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Design of power transformers with performance oriented based on multi purpose optimization for industrial plant applications

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ABSTRACT

The power transformers are considered key and crucial components in electrical systems, serving as power transmission and distribution units for industrial production facilities such as mechanical workshops, pharmaceutical factories, and granite factories. In the context of market globalization, power transformer manufacturers are facing increasingly fierce competition, requiring the application of design strategies to achieve higher efficiency and productivity at lower costs, while ensuring safe and reliable operation during power supply. This paper proposes a design method for large power transformers using multi-objective optimization, combined with time-variant multi-objective particle swarm optimization (TV-MOPSO), to improve power quality and power supply. This method, built with a design-oriented approach and calculated based on target performance, can quickly deduce the design parameters of the transformer. Verification of the proposed method, with results showing significant qualitative and quantitative agreement between the design research results and the measured performance values, based on design calculations and simulations using ANSYS Maxwell software, has shown that the voltage, current, and link flux values of the transformer consistently meet the technical requirements of power transformers in current practice.

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1. INTRODUCTION

As is known, transformers are considered indispensable components in the power supply system at industrial workshops and factories. Power transformers play a key role in the power system, increasing and decreasing voltage, stabilizing voltage, and ensuring continuous, safe, and efficient power supply [1]-[5]. Consequently, transformer design must satisfy a number of technical requirements, including rated voltage, current capacity, magnetic flux density, efficiency, and power losses. This competitive environment requires the application of lean design strategies, ensuring all technical parameters of voltage, current, magnetic flux, efficiency, and power. in order to achieve higher power efficiency, lower costs, and competitiveness in the current industrial plant automation and electrical equipment market [6]-[10].

In previous studies, many power transformer design methods have been proposed [11]-[14]. Adly and Abd-El-Hafiz demonstrated that feed-forward neural networks can be used to predict the design parameters of power transformers after being trained with geometric size and winding detail data of a set of real transformers [3], [6], [15], [16]. In another direction, finite element analysis (FEA) combined with a trial-and-error approach has been introduced in [2], [5], [8], [17]. In addition, a computer-assisted trial-and-error search algorithm aimed at minimizing transformer design costs, taking into account the transformer performance

issue, has also been presented and studied [18]. Other approaches combine FEA with knowledge-based design optimization strategies and genetic algorithms, with particle swarm optimization (PSO) proposed in [19]-[21]. In addition, many techniques have been applied to solve transformer design problems using PSO; according to Gupta and Agarwal [4] and Du *et al.* [19], leakage reactance can be combined into a single objective function through the weighted sum method [22]-[26]. At that time, Wang *et al.* [26] demonstrated the two objectives of minimizing power loss. Other studies have integrated FEA with knowledge-based optimization methods or evolutionary algorithms, including genetic algorithms (GA) and PSO. These approaches have been investigated for different transformer design problems in order to improve electrical performance while reducing computational effort and material-related costs [4], [10], [18].

A research problem of multi-objective optimization problems being reduced to single-objective problems is often done by constructing a weighted sum function of the original objective functions. Although this method is easy to implement and use, determining appropriate weighting coefficients becomes difficult when the problem information is incomplete. Another limitation of these methods is that the algorithm needs to be run multiple times to obtain a set of optimal compromise solutions for selection. Furthermore, in some cases, it is not possible to obtain optimal solutions with certain weight combinations [1], [7], [11], [14], [16]. In particular, optimization methods based on PSO have attracted attention because of their population-based search mechanism and their ability to explore complex design spaces. Several studies have formulated transformer design as an optimization problem involving objectives such as power loss, leakage reactance, measurement accuracy, size, or computational cost [13], [18], [19], [26]. This paper presents a method for designing power transformers using PSO. This method, developed with a performance-oriented design approach, can quickly deduce preliminary transformer design parameters. The parameters and design details estimated by the proposed method can also be used as a basis for further refinement steps through FEAs. This will improve the transformer's operational quality.

2. THE BASIS OF THE RESEARCH METHODOLOGY FOR CALCULATIONS AND DESIGN

The research basis for calculating and designing power transformers for an industrial plant focuses on the quality of primary and secondary voltages, current values, $cos\varphi$, transformer windings, winding connections, magnetic flux density, losses, heat exchange cooling process, etc. In addition, there are parameters such as source frequency f. A three-phase transformer is also designed to optimize power transformers to satisfy the requirements of apparent power S, total copper losses P_{cu}, no-load losses P_{NL}, and equivalent reactance X. Therefore, the design procedure focuses on determining appropriate winding configurations and core dimensions that satisfy the prescribed performance criteria. Based on the transformer design relationships, the relevant performance characteristics can be expressed as functions of the winding arrangement and geometric parameters of the three-phase power transformer, as derived in the following section [15]-[17].

$$\frac{V_{l1}}{\sqrt{3}} = 4.44\, f B K_f K_c \frac{\pi}{4} D^2 N_1 n_1 \quad (1)$$

Where B is the maximum magnetic flux density in the core (load), K_f is the lamination coefficient, K_c is the ratio between the rough core area and the area of the largest circumscribed circle, D is the diameter around the core, and N_1 is the number of turns on the primary winding.

