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RESEARCH ARTICLE

Applications of Novel Heuristic Algorithms in Design Optimization of Energy-Efficient Distribution Transformer

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ABSTRACT Transformers are crucial and expensive assets of power grids. Reducing power losses in power and distribution transformers is important because it increases the efficiency of the transformer, which in turn reduces the costs for the utility company and consumers. Losses in the transformer generate heat, which can reduce the lifespan of the transformer and require additional cooling. Additionally, reducing losses can help to decrease greenhouse gas emissions associated with the generation of electricity. This study presents an optimization method for transformer design problem using variables that have a great impact on the performance of a transformer. Due to the non-convex nature of the transformer design problems, the empirical methods fail to find the optimal solution and the design process is very tedious and time-consuming. Considering No Free Lunch (NFL) theorem, the design problem is solved using four novel heuristic optimization algorithms, the Firefly Optimization Algorithm (FA), Arithmetic Optimization Algorithm (AOA), Grey Wolf Optimization Algorithm (GWO), and Artificial Gorilla Troops Optimizer Algorithm (GTO) and the results are compared to an already manufactured 1000 kVA eco-friendly distribution transformer using the empirical methods. The outcome of the optimization shows that the suggested method along with the algorithms mentioned leads to a notable decrease in power losses by up to 3.5%, and a reduction in transformer weight by up to 8.3%. This leads to an increase in efficiency, decreased costs for materials, longer lifespan and a reduction in emissions. The developed model is capable of optimally designing oil-immersed distribution transformers with different power ratings and voltage levels.

INDEX TERMS Eco-design transformer, energy efficiency, optimization, power losses, transformer design.

I. INTRODUCTION

Transformer is a static electromechanical device with at least two windings used in power systems to connect circuits with different voltage levels to each other. A transformer uses the electromagnetic induction principle to convert one voltage level at its primary winding to a different voltage level at its secondary winding by having the total transferred power almost constant. Power and distribution transformers are essential components of the power system to reduce transmission and distribution losses. Transformer is considered as one of the most efficient components of the power systems with an approximated efficiency of above 98%. Despite the high efficiency of transformers, the remaining 2% of losses will be a great amount of energy due to the continuous operation of these types of equipment in high powers and numerous transformers in the power systems [1].

The need for sustainability and Green House Gas (GHG) reduction has been a vital topic in recent years. To mitigate GHG, an important step is to manufacture low-loss and high-efficiency equipment. For instance, a distribution transformer with a capacity of 1000 kVA, a maximum allowed load loss

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TABLE 1. Tier 2 transformers specifications.

Rated Power (kVA)	Maximum Load Losses (W)	Maximum No-Load Losses (W)	Minimum Peak Efficiency (%)	Short Circuit Impedance (%)
≤25	600	63	98.251	4
50	750	81	98.891	4
100	1250	130	99.093	4
160	1750	189	99.191	4
250	2350	270	99.283	4
315	2800	324	99.320	4
400	3250	387	99.369	4
500	3900	459	99.398	4
630	4600	540	99.437	4 or 6
800	6000	585	99.473	6
1000	7600	693	99.484	6
1250	9500	855	99.487	6
1600	12000	1080	99.494	6
2000	15000	1305	99.502	6
2500	18500	1575	99.514	6
3150	23000	1980	99.518	6

of 7600 watts, and a no-load loss of 693 watts will incur an annual energy loss of 72,646,680 watts at full loading conditions. Through implementation of loss minimization strategies, it can be inferred that a 1% reduction in loss for this particular example transformer would result in an annual energy savings of 726,466 watts. Given the widespread utilization of distribution transformers in power distribution systems worldwide, and considering their typical lifespan of 20-25 years, the implementation of loss minimization techniques not only has the potential to result in substantial cost savings through reduced power generation, but also has the added benefit of reducing emissions associated with power production. To attain low-loss eco-design transformers, European Union (EU) has specified the requirements for products related to the energy sector in Commission Regulation (EU) No. 548/2014 on implementing Directive 2009/125/EC. With reference to Directive 2009/125/EC, there must be up to 33% reduction in load losses and 10% reduction in no-load losses of Tier 2 designs compared to Tier 1 designs respected from 1st July 2021 for three-phase medium power oil-immersed transformers. Maximum allowed load and no-load losses of three-phase oil-immersed transformers is given in Table 1 [2].

