Indonesian Journal of Electrical Engineering and Computer Science
Vol. 25, No. 2, February 2022, pp. 639~647
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v25.i2.pp639-647

Estimation of the transformer parameters from nameplate data using turbulent flow of water optimization technique

Amir Yassin Hassan[1], Mokhtar Said[2], Saber Mohamed Saleh Salem[2]
[1]Department of Power Electronics and Energy Conversion, Electronics Research Institute, Cairo, Egypt
[2]Department of Electrical Engineering, Faculty of Engineering, Fayoum University, Fayoum, Egypt

Article Info

Article history:

Received Mar 29, 2021
Revised Dec 13, 2021
Accepted Dec 27, 2021

Keywords:

Turbulent flow of water optimization
Parameters extraction
Power transformer
Objective function

ABSTRACT

The mismatch between the transformer and its model leads to deviation of the results during the study of the different abnormal phenomena. This paper presents an optimization technique using transformer nameplate data to minimize the difference in the estimation of the parameters between the model and the actual transformer data. The turbulent flow of water through a narrow path (TFWO) in a circular form technique is used for the optimization of the transformer parameters. The optimization algorithms are used in extracting the parameters of the different rating of transformers, this technique needs an objective function for performing the optimization process. Minimizing the sum of square error (SSE) is the objective function of the optimizer technique. The SSE function includes the summation of the square error for the primary current and secondary current and voltage referring to the primary. The proposed optimization transformer parameters evaluation based on the nameplate data is accurate and fulfilled compared with the other methods.

Corresponding Author:

Amir Yassin Hassan
Department of Power Electronics and Energy Conversion, Electronics Research Institute
Street of Joseph Tito, Huckstep, El Nozha, Cairo, Egypt
Email: amir@eri.sci.eg

1. INTRODUCTION

The current decreases to a low value by increasing voltage to the maximum to retain the power constant. Line losses are also decreased in this manner. This means that less power is necessary for transmitting electricity via transformers at higher voltages. For this reason, power transformers are the most suitable choice. There are many types of transformers and transformers have many uses. But the basic purpose of transformers is to raise the voltage at the end of the generation and decrease the voltage at the end of the consumer [1], [2].

The mismatch between the transformer and its model is important specially during fault study. Faults are known as internal and through faults in the transformer. Internal faults are faults that occur within the transformer that can seriously damage the transformer's insulation and cause the transformer to break down. So, the transformer should be protected from these faults immediately. Such faults are split into electrical and mechanical faults [1]-[11]. The model for the transformer is of critical importance to the study of abnormalities phenomena as well as the design process. The more accurate the model, the more reliable and accurate the results [12]. Various researchers use optimization approaches to solve many problems by estimating parameters [13]-[16]. Many techniques are used to improve the estimation of the transformer's parameters by employing various optimization strategies for estimating the parameters from search space, constraints, and objective functions [17]-[19]. The estimated coyote optimization algorithm (COA) parameters lead to a high closeness to the experiments that achieve the most effective parameters compared to other optimizing algorithms between the parameters estimated and the actual parameters [17]. By minimizing certain objective functions, particle swarm optimization, and genetic algorithm are used to track nameplate data. The findings show that transformer equivalent circuit parameters can be precisely defined by evolutionary computation techniques [18]. The imperialist competitive algorithm (ICA) and gravitational search algorithm (GSA) are proposed for estimating transformer parameters from nameplate data. These techniques can give better accuracy in estimating the parameters of power transformers [19]. The load test data is adequate to estimate the parameters using a genetic algorithm at a specific operating point: voltage, load currents, input power, and load impedance. The process is used for the determination of output, power system load flow, and design of three winding Transformer protective circuits [20]. The paper describes the method for determining the parameters of the non-linear current-flow relation which characterizes the saturation. They suit very well with the analytical role for modifying the experimental measurements [21]. To optimize the transformer parameter, the proposed algorithms use manta ray optimization and chaotic manta ray. In contrast with the approach suggested in the previous article, the proposed objective function does not require any loss in the estimation process. The approximate parameters obtained through the proposed optimization and objective function are compared with the values obtained using the classical Institute of Electrical and Electronics Engineers (IEEE) test protocol and the values derived using the literature previously introduced. The measurements of the experimentally defined transformer parameters shall be performed to demonstrate the effects of the proposed parameter estimation algorithm and the correlation shall be studied [22]. The proposed turbulent flow of water-based optimization (TFWO) algorithm used to estimate the transformer parameters of the power transformer from its nameplate data and the accuracy and reliability of the proposed algorithm are higher than the other algorithms.

