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TECHNICAL CONDITION MONITORING OF POWER TRANSFORMERS BASED ON FREQUENCY RESPONSE ANALYSIS USING HYBRID MEYER WAVELET TRANSFORM (MWT) AND BACTERIAL SWARM ALGORITHM (BSA) AND PARTICLE SWARM OPTIMIZATION (PSO)

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Abstract- The issue of an effective assessment of the technical condition monitoring of the electrical structure of the power transformer windings originated the research work discussed in this paper. Also, a new method has been presented based on a mathematical model to identify the parameters of power transformer windings including self-inductance, resistance, ground capacitance, inter-turn capacitance on the basis of the measurement of Frequency Response Analysis (FRA) and using hybrid Meyer Wavelet Transform (MWT) and intelligent Bacterial Swarming Algorithms (BSA) and Particle Swarm Optimization algorithm (PSO). FRA experimental data, which have been measured in power laboratories, were used as reference frequency responses for analysis of the accuracy of identification of these methods. The results of this analysis demonstrate their strength in more accurate calculation of parameters of power transformer winding.

Keywords: Power Transformers, Frequency Response Analysis, Travelling Wave Model, Discrete Meyer Wavelet Transform, Bacterial Swarm Algorithm.

I. INTRODUCTION

During recent years, Frequency Response Analysis (FRA) has been recognized as the most reliable condition monitoring technique for transformer winding displacement and deformation assessment. It is established upon the fact that the shape of a winding frequency response at high frequencies is associated with winding geometry. The appearance of clear shifts in resonance frequencies or new resonant points on a response may characterize faulty conditions of windings [1, 2].

Therefore, FRA is very essential to identify any minor winding deformation as soon as possible and take a proper asset management decision to avoid disastrous failures. FRA is an offline test [3, 4]. Practical experiences, as well as scientific investigations, show that currently no other diagnostic test method can deliver such a wide range of reliable information about the mechanical status of a transformer's active part (core-coil assembly) [4].

In most cases, FRA is used in the low frequency range of up to 3 MHz however, it has been suggested in [5] that at a higher frequency range the frequency response also contains useful information. Therefore, some recent works have increased the frequency range to 10 MHz yet, they are simulated based on the lumped parameter model, which is easier to build and requires less computation time, but is less accurate [5]. There are two ways for making frequency response analysis (FRA) measurements, Sweep Frequency Response Analysis (SFRA) and Low Voltage Impulse method (LVI) [6].

In the past a few years, development of evolutionary algorithms received great attention in the computational intelligence community worldwide [7]. Evolutionary algorithms such as Gene Expression Programming (GEP) [8], Particle Swarm Optimizer (PSO) [9], Artificially Neural Network (ANN) [10-12], etc., were utilized to identify parameters of transformer winding models using FRA measurements. During a learning process, an evolutionary algorithm optimizes model parameters in order to reduce the difference between real FRA measurements and corresponding simulations of winding models [1]. One of the advantages of this model-based approach is that evolutionary algorithms require only approximate range of possible values for each parameter as initial estimates for learning.

This paper presents a novel approach for winding parameter identification of power transformers based on reference FRA measurements with hybrid WT and BSA and compare with PSO. The travelling wave theory principle is applied to establish the equivalent circuit and mathematical model of transformer winding, which is used for model-based parameter identification. The paper is organized as follows. Section II describes a mathematical model of transformer winding, and then in Section III the reference transfer function for transformer winding under study will be described.

Bacterial swarm algorithm processes for transformer winding parameter identification based on frequency response analysis are introduced in Section IV. In Section V the model based on identification of transformer winding parameters with particle swarm optimization algorithm are shown. Subsequently, the simulation results and comparison are shown in Section VI. Finally, conclusions are given in Section VII.

II. MATHEMATICAL MODEL OF TRANSFORMER WINDING

A transformer is one of the most complex electrical elements in a substation. For power flow studies or even short circuit studies, its complex nature is often trivialized as an inductance. However, for the purpose of diagnostics, where the response of the windings is measured over a wide range of frequencies, such simplifications cannot be made and the electrical parameters must be estimated based on the geometry and materials comprising the windings. In the area of diagnostic testing, the transformer has often been modelled using lumped circuits.