Additionally, the window space factor of a three-phase transformer, denoted as S_w, can be represented as in (2).

$$S_w = \frac{2N_1 a_{c1} + 2N_2 a_{c2}}{H_w W_w} n_2 \text{ and } S_w = \frac{4N_1 a_{c1} + K_w}{H_w^2} \quad (2)$$

In this formula, N_2 is the number of turns in the secondary winding, H_w is the winding window height, W_w is the winding window width, while a_{c1} and a_{c2} are the cross-sectional areas of the primary and secondary windings, respectively.

Let K_w be the ratio between the winding window height and width. The total copper losses P_{cu} can actually be considered as a superposition of three components: ohmic losses in the winding $P_{cu-ohmic}$, eddy current losses in the winding $P_{cu-eddy}$, and losses at the copper terminal connections P_{cu-con}. When designing transformers to meet specified technical requirements, maintaining total copper losses below permissible threshold values is mandatory. Achieving this requires precise but time-consuming calculations. Another approach is to apply appropriate calculated safety factors to rapid analysis design methods.

Assuming $P_{cu\text{-}con} \leq 0.05\, P_{cu\text{-}ohmic}$, the eddy current losses in the power transformer windings depend on the ratio between the height and width of the winding window K_w. As recent research has shown, the results of electromagnetic field calculations indicate that when choosing $2 \leq K_w \leq 2.5$, the eddy current losses in the windings can be estimated as $P_{cu\text{-}eddy} \leq 0.15\, P_{cu\text{-}ohmic}$.

Based on the general assumptions about the electrical load mentioned earlier and with the range of K_w values mentioned, the total copper losses can therefore be expressed by (3).

$$P_{cu} \approx 1.2\left(\frac{3I_{ph1}^2\rho_{cu}N_1l_{mt1}}{a_{c1}} + \frac{3I_{ph2}^2\rho_{cu}N_2l_{mt2}}{a_{c2}}\right) \quad (3)$$

In (3), ρ_{cu} is the resistivity of copper, Vol_{cu} is the total volume of copper, and l_{mt1}, l_{mt2}, and l_{mt} respectively represent the average length of a turn in the primary coil, the secondary coil, and both coils combined.

No-load losses P_{NL}, on the other hand, can also be seen as a superposition of two components. Specifically, these two components include core losses P_{Fe} and dissipation losses P_{stray}. It should be emphasized again that accurate estimation of dissipation losses requires very large computational resources, involving complex models combining magnetic, thermal, and mechanical variables (refer, for example, to documents [19]-[23]). By applying standard fabrication methods [13]-[16], dissipation losses can be estimated by the inequality $P_{stray} \leq 0.3\, P_{Fe}$. Therefore, the upper limit of no-load losses can be expressed as (4).

$$P_{NL} \approx 1.3P_{Fe} = 1.3W_{Fe}(B,f)\delta_{Fe}Vol_{Fe} \quad (4)$$

In this formula, δ_{Fe} is the density of the electrical steel sheet, and $W_{Fe}(B,f)$ is the core loss, expressed as a function of magnetic flux density and frequency; this quantity can be determined based on the technical specifications of the core sheet material. It should be noted that the explicit expression of $W_{Fe}(B,f)$ is usually provided directly in the manufacturer's technical documentation or can be derived by interpolation/curve fitting from published data.

