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FEM-based Modeling and Optimization of Dry-Type Transformers with Metaheuristic Algorithms

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Abstract: Transformer optimization is a programming problem with an objective function for calculating the characteristics of a transformer in detail according to user requirements. Especially in recent years, efficient and optimum design of the transformer has become increasingly important. This study presents a comparative analysis of the application of metaheuristic optimization algorithms in transformer design for maximum efficiency of a three-phase dry-type transformer. In addition, transformer modeling was done using FEM analysis, and its magnetic characteristics were shown. The main contribution of this paper is to optimize the determined basic design parameters with optimization methods that have not been used in transformer optimization before and to maximize efficiency by reducing losses. During this process, using the loss constants of the materials in the basic loss equation for core loss, this process was tried to be carried out without any change in the method in applications to be made with different materials. This situation also strengthens the accuracy of the applied method. Crow Search (CSA), Moth-Flame Optimization (MFO), Vortex Optimization (VOA), Particle Swarm Optimization (PSO), and Social Learning-Particle Swarm Optimization (SL-PSO) algorithms were used in the study. The loss values were obtained by performing loaded and unloaded FEM analysis with the ANSYS/Maxwell program. As a result, the best result was obtained with SL-PSO as max 99,05%.

Keywords: dry-type transformer; energy efficiency; metaheuristic optimizations; optimization, SL-PSO

1 INTRODUCTION

With rapidly advancing technology and the increasing human population, energy demand has increased in recent years. In this case, the importance of power systems and transmission distribution networks is increasing, and especially in these systems, transformers that provide power and voltage conversion efficiently and studies related to them gain importance. In addition, the environmentally friendly dry type transformer comes to the fore among the transformers that are divided into two as oily type and dry type. Dry-type transformers are widely used for ease of maintenance and low flammability. Therefore, studies on dry-type transformer design, analysis, optimization, and magnetic characteristics are widespread.

One of the points to be considered in transformer design is losses. These losses are divided into three groups: the core loss caused by the transformer core, the winding losses caused by the windings, and the excess losses caused by other components.

The main variables that affect the losses are the core material, sizing, winding material, and mechanical properties in the transformer structure. The thing to do to increase the efficiency of the transformer is to minimize the losses. For this reason, sizing operations and calculations without the need for a prototype with optimization algorithms provide convenience in terms of time and labor during the design stage. In [1], the methods and objective functions used in transformer optimization are given in detail.

On the other hand, one of the most used software in the electrostatic and electromagnetic field analyses of transformers is the ANSYS/Maxwell program, which simulates according to the finite element method and gives the closest results to practical applications. Numerical values such as magnetic flux density distribution, loss distribution, current, voltage, the loss can be obtained with the help of this program.

The optimization consists of two stages: modeling and solution. The selection of the algorithms to be used, the determination of the objective function and the determination of the variable parameters are the components of the modeling part.

In the literature review, many studies on transformer optimization were examined. The cost, temperature, and efficiency sizing optimizations for oily-type and dry-type transformers were made using different variables. In [2-3], considering the current density (*S*) and transformer iron cross-section acceptability (*C*) limits for dry-type transformers, Firefly, Invasive Weed, and PSO algorithms are used and optimized with minimum weight and/or maximum efficiency functions. In [4-5], Harmony Search, Firefly, and PSO algorithms were used to optimize with the same variables to analyze the efficiency, weight, and temperature of the dry-type transformer. The same variable parameters were also used in the volume optimization of the oil-filled transformer using the Firefly algorithm and compared with the GA results [6]. In these studies, except for the optimized parameters, the values such as the magnetic flux density of the transformer were taken as constant. However, since changes in core size affect the magnetic characteristic, the change in magnetic flux density is also a parameter to be considered. Considering this situation, in the study conducted in [7], eight variables, including the current density, were determined for the minimum cost optimization of the oil-type transformer. These parameters were optimized and compared using methods such as the Artificial bee colony (ABC) algorithm, Backtracking search optimization (BSA) algorithm, Cuckoo search (CS) algorithm, Flower pollination algorithm (FPA), and Competitive-Adaptive Differential Evolution algorithm (b6e6rl).

In [8], in order to minimize losses, five variables, including windings and core thickness, were determined, and optimization was made for maximum efficiency using evolutionary algorithms (EAs), genetic algorithm (GA), differential evolution algorithm, and nondominated sorting GA (NSGA-II). Magnetic flux density was also examined with FEM simulation. In the study conducted in [9], the same objective function was optimized using GA with the same five variables as in the previous study. In addition to these, mathematical constraints that need to be considered mechanically and electrically in the design are considered.