The transmission line model (travelling wave) is a natural extension of the lumped model [13]. For a transformer winding containing more than one disc, each disc in the literature as the smallest discrimination is considered and also by a set of electrical lumped elements represented. In order to undertake a feasibility study, using the travelling wave theory for further research, only uniform transformer winding with the same values of parameters per unit length is to be considered.

Derivation of a transfer function in the notations of Figures 1 and 2 for the parameters per unit length of winding conductor is based upon the Telegrapher's equations for loss transmission lines which are expressed as follows[14, 15]:

$$\frac{\partial u}{\partial X} = -l\frac{\partial i}{\partial t} - ri \tag{1}$$

$$\frac{\partial i}{\partial X} = -c\frac{\partial u}{\partial t} - Gu \tag{2}$$

Upon these fundamental dependencies, the charging current for each element of winding conductor length ΔX of the nth turn, flowing to ground due to external capacitance and insulation conductivity, is described as follows:

$$i_{cn} = c\Delta x\frac{\partial U_n}{\partial T} + U_n\Delta xG \tag{3}$$

The charging current flowing from the nth turn to the (n-1)th one is:

$$\begin{aligned} i'_{sn} &= cs\Delta x\frac{\partial(U_n - U_{n-1})}{\partial t} + (U_n - U_{n-1})\Delta xg = \\ &= cs\Delta x\frac{\partial\Delta' U_n}{\partial t} + \Delta' U_n\Delta xg \end{aligned} \tag{4}$$

and to the (n-1)th turn is:

$$\begin{aligned} i''_{sn} &= cs\Delta x\frac{\partial(U_n - U_{n+1})}{\partial t} + (U_n - U_{n+1})\Delta xg = \\ &= cs\Delta x\frac{\partial\Delta'' U_n}{\partial t} - \Delta'' U_n\Delta xg \end{aligned} \tag{5}$$

The sum of Equations (4) and (5) gives total inter-turn current per unit conductor length as follows:

$$i_{sn} = i'_{sn} + i''_{sn} = -cs\Delta x\frac{\partial\Delta^2 u}{\partial t} - \Delta^2 u\Delta xg \tag{6}$$

where, Δu is the voltage difference between adjacent turns, $\Delta^2 u$ denotes the difference of the Δu between successive turns. Since only inter-turn relations are considered than one turn length α of conductor is assumed to be of interest:

$$\Delta x = a \tag{7}$$

In addition, the second difference of voltage can be rewritten in a differential form:

$$\Delta^2 U = a^2\frac{\Delta^2 u}{\Delta^2 x} = a^2\frac{\partial^2 u}{\partial x^2} \tag{8}$$

Substituting Equation (8) into the sum of Equations (3) and (6), the space derivative of the total current's decrease in the nth turn is obtained as:

$$\begin{cases} \Delta i_n = i_{cn} + i_{sn} = c\Delta x\dfrac{\partial U_n}{\partial t} + u_n\Delta xG = \\ = -cs\Delta xa^2\dfrac{\partial^3 u}{\partial t\partial x^2} - \Delta xga^2\dfrac{\partial^2 u}{\partial x^2} \\ \dfrac{\partial i}{\partial x} = -c\dfrac{\partial u}{\partial t} - uG + csa^2\dfrac{\partial^3 u}{\partial t\partial x^2} + ga^2\dfrac{\partial^2 u}{\partial x^2} \end{cases} \tag{9}$$

If the nth turn having self-inductance λ per unit length, were separated from the rest of the winding, the voltage induced by the current in it can be expressed as:

$$u\lambda_n = \lambda\Delta x\frac{\partial i_n}{\partial t} + r\Delta xi_n \tag{10}$$

The two adjacent turns coupled by the mutual inductance μ per unit length induce a voltage in the nth turn as follows:

$$\begin{aligned} u\mu_n &= \mu\Delta x\frac{\partial(i_{n+1} + i_{n-1})}{\partial t} = \\ &= \mu\Delta x\frac{\partial[i_{n+1} - i_n) - (i_n - i_{n-1}) + 2i_n]}{\partial t} = \\ &= 2\mu\Delta x\frac{\partial i_n}{\partial t} + \mu\Delta x\frac{\Delta 2i_n}{\partial t} \end{aligned} \tag{11}$$