In engineering design problems, computational models are often used to describe the complex behavior of physical systems, and optimal solutions are sought based on certain criteria. Therefore, multi-objective optimization becomes useful in obtaining a set of optimal compromise solutions (Pareto-optimal front), from which designers can choose the best option. The basic concepts of multi-objective optimization are introduced through a d-dimensional search space, denoted as $\mathcal{S} \subseteq \mathbb{R}^{\mathrm{d}}$, and the objective function defined on $\mathcal{S}$, as (5).

$$f(x) = [f_1(x), f_2(x), \ldots, f_k(x)] \quad (5)$$

With inequality constraints:

$$g_i(\mathrm{x}) \leq 0, \mathrm{i} = 1, \ldots, \mathrm{m}. \quad (6)$$

The goal is to find a solution $x^* = (x_1^*, x_2^*, \ldots, x_d^*)$ such that $f(x)$ is minimized. The objective functions $f_i(x)$ can conflict with each other, thus preventing the determination of a single global optimal solution at the same point in the space S. Therefore, the concept of optimality in multi-objective problems is defined differently. A vector $v = (v_1, v_2, \ldots, v_k)$ is said to dominate a vector $u = (u_1, u_2, \ldots, u_k)$ in a multi-objective minimization problem if and only if $v_i \leq u_i$ for all $i = 1, 2, \ldots, k$ and there exists at least one component such that $v_i < u_i$, component k is the dimension of the objective space. A solution $u \in \mathcal{U}$, with $\mathcal{U}$ being the solution space, is called Pareto optimal if there exists no other solution $v \in \mathcal{U}$ such that v dominates u. Such solutions are considered optimal in the transformer design process. The set of all non-dominated solutions forms the optimal Pareto front. For the transformer design problem under consideration, the quantities S, P_{cu}, P_{NL}, and X are considered the target performance requirements. The winding window height H_w is calculated beforehand according to (8). Then, multi-objective optimization is used to determine other key design parameters, including current density J, maximum magnetic flux density B and core diameter D. Thus, we have (7).

$$x^* = (J, B, D). \quad (7)$$

From that, we have (8) and (9) constructed as (8).

$$f(x) = \left[\left(\frac{S^{cmp}(x^*) - S}{2}\right)^4,\ \left(P_{cu}^{cmp}(x^*) - P_{cu}\right)^4,\ \left(\frac{P_{NL}^{cmp}(x^*) - P_{NL}}{4}\right)^4\right] \quad (8)$$

With the following constraints on the decision variable vector x^*.

$$\begin{bmatrix} J_l \\ B_l \\ D_l \end{bmatrix} \leq \begin{bmatrix} J \\ B \\ D \end{bmatrix} \leq \begin{bmatrix} J_u \\ B_u \\ D_u \end{bmatrix} \tag{9}$$

In which, S^{cmp}, P_{cu}^{cmp} and P_{NL}^{cmp} are respectively the calculated apparent power, the calculated total copper losses, and the calculated no-load losses considered for calculation. It should be noted that the inequality intervals given in (8) must conform to the typical lower and upper limits of the parameters J, B and D for power transformers in the power range under consideration.

3. THE PSO ALGORITHM FOR CALCULATING THE DESIGN OF POWER TRANSFORMERS

The extension of PSO to multi-objective optimization can be achieved by incorporating Pareto-dominance-based selection into the particle search mechanism [19], [22], [24], [26]. Besides identifying non-dominated solutions, diversity-preserving strategies are introduced to obtain a more uniform distribution of candidate solutions along the Pareto front. In this work, time-variant multi-objective particle swarm optimization (TV-MOPSO) is employed as the optimization framework, with its search behavior controlled through iteration-dependent inertia and acceleration parameters, as depicted in Figure 1. To further diversify the swarm and improve the ability to escape from locally concentrated solutions, a mutation operator is included in the optimization procedure [24].

The PSO method is a population-based optimization algorithm where individuals (particles) move in the search space to find the optimal solution by updating their velocity and position based on individual experience and the experience of the entire swarm. It is a population-based heuristic method where the set of potential solutions is called the swarm and each solution in the swarm is called a particle. Consider a d-dimensional search space, each i particle is assigned a position in the search space $x_i = (x_{i,1}, \dots, x_{i,d})$, a velocity vector $v_i = (v_{i,1}, \dots, v_{i,d})$, and an individual experience vector $P_{bi} = (P_{bi,1}, \dots, P_{bi,d})$, which stores the position corresponding to the best solution that particle has ever achieved. The experience of the entire flock is represented by the vector $G_b = (G_{b,1}, \dots, G_{b,d})$, corresponding to the position of the global best solution in the flock.

The motion of a particle towards the optimal solution is controlled by updating its velocity and position according to (i) and (ii) as illustrated in Figure 1. In these equations, the parameter w is the inertia coefficient; the parameters c_1 and c_2 are the acceleration coefficients. The parameters r_1 and r_2 are random numbers, generated uniformly in the range [0, 1], and serve to create randomness in the swarm's motion. The second term in equation (i) of Figure 1 is the cognition term, reflecting the individual experience of each particle. The third term in equation (i) of Figure 1 is the social term, representing the interaction between particles in the swarm. The values of c_1 and c_2 allow for adjustment of the degree of influence of the cognition and social terms, respectively. Larger c_1 values enhance exploration capabilities, while larger c_2 values encourage exploitation. The single-objective PSO algorithm has been successfully applied in many engineering problems, such as device and system optimization [22], [25], as well as field computation in nonlinear environments.