Transformers design optimization problem has been comprehensively studied in the literature in recent years. Since the transformer is among the most expensive components of a power system, most of the research done in the area of transformer design and optimization lay in the Total Owning Cost (TOC) minimization of transformers. Design engineers need to meet the specifications given by customers considering thermal, mechanical, dielectric, and, electrical constraints specified by transformer design and test standards such as IEC 60076 and ANSI/IEEE Standard C57.12.00 [1]. The most recent trend in transformer design is the use of heuristic optimization algorithms with TOC as the objective function. However Finite Element Analysis (FEA) is mainly used for transformer losses calculations and design validation combined with heuristic algorithms [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. In [3], five nature-inspired optimization algorithms are used to minimize the shell type distribution transformer's main material cost. The authors have used Artificial Bee Colony (ABC), Backtracking Search Optimization Algorithm (BSOA), Competitive-Adaptive Differential Evolution Algorithm, Cuckoo Search (CS) algorithm, and Flower Pollination Algorithm (FPA). The algorithms are evaluated based on their convergence speed. In [4], the authors have used MATLAB inbuilt *fmincon* function to minimize the Total Owning Cost (TOC) of a hermetically sealed shell type distribution transformer. This function can find the optimum solution of a nonlinear function however; the main disadvantage of this optimization function is determining a suitable vector of the Initial point, which requires expertise in transformer design. Applications of Mixed Integer Nonlinear Programming (MINLP) as a deterministic optimization technique, and Harmony Search (HS), Genetic Algorithm (GA), and Differential Evolution (DE) as stochastic optimization algorithms were studied in the design optimization of a distribution transformer in [5] and [6]. The objective function of this paper is to minimize the cost of the active part of three transformers with different nominal power. In [7], a multi-objective evolutionary optimization algorithm with unrestricted population size and chaotic sequence approach is applied to improve the efficiency of dry-type single-phase distribution transformer with nominal power of 300 VA. Authors in [8] have employed multi-objective Simulated Annealing (SA) and GA for optimization of main material cost and loss reduction of a three-phase high-temperature superconducting (HTS) windings transformer design. The driven results are validated in 2D-FLUX software with the Finite Element Method (FEM). In [9], two cold-rolled grain-oriented silicon steel materials, commonly known as M4 and M5 are analyzed in terms of no-load loss using 2D FEM and compared with test results of an already built transformer. The results of this study reveal that transformers with M4 core material have 30% less no-load loss compared to transformers with M5 core material. TOC optimization of three-phase distribution transformer considering the limitation imposed by Directive 2009/125/EC is studied in [10]. The authors have investigated the impact of grain-oriented steel type core and amorphous type core on transformer losses as well as the total owning cost of the transformer. A single objective optimization has been applied on 800 kVA, 1600 kVA, and 2500 kVA distribution transformers all with copper high voltage and low voltage windings. The results demonstrate that transformers with amorphous type core have less weight and losses in comparison to grain-oriented steels type core transformers, however, they have higher TOC. In [11], the core loss of a conventional three-phase transformer with single core material is compared to a transformer with core material of two different steel grades. The simulation is done using FEM in Ansys Maxwell software. This study claims that up to 6.25% of core loss could be reduced using a combination of steel materials in the transformer's core. However, the major drawback of using a mixed core type may lead to higher labor costs and time-consuming processes during the core stacking stage. In [12] the authors have used GA and SA algorithms to minimize the cost of the active part of a 630 kVA distribution transformer considering only four design variables. The results obtained from optimization algorithms are compared to the congenital design of the same transformer. The proposed design optimization algorithm has reduced the cost of the active part by 1.5% however, the load loss has increased by 4.5% and no-load loss has increased by 4.5% compared to the conventional method. An experimental study was conducted in [13] to reduce transformer losses by focusing on stray losses. The tank walls of the distribution transformer were lined with aluminum foil shields with thicknesses of 1.2 mm and 10 mm. the study shows that the higher the thickness of aluminum shields, the more reduction in stray losses due to less penetration of magnetic fields in the transformer's tank wall. In [14], the total loss of a distribution transformer is set as the objective function of the problem. The optimization problem is then solved using the Pattern Search Method (PSM) and Taguchi Method. The initial searching point vector of the PS is defined with values from the original transformer. The results show that the proposed methods can have a reduction in copper loss by 5.27% and iron loss by 10.94%. In [15], the effects of variable loading are considered in the design optimization of a 200 kVA distribution transformer where the main design variables are the dimensions of the transformer's coil and windings. In [16], FEM and NSGA-II algorithm are used to determine the optimal conductor dimensions of a power transformer with a power rating of 31 MVA. In [17], the exploitation cost of a power transformer due to active and reactive power is defined as the objective function of the design optimization. In [18] the authors present a method for optimizing the design parameters of a three-phase transformer using ANSYS Maxwell 2D software and the multi-objective differential evolution algorithm to minimize the total power losses of the transformer. The research provides optimal design parameters for a 1 kVA transformer, and shows that the highest efficiency is achieved at 75% loading condition with unity power factor. The research in [19], employed a combination of various evolutionary algorithm techniques such as GA, DEA, and NSGA-II, along with the Finite Element Method (FEM) to enhance the design's adaptability and dependability. Five parameters, core thickness, primary turn number, secondary turn number, primary conductor area, and secondary conductor area, were chosen to decrease the total losses and the overall ownership cost. In [20], the authors propose using the Adaptive-Network Based Fuzzy Inference Systems (ANFIS) technique to estimate the core losses of a transformer using FEA analysis. Three input parameters are used for this purpose. To gather the necessary data for ANFIS estimation, the Ansys/Maxwell software's parametric analysis feature is utilized. The ANFIS model used in the study had a Sugenotype FL system, and the error obtained from the confirmation test is considerably small. As a result, the proposed method in this study can be recommended for use in parameter estimation of power transformers as it was successful.

The major contribution of this paper is the introduction of a more manufacturable mathematical optimization framework considering all design variables such as conductor and core dimensions, cooling system and ducts, and material types, technical constraints, and consumer specifications. In this study, all conflicting design objectives are formulated and taken into account in the design process. The use of proper design variables guarantees the optimal objective function in comparison to the empirical method in terms of transformer load losses and no-load losses, transformer weight, thermal constraints, active part cost, and total owning cost of the transformer. The proposed method narrows the search space to find the optimum point which makes it capable of designing any type of oil-immersed transformer. The proposed method is applied to a 1000 kVA core type eco-design distribution transformer considering Directive 2009/125/EC limitations.

This paper is organized as follows: Section II describes the transformer design optimization problem, design variables, objective function, and constraints. Section III describes the design flowchart and introduces the selected heuristic algorithms. Section IV evaluates the optimization results and compares to the empirical method. Finally, section V concludes the paper.

II. TRANSFORMER DESIGN OPTIMIZATION PROBLEM

Transformer design requires the detailed calculation of the transformer's components such as winding, core, insulations, tank, and cooling materials. A transformer design engineer is responsible to consider all performance constraints, customer specifications, and national/international standards to meet the desired specifications using available materials to achieve minimum manufacturing cost, lower weight, and higher efficiency.

Transformer design is a non-convex, Mixed Integer Nonlinear Programming (MINLP) problem with continuous and discrete variable types with both linear and nonlinear constraints [21]. Transformer design engineers input hundreds of customer specifications parameters, performance limitation parameters, and many design variables with different step sizes to do the design calculations. These parameters are generally driven from materials data sheets, graphs, and lookup tables. Due to the extensive number of design variables and conflicting functions, there is a wide optimization search space that makes the empirical methods unable to find the optimal solution. Some of the conflicting factors affecting a transformer's load losses and no-load losses are depicted in Table 2 [1].

As shown in Table 2, it is observed that decreasing one design parameter to reduce no-load losses increases the load losses of the transformer and vice versa. Thus, the optimal design variable must be chosen in a way to not only the losses

TABLE 2. Loss reduction alternatives.

Method	No-Load Loss	Load Loss	Cost
Use lower-loss core material	Lower	No change	Higher
Increase core cross-section area (CSA)	Lower	Higher	Higher
Decrease volt per turn (VPT)	Lower	Higher	Higher
Decrease Conductor CSA	Lower	Higher	Lower
Increase conductor CSA	Higher	Lower	Higher
Decrease core CSA	Higher	Lower	Lower
Increase VPT	Higher	Lower	Lower

are reduced, but also the manufacturing cost is minimized and the other performance constraints are satisfied.

A. INPUT DATA

To perform the transformer design optimization, the user must insert the transformer technical characteristics based on national/international standards and customer specifications. The main parameters are the following:

- The nominal power (kVA)
- Nominal voltage of the primary side ($Volts$)
- Nominal voltage of the secondary side ($Volts$)
- Winding connection type of the primary side
- Winding connection type of the secondary side
- Number of Tapping steps
- Tapping ranges (%)
- Guaranteed short-circuit impedance (%)
- Operating frequency (Hz)
- Low voltage winding conductor material
- Low voltage winding conductor type
- High voltage winding conductor material
- High voltage winding conductor type
- Guaranteed no-load loss ($watt$)
- Guaranteed load loss ($watt$)
- Max allowed oil temperature ($^\circ C$)
- Max allowed winding temperature ($^\circ C$)
- Price of raw materials (copper, aluminum, oil and core sheets)
- Necessary accessories' weight and their prices

B. DESIGN VARIABLES

In the proposed method, there is a total of 14 independent design variables. These variables are integer and continuous variable types which have their specific lower and upper limits. The detail of transformer design variables is given in Table 3 [22].

