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Improved Modeling of Power Transformer Winding Using PSO

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Abstract- The paper discusses an improved modeling of transformer windings based on particle swarm optimization algorithm (PSO) and frequency response analysis (FRA). With the purpose to accurately identify transformer windings parameters a model-based identification approach is introduced using a well-known lumped parameter model. It includes search space estimation using analytical calculations, which is used for the subsequent model parameters identification with a novel PSO. The newly introduced PSO, being developed upon a bacterial foraging behavior, is described in detail. Simulations and discussions are presented to explore the potential of the proposed approach using simulated and experimentally measured FRA responses taken from two transformers. The PSO identification results are compared with those using genetic algorithm. It is shown that the proposed PSO delivers satisfactory parameter identification and improved modeling can be used for FRA results interpretation.

Keywords: **Transformer winding, Mathematical model, Bacterial swarming algorithm, Frequency response analysis, Parameter identification.**

I. INTRODUCTION

Power transformer is a major apparatus in a power system, and its correct functioning is vital to system operation. It is therefore Very necessary to closely monitor their in-service behavior, in order to avoid catastrophic failures and costly outages and improve the management of maintenance and servicing. Among various techniques applied to power transformer condition monitoring, frequency response analysis (FRA) is suitable for reliable winding displacement and deformation assessment and monitoring. It has been established upon the fact that frequency response shape of a transformer winding in high frequencies depends on changes of its internal distances and profiles, which are concerned with its deviation or geometrical deformation [1]. However, the interpretation of FRA data is mainly conducted manually by trained experts. Measured FRA traces are compared with the references taken from the same winding during previous tests or from the corresponding winding of a "sister" transformer, or from other phases of the same transformer. The shifts in resonant frequencies and magnitude of FRA traces are believed to be indicators of a potential winding deformation. However, the question of potential deformation location in a winding is still required To be investigated [2]. A range of research activities have been undertaken to utilize FRA in the development of suitable mathematical models of transformer windings. Considering the simplified equivalent model of transformer winding, various experimental research was performed with the purpose to observe the model behaviors in the frequency domain [3, 4]. A winding equivalent model and an identification method of transformer equivalent circuit were proposed in [5, 6], where equivalent circuits of transformer winding for the Low, medium and high frequency ranges were discussed and its frequency responses were compared with experimental data in order to identify the models' parameters. These models represent the overall windings by combinations of single lumped elements: Inductances, resistances and capacitances, This allows estimating only the overall winding parameters in a particular frequency range, which makes these models unsuitable for deformation analysis of each winding section. The calculation of internal parameters plays important part inaccurate simulations of transformer winding frequency behavior. Modeling of a real winding in order to obtain frequency responses, being close to experimental ones, is an extremely complex task since a detailed transformer model must consider each turn or section of a winding separately. The reason is the fluctuation of real winding parameters such as inductances and resistances per turn length as well as interterm capacitances. The insulation property deviation should also be taken into account, which is frequency dependent. In [7] efficient procedures to calculate turn self inductances, mutual inductances and capacitances were proposed which demanded additional experimental tests and knowledge of geometric and physical characteristics of a transformer. A transfer function approach is used in [2] to study the discriminating changes introduced into a winding physical model. In [8–11] analytical expressions are used to estimate parameters of an equivalent model based on the geometry of windings. The well-known finite-element method was applied in [12, 13] for more precise calculation of winding parameters for an equivalent circuit model. These techniques show higher degree of accuracy compared with experiment measurements.

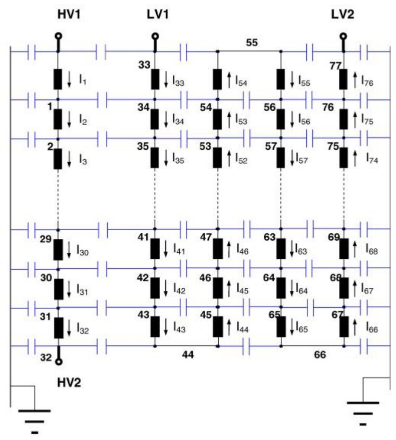

Fig. 3. Node configurations of two windings (all parameters – resistances, inductances and capacitances – are not shown in this simplified model for better illustration), HV1 and HV2 are high voltage terminals and LV1 and LV2 are low voltage terminals and impulse voltage is applied as input voltage to HV1.