Figure 1 illustrates the TV-MOPSO algorithm, which comprises three main steps. The first step generates an initial swarm $Swrm_0$ of size M_s, with initial velocities of zero and coordinate values randomly initialized within the domain of each dimension. A repository of maximum size M_a is initialized to hold uninfluenced solutions from $Swrm_0$. The second step is the main iteration cycle, in which the swarm is updated, the repository is updated, and the swarm is subjected to mutation at each iteration t.

The $Swrm_t$ swarm algorithm is updated by updating the velocity and coordinates of each particle according to equations (i) and (ii) in Figure 1. To update the velocity, the global best solution is taken from the storage, taking into account the diversity criterion. The PSO method allows for the calculation of diversity, which is capable of obtaining solutions based on the nearest neighbor concept. The current solution is compared with the individual best solution and only replaces one if it dominates the other. Furthermore, time-varying parameters are also adjusted, including the inertia coefficient w, the local acceleration coefficient c_1 and the global acceleration coefficient c_2. The inertia coefficient w is linearly reduced with each iteration, from the initial value w_i to the final value w_f. The value of w at the t-*th* iteration is calculated (10).

$$w = (w_i - w_f) \times \frac{M-t}{M} + w_f \tag{10}$$

In which, M is the maximum number of iterations. To achieve a balance between the exploration and exploitation capabilities of the search space, the cognitive acceleration coefficients c_1 and c_2 are linearly changed with each iteration, as given in (10) and (11). Specifically, c_1 gradually decreases from the initial value c_{1i} to the final value c_{1f}, while c_2 gradually increases from c_{2i} to c_{2f}.

$$c_1 = (c_{1f} - c_{1i}) \times \frac{t}{M} + c_{1i}$$
$$c_2 = (c_{2f} - c_{2i}) \times \frac{t}{M} + c_{2i} \quad (11)$$

```
% Algorithm TV-MOPSO_By Chuyen Uneti Design Power Transformer.
M_s: size of the swarm,
M_a: maximum size of the archive,
M: maximum number of iterations,
d: dimension of the search space,
Ω_f: final output
(1) Initialize
   • Randomly generate a swarm, Swrm_0.
   • Initialize an archive A_0.
(2) For t = 1 to M
   For i = 1 to M_s, update the swarm, Swrm_t
   Update the velocity of each particle:
   - Find the global best solution, G_b, from the archive.
   - Find the personal best solution, P_bi.
   - Adjust the time variant parameters.
    v_{i,j} = wv_{i,j}+ c_1 r_1 (P_{b,i,j} - x_{i,j}) +
          + c_2 r_2 (G_{b,j} - x_{i,j}),∀ j ∈ {1, ..., d}   (i)
   Update the coordinates of each particle:
    x_{i,j} = x_{i,j} + v_{i,j}, ∀ j ∈ {1, ..., d}          (ii)
   Update the archive, A_t
   Mutate the swarm, Swrm_t
(3) Return the Pareto optimal front, Ω_f = A_t
  End.
```

Figure 1. The time-varying PSO algorithm

The algorithm's A_t repository is updated by adding non-dominated solutions from the combined population of seed swarms and the repository. If the size of the repository exceeds the maximum limit M_a, the repository will be truncated based on the solution diversity criterion [24]. To exploit the search space to a greater extent, while improving solution diversity, mutation is performed with a probability inversely proportional to the chromosome length d. For a seed p, a randomly selected coordinate k (meaning a design variable) of that seed will be mutated in (12).

$$p_{k'} = \begin{cases} p_k + \Delta(t, p_{ku} - p_k), & \text{if } flip = 0, \\ p_k - \Delta(t, p_k - p_{kl}), & \text{if } flip = 1. \end{cases} \quad (12)$$

Where flip, p_{kl}, and p_{ku} respectively represent the random variable taking the value 0 or 1, the lower and upper bounds of p_k. The function Δ is defined as (13).

$$\Delta(t, x) = x \times \left(1 - r^{\left(1 - \frac{t}{M}\right)^q}\right) \quad (13)$$

In (13), $r \in [0, 1]$ is a randomly generated value, M specifies the total iteration limit, and t denotes the current iteration number. The parameter α governs the dependence of the mutation intensity on the iteration progress. When the optimization process reaches M iterations, the algorithm stops and outputs the resulting archive. The solutions retained in this archive correspond to the non-dominated solution set obtained at the end of the search and define the Pareto-optimal front.