The following is how this paper is structured; section 2 explains the analysis of objective function that solves problem formulation. Section 3 contains the details of the proposed TFWO algorithms. Section 4 analyses the results of the case study and the conclusion is in section 5.

2. PROBLEM FORMULATION AND OBJECTIVE FUNCTION

2.1. Transformer model

The equivalent circuit referred to the primary side of a single-phase two-winding transformer is shown in Figure 1. The conventional method of estimation of transformer parameters requires usually open circuit and short circuit test experimental data. In this paper, the challenge is to estimate transformer parameters by only using the nameplate data without performing tests. The proposed approach is based on a reduction in the square error of the nominal transformer nameplate parameters and the corresponding parameters calculated in Figure 1. Use the circuit laws of Kirchhoff by solving several mathematical equations [23]. The total impedance of transformer is as follows:

$$Z = Z_1 + \frac{Z_o \times (\acute{Z}_2 + \acute{R}_{load})}{Z_o + \acute{Z}_2 + \acute{R}_{load}} \tag{1}$$

where:

$$Z_1 = R_1 + jX_1,\ \acute{Z}_2 = \acute{R}_2 + j\acute{X}_2, \text{ and } Z_o = \frac{R_c \times jX_m}{R_c + jX_m}$$

from Figure 1, the primary current is:

$$I_1 = \frac{V_1}{Z} \tag{2}$$

and the secondary current is:

$$\acute{I}_2 = \frac{Z_o}{Z_o + \acute{Z}_2 + \acute{R}_{load}} \times \frac{V_1}{Z} \tag{3}$$

the secondary voltage calculated as:

$$\acute{V}_2 = \acute{I}_2 \times \acute{R}_{load} \tag{4}$$

Where:
$R_1 = Primary\ winding\ resistance$
$\acute{R}_2 = Secondary\ winding\ resistance\ referred\ to\ primary\ side$
$X_1 = Primary\ leakage\ reactance$
$\acute{X}_2 = Secondary\ leakage\ reactance\ referred\ to\ primary\ side$
$R_c = Resistance\ corresponding\ to\ core\ losses$
$X_m = Magnetizing\ reactance$
$I_1 = Primary\ current$
$\acute{I}_2 = Secondary\ current\ referred\ to\ primary\ side$
$V_1 = Terminal\ voltage\ on\ the\ primary\ side$
$\acute{V}_2 = Secondary\ terminal\ voltage\ referred\ to\ primary\ side$
$I_o = No - load\ current$
$\acute{R}_{load} = load\ resistance$

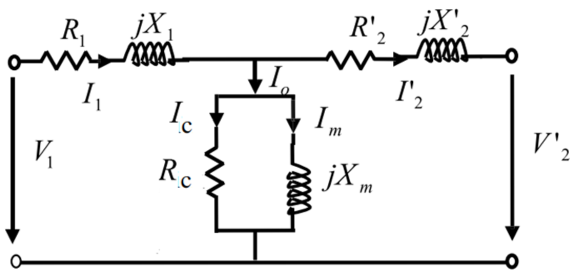

Figure 1. Referred to the primary side transformer equivalent circuit [14]

2.2. The objective function of estimation

The optimization algorithms are used in extracting the parameters of the different ratings of the transformer (4 kVA, 10 kVA, and 15 kVA), these techniques need an objective function for performing the optimization process. Minimizing the sum of square error (SSE) is the objective function of the optimizer technique. The SSE function includes the summation of the square error for the primary current and secondary current and voltage referring to the primary. The mathematical formula to compute SSE is as follow:

$$SSE = (I_{1.act} - I_{1.est})^2 + (I_{2.act}' - I_{2.est}')^2 + (V_{2.act}' - V_{2.est}')^2 \tag{5}$$

where the first term in the SSE is the difference between the primary actual and estimated current, the second term is the difference between the actual and estimated secondary current, and the third term is the difference between the secondary actual and estimated voltage. The optimization algorithm needs boundaries limit; these boundaries are explained in Tables 1-3 [22], [23].