In another study [10], four different minimization objective functions were determined for oily type transformers. These are Active part cost, Total losses, Percentage impedance, and Transformer tank volume. These objectives are addressed to optimize a three-phase distribution transformer using Elitist Genetic Algorithms. Constant K value, magnetic flux density, and current density values of high and low voltage windings are defined as variables and others. The results obtained with the Tournament Selection based Elitist Genetic Algorithm are close to optimum. Optimization of a design using GA and conventional method on a 100 kVA, three-phase core type distribution transformer is shown [10]. In [11, 12], magnetic flux density, current density, and voltage amplitude were optimized with honey bee mating optimization, Artificial bee colony, Ant colony algorithm, Simulated annealing methods to minimize the weight of oil-type transformers. In [13], transformer design software was used to optimize the oily-type transformer in terms of transformer owning cost, total transformer losses, transformer material cost, transformer mass objective functions. The software was performed by designing a 25 kVA, 240/120 V transformer to check the practical solution of the software.

In [14], using variables such as magnetic flux density, current density, primary and secondary winding sizes, and core sizes, the total cost of the oil-type transformer was minimized with Direct Search, Differential Evolution, Simulated Annealing, and Random Search algorithms. The optimized design has been validated by finite element FEM electromagnetic analysis for head loss and temperature rise. The design parameters such as core diameter, flux density in the core, main insulation distance, the current density in the secondary coil, the current density in the primary coil, current density in the regulating coil, the height of the secondary winding are determined as a variable. The minimum ownership cost of the oil-type transformer is optimized with the NSGA-II algorithm, and FEM analysis was made in [15].

Unlike other studies, the current density and magnetic flux density of the primary and secondary windings, as well as the winding height and width, were chosen as variables in the study [16], which aims at minimum cost for an oil-type transformer, and the optimization process was carried out. While optimizing for a total of 5 variables using the non-linear programming (NLP) technique, the necessary constraints for situations such as loss, heating, and short circuit are determined. In [17], besides the core dimensions, winding thicknesses, insulator thickness, the number of turns was determined as variables, and optimization was made considering the constraints such as maximum flux density, temperature increase, and volume.

As a result of the literature review, it is seen that the studies on transformer optimization are increasing day by day. The studies so far are generally on oily types, and with the increase in the use and importance of dry-type transformers recently, studies have started to be made about them. Dry-type transformers are more costly and larger than oil-type transformers. Therefore, optimizing parameters such as cost, loss, temperature becomes important. In addition, the optimization methods used are increasingly diversified. In particular, the application of metaheuristic algorithms and performance comparison is important in terms of applications in industrial areas to give an idea about the optimum situation before prototype production.

Our motivation in this study is to use algorithms that are not used in transformer optimization, unlike previous studies, and determine the variable parameters that should be taken into account for the design and make sizing according to their optimum values. These algorithms are Crow Search (CSA), Social Learning-Particle Swarm Optimization (SL-PSO), Vortex Optimization Algorithm (VOA), Moth-Flame Optimization Algorithm (MFO), Particle Swarm Optimization (PSO). Another highlight is that, by calculating the core loss over the basic loss equation as well as the design equations, the optimization processes can be repeated without being affected by any material change in the core, only by changing the material constants. Here, PSO is used for transformer optimization in [1], but other algorithms are used for transformer optimization for the first time. The reason for choosing the SL-PSO with the best results is that the convergence speed SL-PSO is faster than PSO variants [18]. In addition to optimization, FEM analysis was performed with the help of ANSYS/Maxwell to determine the losses and electromagnetic characteristics of 3-phase 100 kVA dry-type transformers.

It is possible to summarize the main objectives of this study as follows:

- First time application of the CSA, SL-PSO, VOA, and MFO methods to a dry-type transformer design optimization problem
- Comparing results in terms of accuracy, and maximum efficiency performance with other state-of-the-art transformer optimization methods
- Analysis of the electromagnetic transformer characteristics via FEM
- By calculating the core loss over the basic core loss equation, the optimization processes are repeatable by only changing the material constants without being affected by any material change to be made in the core.

The rest of the paper is organized as follows. Section II describes the mathematical design of a three-phase dry-type transformer. The methodology of the optimization technique and objective functions have been explained in Section III. The optimization results and discussion are shown in Section IV. The conclusions are summarized in Section V.