However, in industry measurements it is not always possible to conduct additional tests for precise measurements of transformer geometry or insulation parameter estimation. Recently, evolutionary algorithms were utilized to overcome such difficulties, that off era way to identify model parameters using limited measurement data. Regarding transformer winding modeling, at first, two similar simplified winding model parameter identification approaches using particle swarm optimizer (PSO) [14] and genetic algorithms(GAs) [15] were proposed in [16,17] respectively. However, only simplified one-winding lumped parameter models were considered in these work for parameter identification. The questions of initial estimation of the model parameters to establish search space for the evolutionary algorithms were not discussed either. A variety of well-established biologically inspired computational methodologies has emerged in the past a few years, such as GAs, PSO, evolutionary programming (EP) [18], bacterial foraging algorithm (BFA) [19], etc. However, data processing in these algorithms may be time consuming, especially when a large number of multi-dimensional variables need to be optimized. Thus, it leads to a slow convergence rate and reluctant application in many problems involving a large number of parameters to be optimized, primarily because of the huge computational burden imposed. A key advance in this field will therefore be met by a significant reduction in the computational time-costs whilst further improving the efficiency of global research capabilities of these algorithms [20, 21]. In this paper an improved modeling of transformer windings is presented by using a model-based identification approach to derive the parameters of transformer windings models. The approach, firstly introduced in [16, 17], is further modified with a novel bacterial swarming algorithm (PSO) [21, 22], presented and utilized to undertake parameter identification. The newly introduced PSO is based on BFA, which incorporates ideas from the modeling of bacterial foraging patterns [22]. Simulation studies and discussions are presented to explore the potentials of the proposed modeling approach. The remainder of this paper is organized as follows: Section 2describes a lumped parameter mathematical model of transformer windings utilized in this study, then in Section 3 the analytical expressions for model parameter estimation are presented. PSO and a model-based identification approach are introduced in Section 4. Subsequently, results of parameter identification using simulated and experimentally measures frequency responses from two transformers are presented and discussed in Section 5. Finally, conclusions are given in Section 6.

II. ESTIMATION OF MODEL PARAMETERS

Model parameters are usually estimated using physical dimensions of a winding. In practice some simplification and approximations of winding geometrical structures are accepted which allow to apply analytical formulae [8, 9]. On the other hand, geometry simplifications can be avoided using finite-element method [12, 13] for parameter calculation. In both cases the frequency dependent behavior of resistive elements should be accounted as well as frequency dependent insulation properties. In this study, the analytical expressions for initial estimation of the model parameters are presented.

A. Capacitance and conductance

One of the common methods to calculate the ground and inter winding capacitances C between windings, tank (or core) is to use the expression for cylindrical capacitance having an axial height of the model section [9, 10, 13]. On the other hand, the evaluation of series capacitances K depends on winding types. For instance, for a disc type winding the series capacitance is determined by the amount of stored energy in the disc, which can be estimated by assuming the equal voltage drop across each disc and the existence of equip potential surfaces in the interdict space as stated in [9, 10, 13, 30]. Transformer insulation materials at capacitance calculation are usually represented by effective dielectric permittivity's calculated as proposed in [9,13]using dielectric material reference sources or additional test results. It is known that the insulation conductivity is frequency dependent due to dielectric losses characterized by tan ı. Therefore, expressions for series and ground conductance's g and G can be obtained using the well-known formulae [27, 28]:

$$G = C\omega \tan\delta_g$$

$$g = K\omega \tan\delta_s \quad (1)$$

Where tan ıg and tan ıs are the effective loss tangents of the insulation between winding and ground, and the intersection insulation respectively,

B. Inductance and resistance

Research reported in [8, 29] assumes that in the high frequency region above 10 kHz the core effect is not significant and can be neglected. Hence, the self and mutual inductances of model were calculated using air-core case expressions. This method showed a high degree of accuracy in comparison with the results performed on several experimental transformers with the core removed and substituted by a hollow metal cylinder. However, according to [13] the core effect has to be taken into account during inductance calculation in order to accurately model practical transformers. This can be achieved using the analytical expressions derived by Wilcox [31, 32] as described below, which are adopted in this study. In Fig. 2, two coils representing the kth and mth sections of a transformer winding are illustrated. These coils have Nkand Nmturns respectively wounded concentrically on a magnetic core of radius b at intersection distance z. Each coil is characterized by the average a, internal a1 and external a2 radii respectively, and cross section weight w and height h. The mutual impedance between the coils is given as [32]:

$$Z_{km} = sL_{km} + Z_{1(km)} + Z_{2(km)}, \quad (2)$$

Where s denotes the Laplace transform operator, Lkm corresponds to the mutual inductance upon the air-core assumption, Z1 (km) represents the impedance due to the flux confined to core and Z2 (km) is the impedance owing to leakage flux upon introducing the core. The second and

