu[a]
Department of Electrical Engineering, The Hong Kong Polytechnic University, Hong Kong

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This paper proposes a dynamic multi-level optimal design method for power transformer design optimization (TDO) problems. A response surface generated by second-order polynomial regression analysis is updated dynamically by adding more design points, which are selected by Shifted Hammersley Method (SHM) and calculated by finite-element method (FEM). The updating stops when the accuracy requirement is satisfied, and optimized solutions of the preliminary design are derived simultaneously. The optimal design level is modulated through changing the level of error tolerance. Based on the response surface of the preliminary design, a refined optimal design is added using multi-objective genetic algorithm (MOGA). The effectiveness of the proposed optimal design method is validated through a classic three-phase power TDO problem. https://doi.org/10.1063/1.5006736

I. INTRODUCTION

Power transformers have been serving as the main electric equipment in alternating current power systems since last century. They still play a vital role in modern High Voltage Direct Current system as a connector between systems. With the continuous advance in power industry, transformer design has received considerable attention.[1–4] However, its optimization studies remain a major challenge because of numerous design variables, complicated geometries and conflicting constrained objectives.

Several optimization methods, which are divided into deterministic and non-deterministic methods, have been introduced into power transformer design studies to minimize the cost or to maximize the rated power.[5] Constraints used in transformer design optimization (TDO) studies are classified into two types, the first of which includes international technical specifications on different aspects of transformer properties, such as IEC 60076-1 on general property, IEC 60076-2 on temperature-rise, IEC 60076-3 on insulation and IEC 60076-5 on stability.[3] The other class of constraints stems from the requirements of customers and manufacturing capabilities.

Due to the large number of transformer design variables and computational complexity of finite-element analysis (FEA), transformer design relies heavily on analytical equations with empirical coefficients. The major weakness of such method is the large error of analytical transformer model, resulting from approximation of geometry and field with a uniform value, which plausibly underlies incorrect solutions. To tackle this problem, finite-element method (FEM) is introduced as the last procedure to validate the optimized solutions derived with analytical equations.[6–9] Nevertheless, final validation cannot guarantee the accuracy of selection operation in the intermediate process. This paper proposes a dynamic multi-level optimal design method with embedded finite-element modeling in order to improve the accuracy of the model gradually. Response surface[10,11] is constructed with the

[a]Corresponding author: eewnfu@polyu.edu.hk

results of FEA through second-order polynomial regression analysis and is used to generate samples for the global estimation of this TDO problems with Shifted Hammersley Method (SHM), which would invoke FEA to exclude points violating the constraints and to increase design points for a more accurate model. In the following stage, multi-objective genetic algorithm (MOGA) is applied to obtain more refined solutions.

The remainder of this paper is organized in the following manner. Section II introduces the proposed multi-level design method in detail. Section III exemplifies the proposed method with a case study of optimizing the manufacturing cost of a three-phase power transformer. Finally, section IV presents the conclusion of this paper.

II. METHODOLOGY

In conventional transformer design, a fixed maximum magnetic flux density is of vital importance for several subsequent calculations. As the primary purpose of optimal design is to satisfy the requirements of customers with minimum materials, it is natural that the designers would try to push the materials to their limits. Design optimization using FEM is another attempt to simulate the performance of a machine with determined dimensions under various conditions. Connection of conventional design method and FEM is focused on the rated operating condition, which is used to determine the number of winding turns. Models generated with solutions of FEM and analytic models employed in conventional design are equivalent approaches of representing the transformers under rated operating condition.

Conventional design approximates the entire magnetic field in the core with a uniform magnetic flux density, as no-load losses density at a specific magnetic flux density and frequency can be measured. In essence, the no-load losses can be formulated as follows

$$NLL = M_C \times NLL_{per} \tag{1}$$

where M_C is the mass of core, NLL and NLL_{per} are, respectively, the no-load losses and the specific no-load losses per kilogram at the given magnetic flux density. Obviously, simplification of the inhomogeneous magnetic field with a uniform value introduces large errors, probably leading to incorrect solutions. In contrast, FEM can provide a relatively accurate estimation of the no-load losses but with a huge computing workload. Response surface model, combined with FEM, is introduced into transformer design to produce an approximation model, which has higher precision than the no-load losses model used in conventional transformer design.