2 MATHEMATICAL DESIGN FORMULATION OF THREE PHASE DRY-TYPE TRANSFORMERS

Detailed mathematical modeling to be used for the three-phase transformer optimization process is given in [1] in detail. Equations used for the core loss calculation in [1] publication are calculated using the loss and additional loss factor variables as seen in Eq. (1).

$$p_{\mathrm{fe}} = p_{10}\xi_2 B^2 \tag{1}$$

This paper calculated the core loss using the Steinmetz equation, which is seen in Eq. (2).

$$P_{fe} = K_h B_{pk}^{1,6} f + K_c B_{pk}^2 f^2 + K_e B_{pk}^{1,5} f^{1,5} \quad (2)$$

The variables K_h, K_c and K_e seen here are defined as hysteresis loss constant, eddy current loss constant, and abnormal loss constant. These variables are constants that vary depending on the core material used. Therefore, optimizing this function will prevent the objective function from being affected in case of any change in the core material used in future studies. Moreover, the core loss formulation coefficients of the core material are expressed as W/m^3 and W/kg. These coefficient values of M5 electrical steel used in this study are shown in Tab. 1.

Table 1 Loss coefficients of M5 material

Coefficients	Values
K_h	0,00603995
K_c	3,79302e^{-5}
K_e	0,00027

$$q_c = \frac{V_p}{4,44 k_{cu} N_1 B_{max} f} \quad (3)$$

Eq. (3) is one of the fundamental equations for the transformer, and here q_c, k_{cu}, V_p, N_1, B_{max}, f magnetic core cross-section, window fill factor, primary voltage, primary turn number, magnetic flux density, and frequency, respectively [19]. As can be seen from this formula, the change of even one parameter in transformer design is directly related to other parameters. q_c is also calculated based on the C and S values as seen in the equations in [1]. These two cases show that each parameter selected for optimization in this study directly affects the transformer size and the core weight.

Table 2 Optimization parameter and upper and lower limits

Quantity	Design Variables	Lower Limit	Upper Limit
Iron cross-section acceptability / cm^2/joule$^{1/2}$	C	5,9	10,6
Current density / A/mm^2	S	2,5	3,5
Window fill factor	k_{cu}	0,3	0,6
Magnetic flux density / T	B_{max}	1,5	1,75
Primary turn number	N_1	1500	2000
The cross-section area of the primary winding	q_1	1,5	4,5
The cross-section area of the secondary winding / mm^2	q_2	45	65
Core mass / kg	p_{FE}	328	537

In order to optimize the transformer for maximum efficiency, the optimization process was applied over the parameters shown in Tab. 2 in this mathematical model. The mathematical modeling of dry-type transformers includes the design dimensioning of the transformer and the equations to be used as the objective function.

3 OPTIMIZATION TECHNIQUES FOR TRANSFORMER DESIGN

3.1 Vortex Optimization Algorithm (VOA)

Olmez and Dogan developed the vortex search algorithm in 2015 [20]. The algorithm is a swarm-oriented optimization method inspired by the naturalness of the vortex behavior and consists of nested circles to search the two-dimensional solution space to find the optimal solution.

The algorithm has Gaussian distributions and gamma functions to explore and exploit the solution space to reduce the radius of the largest circle to find the optimal result. This creates a hypersphere to center the vortex sphere in the solution space. The center of the starting outer circle (μ_0) and the functions of the methodology are calculated as follows [21]:

$$\mu_0 = \frac{upper\,limit + lower\,limit}{2} \quad (4)$$

After μ_0, σ_0 circle radius is calculated [21]:

$$\sigma_0 = \frac{max\left(upper\,limit\right) - \min\left(lower\,limit\right)}{2} \quad (5)$$

The objective function is set to infinity for the best solution at the beginning of the iterations to get better values. Thus, it allows us to obtain better and closer values in the subsequent iterations. Because in each iteration, fitness values of each particle are calculated and evaluated, and the closest result is obtained by comparing the better positions recorded earlier in each iteration [21].

Candidate solutions are created randomly according to the Gaussian distribution in the solution space around the initially determined center. It is checked whether the candidate solutions created are within limits. Candidates who are out of bounds are withdrawn to the min or max position using the following equation [21]:

$$C_k\left(S\right) = \mathrm{rand}\left(upper\,limit - lower\,limit\right) + lower\,limit \quad (6)$$

Here, k is the iteration index of the candidate solutions, and 0 and 1 are the range of random variables. The radius of the circles (r_k) is reduced at each iteration by the inverse gamma function. The solutions are compared with the solutions obtained so far at each iteration. The smaller solutions are kept as the best solutions. In addition, the initially calculated center point shifts towards the best solution, and the radius of the swirl is reduced to find the best solution better. The radius according to the center point obtained in each iteration is decreased in each iteration according to the following function [21]:

$$r_k = \sigma_0 \left(\frac{1}{x}\right) gammaincinv\left(x, a_k\right) \quad (7)$$

where x and a are constant value and shape parameter, respectively. a_k is decremented at each iteration and is given as follows [21]:

$$a_k = a_0 - \frac{k}{MaxItr} \quad (8)$$

where $MaxItr$ is the maximum iteration number.