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third terms of Eq. (4) are thoroughly defined in [32]. Regarding the first term, Lkm, it is proposed to use the following approximate formula [32]:

$$L_{km} \cong \mu_0 N_k N_m \sqrt{a_k a_m}\,\frac{2}{k}\left[\left(1-\frac{k^2}{2}\right)K(k) - E(k)\right] \quad (3)$$

Where_0 is a free space permeability, K(_) and E(_) are complete elliptic integrals of the first and the second kinds respectively, and

$$k = \sqrt{\frac{4a_k a_m}{z^2 + (a_k + a_m)^2}} \quad (4)$$

However, a more precise calculation of the usual inductance scan be achieved by the following expression [31]:

$$L_{km} = 2\mu_0 N_k N_m a_k a_m \int_0^{\infty} I_1(\beta a_m) K_1(\beta a_k) \cos(\beta_z) d\beta \quad (5)$$

WhereK1 and I1 are the modified Bessel functions. In both Eqs,(5) and (7) in the case of self impedance calculation, E.g. Zkk, z = 0.2235(h + w) [32].

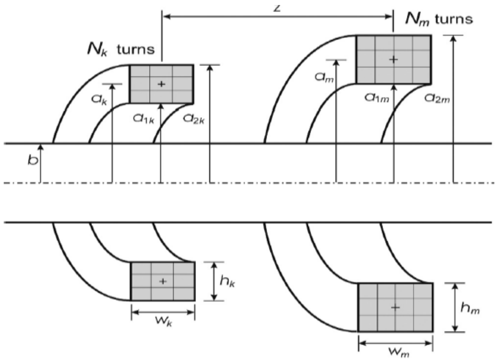

Fig. 2. Two coil sections on a core.

The calculation of winding resistance is the one of the major challenges due to eddy current effect in winding conductor and core. There are a lot of methods being proposed and utilized [8.11.12] for the resistance calculation, among them, the Dowell's approach [33] is one of the most referenced:

$$R = R_{dc}\Delta\left(\frac{\sinh(2\Delta)+\sin(2\Delta)}{\cosh(2\Delta)-\cos(2\Delta)} + \frac{2(p^2-1)}{3}\cdot\frac{\sinh(\Delta)-\sin(\Delta)}{\cosh(\Delta)+\cos(\Delta)}\right) \quad (6)$$

Where Rdc is the DC resistance of one-winding section, p is the number of layers in the section and

$$\Delta = \left(\frac{\pi}{4}\right)^{3/4} \frac{d^{3/2}}{\delta t^{1/2}} \quad (7)$$

in which d is the conductor equivalent diameter and t is the distance between the centers of two adjacent conductors. The skin penetration depth can be found as follows:

$$\delta = \sqrt{\frac{2}{\mu_0 \mu_r \sigma \omega}} \quad (8)$$

Where_ and _r are the conductor conductivity and relative permeability, respectively.

III. PSO ALGORITHM

Particle swarm optimization (PSO) is an algorithm modeled on swarm intelligence, that finds a solution to an optimization problem in a search space, or model and predict social behavior in the presence of objectives. The PSO is a stochastic, population-based computer algorithm modeled on swarm intelligence. Swarm intelligence is based on social-psychological principles and provides insights into social behavior, as well as contributing to engineering applications. The particle swarm optimization algorithm was first described in 1995 by James Kennedy and Russell C. Eberhart, The particle swarm simulates this kind of social optimization. A problem is given, and some way to evaluate a proposed solution to it exists in the form of a fitness function. A communication structure or social network is also defined, assigning neighbors for each individual to interact with. Then a population of individuals defined as random guesses at the problem solutions is initialized. These individuals are candidate solutions. They are also known as the particles, hence the name particle swarm. An iterative process to improve these candidate solutions is set in motion. The particles iteratively evaluate the fitness of the candidate

