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Research Paper

Electrical and Physical Characteristics Improvement in Dry-Type Distribution Transformers Optimal Design

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Abstract— *One of the important pieces of equipment in the power distribution and transmission network is the dry-type transformer. Thus, optimizing construction and operation costs in dry-type transformers is important. At the same power, dry-type transformers weigh less than oil transformers and are also non-flammable. Dry-type transformers do not produce pollution because they do not require oil replacement. Currently, in most gas-fired power plants, dry-type transformers are used to supply electricity for the power plant's internal needs and the rotor excitation system of power plant generators. In this paper, unlike previous research, aside from the transformer insulation and the transformer housing, almost all parameters involved in the optimal design of the transformer have been considered, and the transformer construction and losses are evaluated at the same time. Therefore, the structures of two dry-type transformers are optimized and the minimum losses of the transformers are calculated. Accordingly, the firefly optimization algorithm is used to minimize the transformer weight and losses and to improve the other characteristics of the transformer. On the other hand, the firefly algorithm (FA) results are compared with the results of the metaheuristic particle swarm and grey wolf optimization algorithms to examine and validate the outputs of the design.*

Keywords—Firefly algorithm (FA), transformer, design, losses.

NOMENCLATURE

η	Efficiency
ρ_{cu}	Copper specific weight [kg·m^{-3}]
ρ_{fe}	Iron specific weight [kg·m^{-3}]
ac	Special electrical loading [A·t·m^{-1}]
B	Flux density [T]
C	Transformer core cross-section suitability factor
d	Diameter of the circle surrounding the transformer core [m]
G_{cu1}	High-voltage winding copper weight [kg]
G_{cu2}	Low-voltage winding copper weight [kg]
G_{fel}	Weight of the three transformer core legs [kg]
G_{fey}	Transformer yoke weight [kg]
I_1	High-voltage winding current [A]
I_2	Low-voltage winding current [A]
J	Current density [A·m^{-2}]
k	Loss factor
L_s	Height of the HV and LV windings [m]
L_{m1}	High-voltage winding length [m]
L_{m2}	Low-voltage winding length [m]
P_{cu}	Transformer copper losses
P_{fel}	Transformer core leg losses
P_{fey}	Transformer yoke losses
P_{fe}	Transformer core losses
q_1	Area of the high-voltage winding cross section [m^2]
q_2	Area of the low-voltage winding cross section [m^2]
q_{fe}	Area of the core cross section [m^2]
S	Power [kVA]
T_1	High-voltage winding turn number
T_2	Low-voltage winding turn number
U_1	High-voltage winding voltage [kV]
U_2	Low-voltage winding voltage [kV]
W	Total weight [kg]
FA	Firefly Algorithm
GWO	Grey Wolf Optimization
HV	High Voltage
LV	Low Voltage
PSO	Particle Swarm Optimization

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1. INTRODUCTION

Transformers are one of the most important equipment in electrical power systems that are used in the production, transmission, distribution and consumption of electrical energy. Transformers are divided into two types: oil-immersed and dry-type transformers, based on the type of insulating material used in them. Transformers with dry-insulated structure have high reliability, non-combustible structure, no need for maintenance, and smaller volume. Dry-type transformers are environmentally friendly and due to the use of insulating materials with high thermal and mechanical capacity in their structures, they can withstand more overload conditions than other types of transformers. Dry-type transformers are not flammable and fire-resistant, and have not the costs related to the construction of foundations, and fire alarm systems.

Dry type-transformers do not produce pollution because they do not require oil replacement. They can be placed near the load to reduce the need for long low-voltage cables. Therefore, voltage drop and cost are reduced. Dry-type transformers are suitable for humid and polluted areas because they are protected against moisture penetration and high corrosion resistance.

To supply power to refineries, petrochemical companies and offshore platforms, dry-type transformer are used. Dry-type transformer shows good resistance to moisture and fire, so that if this type of transformer gets wet, it is enough to remove the moisture from its surface. The unique properties of the resin in covering surfaces, penetrating into joints and its relatively good heat transfer properties compared to the other insulations, have increased the use of this type of transformers. However, dry-type transformers have high weight and high manufacturing cost, which has decreased their use in electrical power systems. The most important applications of this type of transformers are in power generation plants, transmission and distribution substations, wind and solar farms, industrial centers, petrochemical and chemical centers, and hospitals. A review of the insulation types used in the structure of the power transformers has been provided in [1].