Table 1. The extracted parameters boundaries for 4 kVA

Parameters	Lower bound	Upper bound
$\boldsymbol{R_1}$	0.2	0.6
$\boldsymbol{X_1}$	0.1	0.3
$\boldsymbol{R_2'}$	0.2	0.45
$\boldsymbol{X_2'}$	1.5	2.5
$\boldsymbol{R_c}$	1400	1500
$\boldsymbol{X_m}$	700	750

Table 2. The extracted parameters boundaries for 10 kVA

Parameters	Lower bound	Upper bound
$\boldsymbol{R_1}$	0.3	1
$\boldsymbol{X_1}$	0.2	1
$\boldsymbol{R_2'}$	0.1	1
$\boldsymbol{X_2'}$	0.2	1
$\boldsymbol{R_c}$	500	1000
$\boldsymbol{X_m}$	200	500

Table 3. The extracted parameters boundaries for 15 kVA

Parameters	Lower bound	Upper bound
$\boldsymbol{R_1}$	1.2	2.5
$\boldsymbol{X_1}$	1.3	3.5
$\boldsymbol{R_2'}$	1.3	2.2
$\boldsymbol{X_2'}$	1.8	2.3
$\boldsymbol{R_c}$	99,000	12,0000
$\boldsymbol{X_m}$	9,000	9,200

3. TFWO ANALYSIS

A circular shape is formed from the turbulent flow of water; this circular form is called a whirlpool. gravity force is affected on this whirlpool so that water forms a spiral path [24]. The random nature behavior in oceans, rivers, and seas is the feature of the whirlpool phenomenon. The suckhole that sucks the objects in the center of the whirlpool. At first, the initial population (X^0, comprising N_p members) of the algorithm is divided equally between N_{wh} groups or whirlpool sets, and then the strongest member of each whirlpool set (The better objective value member $f(X)$ is seen as an object pull whirlpool (X, including N_p - N_{wh} objects)).

Every whirlpool (Wh) behaves as a sucking well, and tends to unify the locations of objects inside its set (X) with its central position by applying a centripetal force on them, and push them into its well. Thus, the jth whirlpool and the local position on $W\ h_j$ combine the ith object position (X_i) with itself ($X_i = Wh_j$). However, other whirlpools produce some deviations (ΔX_i) because of the distance among them ($Wh - Wh_j$) and its objective values ($f(X)$) as well. Accordingly, the new position of the ith object becomes $X_i^{new} = Wh_j - \Delta X_i$. and the objects ($X$) travel through their whirlpool's core and toward it with their unique angle (δ). Hence, this angle at each iteration is changing according to (6):

$$\delta_i^{new} = \delta_i + rand_1 * rand_2 * \pi \tag{6}$$

to model and calculate the farthest and nearest whirlpools (ΔX_i), in (7) depicts the whirlpools with the least weighed distance from all objects, and then ΔX_i is calculated using both in (8). In (9) is used to update the position of the particle.

$$\Delta_t = f(Wh_t) * |Wh_t - sum(X_i)|^{0.5} \tag{7}$$

$$\Delta X_i = \cos(\delta_i^{new}) * rand(1.D) * \left(Wh_f - X_i\right) - \sin(\delta_i^{new}) * rand(1.D) * (Wh_w - X_i)) \\ * (1 + |\cos(\delta_i^{new}) - \sin(\delta_i^{new})|) \tag{8}$$

$$X_i^{new} = Wh_j - \Delta X_i \tag{9}$$

where Wh_f and Wh_w manifest the whirlpools with minimum and maximum of Δ_t, respectively, while δ_i characterizes the ith object's angle. Centrifugal force (FE_i) sometimes overcomes the centripetal of the whirlpool, and randomly transfers the object to a new location. The centrifugal force is modeled as illustrated in (10), which randomly occurs in one dimension of the decision variables. The centrifugal force is determined based on the angle between the whirlpool and the object, as shown in (10), and if this force is greater than a random value in the range [0, 1], the centrifugal action is performed for randomly selected dimension, as shown in (11). This phenomenon can be expressed mathematically as follows:

$$FE_i = ((\cos(\delta_i^{new}))^2 * (\sin(\delta_i^{new}))^2)^2 \tag{10}$$

$$X_{i.p} = X_p^{min} + rand * \left(X_p^{max} - X_p^{min}\right) \tag{11}$$

the whirlpools collide and displace one another. This phenomenon can be modeled as the same as the impacts of whirlpools on the objects, where every whirlpool tends to pull other whirlpools and imply the centripetal force on them. As shown in (12), the closest whirlpool can be mathematically represented using the minimum sum and its objective function. Then, the whirlpool's position can be updated according to (13) and (14):

$$\Delta_t = f(Wh_t) * \left|Wh_t - sum\left(Wh_j\right)\right| \tag{12}$$

$$\Delta Wh_j = rand(1.D) * \left|\cos\left(\delta_j^{new}\right) + \sin\left(\delta_j^{new}\right)\right| * \left(Wh_f - Wh_j\right) \tag{13}$$

$$Wh_j^{new} = Wh_f - \Delta Wh_j \tag{14}$$

where δ_j represents the jth whirlpool holes angle value. Finally, the strongest member of the new members of the whirlpool's set is chosen as the new whirlpool for the next iteration when the value of the objective function is less than the preceding whirlpool. The TFWO flowchart is depicted in Figure 2.