Solutions and remember the location where they had their best success. The individual's best solution is called the particle best or the local best. Each particle makes this information available to their neighbors. They are also able to see where their neighbors have had success. Movements through the search space are guided by these successes, with the population usually converging, by the end of a trial, on a problem solution better than that of non-swarm approach using the same methods. Each particle represents a candidate solution to The optimization problem, the position of a particle is influenced by the best position visited by itself i.e. its own experience and the position of the best particle in its neighborhood i.e. the experience of neighboring particles. When the neighborhood of a particle is the entire swarm, the best position in the neighborhood is referred to as the global best particle, and the resulting algorithm is referred to as the g best PSO. When smaller neighborhoods are used, the algorithm is generally referred to as the l best PSO. The performance of each particle is measured using a fitness function that varies Depending on the optimization problem, Each Particle in the swarm is represented by the following characteristics:

The current position of the particle .The current velocity of the particle the particle swarm optimization which is one of the latest evolutionary optimization techniques conducts searches uses a population of particles. Each particle corresponds to individual in evolutionary algorithm. Each particle has an updating position vector and updating velocity vector by moving through the problem space.

$$v_i^{k+1} = wv_i^k + c_1 rand_1(\ )x\left(Pbest_i - s_i^k\right) + c_2 x\left(Pbest_i - s_i^k\right)$$

$$S_i^{k+1} = S_i^k + V_i^{k+1}$$

Where, vi^k is the velocity of i at iteration k,
si^k is the current position of i at iteration k.

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C1 and c2 are positive constants and rand1 and rand2are uniformly distributed random number in [0,1].The velocity vector is range of [-Vmax,Vmax].In Velocity updating eq (1), eq (3) terms that creates new velocity are,

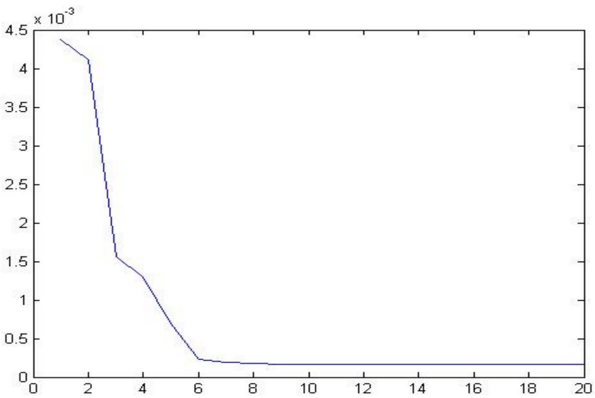
- Inertia term, forces the particle to move in the same direction as before by adjusting the old velocity.
- Cognitive term (Personal best), forces the particle to go back to the previous best position.
- Social Learning term, forces the particle to move to the best previous position of its neighbors.

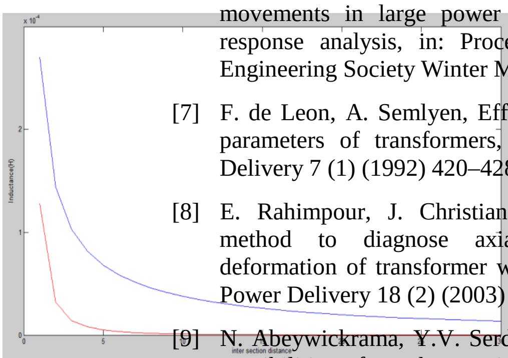
IV. SIMULATION RESULT

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 PSO, its total fitness value is given as Follows:

$$\min \sum_{j=1}^{s} \left\| H_0(\omega_j) - H(\omega_j) \right\| \times w_j$$

where H0(ωj) and H(ωj) $\in R^1$ are the reference and simulated with the identified parameters frequency responses at frequency ωj, j = 1, . . . , S, where S is the number of frequency points involved in PSO learning process and wjis 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 ant resonance frequencies and corresponding magnitude values. Therefore, as proposed in [17], the dimension of processed FRA data can be reduced by selection of points of resonance and ant resonance and its vicinities for more speedy analysis, which are weighted accordingly. Fitness functions convergence in 20 iteration by pso. Mutual inductances of the 1st section of the tested winding.





V. CONCLUSION

In this paper a model-based identification approach is formulated to determine the parameters of a well-known lumped parameter model of transformer winding with PSO learning. The analysis of the PSO performance using simulated reference frequency responses and a comparison with GA has shown that that PSO is more accurate for the considered case of the model-based parameter identification of transformer windings. There is a slight difference between the identified and preset parameters, which is negligible in a practical sense. The model parameter identification using experimental input admittance frequency responses shows that the proposed approach can be utilized for the experimental FRA results interpretation aiming at winding fault diagnosis. In the current study, only single-phase model transformers without a laminated core are considered. However, further study needs to be undertaken to verify the model by simulation studies of real transformers with core involved.

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