In [2] different methods are used to optimize dry-type transformer parameters. The particle swarm optimization (PSO), the simulated annealing (SA), and the tree seed algorithm (TSA) have been used in [3] to optimize three phase dry-type transformer efficiency. In [4] optimal design of cast-resin transformer using nature-inspired algorithms has been presented. Hybrid grey wolf-whale optimization algorithm has been proposed in [5] to reduce the weight of oil transformer and to optimize the distribution and power transformer parameters. In [6] ant/firefly hybrid heuristic algorithm has been used to optimize design of power transformer tank. In [7], several meta-heuristic algorithms have been considered to study and optimize dry-type transformers for industrial applications. In [8], high performance cloud computing has been applied to conduct a parametric study of the core window clearance distance in dry-type transformer. The development of dry-type transformers for underground distribution networks, partially submerged or completely submerged without enclosure and in contact with water, has been presented in [9]. The numerical calculation of dry-type transformer leakage impedance with three sections in the high-voltage winding and a single section in the low-voltage winding have been investigated in [10] and comprehensively are examined the variations of cross-sectional areas of the various sections of the high-voltage winding. Effect of tapping position on leakage reactance of a two winding transformer is analyzed in [11]. A prototype converter transformer of the electric transport system is developed in [12] to obtain the experimental results and to verify the finite element accuracy.

The effect of the gap's position in four different sections of the high voltage winding on the leakage impedance of the two-winding transformer has been evaluated in [13] and are proposed effective design options for minimizing the leakage impedance. In [14] FEM and experimental measurements has been used to calculate the leakage magnetic field of a three-phase dry type transformer. Influence of core's window height on leakage reactance of dry type power transformers has been investigated in [15] so that it is one of the major problems which is practically encountered during the leakage reactance evaluation. Structural optimization of acoustic imaging sensor unit for detecting abnormal noises in dry-type transformer has been presented in [16]. Electrical field distribution has been calculated in dry-type transformer insulation gaps in reference [17] and the insulation distances are changed and computed the maximum electrical field applied to the dielectric. Then the minimum allowable insulation distances in dry-type transformer are estimated.

In [18] the copper loss of a three-phase dry- type transformer under various geometry designs has been numerically investigated and the simulation of electrical and magnetic fields has been prepared using FEM. The design parameters of high-voltage coils of three-phase dry type transformers and the effects of eddy current losses have been proposed in [19]. Machine learning and artificial neural network have been used in [19] to predict the eddy current in the clamps and the windings.

In [20], transformer weight optimization has been investigated using a multi-objective genetic algorithm. In [21] the weights of dry-type and oil-immersed power transformers are compared and optimized. In [22], the optimization of the iron weight of the oil-insulated transformer has been studied using heuristic search algorithms and the results have been compared to each other.

Electromagnetic analysis are proposed in [23] concerning the reduction of losses in the transformer and winding temperature distribution is numerically investigated. The electromagnetic analysis and grey wolf optimization algorithm are presented in [24] to model the losses distribution and heat transfer in an oil transformer. Electromagnetic-thermal analysis accompanied by conjugate heat transfer, in presence of different types of vegetable oils, along with grain-oriented silicon steel, amorphous and vitroperm alloy cores are investigated in a distribution transformer in [25]. An equivalent thermal network is proposed in [26] to analyze the thermal behavior of dry-type transformers and the effects of convection and radiation in the inner areas of the core windows are also considered to provide higher accuracy. The temperature rise characteristics of hot-spots in dry-type transformer windings are presented in [27] and using the results of transformer temperature rise tests, a predictive computational model based on various load rates is developed. The temperature distribution in four dry-type power transformers using finite element models are proposed in [28] to examine the impact of the core window height on the thermal conditions of the transformers. In this paper, the use of the meta-heuristic firefly optimization algorithm is proposed to optimize the dry-type transformer design. Although several papers have studied dry-type transformer optimal design, but based on the authors' knowledge, no proper study is found in the literature which uses construction and losses together at the same time in the optimal transformer design. On the other hand, unlike previous researches, in this article, except the transformer insulation and the transformer housing, almost all parameters involved in the optimal design of the transformer have been considered.

Therefore, in the Section 2 of this paper, firefly optimization algorithm is introduced. In the Section 3, transformer design mathematical formulation and the objective functions are described. The Section 4 gives transformers design optimization results, and validation. At the end and in Section 5, conclusions will be proposed.