3.2 Particle Swarm Optimization (PSO)

Eberhart and Kennedy developed the Particle Swarm Optimization (PSO) in 1995, a swarm-based metaheuristic optimization method [22]. Particle Swarm Optimization is a heuristic method that performs a fast convergence to optimal solutions [23, 24]. PSO gives successful results in many engineering problems from different areas [25, 26]. Each particle is assumed to be one part of the swarm and could update the position of the particle and velocity of the particle by using the best results in PSO. The equations related to position and velocity for a classical PSO are shown in Eqs. (9) and (10):

$$v_i(t+1) = \omega v_i(t) + c_1\left(p_{\text{best}}(t) - x_i(t)\right) - \\ -c_2\left(g_{\text{best}}(t) - x_i(t)\right) \tag{9}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{10}$$

where p_{best}, g_{best}, $x_i(t)$ and $v_i(t+1)$ are the local best particle, the global best particle, the position of particle *i* in iteration *t*, the velocity of particle *i* in iteration $(t+1)$, respectively. In Eq. (10) and Eq. (11), *t*, $v_i(t)$ and $x_i(t)$ represents the number of iterations, the speed value of the particle *i* and the position values of the particle *i*, respectively.

The acceleration coefficients which call c_1 and c_2 vary to interval $0 < c_1, c_2 \leq 2$. The inertia weight is indicated by $\omega\in[0,8; 1,2]$. In this work, the inertia weight is equal to 1 in Eq. (10). We use the inertia weight to balance local and global searches. The aim is that the optimal outputs are achieved with less iteration. Therefore, determining the appropriate value of inertia weight is important.

3.3 Social Learning Particle Swarm Optimization (PSO)

Particle Swarm Optimization could give better results in low-dimensional optimization issues. However, particle swarm optimization cannot perform well as the dimension increases. The social learning particle swarm optimization (SL-PSO), which is one of the particle swarm optimization method variants, has proposed improving the search performance by Cheng [18]. SL-PSO methods start as PSO, an initial vector (X_{ij}) is created randomly. Each vector is a candidate solution. After that, the SL-PSO sorts the candidate solution according to the evaluation of the fitness function. Then, every particle learns from other particles to correct its behavior. The mathematical equation about the social learning process between the particles is described in Eq.(11);

$$X_{i,j}(t+1) = \begin{cases} X_{i,j}(t) + \Delta X_{i,j}(t+1), \text{if } p_i(t) \leq p_i^l \\ X_{i,j}(t), \quad \text{otherwise} \end{cases} \tag{11}$$

where $X_{i,j}(t+1)$ is the particle that learns, $X_{i,j}(t)$ is the particle that teaches, p_i is the probability of learning. In detail, $\Delta X_{i,j}(t+1)$ is constructed as follows;

$$\Delta X_{i,j}(t+1) = r_1(t)\Delta X_{i,j}(t) + r_2(t) I_{i,j}(t) + \\ +r_3(t) \in C_{i,j}(t) \tag{12}$$

$$I_{i,j}(t) = X_{k,j}(t) - X_{i,j}(t) \tag{13}$$

$$C_{i,j}(t) = \bar{X}_j(t) - X_{i,j}(t) \tag{14}$$

As seen in Eq. (15), three components update the position in SL-PSO. The updated first component is $X_{i,j}(t)$. The $X_{i,j}(t)$ act as an inertia component in the classical particle swarm optimization. The second one is $I_{i,j}(t)$ which called the demonstrators. The demonstrator is used to update correct position correction. The social influence factor is the last component. There are three random coefficients, r_1, r_2, and r_3, randomly generated within [0; 1]. Specifically, the *j*-element in the behavior vector of the particle *i*; $X_{i,j}(t)$ simulates $X_{k,j}(t)$ the j-th element in the behavior vector of the particle *k*.

Eq.(15) gives the relation between learning possibility $\left(P_i^L\right)$ and problem dimensionality;

$$P_i^L = \left(1 - \frac{i-1}{m}\right)^{\log\left(\left[\frac{1}{M}\right]\right)} \tag{15}$$

where the dimension of the problem and swarm size is represented by *M* and m, respectively.