Accuracy of response surface mainly depends on the type of response surface model and the number of design points. For transformer design with many design variables, second-order polynomial regression model is one of the preferred models. For demonstration purpose, it is formulated with two variables

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \alpha_{11} x_1^2 + \alpha_{22} x_2^2 + \alpha_{12} x_1 x_2 + \varepsilon \tag{2}$$

For a given model, improving accuracy means increasing design points and calculation effort. In addition, it is well recognized that the accuracy in some regions with a large number of design points is higher than that in a region with less design points. Subsequently, accurate and appropriate selection of supplementary design points improve the computational efficiency dramatically. A set of initial design points is generated firstly and calculated by using FEA, solutions of which are inputs of the regression analysis, which aims to generate a response surface model for the no-load losses. However, the preliminary model may be coarse and refinement points are indispensable for deriving an accurate model. In this paper, determination of refinement points is achieved by SHM, which provides a global overview of the optimization problem including global and local extrema through generating a large number of samples from the response surface and then sorting them based on objectives and constraints. After SHM selects the optimal candidates, FEM is invoked to verify the solutions of these candidates and to eliminate candidates outside the constraints. Moreover, left candidates with their accurate solutions previously obtained through FEA are added into the set of design points. Certain criteria require more points adjacent to these candidates to improve the accuracy of model. This procedure will circulate until the maximum error of optimal solutions is less

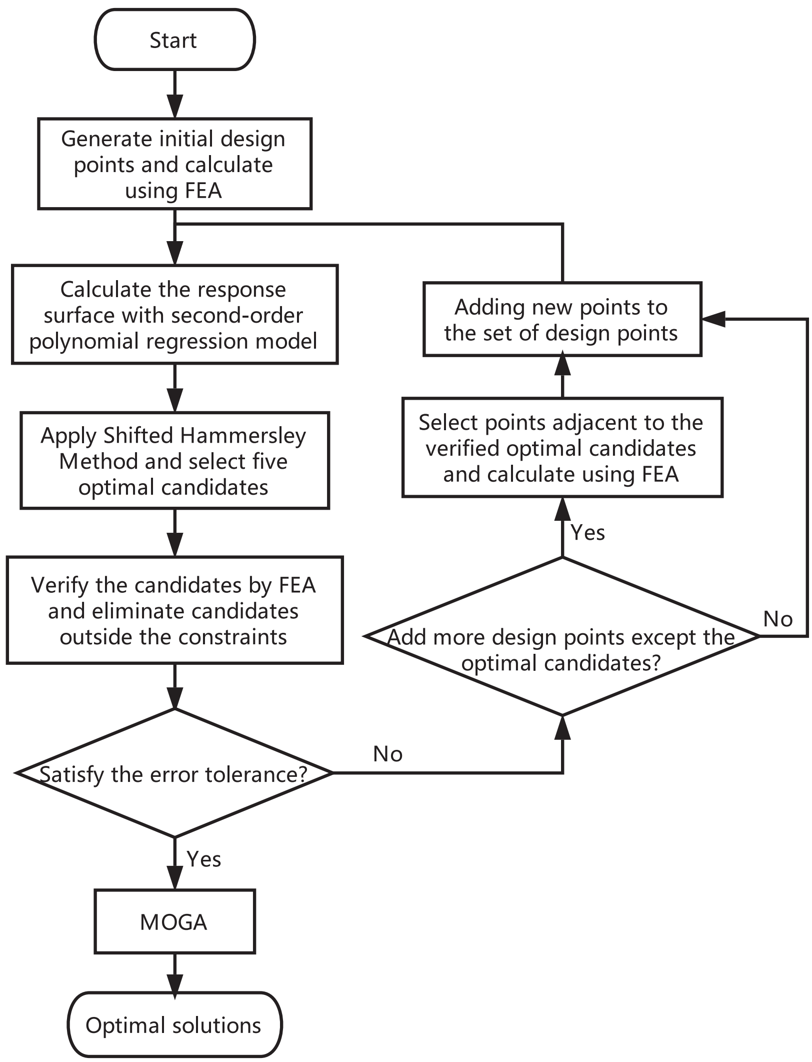

FIG. 1. Flowchart of the proposed design method.