2. Firefly Optimization Algorithm

The firefly algorithm is population-based and derives its solution based on the characteristics of the firefly [29]. One of the important points related to the optical flashing pattern of fireflies is that the light intensity at a certain distance from the light source follows the inverse square law. In other words, the light intensity decreases with increasing distance, and it is proportional to the inverse of the square of the distance. In addition, air absorbs light, which causes the light intensity to become weaker with increasing distance.The combination of these two important factors cause fireflies to be visible only from a certain distance.

Usually, in the night, the flashing light of fireflies can be seen from a distance of several hundred meters, which is sufficient for other fireflies to see and communicate with them. The flashing light produced by fireflies can be formulated in such a way that it corresponds to the objective function that is to be optimized. To simplify the formulation of the firefly algorithm, the following rules are used:

1- All fireflies are unisex and will be attracted to the other fireflies.

2- In the firefly algorithm (FA), the attractiveness of a firefly is proportional to its brightness. In other words, for every two fireflies flashing, the one with less brightness will be attracted to the one with more brightness. Therefore, the attractiveness of a firefly is proportional to its brightness.

3- As the distance between two fireflies increases, their attractiveness and brightness decrease. Therefore, as the distance increases, their attractiveness to each other decrease and their brightness also decreases. In this case, a firefly will move randomly in the environment.

When formulating a firefly algorithm, it is necessary to address two fundamental issues: variations in light intensity and formulating the mutual attraction of fireflies. To simplify the process, we can assume that the attraction of a firefly is determined by the brightness of the firefly. The brightness of the firefly, is related to a particular problem objective function. The value of a firefly's attractiveness ε is relative and must be determined by other fireflies. Therefore, ε will change based on the distance d_{ij} between firefly i and firefly j. Furthermore, the intensity of light decreases with distance from the light source. Also, light is absorbed when it passes through media such as air. As a result, the firefly algorithm must be formulated in such a way that the value of the attraction parameter changes based on different degrees of absorption. Therefore, the intensity of light will change according to the inverse square law [29]:

$$I_r = \frac{I_s}{d^2} \tag{1}$$

Where I_s represents the intensity of light source. Considering of light absorption coefficient, the intensity of light is given as:

$$I_r = I_0 e^{-\delta d} \tag{2}$$

Sometimes a function needs that can decrease uniformly and at a slower rate:

$$I_r = \frac{I_0}{1 + \delta d^2} \tag{3}$$

Since the attractiveness of a firefly is proportional to the intensity of light seen by nearby fireflies, the attractiveness parameter of a firefly can be defined as follows [29]:

$$\varepsilon_r = \varepsilon_0 e^{-\delta d^2} \tag{4}$$

The distance between two fireflies is defined as:

$$d_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{dim} (x_{i,k} - x_{j,k})^2} \tag{5}$$

In Eq. (5), dim is the dimension of the problem and $x_{i,k}$ is the position of the i-th firefly. In a two-dimensional search space we have:

$$d_{ij} = \|x_i - x_j\| = \sqrt{(x_i - x_j)^2 - (y_i - y_j)^2} \tag{6}$$

The movement of firefly i that is attracted to another more attractive firefly is described as [29]:

$$x_i' = x_i + \varepsilon_0 e^{-\delta d_{ij}^2} (x_j - x_i) + \alpha \left(\text{rand} - \frac{1}{2} \right), 0 < \text{rand} < 1$$

In Eq. (2), the second term on the right hand side of the equation shows the effect of the attraction parameter in calculating the movement amount of the firefly i. Also, the value δ plays a very important role in the convergence speed of the algorithm and usually takes a value between 0.01 and 100 in the most applications. If the scale of the optimization problem is for a large number of fireflies, it is better the initial locations of the fireflies in the population are distributed uniformly in the search space. If the parameter δ tends to infinity, then the attractiveness of a firefly to other fireflies in the environment (the problem search space) is zero. This means that the fireflies fly completely randomly in an unclear area. In such a case, other fireflies will not be visible.