3.4 Moth-Flame Optimization Algorithm (MFO)

Recently one of the most population-based algorithms is Moth flame optimization (MFO). The MFO algorithm is modeled based on the navigation method of moths. Moths can travel long distances at night since they can fly at a fixed angle to the moon [27]. Despite the efficient navigation feature of moths, they are confused in artificial light sources. That's why moths follow a spiral path around artificial light sources.

The mathematical model of MFO is explained according to moths and flames. Whereas moths are search agents, flames are candidate solutions. The MFO algorithm starts by assigning the random position of moths in the solution space. Then, the fitness values of moths are calculated. The moths are sorted according to their fitness values and assigned as flames. The moths' positions depending on a flame, are updated. The new position of each moth is determined as the following equations:

$$M_i = P\left(M_i, F_j\right) \tag{16}$$

where M_i refers to *i*-th moth and $P\left(M_i, F_i\right)$ is the logarithmic spiral for MFO, and it can be defined as follows:

$$P\left(M_i, F_i\right) = D_i \mathrm{e}^{\mathrm{b}t} \cos(2\pi t) + F_j \tag{17}$$

where F_j refers to the *j*-th flame, *t* is a random number in [−1, 1], b is a constant to define spiral function shape and D_i indicates the distance between the *i*-th moth and the *j*-th flame, and it is defined as the following equation:

$$D_i = \left|F_j - M_i\right| \tag{18}$$

The new individual best position of a moth is updated by comparing the fitness values corresponding to a new position and the current position. On the other hand, the best flame position is saved as the optimum solution in each iteration. Moreover, the flame number is updated with the following equation.

$$flameno = \text{round}\left(N - l\frac{N-1}{T}\right) \tag{19}$$

where N indicates the maximum number of flames, l is the current iteration number, and T is the maximum number of iterations. This process continues until reaching the stopping criterion (maximum iteration, etc.). The best flame position indicates the optimum solution.

3.5 Crow Search Algorithm (CSA)

Crow search algorithm (CSA) is a metaheuristic algorithm developed by Askarzadeh in 2016 [28]. The CSA is modeled by inspiring the intelligent behavior of crows. Crows are considered one of the most intelligent birds since they can hide their food and keep hiding food in their memory.

For a d-dimensional problem, the number of crows in the flock, and the maximum iteration are assumed as N and $iter_{\max}$, respectively. $x^{i,iter}$ position of crow at iteration can be defined as follows:

$$x^{i,iter} = \left[x_1^{i,iter}, x_2^{i,iter}, \ldots, x_d^{i,iter}\right] \tag{20}$$

where $i \in \{1, 2, \ldots, N\}$ and $iter \in \{1, 2, \ldots, iter_{\max}\}$

At iteration iter, the best position of crow i is $x^{i,iter}$ and this is kept as $m^{i,iter}$ in memory of crow i. The position of crow i in the next iteration is determined according to the following two conditions.

Condition 1: In the case of crow j does not know the crow i, it approaches the hiding place of crow j. Consequently, the position of crow i is updated as follows:

$$x^{i,iter+1} = x^{i,iter} + r_i fl^{i,iter}\left(m^{j,iter} - x^{i,iter}\right) \tag{21}$$

Condition 2: if crow j knows the crow i, crow j protects its hiding place. Thus, the position of crow i updates by choosing a random position in search space. As a result, the new position of crow i for Condition 1 and Condition 2 is determined as follows:

$$x^{i,iter+1} = \begin{cases} X_{i,j}(t) + \Delta X_{i,j}(t+1) x^{i,iter+1} + \\ + r_i fl^{i,iter}\left(m^{j,iter} - x^{i,iter}\right) \\ r_j > AP^{i,iter} \text{ a random position, otherwise} \end{cases} \tag{22}$$

where r_i and r_j is a random number in the range of $[-1, 1]$ for crow i and crow j, respectively, $fl^{i,iter}$ and $AP^{i,iter}$ is flight length of and awareness probability of crow i at iteration *iter*, respectively.

The memory of the crow i is updated by comparing the fitness values of $m^{i,iter}$ and $m^{i,iter}$. This can be defined as follows:

$$m^{i,iter+1} = \begin{cases} x^{i,iter+1}, f\left(m^{i,iter}\right) < f\left(x^{i,iter+1}\right) m^{i,iter} \\ \text{otherwise} \end{cases} \tag{23}$$

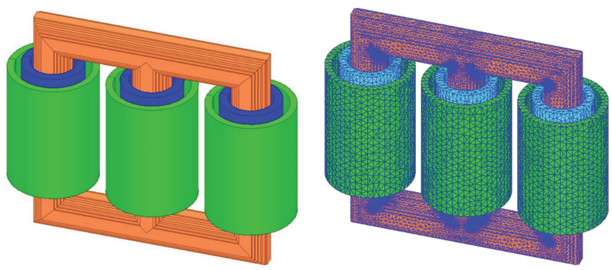
where f is the fitness function.