The common core materials used in low-frequency transformers manufacturing industry is Cold Rolled Grain Oriented (CRGO) silicon steel. To reduce the eddy loss resulting from the circulating current, the core material is laminated in thin sheets. The laminated steel with a thickness of 0.23 mm is commonly known as M3 graded material and laminations with thicknesses of 0.27 mm and 0.30 mm are known as M4 and M5 graded materials respectively. The test result of specific losses of these materials for different values of magnetic induction at an operating frequency of 50 Hz is shown in Figure 1.

TABLE 3. Design variables.

Variable	Definition	Unit	*lb*	*ub*	Step Size
x_1	Core Cross Section Area	cm^2	275	550	1
x_2	LV foil sheet lenght	mm	300	1000	10
x_3	LV foil sheet thickness	mm	0.5	5	0.1
x_4	HV conductor lenght	mm	2	16	0.1
x_5	HV conductor width	mm	1.8	3.5	0.1
x_6	LV number of turns	-	8	30	1
x_7	LV cooling full ducts	-	0	5	1
x_8	LV cooling half ducts	-	0	2	1
x_9	HV cooling full ducts	-	0	5	1
x_{10}	HV cooling half ducts	-	0	2	1
x_{11}	LV radial auxiliary conductor	-	1	2	1
x_{12}	HV axial auxiliary conductor	-	1	2	1
x_{13}	Core aspect ratio	-	1.3	1.9	0.01
x_{14}	Core material type	M3, M4, M5			

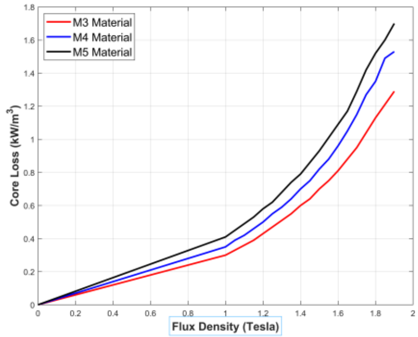

FIGURE 1. Loss graph of different core materials.

C. OBJECTIVE FUNCTION

The objective of eco-design transformer design is minimization of load losses and no-load losses of the transformer considering national/international standards and regulations while achieving the most economic design in terms of total owning cost, manufacturing cost, and the total weight of the transformer.

$$min\, f(x_i) \quad \text{for } i = 1, 2, \ldots, 14 \tag{1}$$

$$\text{Subject to: } h_j(x_i) \leq 0 \quad j = 1, 2, \ldots, J \tag{2}$$

$$g_k(x_i) = 0 \quad k = 1, 2, \ldots, K$$

$$x_i^{lb} \leq x_i \leq x_i^{ub} \tag{3}$$

where, x_i is the i^{th} design variable, h_j is the j^{th} inequality constraint, g_k is the k^{th} equality constraint, x_i^{lb} and x_i^{ub} are lower and upper limits of the i^{th} design variable, J and K are the number of inequality and equality constraints respectively. In this work, the objective function $f(x_i)$ is the total losses (P_{total}) of the transformer. The total loss of a transformer is the combination of load and no-load losses.

$$P_{total} = P_{LL} + P_{NLL} \tag{4}$$

where, P_{LL} is the load losses and P_{NLL} is the no-load losses of transformer.

1) LOAD LOSSES

Load losses occur due to load currents at both primary and secondary windings of the transformer. When Alternating Current (AC) is applied to the windings, the measured losses are always greater than the losses measured when Direct Current (DC) is applied to the windings. The measured losses from the current DC current are called dc losses, copper losses, joules losses, or I^2R losses in different books and papers. The difference between calculated AC losses and DC losses is called Stray Losses. The stray losses are also divided into two portions. Eddy losses of the winding due to current circulating in the winding and other stray losses due to the leakage magnetic flux from windings affecting the structure of the transformers such as tank and bushings [23]. To reduce load losses in a transformer, the use of low resistivity conductor material and proper conductor dimensions is essential.

$$P_{LL} = P_{DC} + P_{eddy} + P_{stray} \tag{5}$$

$$P_{DC} = P_{W\_LV} + P_{W\_HV} + P_{lead\_LV} + P_{lead\_HV} \tag{6}$$

where, P_{W_LV} is the dc loss at LV winding, P_{W_HV} is the dc loss at LV winding, P_{lead_LV} is the dc loss at LV leads (the conductors between the bushings and the windings) and P_{lead_HV} is the dc loss at HV leads. The dc loss of a conductor is calculated as follows:

$$P_{DC} = I^2R = I^2\frac{\rho \cdot l}{A_w} \tag{7}$$

where, I is the current passing through the conductor in ampere (A), R is the resistance of the conductor in ohm (Ω), ρ is the resistivity of the conductor material in ohm-meters ($\Omega \cdot m$), A_w is the cross-sectional area of the conductor in square meters (m^2) and l is the length of the conductor in meter (m).

$$P_{eddy} = \alpha \cdot \beta \cdot f^2 \cdot B_m^2 \cdot t_w \cdot w \cdot 10^{-3} \tag{8}$$

In the calculation of losses in conductors, several parameters are considered, including a constant value represented by α ($\alpha = 9$ for copper and $\alpha = 19$ for aluminum windings), β which is another constant value ($\beta = 1$ for rectangular conductors and $\beta = 0.49$ for round conductors), B_m which is the maximum flux density, t_w represents the thickness of the conductor, and w which denotes the weight of the winding without any covering.

When using Alternating Current (AC) to determine the losses in conductors, the results are always higher compared to when Direct Current (DC) is applied. The discrepancy between the losses measured using AC and DC is due to eddy current losses and stray losses. It is widely acknowledged that stray losses are generally proportional to the square of the load current and to the frequency raised to the power of 0.8.

$$P_{stray} \propto \sum_{1}^{n} \left(\frac{I_h}{I_1}\right)^2 \cdot h^{0.8} \tag{9}$$

where h is the harmonic order, I_h is the Real Mean Square (RMS) value of the h^{th} harmonic, and I_1 is the RMS value of the fundamental load current.

2) NO-LOAD LOSSES

No-load losses of the transformer are independent of the load connected to the secondary side of the transformer and core temperature. These losses occur mainly in the core of the transformer due to time-varying magnetization force. No-load losses is sum of hysteresis loss and eddy current loss in the core.

$$P_{NLL} = P_h + P_e \tag{10}$$

where P_h is the hysteresis loss and P_e is the eddy current loss.

$$P_h = K_h \cdot f \cdot B_m^n \tag{11}$$

$$P_e = K_e \cdot f^2 \cdot t^2 \cdot B_m^2 \tag{12}$$

where, K_h and K_e are hysteresis coefficient and eddy current coefficients respectively, f is the operating frequency of the transformer (50 or 60 Hz), t is the thickness of core lamination strips (the thickness of grain-oriented steel type with grade M3 is 0.23 mm, M4 is 0.27 mm and M5 is 0.3 mm), n is the *steinmetz* coefficient having a value ranging from 1.5 to 2.5 depending on core material type [24], and B_m is the maximum flux density.