In the Firefly Algorithm, the light absorption coefficient, controls how the attractiveness of a firefly decreases with distance, with higher values leading to a faster decrease in attractiveness. This coefficient models the absorption of light by the medium, such as air, causing the light from more distant fireflies to become weaker and thus less attractive. It is a critical parameter for defining the attractiveness function, which governs the firefly movement towards brighter solutions. This coefficient determines how rapidly the attractiveness fades with distance. A larger coefficient means the light intensity diminishes more quickly, causing the attraction to be limited to shorter ranges. By adjusting δ, the algorithm can control the search space exploration. A higher δ can facilitate local search by focusing on nearby, brighter fireflies, while a lower δ allows for broader exploration over longer distances. Fig. 1 shows the flowchart of the firefly algorithm.

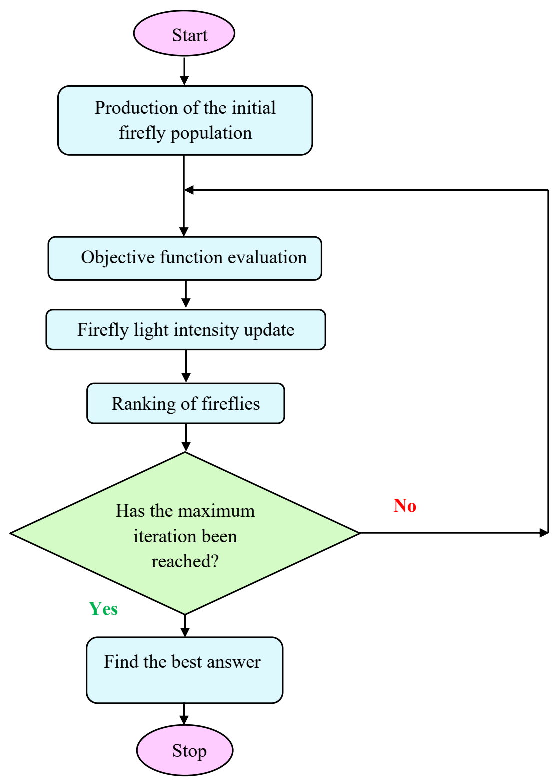

Fig. 1. Flowchart of the firefly algorithm.

3. Transformer Design Mathematical Formulation

The selection of the number of design variables in the optimization process is very important. Because if the number of independent variables is selected more than the required number, then there is no possibility of all variables being independent and solving the problem will be complicated. If the number of independent variables is less than the required number, the optimal design will not be carried out. Although the choice of design variables is somewhat arbitrary, these variables should be chosen in such a way that the cost functions and constraints can be easily expressed in terms of them. The variables considered to optimize the transformer design are given in Table 1.

Table 1. Selected parameters for optimal design.

Parameter Name	Symbol
Current density	J
Area of the core cross section	q_{fe}
Diameter of the circle surrounding the transformer core	d
Area of the primary winding cross section	q_1
Area of the secondary winding cross section	q_2
Height of the primary and secondary windings	L_s
Weight of three legs of the transformer	G_{fel}
Transformer yoke weight	G_{fey}
Transformer total weight	W
Efficiency	η
Primary winding length	L_{m1}
Secondary winding length	L_{m2}
Transformer core losses	P_{fe}
Transformer copper losses	P_{cu}

The cost function to minimize the weight of the transformer is considered as follows [22]:

$$W = G_{cu1} + G_{cu2} + G_{fel} + G_{fey} \tag{7}$$

Where W is the total weight of the transformer, G_{cu1} is the high voltage (HV) winding copper weight, G_{cu2} is the low voltage (LV) winding copper weight, G_{fel} is the iron weight of three legs of the transformer and G_{fey} is the iron weight of the transformer yoke. The copper weight of the HV and LV windings are calculated as [22]:

$$G_{cu1} = 3 \times \rho_{cu} \times T_1 \times q_1 \times L_{m1} \tag{8}$$

$$G_{cu2} = 3 \times \rho_{cu} \times T_2 \times q_2 \times L_{m2} \tag{9}$$

Where ρ_{cu} is the copper specific weight, T_1 is the HV winding turn number, T_2 is the LV winding turn number, q_1 is area of the HV winding cross section, q_2 is area of the LV winding cross section, L_{m1} is the HV winding length and L_{m2} is the LV winding length. The transformer HV and LV windings turn numbers are calculated as follows:

$$T_1 = \frac{U_1}{\sqrt{3} \times 4.44 \times f \times B_{\max} \times q_{fe}} \tag{10}$$

$$T_2 = \frac{U_2}{\sqrt{3} \times 4.44 \times f \times B_{\max} \times q_{fe}} \tag{11}$$

$$q_1 = \frac{I_1}{J} \tag{12}$$

$$q_2 = \frac{I_2}{J} \tag{13}$$

The magnetic flux density in terms of transformer power is given in Table 2.