than the predefined tolerance. The number of finite-element calculations also varies with the tolerance level. At the end of this phase, the preliminary design provides a refined surface model based on the extrema distribution and several optimal candidates, which is normally being treated as the final solutions. Optimal solutions, moreover, can be set as the starting points for deterministic optimization algorithms, such as non-linear programming by quadratic Lagrangian method and mixed-integer sequential quadratic programming method, for optimizing the original problem, which may require tremendous computing workload of FEA to obtain a qualified solution. In the second-level design, this paper adopts MOGA combined with the response surface, as MOGA provides several accurate solutions in different regions without heavy computational effort through a couple of iterations, i.e. selecting elite samples and generating the next generation until finding the optima. Flowchart of the proposed design method is depicted in Fig. 1.

III. RESULTS AND DISCUSSION

To validate the proposed method, a three-phase power transformer with a power rating of 30000kW is studied in this paper. Parameters and front view are shown in Table I and Fig. 2, respectively. The transformer model neglects insulations between windings and core, structural parts and cooling system. Four dimensional parameters, namely, the depth of transformer (D), the thickness

TABLE I. Parameters of transformer.

Parameter	Value
Rated power (kW)	30000
Internal coil voltage (kV)	13.8
External coil voltage (kV)	115
Connection of internal coil	Star
Connection of external coil	Delta
Frequency (Hz)	60

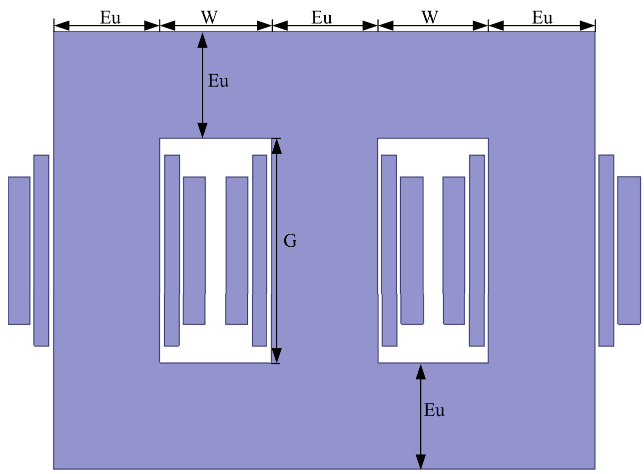

FIG. 2. Front view of transformer.

of core leg (E_u), the height of window (G), and the width of window (W), are chosen as the deign variables. Object of the optimization problem is to minimize the manufacturing cost with constraints on no-load losses and load-losses. This typical TDO problem is formulated as follows

$$\begin{aligned} & f(X) = \min(\mathrm{CMM}) \\ \text{s.t.}\quad & \mathrm{NLL} < \mathrm{NLL}_{max} \\ & \mathrm{LL} < \mathrm{LL}_{max} \end{aligned} \tag{3}$$

where CMM is the cost of transformer's main materials; X is the set of design variables; LL are load losses; NLL_{max} and LL_{max} are the no-load losses constraint (27000W) and the load losses constraint (99500W), respectively.

In the phase of the design of experiments, twenty-five design points are generated through central composite designs and calculated using FEA, which are used to calculate the initial response surface model through regression analysis. Then five optimal candidates are selected in all the samples generated from the response surface with SHM in each round. These five optimal candidates are verified using FEA to determine whether constraints are violated and to calculate the error of the approximation model. As the criterion of error is not satisfied, these optimal candidates with their FEA solutions are added into the set of design points to refine the response surface model. This procedure is cycled by five rounds before the error tolerance is reached. In the last two rounds, two more design points in the optimal region identified by SHM are added as design points. A total of ten design points, including optimal candidates and their adjacent points, are added into the set of design points in five rounds. Fig. 3 (a) shows that the increase in the number of design points between two rounds gradually slows down and the maximum error of no-load losses of optimal candidates is reduced to less than 0.5% with 35 design points. Fewer design points are required for a larger error tolerance, as shown in Fig. 3 (a). Five optimal candidates of the last round are shown in Table II, and it can be observed from this table that the optimal candidates found by SHM are from different