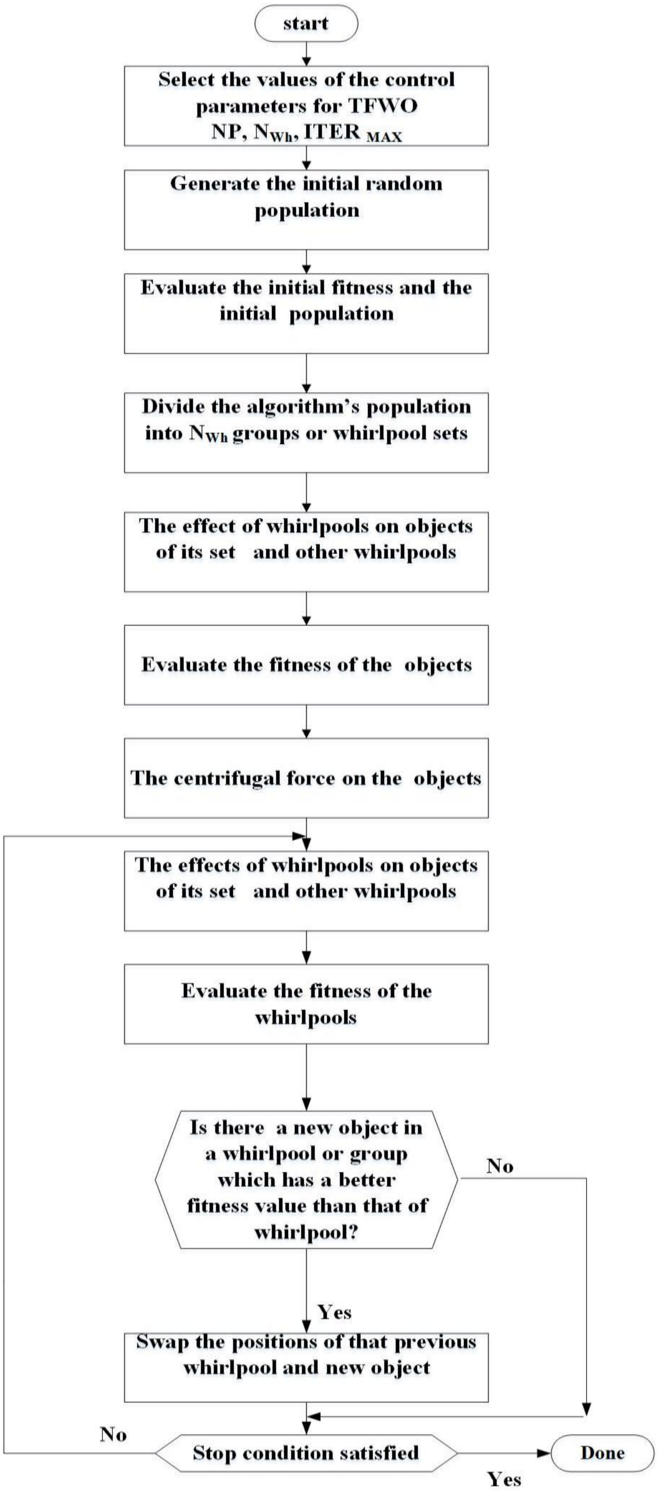

Figure 2. Flowchart of the proposed TFWO algorithm

4. ANALYSIS OF RESULTS

This section presents an analysis of the parameters extracted using the proposed TFWO algorithm for various transformers rating. The objective function is applied in this paper on the main proposed algorithm TFWO and it's applied also on the Cuckoo search algorithm (CSA) [25]. The performance of TFWO is validated by comparison of its results with this CSA and other algorithms from the previous work such as genetic algorithm (GA), practical swarm optimization (PSO) [18], imperialist competitive algorithm (ICA), and gravitational search algorithm (GSA) [19].

4.1. Results for transformer types

In this subsection, the details of extracted parameters and the best objective function by TFWO is performed. The proposed TFWO algorithm is compared with the cuckoo search algorithm (CSA) for 30 independent runs. The proposed algorithm test is applied to transformers rated at 4 kVA, 10 kVA, and 15 kVA, and the results are compared to existing approaches.