Thus, as stated in, due to the mutual inductances the induced voltages proportional to *in* will be produced in the nth turn by each succeeding turn and, hence, it can be collected together using Equations (10) and (11), which leads to:

$$\begin{aligned} u\lambda_n &= (\lambda + \sum\mu)\Delta x\frac{\partial i_n}{\partial t} + r\Delta x_{in} = \\ &= l\Delta x\frac{\partial i_n}{\partial t} + r\Delta x_{i_n} \end{aligned} \tag{12}$$

where, l is the self-inductance of winding per unit length, derived by the total inductive effects between all turns or simply it is the self-inductance of the entire winding divided by its total length.

Considering inter-turn relationships second difference of current has a form of second order space derivative we get:

$$\Delta^2 i = a^2\frac{\Delta^2 i}{\Delta x^2} = a^2\frac{\partial^2 i}{\partial x} \tag{13}$$

In addition, that is related to an influence of the immediately adjacent turns, because the induced effects of another turns have already been included in Equation (12). The total voltage in the *n*th turn is equal to decrease $-\Delta u_n$ which, using Equations (11) and (12), becomes:

$$-\Delta u_n = l\Delta x \frac{\partial i_n}{\partial t} + \mu a^2 \Delta x \frac{\partial^3 i_n}{\partial t \partial^2 x} + r\Delta x_{i_n} \quad (14)$$

and the voltage space derivative along the winding, with aid of Equation (13), transforms into:

$$\frac{\partial u}{\partial x} = -l\frac{\partial i}{\partial t} - ri - \mu a^2 \frac{\partial^3 i}{\partial t \partial x^2} \quad (15)$$

Thus, the Equations (9) and (15) in a detail describe the propagation of wave signal along uniform transformer winding.

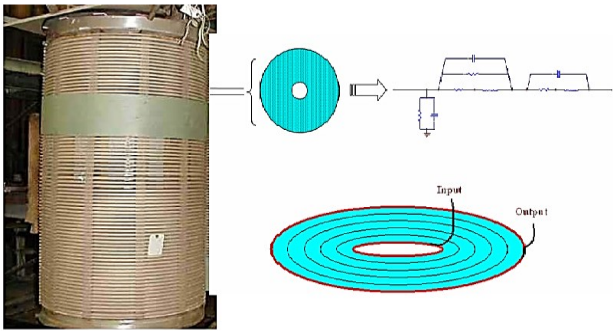


Figure 1. Continuous parameter model of transformer winding [14]

III. REFERENCE TRANSFER FUNCTION OF TRANSFORMER WINDING

In order to obtain a transfer function of transformer winding, Equations (9) and (15) are to be considered. Consequently, with a purpose of further processing simplification, the last term of Equation (15) is to be neglected within practical accuracy tolerance, since the mutual inductance μ of the adjacent turns is much less than self-inductance l which already includes mutual inductances itself. The Laplace transform is used for converting the expressions to the frequency domain. Thus, with the zero initial conditions we have:

$$i(t=0,x)=0 \quad , \quad u(t=0,x)=0 \quad (16)$$

The Laplace transform of the space derivatives would be:

$$L\left[\frac{\partial u}{\partial x}\right] = \frac{\partial U(s.x)}{\partial x} \quad (17)$$

$$L\left[\frac{\partial i}{\partial x}\right] = \frac{\partial I(s,x)}{\partial x} \quad (18)$$

where, Z, Y, and Y_s are the impedance and admittance of winding and admittance of insulation per unit length respectively, and:

$$\begin{cases} Z = ls + r \\ Y = cs + G \\ Y_S = g_s S + g \end{cases} \quad (19)$$