For verification and estimation purposes, the proposed design method was implemented numerically. This method was specifically applied to the design of 25 to 50 MVA; 66 kV/11 kV; 50 Hz transformers with various design performance constraints. Based on the actual transformer stacking and assembly methods for the MVA power range under consideration, the values selected throughout the

calculation process were $S_w = 0.2$, $K_H = 0.9$, $K_f = 0.95$, and the use of an 11-leaf composite core (corresponding to $K_c = 0.958$). The common constant values used for μ_0, ρ_{cu}, and δ_{Fe} are $4\pi \times 10^{-7}$ H/m; 2.1×10^{-8} Ωm; and 7.65×10^3 kg/m^3, respectively. Using Arco Steel core material, the expression $W_{Fe}(B, 50\ Hz)$ is derived from the manufacturer's provided data. Typical values of J_l, J_u, B_l, B_u, D_l, and D_u for transformers in the power range under consideration are selected as 1.1×10^6, 3.2×10^6, 1{,} 0. 1{,} 8, 0{,}1 and 0{,} 7 respectively. From these, we determine the proposed performance-oriented design method, using transformers with known manufacturer design information and measured performance characteristics selected for study.

4. RESULTS AND DISCUSSION

Based on the calculations and algorithmic modeling above, we will study the calculation and simulation modeling of a power transformer with the following parameters: Rated power S = 630 kVA, High voltage U_1 = 22 kV; Low voltage U_2 = 0.4 V; Magnetic circuit window width W_w = 305 mm; Magnetic circuit window height H_w = 1165 mm; Winding height l_{WH} = 1085 mm; No-load losses P_o = 1414 W; Short-circuit losses P_n = 7100 W. The FEM method is a numerical method widely used to solve integral calculus problems in engineering. Based on that, we used Ansys Maxwell software combined with the PSO method, TV-MOPSO algorithm, and FEM to calculate, design, and build a model to solve electromagnetic field problems for the object model through different types of power transformer design calculations. From this, we have the following research results: Figure 2 illustrates the B-H magnetic induction characteristics of the steel core. Figure 3 illustrates the power (P) and magnetic induction (B) characteristics of the power transformer core. For transformer analysis, we first need to design a simple 3D model. We will calculate the ferromagnetic core and the space between the windings and the steel core. Of course, all simulations are completed with the transient solution. Figure 4 shows the magnetic flux density of a 3-phase transformer with the given parameters.

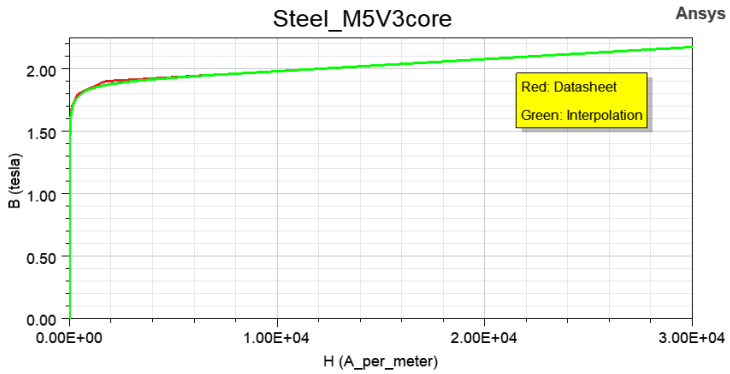

Figure 2. The B and H characteristics of the steel core

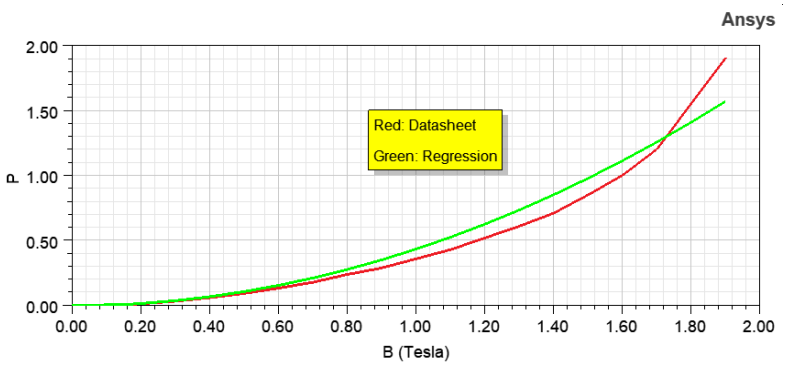

Figure 3. Power (P) and magnetic induction (B) characteristics of the power transformer core