3.6 FEM Analysis

Electromagnetic modeling of transformer is one of the essential parameters for performance and characteristic analysis. Progress in numerical methods applications enables more accurate and practical solutions to electromagnetic problems with boundary conditions and complex structures. These methods are widely used as functional tools in electrical, structural, thermal, fluid flow, and electromagnetic analysis of transformer designs. One of the most used and common mathematical methods is FEM. FEM is a numerical method for solving non-linear and linear problems that divide the simulation surface into tetrahedral meshes and use integral and differential operations [29]. In this study, ANSYS/Maxwell was used for the FEM simulation of the transformer. This method makes it possible to analyze core and winding loss of dry type transformer, frequency or time-based analysis of the magnetostatic, electric field, and eddy current problems. Sinusoidal voltage excitation of transformer is applied as seen Eq. (24):

$$U_{\text{p}} = V_{\text{p}}\left(1 - \exp(-50t)\right)\cos(2\pi ft) \tag{24}$$

This paper performed a 100 kVA 3-limb 3-phase transformer using ANSYS/Maxwell software 3D modeling based on time to obtain core loss, winding loss, and magnetic flux density within the core and coils. The transformer and modeled transformer specifications and the Maxwell 3D model with mesh are shown in Tab. 3 and Fig. 1. The mesh structure seen in Fig. 1b is important for the FEM solution. Mesh quality, structure, and size directly affect the accuracy of the calculated results. Also, not every ANSYS/Maxwell program solution has an adaptive mesh feature, so meshing can be transferred to transient analysis after it is done in eddy current analysis.



a b

Figure 1 a) ANSYS/Maxwell model; b) Mesh model of the transformer

Table 3 General specifications of 3 phase dry-type transformers

Quantity	Values
Power Level	100 kVA
Voltages	10/0,4 kV
Connection Type	Δ/Y
Turns	1819/42
Core Material	M5
Winding Material	Aluminum
Lamination Thickness	0,30 mm
Core Volume	0,05498 m^3
Pcoreloss	400 ± 10% W
Pcu	2000 ± 10% W
Impedance Voltage	4%

4 RESULTS AND DISCUSSIONS

In this paper, the optimization process of the 3-phase transformer is obtained depending on the iron cross-section acceptability, current density, window fill factor, magnetic flux density, primary turn number, the cross-section area of the primary winding, the cross-section area of the secondary winding, core mass variables, respectively. In the mathematical model shown, optimization is performed with these eight variables to minimize the total loss, in other words, to maximize efficiency. Unlike other studies, the basic loss equation obtained using the material constants seen in Eq. (3) was used instead of the formula based on the standard loss variables in calculating core loss. In addition, the magnetic flux density distribution on the transformer model and the loss values obtained according to the label values were obtained with the help of the FEM simulation. This situation allowed us to compare the optimum efficiency values obtained from the optimizations with the simulation and label values.

This study used five optimization methods, namely CSA, MFO, VOA, PSO, and SL-PSO, to achieve maximum efficiency in a 100 kVA dry-type transformer.

According to the label values, it is stated that the efficiency of the transformer is 97,6%. In this study, the average results obtained after each method was run 20 times were considered.

In addition, we ran all optimization methods with 2000 iterations so that our comparison criteria were under the same conditions. We choose 2000 iterations because there is no change in the last 100 iterations as a stop criteria.

As a result, the optimization process based on maximum efficiency is directly related to the design parameters of the transformer. The values obtained at the end of the optimizations are given in Tab. 4 in detail for the 100 kVA transformer.

Table 4 Variable values obtained from optimization algorithms

Design Variables	CSA	MFO	VOA	PSO	SL-PSO
C / cm^2/joule$^{1/2}$	6,73	5,9	6,16	5,9	7
s / A/mm^2	2,5	3,43	2,62	2,5	2,56
k_{cu}	0,3	0,3	0,42	0,6	0,34
B_{max} / T	1,5	1,5	1,51	1,5	1,51
N_1	1500	1500	1500	1500	1577
q_1 / mm^2	1,5	5	4,42	5	4,4
q_2 / mm^2	45	65	61,9	65	47,7
p_{FE} / kg	328	328	328	340,5	396
Max. Efficiency / %	98,9	98,99	98,88	98,99	99,05

As shown in Fig. 2 and Tab. 4, among these algorithms used, the SL-PSO algorithm gave the best result with the 99,05 %. The results show that when compared with previous studies, the success of SL-PSO in increasing efficiency stands out compared to others.