D. TRANSFORMER DESIGN CONSTRAINTS

The transformer design optimization problem is subjected to performance constraints (*i-vi*), dielectric constraints (*vii*), thermal constraints (*viii, x*), and loss constraints (*xi, xiv*).

i. Induced voltage constraint

The induced voltage at the secondary winding of the transformer (V_2), maximum flux density (B_m) and the effective cross-section area of the core (A_{eff}) should satisfy the equation.

$$V_2 = 4.44 \cdot B_m \cdot A_{eff} \cdot f \cdot N_2 \tag{13}$$

$$A_{eff} = CSF \cdot A_c \tag{14}$$

where f is the frequency, N_2 is the number of turns of the secondary winding, A_c is the cross-section area of the core, and CSF is the core stacking factor (CSF $=$ 0.95, 0.96, ..., 0.99).

ii. Turns ratio constraint

The ratio of phase primary voltage (V_1) to phase secondary voltage (V_2) must be equal to the ratio of the number of turns of the primary winding (N_1) to the number of turns of the secondary winding (N_2).

$$\frac{V_1}{V_2} = \frac{N_1}{N_2} \tag{15}$$

iii. Impedance voltage constraint

Transformer impedance voltage (U_k), must be between the minimum guaranteed impedance voltage ($U_k^{\min}$) and the maximum guaranteed impedance voltage ($U_k^{\max}$). The lower U_k

imposes more stress on the transformer winding during short circuit conditions and the higher U_k causes winding and oil temperature rise that leads to an increase in copper losses, as a result decreases the efficiency of the transformer. Thus, having the impedance voltage in the guaranteed region is very important during transformer design optimization. The guaranteed tolerance for impedance voltage is usually ±10% of U_k.

$$U_k^{\min} \leq U_k \leq U_k^{\max} \tag{16}$$

iv. Maximum flux density constraint

The maximum flux density (B_m) should be smaller than the saturation flux density (B_{sat}).

$$B_m \leq B_{sat} \tag{17}$$

v. Voltage regulation constraint

The voltage regulation of the transformer (ΔV) should be smaller than maximum voltage regulation ($\Delta V_{\max}$).

$$\Delta V < \Delta V_{\max} \tag{18}$$

vi. No-load current constraint

The no-load current is defined as a percentage of the value of the rated primary current when the secondary winding of the transformer is open-circuited. The transformer no load current (i_o) is required to be smaller than the maximum no load current ($i_o^{\max}$).

$$i_o < i_o^{\max} \tag{19}$$

vii. Insulation constraints

The induced voltage in the internal winding ($Induced_{LV}$), is required to be smaller than the maximum induced voltage ($Induced_{LV}^{\max}$), that the insulating paper between the layers of the internal winding can withstand. Similarly, the constraint must satisfy for HV winding as well.

$$Induced_{LV} < Induced_{LV}^{\max} \tag{20}$$
$$Induced_{HV} < Induced_{HV}^{\max} \tag{21}$$

viii. Winding temperature gradient constraint

The winding temperature gradient is the difference between the average temperature of the winding and the average oil temperature. It is very important to keep the temperature gradient of LV winding ($Grad_{LV}$) and temperature gradient of HV winding ($Grad_{HV}$), that is generated by losses, within their guaranteed practical limits ($Grad_{LV}^{\max}$ and $Grad_{HV}^{\max}$).

$$Grad_{LV} \leq Grad_{LV}^{\max} \tag{22}$$
$$Grad_{HV} \leq Grad_{HV}^{\max} \tag{23}$$

ix. Transformer oil temperature rise constraint

The transformer oil temperature (T_{oil}) should be smaller than maximum allowed oil temperature ($T_{oil}^{\max}$).

$$T_{oil} < T_{oil}^{\max} \tag{24}$$

x. Transformer windings temperature rise constraint

The transformer winding temperature (T_w) should be smaller than maximum allowed winding temperature ($T_w^{\max}$).

$$T_w < T_w^{\max} \tag{25}$$

xi. No-load loss constraint

The transformer no-load loss (P_{NLL}), must be smaller than maximum allowed no-load loss ($P_{NLL}^{\max}$).

$$P_{NLL} < P_{NLL}^{\max} \tag{26}$$

xii. Load loss constraint

The transformer load loss (P_{LL}), must be smaller than maximum allowed load loss ($P_{LL}^{\max}$).

$$P_{LL} < P_{LL}^{\max} \tag{27}$$

xiii. Total loss constraint

The transformer total loss ($P_{NLL} + P_{LL}$), must be smaller than maximum allowed total loss ($P_{NLL}^{\max} + P_{LL}^{\max}$).

$$P_{total} < P_{total}^{\max} \tag{28}$$
$$P_{NLL} + P_{LL} < P_{NLL}^{\max} + P_{LL}^{\max} \tag{29}$$

xiv. Peak efficiency constraint

The transformer efficiency (η) must be greater than the minimum peak efficiency ($\eta_{\min}$) of the transformer given in Table 1.

$$\eta > \eta_{\min} \tag{30}$$
$$\eta = \left[1 - \frac{2 \cdot P_{NLL}}{S_r \cdot \sqrt{\frac{P_{NLL}}{P_{LL}}}}\right] > \eta_{\min} \tag{31}$$

where, S_r is the rated power of the transformer.

III. OPTIMIZATION ALGORITHMS

The Search Space (SS) to find the optimum design of a distribution transformer with 14 design variables, as given in Table 3, is:

$$SS = \prod_{i=1}^{14} \mathrm{P}(x_i) = 10,580,845,968,000,000 \tag{32}$$

where, $\mathrm{P}(x_i)$ is the number of iteration for the i^{th} design variable.

The exhaustive search method that iterates the entire combination of variables and calculates the problem's objective function is very tedious and time-consuming. In the empirical method of transformer design, the design engineer relies on his/her previous experiences and makes approximations of the lower and upper limits of variables to reduce the number of iterations and narrow the search space. Since the design problem has a non-convex, multivariable and nonlinear nature, the above-mentioned method leads to a local search in a local optimum region which may result in missing any other possible optimal solutions. By increasing the complexity of the design requirements, the outputs of the empirical method may not comply with the desired constraints. To handle this challenge, heuristic optimization algorithms provide a much more faster and efficient solution. However, according to the No Free Lunch (NFL) theorem, there is no heuristic algorithm capable of solving all kinds of real-world optimization problems [25]. with respect to this theorem, to solve transformer design optimization problem, some novel heuristic optimization algorithms were tested on some benchmark problems and based on their performance, the Firefly Optimization Algorithm (FA) [26], Arithmetic Optimization Algorithm (AOA) [27], Grey Wolf Optimization Algorithm (GWO) [28], and Artificial Gorilla Troops Optimizer Algorithm (GTO) [29] were chosen.