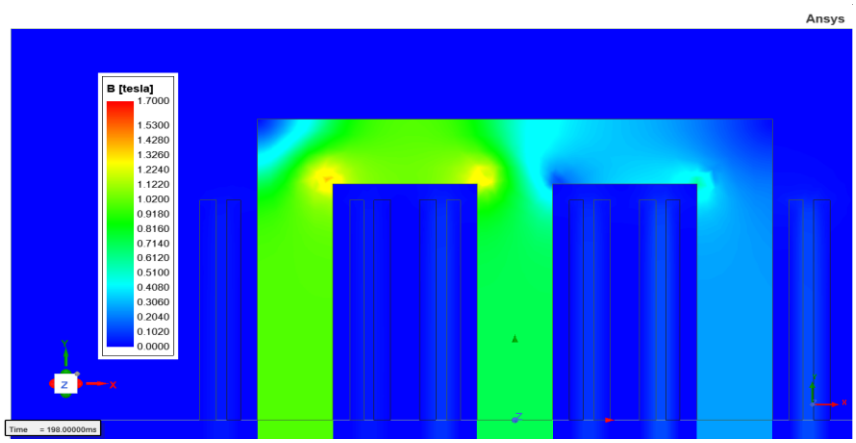

Figure 4. Simulation results of magnetic flux density on a power transformer

Figures 5 to 8 show the voltage values on the high-voltage side as shown in Figure 5 and the low-voltage side as shown in Figure 6. In general, stable voltage values indicate that the power supply system is operating well, with minimal fluctuations, helping the terminal equipment (load) to operate more stably and reducing the risk of damage due to overvoltage or sudden voltage drops. The high-voltage current values are shown in Figure 7, and low-voltage current values are shown in Figure 8 of the transformer. With negligible error components, the low-voltage side current value in Figure 8 is approximately 922, with an error of about 1.41%. The results indicate that the transformer's performance is reliable, high-efficiency, and stable over a long period.