Considering the optimization results in Fig. 2, it is seen that even the initial values are higher than the 97,6% efficiency value calculated according to the label values. The initial values of CSA, MFO, VOA, PSO, and SL-PSO are 98,79%, 98,63%, 98,8%, 98,66%, and 99,01%, respectively. When evaluated according to the maximum efficiency values, the results can be listed as 98,9%, 98,99%, 98,88%, 98,99%, and 99,05%. When the improvement increases in optimizations are compared in terms of initial and final values, they are 0,11%, 0,36%, 0,08%, 0,33% and 0,04%, respectively. While MFO converges to its maximum efficiency value in the 50th iteration, it increases to 280 in the CSA, 300 in the VOA, and 1150 in the PSO. SL-PSO found better results than other methods in the first iteration, and as the number of iterations increases, the efficiency increases, but this increase is limited to 0,04%. Therefore, even running SL-PSO with a very small number of iterations gives almost the best results.

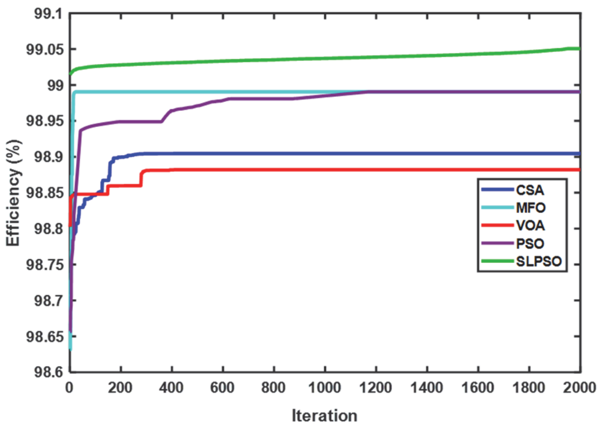


Figure 2 Optimization results of transformer in terms of efficiency

SL-PSO gives the best result from the first iteration to the last iteration. There is a slight 0,04% increment in Fig. 3.