4.1.1. The transformer of rating 4 kVA

Parameters were extracted from a single-phase transformer based on the analysis in section two and three. Table 4 explains the value of the parameters for the 4 kVA transformer. Table 5 explains the current I_1 and I'_2 and the voltage $V_{2'}$ for this transformer based on the parameters extracted from each algorithm at the best objective function. The value of the best SSE for each algorithm is illustrated in Table 6. The statistical results of 30 run for TFWO and CSA algorithms are presented in Table 7. From the results in Tables 4-6, it can be observed that the proposed algorithm TFWO is the best algorithm in extract transformer parameters and the CSA algorithm is the second algorithm then ICA, GSA, PSO, and GA respectively. From Table 7 the accuracy and reliability of the TFWO algorithm are higher than the CSA algorithm.

Table 4. The parameters extracted for a 4 kVA transformer at the best SSE

Algorithm	actual	TFWO	CSA	GA	PSO	ICA	GSA
R1	0.4	0.387421895	0.35306923	0.598	0.587	0.430	0.425
X1	0.2	0.1	0.298748267	0.226	0.2554	0.202	0.203
R2'	0.4	0.45	0.45	0.336	0.209	0.394	0.415
X2'	2	2.5	2.5	1.957	1.602	2.5	2.399
Rc	1500	1400	1400	1410	1476	1200	1426
Xm	700	700	700	707	738	700	745.3

Table 5. The value of the current and voltage for the 4 kVA transformer of each algorithm

Transformer data	Actual	TFWO	CSA	GA	PSO	ICA	GSA
I1	14.0813	13.91535929	13.91535929	14.1035	14.0818	13.82729	13.8077
I2'	13.6893	13.68986622	13.68986622	13.6654	13.6972	13.6196	13.5916
V2'	235.8759	235.8856563	235.8856563	234.2131	237.2283	235.8917	235.407

Table 6. The value of the best objective function for 4 kVA transformer of each algorithm

Algorithm	The best SSE
TFWO	0.027631826
CSA	0.027631826
GA	2.76596789
PSO	1.82904842
ICA	0.06962881
GSA	0.30426946

Table 7. Statistical analysis of fitness function for 4 kVA transformer

Objective function (SSE)	TFWO	CSA
Minimum	0.027631826	0.027631826
Mean	0.027631826	0.027631826
Maximum	0.027631826	0.027631827
Standard deviation	2.31E-15	2.19E-10

4.1.2. The transformer of rating 10 kVA

One phase transformer of rating 10 kVA, 50 Hz, 500/125 V is used to extract their parameters based on the analysis in section two and three. Table 8 explains the value of the parameters for the 10 kVA transformer. Table 9 explains the current I_1 and I'_2 and the voltage $V_{2'}$ for this transformer based on the parameters extracted from each algorithm at the best objective function. The value of the best SSE for each algorithm is illustrated in Table 10. The statistical results of 30 run for TFWO and CSA algorithms are presented in Table 11. From the results in Tables 8-10, it can be observed that the proposed algorithm TFWO is the best algorithm in extract transformer parameters and the CSA algorithm is the second algorithm then PSO, GA, ICA, and GSA respectively. From Table 11 the accuracy and reliability of the TFWO algorithm are higher than the CSA algorithm.

Table 8. The parameters extracted for 10 kVA transformer at the best SSE

Algorithm	Actual	TFWO	CSA	GA	PSO	ICA	GSA
R1	0.9	0.3	0.300000525	1.025	0.811	0.8	0.8001
X1	0.94	0.315511728	0.31550416	0.8	0.8608	0.8	0.8119
R2'	1.6	0.1	0.1	1.507	1.678	1.5	1.5004
X2'	0.44	0.2	0.2	0.493	0.7540	0.4259	0.4236
Rc	700	1000	1000	651.5	713	692.48	695.54
Xm	250	500	500	204.4	314.2	255	251.35

Table 9. The value of the current and voltage for 10 kVA transformer of each algorithm

Transformer data	Actual	TFWO	CSA	GA	PSO	ICA	GSA
I1	19.688	19.82456533	19.82456533	19.6072	19.7012	19.0427	19.0417
I2'	19.299	19.29878424	19.29878424	19.1979	19.3189	18.2217	18.2207
V2'	491.729	491.7235026	491.7235026	487.847	487.9916	455.5431	455.5186

Table 10. The value of the best objective function for the 10 kVA transformer of each algorithm

Algorithm	The best SSE
TFWO	0.018680358
CSA	0.018680358
GA	15.08667385
PSO	13.96872901
ICA	1310.996346
GSA	1312.773503