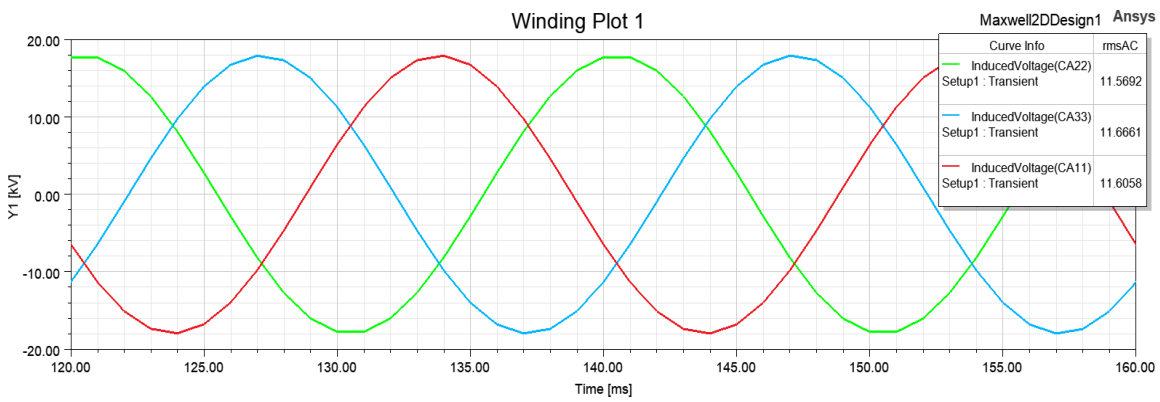

Figure 5. High-voltage side voltage of the power transformer

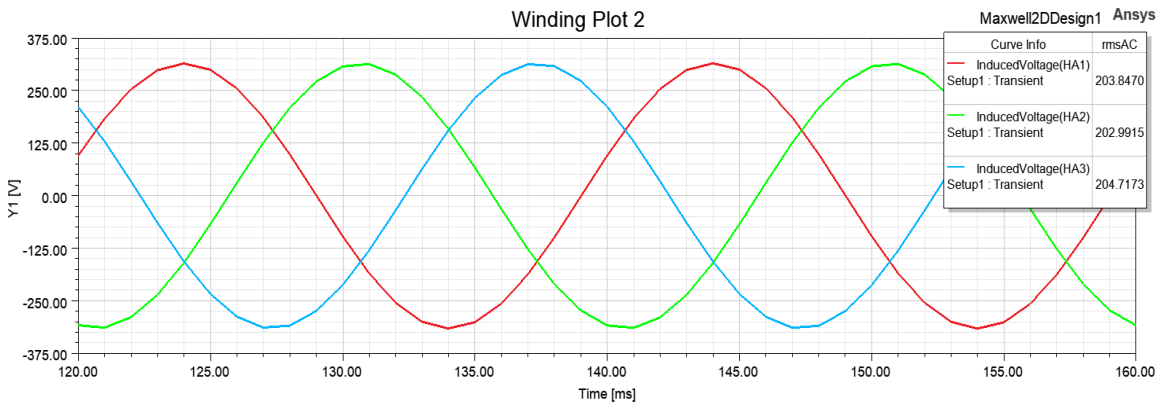

Figure 6. Step-down voltage of the power transformer

From the simulation results, we observe that the simulated no-load loss value is 1318 W, while the design calculation value is 1300 W, a difference of 1.38%. The copper loss is 6506 W, while the design value is 6500 W; this difference is negligible. This is because a finite element model in the calculation cannot consider all the effects of losses on the steel core and windings in terms of physics and manufacturing. According to regulations, very small losses can be ignored (not considered). These effects include: mechanical stress on the insulating coating; losses at the edges of the steel sheets due to the cutting and stamping process and steel burrs; losses in air gaps at the joints; eddy current losses, iron losses as shown in Figure 9, copper losses as shown in Figure 10, and calculations considering multi-stage magnetic circuit structures. These issues, encountered during the research, calculation, and design process, are reflected in the simulation results.