Thus, the mathematical model of transformer winding is similar to the model of the uniform homogenous transmission line and has a solution in a form:

$$U(s.x) = A_1 e^{-\gamma x} + A_2 e^{\gamma x} \quad (20)$$

$$I(s.x) = \frac{1}{Z_0}(A_1 e^{-\gamma x} - A_2 e^{\gamma x}) \quad (21)$$

where, the propagation constant is:

$$\gamma = \sqrt{\frac{ZY}{1 - ZY_s a^2}} \quad (22)$$

And the surge (characteristic) impedance of the transformer winding is:

$$Z_0 = \sqrt{\frac{(1+ZY_s a^2)Z}{Y}} \quad (23)$$

Only the impedance of measurement coaxial cable Z_{inp} = 50 Ω being serially incorporated into the model has represented the analysis of the proposed equivalent circuit model of transformer winding at FRA testing shows that measurement chain of multi-frequency input signal. However, at FRA testing, the input signal is measured directly at the bushing terminals of a transformer with an additional measurement cable connected in parallel to the first signal transmitted cable, in order to reduce the influence of measurement chains.

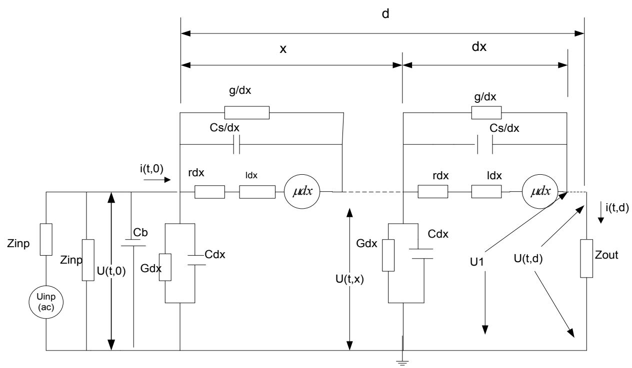


Figure 2. Equivalent circuit of transformer winding at FRA testing [14]

Thus, the second parallel cable impedance has to be included into the equivalent circuit of the transformer winding. In addition, the capacitance with respect to tank ground C_b of the high voltage input bushing terminal and the impedance Z_{out} of output signal measurement chain are included. Consequently, equivalent circuit of transformer winding being refined is illustrated in Figure 2 and the boundary conditions can be expressed by the following equations in the Laplace form:

$$U(s,0) = \frac{1}{Y_{inp}}\left(\frac{U_{inp}(s)}{Z_{inp}} - I(s,0)\right) \quad (24)$$

$$I(s,0) = \frac{U_{inp}(s)}{Z_{inp}} - U(s,0)Y_{inp} \quad (25)$$

$$U(s,d) = Z_{out} I(s,d) \quad (26)$$

$$Y_{inp} = \frac{2}{Z_{inp}} + sC_b \quad (27)$$

Equation (27) denotes the admittance at the input of the winding during FRA testing. Paying attention that the transfer function of transformer winding is to be succeeded in a form as:

$$H(s) = \frac{U_{out}(\omega)}{U_{inp}(\omega)} = \frac{U(s,d)}{U_{inp}(s)} \tag{28}$$

The Equations (20) and (21) with boundary conditions suitable must be solved. Consequently, the transfer function of transformer winding becomes:

$$H(s) = \frac{Z_{out}}{Z_{inp}\begin{bmatrix}(1+Z_{out}Y_{inp})\cosh\gamma d + \\ +\left(Y_{inp}Z_0 + \dfrac{Z_{out}}{Z_0}\right)\sinh\gamma d\end{bmatrix}} \tag{29}$$

Using the derived Equation (29) for the transfer function of transformer winding with substitution $s = j\omega$ it is possible to produce the frequency response of transformer winding.

IV. BACTERIAL SWARM ALGORITHM

This algorithm is used in this study to perform intelligent optimization with the purpose to identify transformer winding model parameters. BSA has demonstrated a superior performance in comparison with some popularly used algorithms, such as PSO and Fast Evolutionary Programming. In summary, a BSA process can be expressed briefly in the form of a sequence of the following operations [7]:

1- Random generation of the initial population
2- Performing chemo-tactic process for fitness evaluation of each bacterium in the population
3- Performing the 'group-based attraction and dispersion' process
4- Repeating steps 2 to 4 until a termination criterion is met
5- Presentation of the best bacterium in the population as the BSA output

A. Bacterial Foraging Algorithm

Bacterial foraging algorithms are a new class of stochastic global search techniques [16]. Pasino first presented the BF algorithm in 2002. The idea in this algorithm was adopted from biological and physical living behavior of E coli bacteria existing in the human intestine. In principle, bacteria try to reach the nutrients, to avoid noxious materials, and to find a way to exit the neutral and noxious nutrient environment [17].