Table 11. Statistical analysis of objective function for 10 kVA transformer

Objective function (SSE)	TFWO	CSA
Minimum	0.018680358	0.018680358
Mean	0.018680358	0.018680358
Maximum	0.018680358	0.018680358
Standard deviation	1.84E-16	4.99E-15

4.1.3. The transformer of rating 15 kVA

One phase transformer of rating 15 kVA, 50 Hz, 2400/240 V is used to extract their parameters based on the analysis in section two and three. Table 12 explains the value of the parameters for the 15 kVA transformer. Table 13 explains the current I_1 and I'_2 and the voltage $V_{2'}$ for this transformer based on the parameters extracted from each algorithm at the best objective function. The value of the best SSE for each algorithm is illustrated in Table 14. The statistical results of 30 run for TFWO and CSA algorithms are presented in Table 15. From the results in Tables 12-14, it can be observed that the proposed algorithm TFWO is the best algorithm in extract transformer parameters and the CSA algorithm is the second algorithm then PSO, GA, GSA, and ICA respectively. From Table 15 the accuracy and reliability of the TFWO algorithm are higher than the CSA algorithm.

Table 12. The parameters extracted for a 15 kVA transformer at the best SSE

Algorithm	Actual	TFWO	CSA	GA	PSO	ICA	GSA
R1	2.45	1.2	1.216390598	2.76	2.25	2	2
X1	3.14	2.130401219	1.811673414	3.414	4.082	3	3.11
R2'	2	1.3	1.3	1.68	2.2	1.8	1.81
X2'	2.2294	1.8	1.8	1.846	1.8526	2	2.26
Rc	10,500	12,000	12,000	97,001	99517	120000	104281
Xm	9,106	9,200	9,200	8,951	9,009	9,200	9094.87

Table 13. The value of the current and voltage for the 15 kVA transformer of each algorithm

Transformer data	Actual	TFWO	CSA	GA	PSO	ICA	GSA
I1	6.2	6.226571224	6.226571224	6.2017	6.2004	6.1653	6.1693
I2'	6.2	6.199999819	6.199999819	6.2001	6.2008	6.1387	6.1393
V2'	2383.8	2383.799931	2383.799931	2381.8	2384.7	2375.662	2375.917

Table 14. The value of the best objective function for the 15 kVA transformer of each algorithm

Algorithm	The best SSE
TFWO	0.000706035
CSA	0.000706035
GA	4.0000029
PSO	0.8100008
ICA	66.23200578
GSA	62.14631598

Table 15. Statistical analysis of objective function for 15 kVA transformer

Objective Function (SSE)	TFWO	CSA
Minimum	0.000706035	0.000706035
Mean	0.000706035	0.000706035
Maximum	0.000706035	0.000706035
Standard deviation	1.00E-17	1.31E-12

5. CONCLUSION

This paper proposes a turbulent flow of water optimization for transformer parameter extraction using nameplate data, which is applicable to single-phase and three-phase transformers. The parameters extracted from the proposed TFWO algorithm are executed successfully for three separate transformer ratings. The results of comparisons between TFWO, ICA, GSA, PSO, and GA estimate errors in the transformer parameters show that the TFWO results are more accurate and reliable than the ICA, GSA, PSO, and GA estimate errors. The transformer nameplate and the search space direct the TFWO method's objective function, ensuring that the proposed method is accurate, reliable, and complete. As compared to other methods, the TFWO method has the lowest objective function standard deviation of summation of square errors for primary current and secondary current and voltage corresponding to the primary. If experimental testing is not possible, the proposed TFWO technique can execute for the transformer three times instead. The proposed TFWO technique can be adjusted for more than six parameters optimization. Then for the three-phase transformer model includes distributed resistance and inductance, mutual inductance and three capacitances including self and ground capacitance and inter-winding may be optimized in future work. The results of the proposed method are compared with actual measurements obtained from previous publications to prove the validity of the proposal.

REFERENCES

[1] J. H. Harlow, “Electric Power Transformer Engineering,” *CRC Press Taylor & Francis Group*, 2012.

[2] I. Fofana and Y. Hadjadj, “Power Transformer Diagnostics, Monitoring and Design Features,” Energies, vol. 11, no. 12, 2019, doi: 10.3390/en11123248.

[3] H. Zhang *et al.*, “Dynamic Deformation Analysis of Power Transformer Windings in Short-Circuit Fault by FEM,” *IEEE Transactions on Applied Superconductivity*, vol. 24, no. 3, pp. 1-4, Jun. 2014, doi: 10.1109/TASC.2013.2285335.