A. FIREFLY OPTIMIZATION ALGORITHM

The Firefly optimization algorithm (FA) is a nature-inspired optimization technique that simulates the light emission behavior of fireflies. Three main assumptions in the implementation of FA are: 1) all fireflies are considered unisex and can attract each other regardless of their gender; 2) the attractiveness of each firefly is proportional to its brightness, thus the less bright firefly will go towards the brighter one; 3) the brightness of a firefly is affected by its value at objective function. In general, the light intensity (I) varies by the light intensity of the emitted source of light (I_s) and the distance from the light source (r).

$$I(r) = \frac{I_s}{r^2} \tag{33}$$

However in a medium with an absorption coefficient (γ), the light intensity is described as (34).

$$I(r) = I_s e^{(-\gamma r^2)} \tag{34}$$

The attractiveness of each individual firefly is described in (35) where it monotonically decreases as the distance increases.

$$\beta(r) = \beta_0 e^{-\gamma r^m}, \quad (m \geq 1) \tag{35}$$

where, β_0 is the attractiveness of the firefly when the distance is zero ($r = 0$). The distance between any two fireflies is described in (36). Where X_i and X_j are the current positions of i and j fireflies, $x_{i,k}$ and $x_{j,k}$ are the k^{th} components of the spatial coordinate X_i and X_j of i^{th} and j^{th} fireflies.

$$r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{d} (x_{i,k} - x_{j,k})^2} \tag{36}$$

The movement of less bright firefly i, towards the brighter firefly j is mathematically modeled in

$$X_i = X_i + \beta_0 e^{-\gamma r_{ij}^2}(X_j - X_i) + \alpha(rand - \frac{1}{2}) \tag{37}$$

where α is the randomization parameter and $rand$ is a random number in the interval of [0, 1].

B. ARITHMETIC OPTIMIZATION ALGORITHM

The concept of Arithmetic Optimization Algorithm (AOA) is based on the distribution behavior of four principal arithmetic operations of mathematics. The operators are multiplication ("×"), subtraction ("−"), division ("÷"), and addition ("+"). The initial set of random solutions (X) is generated as shown in (38), then Math Optimization Accelerated (MOA) function (38) is used for the exploration and exploitation phases of the algorithm.

$$X = \begin{bmatrix} x_{1,1} & \cdots\cdots & x_{1,j} & x_{1,n-1} & x_{1,n} \\ x_{2,1} & \cdots\cdots & x_{2,j} & \cdots & x_{2,n} \\ \cdots & \cdots\cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots \;\; \vdots & \vdots & \vdots & \vdots \\ x_{N-1,1} & \cdots\cdots & x_{N-1,j} & \cdots & x_{N-1,n} \\ x_{N,1} & \cdots\cdots & x_{N,j} & x_{N,n-1} & x_{N,n} \end{bmatrix} \tag{38}$$

$$MOA(It_c) = Min + It_c \times (\frac{Max - Min}{It_{\max}}) \tag{39}$$

where $MOA(It_c)$ is the value of the function at the current iteration, It_c is the current iteration in the interval of 1 and the maximum number of iteration It_{max}. Min and Max are the minimum and maximum values of the accelerated function, respectively. To perform the exploration stage of the AOA algorithm, division (÷) or multiplication (×) operators are used. The exploration stage is modeled in (42) and will be executed if $r_1 > MOA$. To perform the exploitation stage of the AOA algorithm, addition (+) or subtraction (−) operators are used. The exploitation stage is modeled in (43) and will be executed if $r_1 < MOA$.

$$MOP(It_c) = 1 - \frac{(It_c)^{1/\alpha}}{(It_{\max})^{1/\alpha}} \tag{40}$$

$$Z = (ub_j - lb_j) \times \mu + lb_j \tag{41}$$

$$x_{i,j}(It_c + 1) = \begin{cases} best(x_j) \times MOP \times Z, & for\ r_2 < 0.5 \\ best(x_j) \div (MOP + \varepsilon) \times Z, & for\ r_2 \geq 0.5 \end{cases} \tag{42}$$

$$x_{i,j}(It_c + 1) = \begin{cases} best(x_j) + MOP \times Z, & for\ r_3 < 0.5 \\ best(x_j) - MOP \times Z, & for\ r_3 \geq 0.5 \end{cases} \tag{43}$$

where the r_1, r_2 and r_3 are random numbers within [0, 1], It_c is the current iteration, MOP coefficient stands for Math Optimizer Probability, Where $MOP(It_c)$ is the value of the function at the t^{th} iteration, ub_j and lb_j represent the upper and lower bounds of the j^{th} position respectively, α is the exploitation accuracy over iteration with a constant value equal to 5, μ is the control parameter adjusting the search process with a value of 0.5, ε is a small integer number, $x_{i,j}(It_c)$ is the j^{th} position for the i^{th} solution at the current iteration, $best(x_j)$ is the j^{th} position of the best solution calculated so far and $x_{i,j}(It_c + 1)$ is the i^{th} solution in the updated iteration.

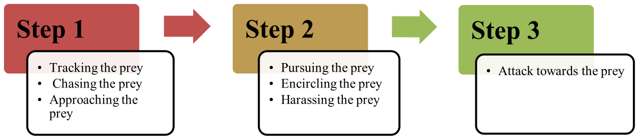

FIGURE 2. Grey wolves hunting steps.

C. GREY WOLF OPTIMIZATION ALGORITHM

The Grey Wolf Optimization (GWO) algorithm, mimics the hunting and social behavior of the grey wolves pack. Grey wolves pack has 5-12 members on average and each individual belongs to a certain statute with defined duties. At the top of the hierarchy of grey wolves, there are the leaders, called alpha (α) wolves. After alphas, there are beta (β) wolves that assist the alphas in the decision-making and hunting process. The omega (ω) wolves are placed at the bottom of the hierarchy of grey wolves and act as scapegoats of the pack. The remaining wolves are called delta (δ). The deltas are generally scouts, sentinels, elders, hunters, and caretakers of the pack. The hunting process of the grey wolf pack in shown in Figure 2. In GWO algorithm, alpha represents the best solution of the problem. Beta and delta represent the second and third best solution of the problem. The other solutions are represented by omega wolves.