The main difference between BSA and BFA is the absence of the reproduction process in BSA. All bacteria are kept in the population with only their positions updated in the search domain according to their fitness values. The BSA model executes a combination of both chemo-tactic and "group-based attraction and dispersion" processes [7]. BSA process is generally expressed in the [18-21].

B. Parameter Identification with BSA

The model-based learning approach is based on searching of the optimal model parameters by minimizing the difference, i.e. fitness, between reference frequency responses and simulated model outputs. It is achieved by measuring the errors between the original responses and the model outputs. Therefore, for each individual (bacterium) of a population in BSA, its total fitness value is given as follows:

$$\min \sum_{j=1}^{S} \left\| H_0(\omega j) - H(\omega j) \right\| \times Wj \tag{30}$$

where, $H_0(\omega j)$ and $H_0(\omega j) \epsilon R^1$ are the reference and simulated with the identified parameters frequency responses at frequency ωj, j=1, 2, ..., s, where s is number of frequency points involved in BSA learning process and Wj is the relative weight of the jth point.

Due to iterative nature of evolutionary algorithms, processing a large number of data points can greatly slow down a learning process. In the case of FRA, frequency responses are characterized mainly by resonant and anti-resonance frequencies and corresponding magnitude values. Therefore, as proposed in [22], the dimension of processed FRA data can be reduced by selection of points of resonance and anti-resonance and its vicinities for more speedy analysis, which are weighted accordingly. The following steps are performed for the core parameter identification in this study.

• Experimental FRA data or simulation data derived from a transformer-winding model with predefined parameters are used as reference frequency responses.
• Reference response points in a frequency range of interest are selected to create a reference dataset, being employed as training targets for BSA learning.
• The initial search space for the identified parameters is established based on approximate estimations.
• BSA learning is performed, in each step of which the predefined training dataset is compared with the corresponding values of the simulated frequency responses at the same frequency points. The simulated frequency responses are generated using the established transformer core model with the parameters obtained during the BSA learning process.

The BSA learning parameters are selected based on the previous study on bacterial foraging optimization and numerous trials with various BSA parameters. The parameters are listed in Table 1.

Table 1. The BSA parameters

Parameter	Notation	Value
dimension of search space	p	90
The number of bacteria	s	2
No. of chemo-tactic steps per bacteria lifetime	N_c	5
Swim length limit when bacteria is on a gradient	N_s	6
No. of iteration steps	N_{re}	20
The number of elimination-dispersal events	N_{ed}	2
Number of bacteria reproductions (splits) per generation	S_r	1
Probability for attraction	P_{ed}	0.025
Initial step length	C_{init}	0.001

V. FOUNDATION BY USING PSO METHOD

Particle Swarm Optimization (PSO) is a population based on computational technique inspired from the simulation of social behavior of flock of birds. PSO originally designed and developed by Eberhart and Kennedy [23, 24]. A newer version was introduced in [1998] by incorporating inertia weight. In the group of the particles, the optimization problem is the same answers and they are scattered randomly in the search space. The position of these particles, which refers to their swarms, is collected from one another. The particles positions are updated by using their experiences and the experiences of neighboring particles.

However, PSO tries to find the optimal solution to the problem by moving the particles and evaluating the fitness of the new position. The particle velocity vector [25] does this update, i position vector and velocity vector of ith particle in a d-dimensional search space, are expressed as follows [26, 27]:

$$X_i = \left(X_{i1}, X_{i2}, ..., X_{id}\right) \tag{31}$$

$$V_i = \left(v_{i1}, v_{i2}, ..., v_{id}\right) \tag{32}$$

The best previous position of a particle is recorded and displayed, based on the evaluation function value as follows [28]:

$$p_{best} = \left(p_{i1}, p_{i2}, ..., p_{id}\right) \tag{33}$$

If the g the particle has the best position in swarm in comparison with other particles then the situation is shown below:

$$g_{best} = p_{best\,g} = (p_{g1}, p_{g2}, ..., p_{gd}) \tag{34}$$

$$\left|g_{best}^{k} - g_{best}^{k-1}\right| < \varepsilon \tag{35}$$

PSO process is generally expressed in the [29-31].