[4] J. Jiang, R. Chen, M. Chen, W. Wang, and C. Zhang, “Dynamic Fault Prediction of Power Transformers Based on Hidden Markov Model of Dissolved Gases Analysis,” *IEEE Transactions on Power Delivery*, vol. 34, no. 4, pp. 1393–1400, Aug. 2019. doi: 10.1109/TPWRD.2019.2900543.

[5] N. Farzin, M. Vakilian, and E. Hajipour, “Transformer Turn-to-Turn Fault Protection Based on Fault-Related Incremental Currents,” *IEEE Transactions on Power Delivery*, vol. 34, no. 2, pp. 700–709, Apr. 2019, doi: 10.1109/TPWRD.2019.2893279.

[6] S. M. Saleh, S. H. EL-Hoshy, and O. E. Gouda, “Proposed diagnostic methodology using the cross-correlation coefficient factor technique for power transformer fault identification,” *IET Electric Power Applications journal*, vol. 11, no. 3, pp. 412–422, 2017, doi: 10.1049/iet-epa.2016.0545.

[7] O. E. Gouda, S. M. Saleh, and S. H. EL-Hoshy, “Power Transformer Incipient Faults Diagnosis Based on Dissolved Gas Analysis,” *Indonesian Journal of Electrical Engineering and Computer Science (IJEECS)*, vol. 16, no. 3, pp. 409–416, 2015, doi: 10.11591/ijeecs.v16.i3.pp409-416.

[8] H-C. Sun, Y-C. Huang, and C-M. Huang, “A Review of Dissolved Gas Analysis in Power Transformers,” *Energy Procedia*, vol. 14, pp. 1220-1225, 2012, doi:10.1016/j.egypro.2011.12.1079.

[9] O. E. Gouda and S. H. El-Hoshy, “Diagnostic technique for analysing the internal faults within power transformers based on sweep frequency response using adjusted R-square methodology,” *IET Science, Measurement & Technology*, vol. 14, no. 10, pp. 1057-1068, 2020, doi: 10.1049/iet-smt.2020.0048.

[10] O. E. Gouda, S. H. El-Hoshy, and S. M. Saleh, “Diagnostic Techniques used in Power Transformer Turn to Turn Faults Identification Based on Sweep Frequency Response Analysis (SFRA),” In *2016 Eighteenth International Middle East Power Systems Conference (MEPCON)*, Dec. 2016, pp. 27-29, doi: 10.1109/MEPCON.2016.7836880.

[11] K. H. Ibrahim, N. R. Korany, and S. M. Saleh, “Effects of VA rating on the fault diagnosis of power transformer using SFRA test,” *European Journal of Electrical Engineering*, vol. 23, no. 5, pp. 381-389, 2021, doi: 10.18280/ejee.230504.

[12] B. Trkulja, Ž. Štih, and Ž. Janić, “5th International Colloquium on Transformer Research and Asset Management,” *Springer Nature*, 2020.

[13] O. M. Arafa, S. A. Wahsh, M. Badr, and A. Yassin, “Grey wolf optimizer algorithm based real time implementation of PIDDTC and FDTC of PMSM,” *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 11, no. 3, pp. 1640-1652, 2020, doi: 10.11591/ijpeds.v11.i3. pp1640-1652.