The encircling and hunting process of the grey wolf pack is mathematically formulated as follows:

$$\vec{D} = \left|\vec{C} \cdot \vec{X}_p(t) - \vec{X}(t)\right| \tag{44}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \cdot \vec{D} \tag{45}$$

$$\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a} \tag{46}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{47}$$

$$\vec{D}_\alpha = \left|\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}\right|, \quad \vec{D}_\beta = \left|\vec{C}_2 \cdot \vec{X}_\beta - \vec{X}\right|,$$
$$\vec{D}_\delta = \left|\vec{C}_3 \cdot \vec{X}_\delta - \vec{X}\right| \tag{48}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot (\vec{D}_\alpha), \quad \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot (\vec{D}_\beta),$$
$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot (\vec{D}_\delta) \tag{49}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_2}{3} \tag{50}$$

where, t is the current iteration, $\vec{A}$ and $\vec{C}$ are coefficient vectors, $\vec{D}$ is the new position of the grey wolf, $\vec{X}$ is the position vector of the grey wolf, $\vec{a}$ is the value linearly decreased from 2 to 0 as the iteration continues, $\vec{X}_p$ is the position vector of the prey, $\vec{r}_1$ and $\vec{r}_2$ are random number vectors in the interval of [0, 1].

D. ARTIFICIAL GORILLA TROOPS OPTIMIZER ALGORITHM

The Gorilla Troops Optimization (GTO) algorithm mimics the social behavior of gorillas in their group known as a troop. In every troop of gorillas, there are some adult male gorillas called silverback gorillas and several adult females and their infants. The leader of the troop is the strongest adult male gorilla called the silverback gorilla that is responsible to make decisions about fights, migrations, and movements towards the food sources. The younger male gorillas are called blackbacks and their responsibility is to be the backup protectors of the troop. The social behavior of the gorillas in their troops can be summarized in five stages where the first three stages form the exploration phase of the optimization algorithm and the other two stages form the exploitation phase. These five stages are as follows.

1. Migration to unknown places.
2. Migration around known places.
3. Move to the other gorilla.
4. Follow the silverback gorilla.
5. Compete for adult females.

The exploration phase of the GTO algorithm is the mathematical model of the first three stages of the gorillas' behavior. The mechanism of exploration phase is chosen based on a pre-defined parameter ρ in the range of 0 to 1. This parameter is defined before the execution of the algorithm and determines the probability of selecting migration mechanism towards an unknown location. The exploartion phase is medeled in (51).

$$XG(t+1) = \begin{cases} r_1 \times (ub - lb) + lb & rand < \rho \\ X_r(t) \times (r_2 - \mathrm{T}) + \Gamma \times \mathrm{K} & rand \geq 0.5 \\ X(i) - \Gamma \times (\Gamma \times (X(t) - GX_r(t)) & \\ \quad + r_3 \times (X(t) - GX_r(t))) & rand < 0.5 \end{cases} \tag{51}$$

where $XG(t+1)$ is the position of the gorilla candidate in the updated iteration t, $X(t)$ is the current position of the gorilla, $X_r(t)$ is a randomly selected gorilla from the whole troop at iteration t, $X(i)$ is the initial position vector of gorillas, $GX_r(t)$ is the randomly selected position vector of gorillas at iteration t, and r_1, r_2, r_3, $rand$ are the random numbers in the interval of [0, 1]. The intermediate variables of T, Γ, and K are calculated using equations (52)-(54).

$$T = [\cos(2 \times r_4) + 1] \times [(1 - \frac{It_c}{It_{\max}})] \tag{52}$$

$$\Gamma = T \times l \tag{53}$$

$$K = X(t) \times \mathrm{Z} \tag{54}$$

where It_c and $It_{\max}$ are the current iteration number and the maximum number of iterations respectively, r_4 is a random number within 0 to 1, l is a random number within $[-1, 1]$ and Z is in the interval of $[-T, T]$.

The remaining two stages of the gorillas' social behavior form the exploitation phase of the optimization algorithm. A silverback gorilla may get weakened or die in this case, the strongest blackback gorilla substitutes the silverback gorilla and dominated the troop. The mechanism to choose for exploitation, whether to follow the silverback gorilla or compete for an adult female, depends on the value of T in (52) and a predefined parameter (ω). The mathematical formulation of the exploitation phase is described in i and ii:

TABLE 4. Control parameters of the proposed optimization algorithms.

Algorithm	Parameter	Value
FA	α	0.2
	β	2
	γ	1
AOA	α	5
	μ	0.5
GWO	Convergence parameter (a)	Linear reduction from [0,2]
GTO	β	3
	ω	0.8
	ρ	0.03

i) **Follow the silverback gorilla** (if $T \geq \omega$)

$$XG(t+1) = \Gamma \times M \times [x(t) - x_{sb}] + x(t) \quad (55)$$

$$M = \left[\left| \frac{1}{N} \sum_{i=1}^{N} XG_i(t) \right|^{\alpha} \right]^{1/\alpha} \quad (56)$$

$$\alpha = 2^{\Gamma} \quad (57)$$

where $x(t)$ is the position vector of the gorillas, x_{sb} is the position vector of the silverback gorilla, $XG_i(t)$ is the position vector of the candidate gorilla at iteration t, N is the population size of the gorillas, M and α are calculated using equations (56) and (57).

ii) **Compete for adult female gorilla** (if $T < \omega$) The competition of young male gorillas to attract adult females to expand their troop is modeled in (58).

$$XG(i) = x_{sb} - [(x_{sb} \times \mathrm{H}) - (x(t) \times H)] \times \mathrm{Z} \quad (58)$$

$$H = 2 \times r_5 - 1 \quad (59)$$

$$\mathrm{Z} = \beta \times \mathrm{B} \quad (60)$$

$$\mathrm{B} = \begin{cases} N_1, & rand \geq 0.5 \\ N_2, & rand < 0.5 \end{cases} \quad (61)$$

where x_{sb} is the silverback gorilla's position vector, $x(t)$ is the position vector of the gorillas, H is the impact force calculated in (59), r_5 is a random number within 0 to 1, Z is the violence coefficient during the competition for adult female, β is a predefined parameter to be given before the execution of the algorithm, B simulates the effect of the violence on the dimension of the solutions in the normal distribution of N_1 and N_2.

The control parameters of the proposed optimization algorithms suggested by the authors are given in Table 4.

To have a fair comparison between algorithms, the maximum number of iterations for all four optimization algorithms is set to be 300 and the population size is set to be 70 as well. Because of the randomness nature of heuristic optimization algorithm, each algorithm is executed for 40 times and the best result is presented in this paper. The constraints are added to the fitness function using the weighted penalty function method. The design flowchart of the proposed method containing the calculation steps is shown in Figure 3.