A. Parameter Identification with PSO

In order to compare the performance between BSA and an evolutionary algorithm widely utilized for parameter identification purposes, PSO is employed to conduct parameter identification of the equivalent lumped parameter model using the same reference responses and fitness function. Due to the stochastic nature of both the algorithms, BSA and PSO, initial populations of individuals (bacteria) are generated in random order using the same search space limits, specified in Section IV.B. The PSO parameters are chosen based on various preliminary trials and listed in Table 2.

Table 2. PSO parameters

Parameter	Notation	Value
Inertia weight parameter	W	0.4-1
The number of Optimized Parameter	n_{var}	2
Cognitive coefficient	C_1	5
Social coefficient	C_2	2
Random number	Rand1,2	0-1
The maximum number of iterations	$iter_{\max}$	100

VI. SIMULATION RESULT

In this section, simulations has been ran on the high voltage winding of a transformer with the specifications mentioned in Table 3 and based on the theory of transmitting wave propagation and the reference transfer function of transformer winding has been shown in Figures 3 and 4 based on amplitude and phase. The proportion of an output voltage to an input signal is used to measure frequency responses.

Finally, as Figure 5 shows, transformer reference transfer function is resolved using discrete Meyer wavelet transform through passing low-pass filter and calculating approximate signal and passing high-pass filter and calculating details signal. Having applied this range to the intelligent Bacterial Swarming Algorithm, the parameters of power transformer winding are estimated at the best condition and the resultant transfer functions are compared with the Particle Swarm Optimization algorithm. The test object is a disc-type winding consisting of 46 discs with 6 turns in each discs.

Table 3. Transformer parameters

Parameter	Symbol	Value
Transformer Power (KVA)	S	3150
Transformer ratio (KV)	N_2/N_1	20/3.3
Vector Group	-	DYn5
Number of disks	N_d	52
Number of turns per a disk	N_t	17
Self-inductance, μH/m	l	4.5247
Resistance W/m	r	0.01217
Ground capacitance, PF/m	C	1.06818
Inter-turn capacitance, PF/m	C_s	0.10883
Bushing capacitance, PF/m	C_b	500
Ground conductivity, nSi/m	G	0.479
Inter-turn conductivity, μSi/m	g	31.102
Average length of turn, m	a	3.44
Total length of winding, m	d	3041

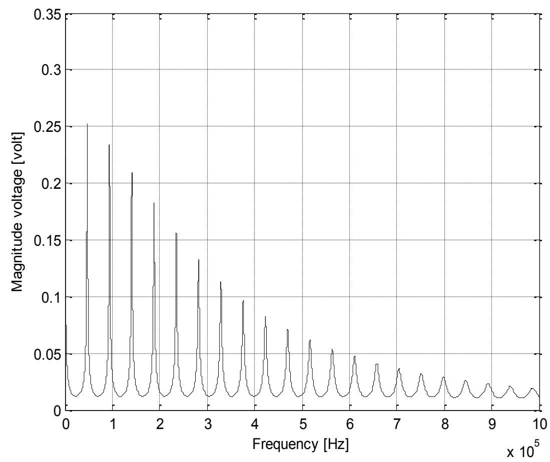


Figure 3. The reference transfer functions of transformer winding

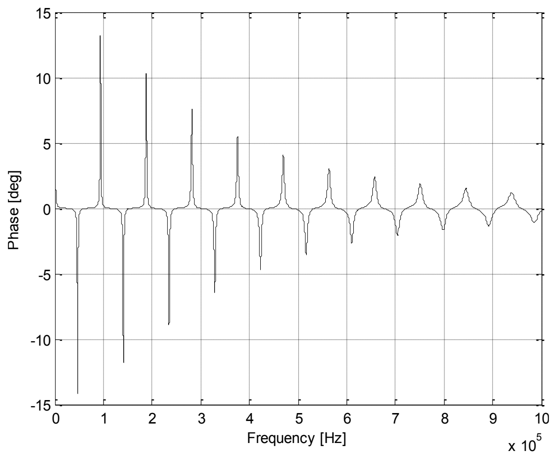
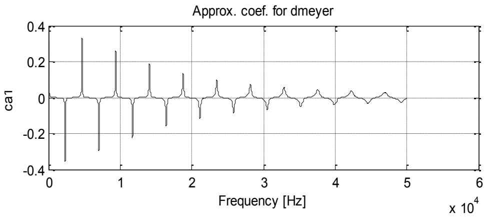
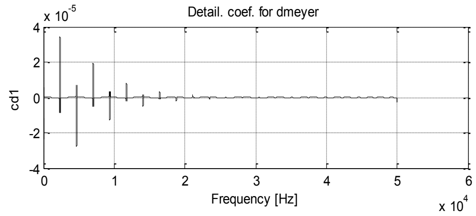