Table 2. Magnetic flux density versus transformer power.

B (T)	1.15	1.27	1.33	1.37	1.41	1.42	1.43	1.44	1.45	1.45
S (kVA)	10	40	70	100	400	700	1000	4000	7000	10000

To calculate the cross section and diameter of the transformer core circumference, we have [10]:

$$q_{fe} = C \times \sqrt{\frac{1000 \times S}{3 \times f}} \tag{14}$$

$$d = 2 \times \sqrt{\frac{q_{fe}}{0.677 \times \pi}} \tag{15}$$

Special electrical loading is brought in Table 3:

Table 3. Special electrical loading in term of transformer power.

S (kVA)	50	100	200	300	500	1000	2000	3000	5000
a_c (A/cm)	330	440	540	600	680	800	930	1000	1100

Table 4. Specifications of 1150kVA dry-type transformer.

Parameter	Value
Rated power (kVA)	1150
Frequency (Hz)	50
HV voltage (V)	6600
LV voltage (V)	520
HV rated current (A)	100.6
LV rated current (A)	1277
No-load losses (kW)	2.2
Full-load losses (kW)	11
Total weight of the transformer (kg)	3200

Table 5. 1150kVA dry type transformer optimum design using PSO, GWO and FA algorithms.

PSO	GWO	FA	Parameter
5.9022	5.9000	5.8900	C
3.5000	3.5000	3.5000	J (A/mm^2)
516.7950	516.6011	516.5202	q_{fe} (cm^2)
31.1760	31.1701	31.0230	D (cm)
28.7429	28.7429	28.7311	q_1 (mm^2)
364.8571	364.8571	364.8485	q_2 (mm^2)
1.4130	1.4130	1.4130	B (T)
407.1276	407.2804	407.2591	T_1
32.0767	32.0888	32.0714	T_2
99.9561	99.9937	99.9662	L_s (cm)
819.5	819.5	819.5	a_c (A/cm)
117.7776	117.7776	117.2136	G_{fel} (kg)
2314.2155	2313.1807	2312.9856	G_{fey} (kg)
340.8854	340.9556	340.8327	G_{cu1} (kg)
316.0206	316.0814	316.0139	G_{cu2} (kg)
108.3723	108.3539	108.3512	L_{m1} (cm)
100.4554	100.4371	100.4163	L_{m2} (cm)
3879.8	3880.6	3878.7	P_{cu} (W)
1686.4	1685.6	1685.2	P_{fe} (W)
5566.2	5566.2	5563.9	P_{total} (W)
99.39	99.39	99.40	η (%)
3088.90	3087.99	3087.68	W (kg)

Table 6. PSO algorithm parameters.

Parameter	Value
Number of Variables	4
Lower Bound of Velocity	−0.8
Upper Bound of Velocity	0.8
Inertia Weight	1
Personal Best Learning Coefficient	2
Global Best Learning Coefficient	2
Number of Population	100
Maximum Iteration	100

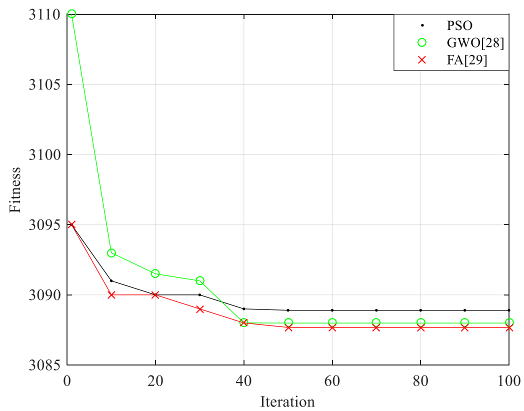

Fig. 2. PSO, GWO and FA algorithms fitness curves comparison for 1150kVA transformer optimum design.

Table 7. GWO algorithm parameters.