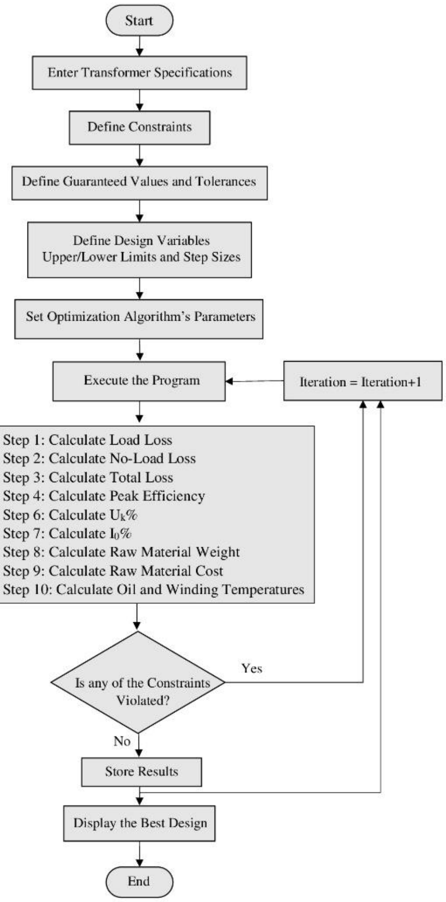

FIGURE 3. Transformer design flowchart.

IV. TRANSFORMER DESIGN EVALUATION AND RESULTS

The mathematical model of the proposed method is used to design a three-phase, oil-immersed EI core type, 1000 kVA distribution transformer concerning Directive 2009/125/EC restrictions for eco-design transformers. The objective function of eco-design transformers is the minimization of losses in order to have minimum possible emissions during the life span of the transformer. The optimization problem is then solved by employing FA, AOA, GWO, and GTO optimization algorithms. The technical specification of the test eco-design distribution transformer is given in Table 5.

The robustness of the proposed method is compared with that of the empirical method currently being used in the manufacturing lines. Two main drawbacks of the conventional method is i) very time-consuming process of calculation which may take hours to find a solution complying with all design restrictions and ii) the conventional methods never guarantee the global optimum solution. To overcome the aforementioned drawbacks, the use of heuristic methods not only guarantee a near-optimal solution but also the calculation time decreases significantly. The average execution time required to perform the transformer design optimization, minimum and maximum value of the solution obtained after 40 executions as well as percentage of Standard Deviation

TABLE 5. 1000 kVA Oil-immersed transformer specifications.

Rated power (S_r)	1000 kVA
Primary voltage (V_{HV})	20 kV
Secondary voltage (V_{LV})	0.4 kV
Vector group	Dy11
Tap changer	Off-load ±2.5%
Cooling method	ONAN
Frequency (f)	50 Hz
Average winding temperature ($T_{winding}^{max}$)	65 °C
Maximum oil temperature (T_{oil}^{max})	60 °C
Maximum winding temperature gradient at LV ($Grad_{LV}^{max}$)	18 (k/m)
Maximum winding temperature gradient at HV ($Grad_{HV}^{max}$)	18 (k/m)
Maximum allowed load loss (P_{LL}^{max})	7600 watt
Maximum allowed no-load loss (P_{NLL}^{max})	693 watt
Minimum allowed peak efficiency (η_{min})	99.484 %

TABLE 6. Minimum, maximum, and average fitness values and SD results of the proposed algorithms.

Algorithm	Min	Max	Mean	SD%	Time (s)
AOA	7920	8091	8019.75	0.77	20
GWO	7966	8250	8064.37	1.17	22
FA	7961	8218	8135	0.95	62
GTO	8047	8257	8157.62	0.78	26

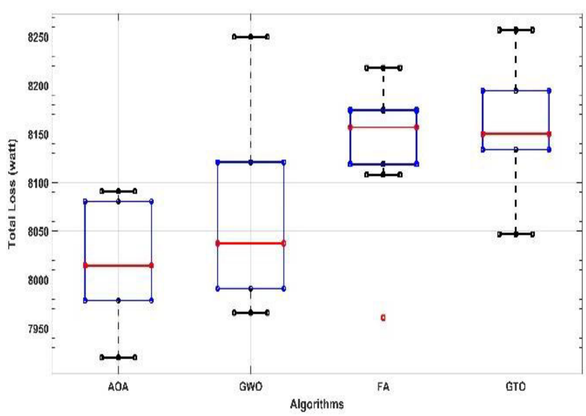

FIGURE 4. The boxplot presenting the distribution of the results using the proposed algorithms.

(SD) using the proposed method with heuristic algorithms is given in Table 6. The convergence graph of the mentioned heuristic algorithms is shown in Figure 5 as well.

The proposed method uses a set of independent variables to calculate optimal values for conductor diameters and the number of cooling ducts for thermal calculations. The other major design parameters like volt per turn (VPT), current densities in LV and HV windings, and height of core window

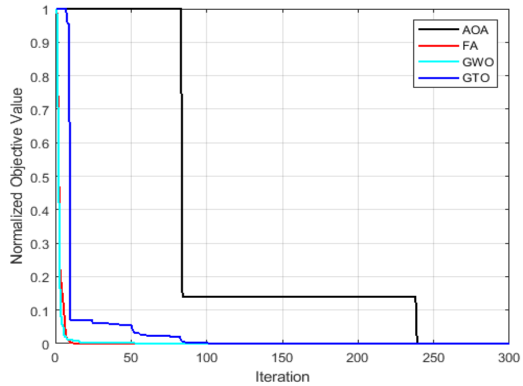

FIGURE 5. Optimization convergence of the proposed algorithms.

TABLE 7. Design values of 1000 kVA transformer using the proposed algorithms.

Variables	AOA	GWO	FA	GTO
x_1	416	443	418	441
x_2	810	720	790	740
x_3	0.8	0.7	1.1	1.1
x_4	2	2	1.8	2
x_5	1.9	1.8	2	1.8
x_6	20	19	20	19
x_7	0	0	0	1
x_8	0	0	0	0
x_9	0	4	4	3
x_{10}	0	0	0	0
x_{11}	3	3	2	2
x_{12}	2	2	2	2
x_{13}	1.8	1.35	1.39	1.62
x_{14}	M3	M3	M3	M3

are calculated as sub-functions of the independent design variables.

The mathematical expression of the suggested technique and chosen heuristic optimization algorithms were implemented in the MATLAB 2022a environment using a personal computer equipped with a 3.00 GHz Intel(R) Core i7-3540M CPU and 8 GB of RAM. The method is able to efficiently design a broad range of practical eco-friendly distribution transformers. The results obtained from both the proposed method and the empirical method are presented in Table 7, and the results of the proposed model using heuristic optimization algorithms are compared to the already-manufactured 1000 kVA eco-design transformer in Table 8.