Figure 4. Phase of reference transfer function of transformer winding

The reason for using the discrete Meyer wavelet in simulations is that it supports compression. In the sense, which that has value only in a finite interval and disappeared outside the interval, this property greatly helps to get responses close to the experimental ones.



(a)



(b)

Figure 5. The magnitudes of resolved frequency transfer function of Figure 3 using discrete Meyer wavelet transform, (a) Approximate coefficient, (b) Detail coefficient

A. Parameter Estimation of Transformer Winding Model with BSA and PSO

The aim of this task is to identify accurately transformer winding parameters using a detection theory based on a mathematical model described in Section II. In order to identify the winding parameters, an evolutionary algorithm called bacterial swarming algorithm was used then the same activity was carried out for the intelligent method of particle swarm optimization algorithm, the final estimated amounts and their resultant output transfer function were compared together and the conclusion was reached. The described flowchart of this method has been presented in Figure 6.

Table 4 in the Appendix summarizes the reference parameter and the identified parameter values with BSA and PSO, which given the end of article. The table contains the results of one successful run with BSA and its deviation from the reference, the analysis of which shows negligible difference between the identified parameters.

Considering resistance parameters, BSA provides its accurate identification from the corresponding reference values. The large deviation of the initial estimation of l, r from the reference caused failure to repeat all resonance frequencies when using the model with PSO. This results in clear shifts to the left of the resonant points with regard to the reference frequency responses in Figures 7 and 8. As seen from the Table 4, the deviation of the PSO identified parameters becomes greater than obtained values with BSA. Nevertheless, despite of slight deviation from the reference values, the utilization of estimated parameters as a search basis for BSA parameter identification essentially improves the model performance as illustrated in Figures 7 and 8.

The large deviation of the initial estimation of l, r from the reference in model with PSO caused shifts to the right of the resonant points with regard to references frequency responses in Figures 7 and 8. The difference in the identified results can be explained by the fact that the algorithms are generally guided by the fitness function, which computes only the total deviation of the model outputs from the reference.

Therefore, due to different learning principles, BSA and PSO identify diverse parameters, despite of achieving a close resemblance with the reference. In summary, considering more accurate parameter identification using BSA in comparison with the reference values, it can be assumed that BSA is more appropriate for the given optimization case.