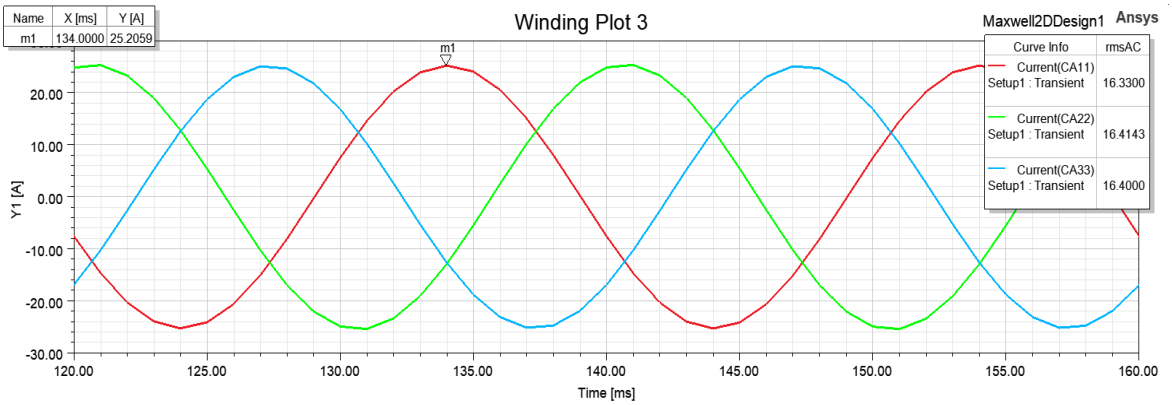

Figure 7. High-voltage current of the power transformer

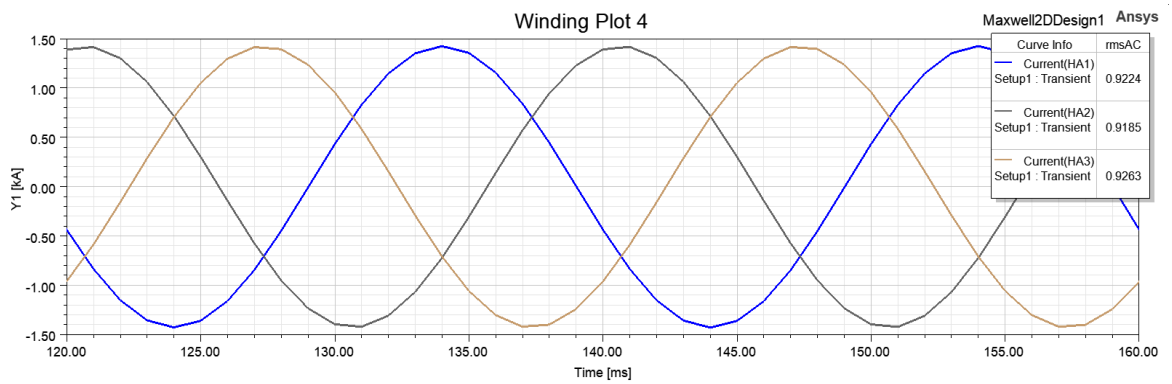

Figure 8. Low voltage current of power transformer

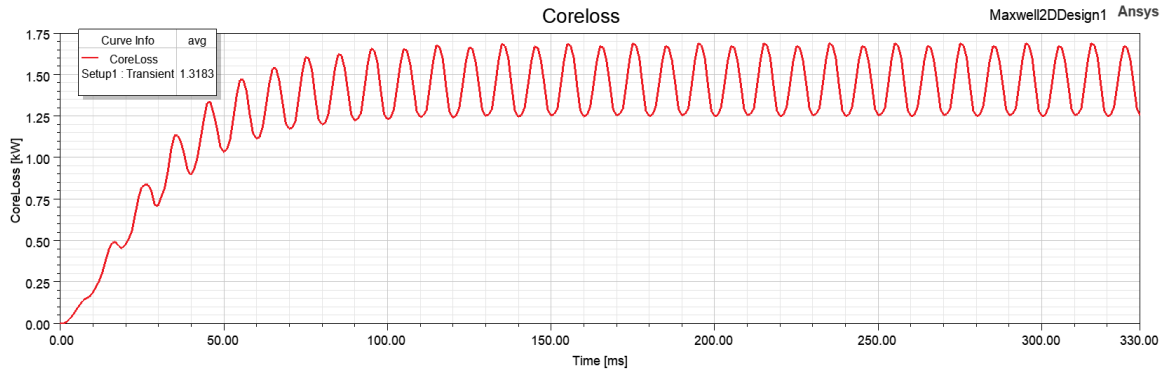

Figure 9. Results regarding iron loss

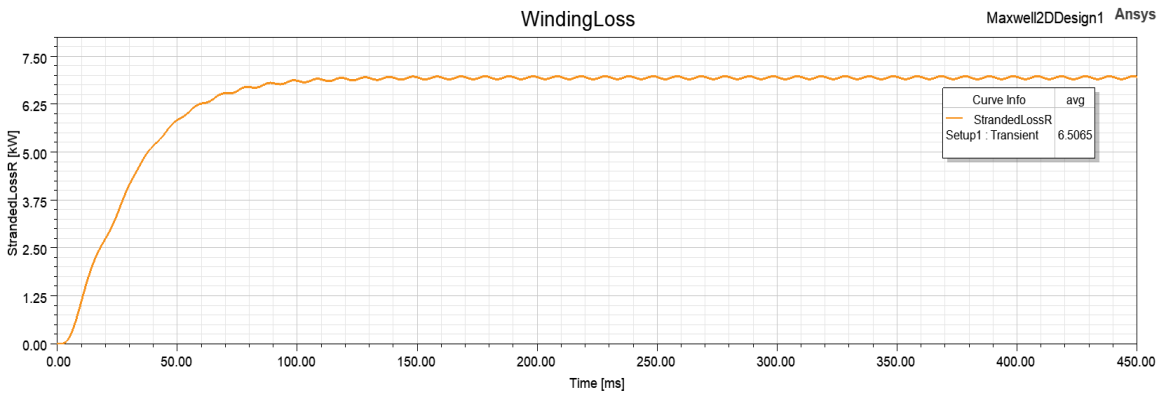

Figure 10. Results regarding copper loss

5. CONCLUSION

This paper presents a novel particle swarm optimization (PSO) method for multi-objective optimization, called TV-MOPSO, for designing high-performance power transformers in industrial and civil applications. Design calculations related to magnetic fields, steel structure, efficiency, voltage, and current have been studied and tested. The time-variant multi-objective particle swarm optimization (TV-MOPSO) method, combined with the FEA method, optimizes design calculations adaptively by allowing its key parameters to vary with the number of iterations. This adaptability makes the algorithm more efficient in exploring the search space, resulting in more accurate calculations. The transformer simulation quality in Ansys Maxwell software shows the elimination of many design calculation drawbacks. A new diversity parameter has been used to ensure sufficient diversity among solutions of the undominated matrices while maintaining convergence to the optimal multi-objective matrix with the best results. The next research direction is to combine the TV-MOPSO method with reinforcement learning, Q-learning, deep Q-network to identify and calculate parameters quickly and achieve high results, thereby improving the accuracy of the proposed method and expanding its applicability to include more detailed aspects of transformer design.

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Phan Hoai Nam	✓	✓	✓		✓	✓			✓	✓	✓		✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
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I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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