Parameter	Value
Domain search for α	$[-1000, 1000]$
Domain search for β	$[-1, 1]$
Domain search for δ	$[0, 1000]$
Search dimensions	2
Maximum iteration	100

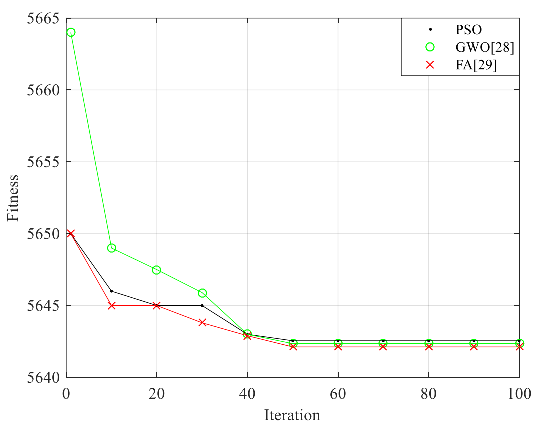

Fig. 3. PSO, GWO and FA algorithms fitness curves comparison for 2300kVA transformer optimum design.

The iron weight of the transformer core legs is calculated as [22]:

$$L_s = \frac{2 \times T_1 \times I_1}{a_c} \tag{16}$$

$$G_{fel} = 3 \times \rho_{fe} \times q_{fe} \times L_s \tag{17}$$

The function to minimize the transformer losses is considered as follows:

$$P_{fel} = k \times p_{base} \times B^n \times G_{fel} \tag{18}$$

$$P_{fey} = k \times p_{base} \times B^2 \times G_{fey} \tag{19}$$

Table 8. FA algorithm parameters.

Parameter	Value
Number of population	50
Light absorption coefficient	1
Attraction coefficient base value	0.5
Mutation vector coefficient	0.9
Uniform mutation range	$0.05\ (\mathrm{Var}_{\max} - \mathrm{Var}_{\min})$
Maximum iteration	100

Table 9. Specifications of 2300kVA dry-type transformer.

Parameter	Value
Rated power (kVA)	2300
Frequency (Hz)	50
HV voltage (V)	6600
LV voltage (V)	1400
HV rated current (A)	201
LV rated current (A)	948.5
No-load losses (kW)	4.7
Full-load losses (kW)	14.7
Total weight of the transformer (kg)	5750

$$\begin{aligned} P_{total} &= P_{cu} + P_{fe} \\ &= P_{cu} + P_{fel} + P_{fey} \end{aligned} \tag{20}$$

4. Results of Dry-type Transformer Optimal Design

Solution instability, dependency on initial conditions, and model simplifications are significant challenges in metaheuristic algorithms, stemming from their inherent stochastic nature and reliance on random initialization or heuristic rules, which can lead to varying results, trap solutions in local optima, and introduce inaccuracies into complex problem models. Most metaheuristic algorithms are non-deterministic, meaning they use random processes for generating solutions and exploring the search space. This inherent randomness, particularly in how initial solutions are generated, means that running the same algorithm multiple times can yield different outcomes. The initial population or starting point of the algorithm significantly influences the subsequent solutions it generates. A poor or unlucky initial solution can trap the algorithm in suboptimal regions, preventing it from finding the true global optimum. The degree of dependence on initial conditions is not uniform; it varies depending on the specific problem and the meta-heuristic algorithm being used.

The current density in HV and LV windings is selected between 2.2 and 3.5 [9], because higher values increase copper losses and the windings temperature, which leads to heat transfer problems. Values less than 2.2 increase the amount of copper consumed and the volume of the winding. Increasing the flux density causes core saturation, no-load losses, and increase of the winding temperature. A low flux density is also increases the weight of the core. Typically, the flux density is chosen around the knee point of the magnetic curve. Transformer optimum efficiency range is selected between 0.9 and 1. The desired range for the core cross-sectional suitability factor of a dry-type transformer is chosen between 5.9 and 10.6. FA, GWO and PSO algorithms have been run several times with different initial conditions, but little change is observed in the final results. Table 4 shows the specifications of the first sample dry-type transformer with rated power 1150kVA. The characteristics of this transformer are optimize using PSO, GWO and FA algorithms and are given in Table 5.

Efficiency values of 1150 kVA transformer at power factor 0.8 with three optimization algorithms are calculated as:

Table 10. 2300kVA dry type transformer optimum design using PSO, GWO and FA algorithms.