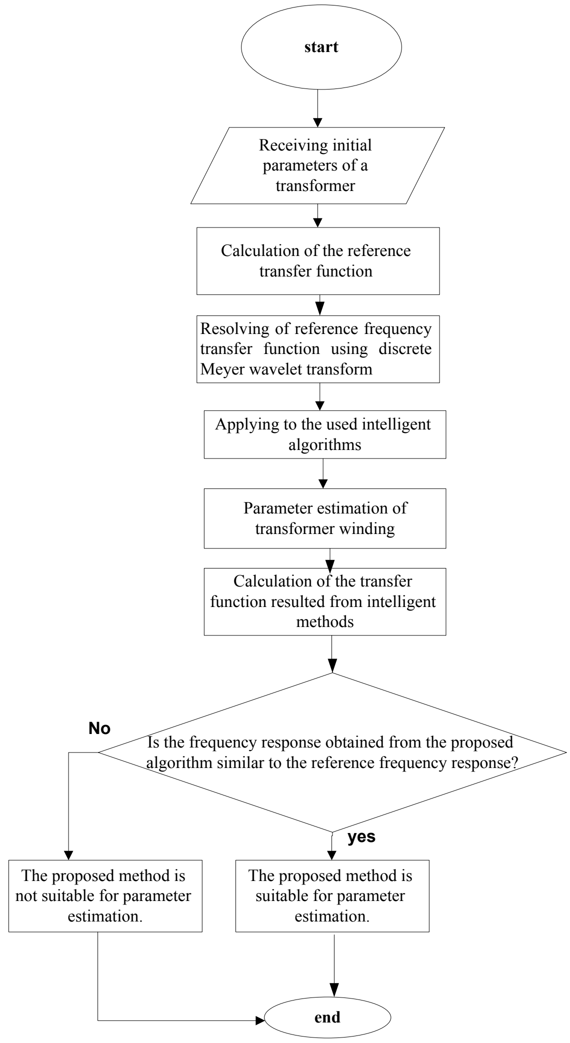


Figure 6. Flow chart describing the methodology used in the analysis

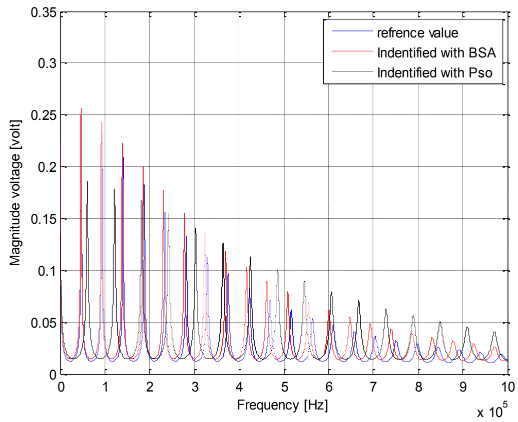


Figure 7. Comparison of the transfer function magnitude frequency response, identified with PSO, BSA and reference

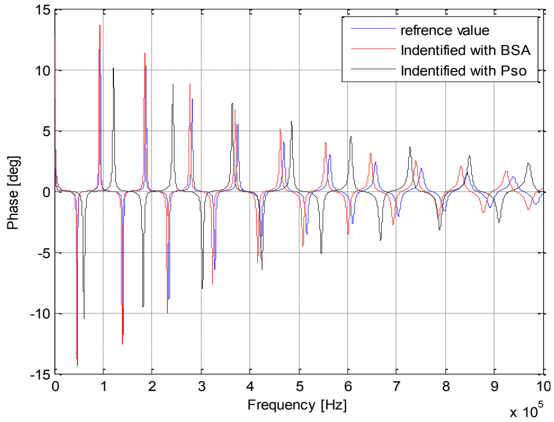


Figure 8. Comparison of the transfer function phase's frequency response, identified with PSO, BSA and reference

VII. CONCLUSIONS

In this paper, in order to identify and estimate the model parameters of transformer windings based on frequency response analysis, Bacterial Swarming Analysis (BSA) and Particle Swarm Optimization (PSO) algorithms using the travelling wave theory were used. During the learning process, these evolutionary algorithms optimize the model parameters to decrease the difference between the corresponding real and simulated measurements of FRA of winding models. Comparing with the previously developed methods for transformer winding parameters estimation [1, 3, 7], the proposed approach establishes and utilizes the frequency dependent core model, which has a simple form.

The simulation results show that in the PSO method, parameter setting based on the nature and type of the problem studied is an important factor in accurate and efficient attainment of optimum answer. Although the PSO method using time variant inertial parameter can quickly lead to an acceptable answer, but due to its diversity at the end of the search, its ability to adapt to the optimal answer is weak. But considering the results of bacterial swarming algorithms, it can be found out that at the end of the search and achieving the best bacteria, there is a great capability to adapt reference and optimized answer.

APPENDIX

Comparison of the Reference and Identification Parameters

Table 4. Comparison of the reference and identification parameters of the transformer winding model

Parameter	Reference Value	Identified Value		Deviation from the reference	
		BSA	PSO	BSA	PSO
L	4.5247	3.8885	2.9487	0.6362	1.576
r	0.01217	0.01217	0.03651	0	0.02434
C	1.06818	1.1818	0.9824	0.11362	0.08578
C_s	0.10883	0.14741	0.1986	0.03858	0.08977

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