[14] S. Wahsh, M. Badr, A. Yassin, and M. Algabalawy, "Cuckoo search meta-heuristic algorithm: developments and applications," In *5th International Conference on Advanced Control Circuits and Systems (ACCS'017)*, Nov. 2017, pp. 5-8, doi: 10.1007/s00366-012-0308-4.
[15] A. Yassin, M. Badr, and S. Wahsh, "Cuckoo Search Based DTC of PMSM," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 9, no. 3, pp. 1106-1115, 2018, doi: 10.11591/ijpeds.v9.i3.pp1106-1115.
[16] A. Y. Hassan, A. M. Soliman, D. Ahmed, and S. M. Saleh, "Wind cube optimum design for wind turbine using meta-heuristic algorithms," *Alexandria Engineering Journal*, 2021, doi: 10.1016/j.aej.2021.09.059.
[17] M. I. Abdelwanis, A. Abaza, R. A. El-Sehiemy, M. N. Ibrahim, and H. Rezk, "Parameter Estimation of Electric Power Transformers Using Coyote Optimization Algorithm with Experimental Verification," *IEEE Access*, vol. 8, pp. 50036-50044, 2020, doi: 10.1109/ACCESS.2020.2978398.
[18] M. Mossad, M. Azab, and A. Abu-Siada, "Transformer parameters estimation from nameplate data using evolutionary programming techniques," *IEEE transactions on power delivery*, vol. 29, no. 5, pp. 2118–2123, 2014, doi: 10.1109/TPWRD.2014.2311153.
[19] H. A. Illias, K. J. Mou, and A. H. A. Bakar, "Estimation of transformer parameters from nameplate data by imperialist competitive and gravitational search algorithms," *Swarm and Evolutionary Computation*, vol. 36, pp. 18-26, 2017, doi: 10.1016/j.swevo.2017.03.003.
[20] S. H. Thilagar and G. S. Rao, "Parameter estimation of three-winding transformers using genetic algorithm," *Engineering Applications of Artificial Intelligence*, vol. 15, no. 5, pp. 429-437, Sep. 2002, doi: 10.1016/S0952-1976(02)00087-8.
[21] S. Bogarra, A. Font, I. Candela, and J. Pedra, "Parameter estimation of a transformer with saturation using inrush measurements," *Electric Power Systems Research*, vol. 79, no. 2, pp. 417-425, Feb. 2009, doi: 10.1016/j.epsr.2008.08.009.
[22] M. P. Ćalasan, A. Jovanović, V. Rubežić, D. Mujičić; and A. Deriszadeh, "Notes on Parameter Estimation for Single-Phase Transformer," *IEEE Transactions on Industry Applications*, vol. 56, no. 4, pp. 3710–3718, Aug. 2020, doi: 10.1109/TIA.2020.2992667.
[23] M. C.´ Alasan, D. Mujicic´, V. Rubežic, and M. Radulovic, "Estimation of Equivalent Circuit Parameters of Single-Phase Transformer by Using Chaotic Optimization Approach," *Energies*, vol. 12, no. 9, pp. 1-15, 2019, doi: 10.3390/en12091697.
[24] M. Ghasemi, I. F. Davoudkhani, E. Akbari, A. Rahimnejad, S. Ghavidel, and L. Li, "A novel and effective optimization algorithm for global optimization and its engineering applications: Turbulent Flow of Water-based Optimization (TFWO)," *Engineering Applications of Artificial Intelligence*, vol. 92, 2020, doi: 10.1016/j.engappai.2020.103666.
[25] A. B. Mohamad, A. M. Zain, and N. E. N. Bazin, "Cuckoo search algorithm for optimization problems—a literature review and its applications," *Applied Artificial Intelligence*, vol. 28, pp. 419–448, 2014, doi: 10.1080/08839514.2014.904599.

BIOGRAPHIES OF AUTHORS

Amir Yassin Hassan received his B.Sc. with excellent grade with honor degree in electrical engineering from Fayoum University, Egypt, in June 2010. In 2011 he joined the Electronics Research Institute (ERI) as a researcher assistant at power electronics and energy conversion department. A. Yassin obtained his M. Sc. from Fayoum University at 2014 and he became an assistant researcher in ERI. He received his Ph. D. in electric drives from Ain Shams University in January 2019 and he became a researcher in ERI. He was honored as "the best assistant researcher" at ERI for years 2015, 2016, 2017 and 2018 respectively also he is awarded as the winner in "engineering innovation competition 2015" at Egyptian Engineers Syndicate. His major interests are: electrical drives control, modeling and simulation of electrical systems, artificial intelligence, thermal modelling and electrical/hybrid vehicles modeling, simulation, and control. He can be contacted at email: amir@eri.sci.eg.

Mokhtar Said received his B. Sc. with excellent grade with honor degree in electrical engineering from faculty of engineering, Fayoum University, Egypt, in June 2009. M. Said obtained his M.Sc. from faculty of engineering, Fayoum University, Egypt, in Sep 2013. He received his Ph. D. in renewable energy from faculty of engineering, Fayoum University, Egypt, in 2018. His major of interests is: modeling and simulation of electrical system, electrical drives control and optimization of renewable energy system. He can be contacted at email: msi01@fayoum.edu.eg.

Saber Mohamed Saleh Salem was born in Egypt. He received the M.Sc. and Ph.D. degrees in digital protection from Cairo University, Cairo, Egypt, in 2005 and 2009. He worked for eight years for Kureimat Power Station, Giza, Egypt, as a protection and maintenance engineer. In 2013 and 2018, he became an assistant professor and associate professor with Fayoum University, Fayoum, Egypt while continuing his research. He was active in the field of engineering consultancy at the engineering research and consulting center at the faculty of engineering, Fayoum University. He also has contributions as director of the disaster and crisis management center at the Faculty of Engineering, Fayoum University. His research interests include digital protection, renewable energy, electronic control of electric machines, and digital signal processing. He can be contacted at email: sms08@fayoum.edu.eg.