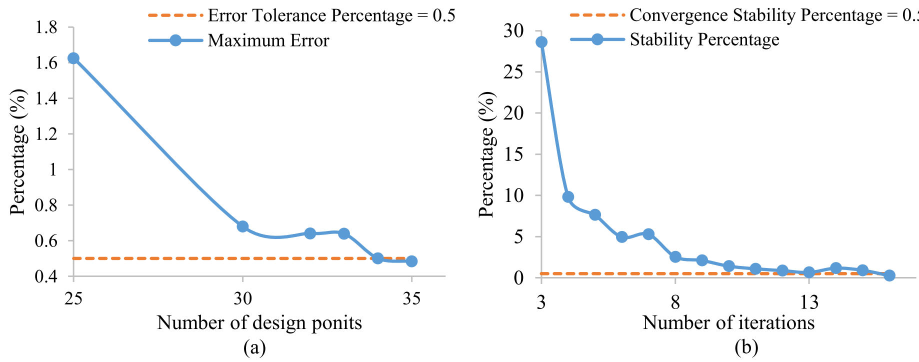

FIG. 3. (a) Maximum error of no-load losses of optimal candidates versus number of design points and (b) convergence curve of MOGA.

TABLE II. Optimal candidates derived by SHM.

Parameter	Candidate 1	Candidate 2	Candidate 3	Candidate 4	Candidate 5	Candidate 5[a]
D / mm	472.06	500.86	415.66	479.26	508.06	426.46
Eu / mm	352.97	343.60	401.41	371.72	362.35	393.91
G / mm	424.19	412.85	453.55	415.96	404.62	447.79
W / mm	503.89	514.64	504.21	508.88	501.20	518.61
NLL / W	12261	12521	13126	13349	13477	13086
LL / W	98901	98270	98444	94299	91859	99100
CMM / $	59867	60735	62753	62757	62784	63142

[a]Candidate 5 is the fifth optimal candidate of the second case.

regions. The solutions of this case are compared with solutions from another case with 50 initial design points generated by the same design type. The first four optimal candidates of the second case are the same as those of the first case, while the fifth optimal candidate of the first case is better than the second case, as shown in the fifth and sixth columns in Table II. Moreover, these five optimal candidates of case two have a maximum error of 1.2%. The computation effort of FEA is much larger than other computational processes, encompassing calculating the response surface model, generating and sorting samples form the response surface. The number of design points used in case one is 35, whereas the number of design points of case two is 50. The proposed dynamic multi-level design method, therefore, saves roughly 30% of the calculation effort and contributes to obtaining more accurate solutions, which are verified with these two cases.

In the refined optimal design, MOGA is used to optimize this problem based on the response surface model generated by the first case. With convergence stability percentage of 0.5%, different population sizes have been tried to find the best configuration for this specific problem. It is found that the population size of 90 samples per generation provides the best optimal solutions, the convergence curve of which is shown in Fig. 3 (b). The comparison of solutions of SHM and MOGA is listed in

TABLE III. Comparison of solutions of SHM and MOGA.

Parameter	SHM	MOGA
D / mm	472.06	500.56
Eu / mm	352.97	332.58
G / mm	424.19	402.51
W / mm	503.89	502.6
NLL / W	12266	11815
LL / W	98901	99272
CMM / $	59867	58426

Table III, which indicates that the refined optimal design brings 2.4% manufacturing cost savings when compared with the preliminary design.

IV. CONCLUSION

In this paper, a dynamic multi-level optimal design method for TDO problems is presented. Based on an overall estimation of the problem, the response surface model is improved gradually with embedded finite-element modeling according to the accuracy requirement. The refined optimal design adopts this model and provides a better solution compared with the preliminary optimal design. Effectiveness of the proposed method is validated with a typical TDO problem.

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