Parameter	PSO	GWO	FA
C	6.5416	6.5413	6.5409
J (A/mm^2)	3.5000	3.5000	3.5000
q_{fe} (cm^2)	810.0282	809.9950	809.6830
D (cm)	39.0311	39.0303	39.0164
q_1 (mm^2)	57.4286	57.4286	57.4167
q_2 (mm^2)	271.0	271.0	271.0
B (T)	1.4323	1.4323	1.4323
T_1	256.2458	256.2563	256.2368
T_2	54.3552	54.3574	54.3087
L_s (cm)	109.1216	109.1261	109.0923
a_c (A/cm)	944	944	944
G_{fel} (kg)	201.5329	201.5329	201.1964
G_{fey} (kg)	4419.2655	4419.0437	4418.9823
G_{cu1} (kg)	526.2945	526.3062	526.1963
G_{cu2} (kg)	495.4635	495.4738	495.2602
L_{m1} (cm)	133.0499	133.0474	133.0087
L_{m2} (cm)	125.1331	125.1306	125.0934
P_{cu} (W)	6034.8	6034.9	6034.3
P_{fe} (W)	5817.7	5817.4	5817.1
P_{total} (W)	11852.5	11852.3	11851.4
η (%)	99.35	99.35	99.36
W (kg)	5642.55	5642.35	5642.12

Table 11. Fitness function values, number of iterations, and run times of the FA, GWO, and PSO for the 1150 kVA transformer.

Method	Final Fitness Function Value	Number of Iterations	Run Time (s)
FA	3087.68	42	8
GWO	3087.99	49	17
PSO	3088.90	51	14

$$\begin{aligned}\eta_{firefly} &= \frac{P_{out}}{P_{out}+P_{cu}+P_{fe}} \\ &= \frac{P_{out}}{P_{out}+P_{total}} \\ &= \frac{1150*0.8}{1150*0.8+5.5639} \times 100 = 99.40\%\end{aligned} \tag{21}$$

$$\eta_{GWO} = \frac{1150*0.8}{1150*0.8+5.5662} \times 100 = 99.39\% \tag{22}$$

$$\eta_{PSO} = \frac{1150*0.8}{1150*0.8+5.5662} \times 100 = 99.39\% \tag{23}$$

Table 9 shows the specifications of the second dry-type transformer with rated power 2300KVA. The characteristics of this transformer are optimize using PSO, GWO and FA algorithms and are given in Table 10.

As it can be seen from Tables 5 and 10, the 1150KVA dry-type transformer efficiency is 99.2% at power factor 0.8 according to the datasheet, but this efficiency has been increased to 99.40%, 99.39%, and 99.39% using the Firefly, Gray Wolf, and Particle Swarm optimization algorithms, respectively. On the other hand, the 2300KVA dry-type transformer efficiency is 99.31% at power factor 0.8 according to the datasheet, but this efficiency has been increased to 99.36%, 99.35%, and 99.35% using the Firefly, Gray Wolf, and Particle Swarm optimization algorithms, respectively. Fig. 3 compares the PSO, GWO and FA algorithms fitness curves and convergence performances for 2300kVA transformer optimum design.

The final values of fitness function, number of iterations and run times of optimization algorithms for two transformers are presented in Tables 11 and 12. As it can be seen from two tables, FA algorithm has the minimum fitness function and at

Table 12. The fitness function values, number of iterations and run times of the FA, GWO, and PSO for 2300kVA transformer.

Method	Final Fitness Function Value	Number of Iterations	Run Time (s)
FA	5642.12	40	6
GWO	5642.35	48	15
PSO	5642.55	49	13

Table 13. Statistical metrics of PSO, GWO, and FA algorithms for 1150kVA dry type transformer.

Metric	PSO	GWO	FA
Losses-Variance			
Run 1	5570.3	5570.3	5567.1
Run 2	5570.6	5570.4	5567.2
Run 3	5569.5	5569.5	5565.8
Run 4	5566.2	5566.2	5563.9
Run 5	5566.8	5566.9	5564.2
Mean	5568.68	5568.66	5565.64
Variance	3.3336	3.1144	1.9384
Weight-Variance			
Run 1	3092.10	3091.79	3091.25
Run 2	3092.18	3091.96	3091.33
Run 3	3089.93	3089.86	3089.74
Run 4	3088.90	3087.99	3087.68
Run 5	3088.68	3088.54	3088.37
Mean	3090.35	3090.03	3089.67
Variance	2.29577	2.64661	2.18138

fewer iterations converges to the final value of its fitness function compared to the other algorithms.

Each optimization algorithm was run 5 times and the best state was obtained after running it five times. Table 13 show mean, variance, best/worst cases. Run2 and Run4 are the worst and the best cases respectively.