As shown in Table 8, all heuristic algorithms present a better solution to the transformer design problem than the empirical method. In terms of power loss reduction, the AOA algorithm presents a 5.96% reduction of no-load losses and 3.22% reduction of load losses while GWO, FA, and GTO algorithms present 3.27%, 3.27%, and 3.58% for no-load losses reduction and 2.99%, 2.91% and 1.76% for load losses reduction respectively. The study demonstrates that the application of the AOA algorithm resulted in a significant reduction of annual power loss in the examined distribution

TABLE 8. Performance comparison of the proposed method.

	AOA	GWO	FA	GTO	Empirical Method
P_{NLL} (watt)	654	671	671	669	693
P_{LL} (watt)	7266	7290	7295	7378	7508
P_{total} (watt)	**7920**	**7961**	**7966**	**8047**	**8201**
η (%)	99.564	99.558	99.557	99.555	99.543
U_K (%)	5.59	5.61	5.89	5.82	6.49
I_o (%)	0.14	0.15	0.15	0.15	0.14
$Grad_{LV}$ (k/m)	12.7	16.6	14.3	8.6	17.6
$Grad_{HV}$ (k/m)	17.8	4.7	4.5	5.6	18
T_{oil} (°C)	50.09	47.19	47.22	47.04	45.65
T_w (°C)	58.90	54.33	52.03	46.19	45.65
W_{total} (kg)	3219	3261	3330	3268	3489
Cost ($)	14429	14411	12706	14482	14954

Algorithm 1 Pseudo-Code of the FA Optimization Algorithm

```
Set objective function f(X), X = (x_l, ..., x_d)^T
Generate initial population of fireflies X_i(i = 1, 2, ..., n)
Light intensity Ii at x_i is determined by f(x_i)
Define light absorption coefficient ϒ
while (t < Max Generation)
   for i = 1 : n all n fireflies
      for j = 1 : i all n fireflies
         if (I_j > I_i)
            Move firefly i towards j in d-dimension
         end if
            Attractiveness varies with distance r via e^(-ϒr)
            Evaluate new solutions and update light
              intensity
      end for
   end for
Rank the fireflies and find the current best
end while
Post process results and visualization
```

transformer, with a value of 2461 kW. In contrast, the GWO, FA, and GTO algorithms yielded respective annual power loss reductions of 2102 kW, 2058 kW, and 1349 kW. In terms of the transformer's weight, there is a reduction of 8.38%, 6.99%, 4.47%, and 6.76% respectively for AOA, GWO, FA, and GTO algorithms in comparision to the manufactured transformer. In terms of oil and winding temperature, based on IEC 600076-2 standard, the oil temperature in the tank of the transformer and the average temperature in LV and HV windings must not exceed the guaranteed temperatures given in Table 5, where the results show that the temperature limitations are satisfied in all algorithms.

V. CONCLUSION

Environmental issues, the competitive power, and distribution transformer industry market to manufacture low-loss and low-cost transformers are the primary motivation for researchers to find alternative designs. In this study, a mathematical model of transformer design considering more comprehensive design variables is introduced. Considering the No

Algorithm 2 Pseudo-Code of the AOA Optimization Algorithm

```
Initialize the AOA parameters α, μ
Initialize the solutions' positions randomly. (Solutions: i = 1...N)
while (It_c < It_max) do
   Calculate the Fitness Function for the given solutions
   Find the best solution (Determined best so far)
   Update the MOA value using (39)
   Update the MOP value using (40)
   for (i=1 to Solutions) do
      for (j=1 to Positions) do
         Generate a random values within [0, 1] (r1, r2, and
           r3)
         if (r1 > MOA) then
                    % Exploration phase
            if(r2 > 0.5) then
            (1) Apply the Division operator ("÷")
            Update the i^th solutions' positions using the 2^nd
              rule in (42)
            else
            (2) Apply the Multiplication math operator
              ("×")
            Update the i^th solutions' positions using the 1^st
              rule in (42)
            end if
         else
                    % Exploitation phase
            if (r3 > 0.5) then
            (1) Apply the Subtraction operator ("−")
            Update the i^th solutions' positions using the
              1^st rule in (43)
            else
            (2) Apply the Addition operator ("+")
            Update the i^th solutions' positions using the 2^nd
              rule in (43)
            end if
         end if
      end for
   end for
It_c=It_c+1
end while
Return the best solution (x)
```

Free Lunch theorem, four heuristic algorithms are applied to solve the non-linear mixed integer programming (MINLP) problem of the design optimization problem and the results are compared to an already designed 1000 kVA eco-design distribution transformer. The results show that while the empirical design method has 1.12% of total loss minimization according to maximum allowed losses in Commission Regulation (EU) No. 548/2014, the AOA algorithm with a 4.71% reduction of total losses has a better performance in terms of power losses minimization in comparison to GWO with 4.17%, FA with 4.10% and GTO with 3.05%. In terms

Algorithm 3 Pseudo-Code of the GWO Optimization Algorithm

Initialize a, A, and C
Calculate the fitness of each search agent
X_α = the best search agent
X_β = the second best search agent
X_δ = the third best search agent
while ($t < Max$ number of iteration)
  for each search agent
    Update the position of the current search agent by equation (50)
  end for
Update a, A, and C
Calculate the fitness of all search agents
Update X_α, X_β, and X_δ
t=t+l
end while
return X_α

Algorithm 4 Pseudo-Code of the GTO Optimization Algorithm

Set inputs parameters β, ρ, ω
Initialize the random population X_i ($i = l, 2, \ldots, N$)
Calculate the fitness values of Gorilla
% Main Loop
while (stopping condition is not met) **do**
  Update the T using Equation (52)
  Update the Γ using Equation (53)
% Exploration phase
  for (each Gorilla (X_i)) **do**
  Update the gorilla position vector using Equation (51)
  end for
% Create Group
  Calculate the fitness values of Gorilla
  if XG is better than X, replace them
  Set x_{sb} as the location of silverback (best location)
% Exploitation phase
  for (each Gorilla (X_i)) **do**
  if ($1 \leq |T|$) **then**
  Update the location Gorilla using Equation (55)
  else
  Update the location Gorilla using Equation (58)
  end if
  end for
% Create group
Calculate the fitness values of Gorilla
if New Solutions are better than previous solutions, replace them
Set x_{sb} as the location of silverback (best location)
end while
Return $X_{BestGorilla}$, $BestFitness$

of raw material cost, the manufacture distribution transformer with the given nominal power rating, costs 14945 US$, where the design obtained using the proposed algorithms has 3.63%, 3.76%, and 3.25% cost reduction in raw material costs respectively for AOA, GWO, and GTO algorithms however the cost reduction using FA algorithm reaches 17.69% of the manufactured transformer. In conclusion, all proposed heuristic algorithms provide a significant saving of time in the designing process and reduce the costs and losses in comparison to the empirical method. As a future work, the authors are planning to consider the effects of current and voltage harmonics in design optimization of distribution transformers and provide a graphical user interface for this optimization program to be utilized in the design and manufacturing of eco-design transformers.

APPENDIX

See Algorithms 1–4.

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