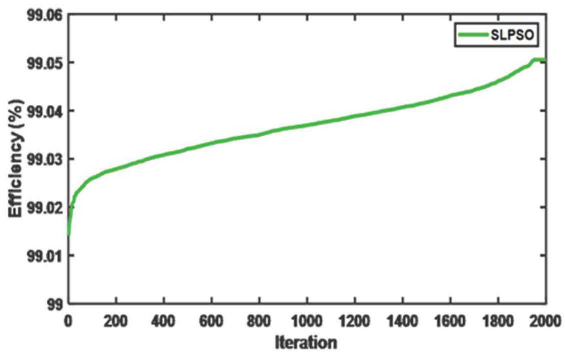


Figure 3 SL-PSO result of transformer in terms of efficiency

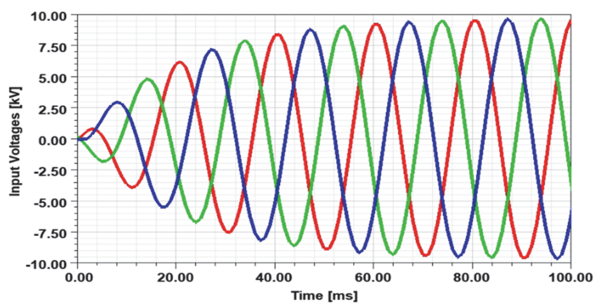


Figure 4 Input voltages results obtained by FEM analysis

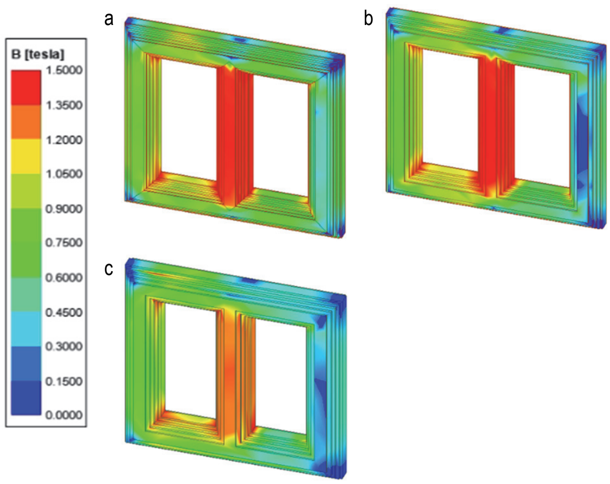
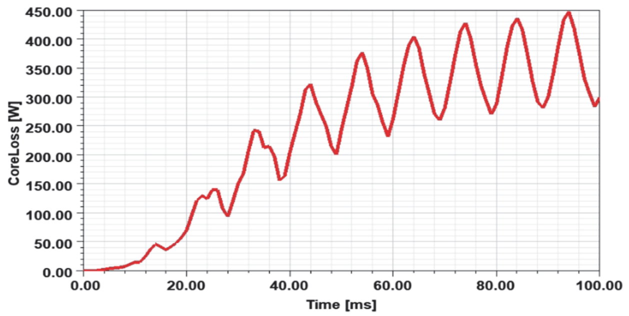
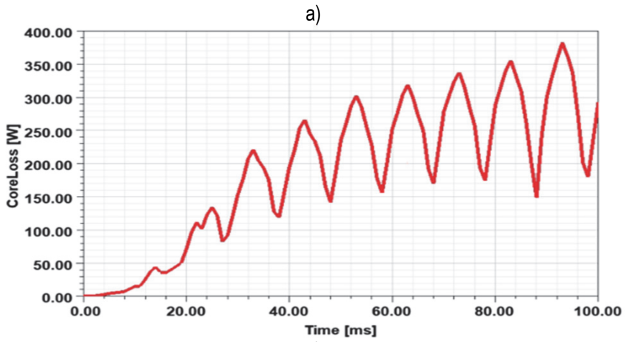


Figure 5 Electromagnetic flux density distribution using ANSYS/Maxwell transient analysis for a) label value; b) C = 5,9; c) C = 7

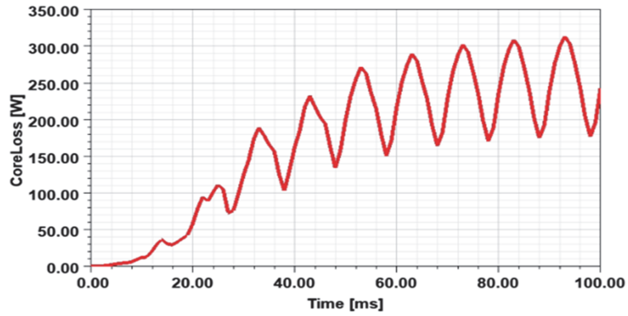
As a result of the optimization, the transformer core size was changed according to the new values obtained. In order to make a comparison, the core size was changed by considering the label value versus the c values of PSO and SLPSO. Fig. 4 shows the three-phase excitation voltage given to the transformer during the analysis and expressed by Eq. (24). Fig. 5 shows the instantaneous magnetic flux density distributions obtained as a result of time-dependent FEM analyses for three different C values. Since the excitation voltage is sinusoidal, the flux density on the core changes instantaneously. For this reason, the moment when the flux density on the middle leg is maximum was chosen visually. As can be seen in the figures, the change in core size directly affects the magnetic flux density. Since the core size obtained for C = 5,9 is very close to the label value, the difference is not clear. However, even though the maximum flux density in the core obtained for C = 7 obtained from SLPSO is the same, the loss value also decreases as the average value decreases due to the distribution. This distribution is also a figure that allows us to understand the loss distribution.



a)



b)



c)

Figure 6 The core loss of cross-section area for a) label value; b) C = 5,9; c) C = 7 results using FEM analysis

Fig. 6 also shows the core losses obtained as a result of the analyses made for all three c values. As mentioned above, the loss value of the core decreased for the value obtained as a result of SLPSO. The results of these analyses also support the effect of the optimizations on the efficiency.

5 CONCLUSION

Dry-type transformers are becoming increasingly important in environmental friendliness, cooling, and ease of maintenance. This makes dry-type transformer design and optimization studies important. In this study, 100kVA 3-phase dry type transformer is optimized in terms of efficiency. Five different algorithms and eight different design variables were used for this optimization process. Transformers are also electromagnetically analyzed. The results show that the parameters used are essential for optimizing the parameters and losses of transformers. When the methods used in the study were compared in terms of result and performance, SLPSO gave the best result with 99,05% efficiency. When we look at the increases in the improvement rates of the optimizations, they are 0,33%, 0,11%, 0,08%, 0,04%, and 0,36%, as PSO, CSA, VOA, SLPSO, and MFO, respectively. This paper is essential in a transformer design to facilitate production and give information about optimum parameters. Future studies aim to make structural multi-objective optimizations in cost analysis by adhering to these methods.

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