To verify the results obtained from the transformer design, the leakage inductance of 1150kVA transformer winding is calculated using the relevant formulas and compared with the test results. The voltage drop in the windings is also due to leakage impedance. By increasing the height of the windings, the leakage flux of the transformer can be minimized. On the other hand, by decreasing the gap of the radial depth between the secondary and primary winding, the leakage flux of the transformer can also be reduced. Likewise, the leakage flux of the transformer is reduced by decreasing turns of the secondary and primary windings. Leakage reactance can be calculated by [15, 30]:

$$\begin{aligned}X_l = 2\pi f \frac{\mu_0 \cdot \pi \cdot N^2}{H_{eq}} \Big(\frac{X_p \cdot Y_p}{3} + \\ X_{ins} \cdot Y_{ins} + \frac{X_s \cdot Y_s}{3}\Big)\end{aligned} \tag{24}$$

Where H_{eq} is the equivalent height, X_{ins} is radial depth of the insulation between windings, Yins is mean diameter of the insulation between windings, X_p is radial depth of the HV winding, Y_p is mean diameter of the HV winding, X_s is radial depth of the LV winding and Y_s is mean diameter of the LV winding. The average height of the HV and LV windings is divided by the Rogowski factor to determine the equivalent winding height [31]:

$$H_{eq} = \frac{H_{average}}{K_R} \tag{25}$$

$$K_R = 1 - \frac{1 - e^{\frac{\pi \cdot H_{average}}{X_p + X_{ins} + X_s}}}{\frac{\pi \cdot H_{average}}{X_p + X_{ins} + X_s}} \tag{26}$$

Table 14. Calculated and measured leakage reactance values.

Method	Leakage reactance (%)
Eq. (24)	3.81
Eq. (27)	3.89
Measured [15]	4.07

Another analytical method for the estimation of leakage reactance is given by [32, 33]:

$$X_l = 2\pi f \frac{\mu_0 \cdot 2\pi \cdot N^2}{(H_{average} + 0.32 \cdot (r_p - r_c))} \left(\frac{X_p \cdot Y_p}{3} + X_{ins} \cdot Y_{ins} + \frac{X_s \cdot Y_s}{3} + \frac{X_s^2 - X_p^2}{12}\right) \quad (27)$$

Where r_c is radius of the core and r_p is external radius of the HV winding. On the other hand, the leakage reactance in percentage is:

$$X_l(p.u.) = \frac{X_l}{V_{base}^2} \cdot S_{base} \quad (28)$$

To verify the accuracy of the design output, results are compared with the experimental test in [15] to evaluate the leakage reactance of the transformers. Table 14 shows the leakage reactance values of 1150kVA dry-type transformer calculated using equations and measured using experimental test in [15].

5. CONCLUSION

Transformers are widely used in power systems and are among the most expensive equipment in substations. Thus, their construction cost optimization is important. Consequently, there has been growing interest in developing energy-efficient transformers, such as those utilizing optimal sizes of windings and cores. Dry-type transformers have a larger core size than oil-immersed three-phase transformers. In this paper, the metaheuristic firefly, particle swarm, and grey wolf optimization algorithms are used to minimize the weight and losses of the dry-type transformer and to improve the other characteristics of the transformer. In order to examine the efficiency of the algorithms, optimization is performed on two dry-type commercial transformers. Results show that the 1150 kVA dry-type transformer efficiency is 99.2% at a power factor of 0.8 according to the datasheet, but this efficiency increases to 99.40%, 99.39%, and 99.39% using the FA, GWO, and PSO algorithms, respectively. The 2300 kVA dry-type transformer efficiency is 99.31% at a power factor of 0.8 according to the datasheet, but this efficiency increases to 99.36%, 99.35%, and 99.35% using the FA, GWO, and PSO algorithms, respectively. On the other hand, the 1150 kVA dry-type transformer's original weight was 3200 kg, but this weight decreases to 3087.68 kg, 3087.99 kg, and 3088.90 kg using the FA, GWO, and PSO algorithms, respectively. The 2300 kVA transformer's original weight was 5750 kg, but the optimized weight is 5642.12 kg, 5642.35 kg, and 5642.55 kg using the FA, GWO, and PSO algorithms, respectively. It is shown that the parameter values calculated by the FA are close to the results of the PSO and GWO algorithms, which indicates the accuracy of the optimization.

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