Winding Deformation Identification Using A Particle Swarm Optimiser with Passive Congregation for Power Transformers

W. H. Tang, S. He, Q. H. Wu, Z.J. Richardson

Abstract

This paper presents a new approach to identify distributed parameters of a lumped-element model for a power transformer. A simplified circuit of a lumped-element model is developed to calculate frequency responses of transformer windings in a wide range of frequency domain. In order to seek optimal parameters of the simplified circuit of the transformer, an intelligent learning technique, based on particle swarm optimiser with passive congregation (PSOPC), is developed to identify model parameters using frequency response measurements. Simulations and discussions are presented to explore potentials of the developed approach.

Index Terms – *Transformer modelling, winding deformation, particle swarm optimiser, passive congregation.*

I. INTRODUCTION

POWER transformers are specified to withstand the mechanical forces arising from both shipping and subsequent in-service events, such as faults and lightning. Once a transformer is damaged, replacement costs of a large HV transformer might reach up to 2.0 million pounds in the UK. If an incipient failure of a transformer is detected before it leads to a catastrophic failure, the transformer may be repaired on site or replaced according to a scheduled arrangement. Therefore, conditions of critical assets, i.e. transformers, for utilities should be closely and continuously monitored in order to ensure maximum uptime. The so-called condition-based maintenance may reduce risks of forced outages and damages to adjacent equipments.

Transformer interruptions in service and failures usually result from dielectric breakdown, winding distortion caused by short circuit withstand, winding and magnetic circuit hot spot, failure of accessories such as load tap changers and bushings, etc. Winding distortion faults may cause catastrophic failures of transformers such as dielectric breakdown and short circuit. A typical winding deformation found in a scrapped transmission transformer is shown in Fig. 1. The research into the field of winding deformation identification has drawn a great deal of attention for the last two decades. The frequency response analysis (FRA) test, first proposed in (Dick *et al*. 1978), is a very sensitive technique for detecting winding movement caused by loss of clamping pressure or by short circuit forces. This test has been used extensively to successfully detect winding movements. In Fig. 2, three frequency response curves of a three-phase transformer are displayed in a wide range of frequency up to 1MHz.

Figure 1 Typical winding deformation found in a scrapped transmission transformer

In most cases, a FRA technique is considered as a comparative approach with regard to a manufactory FRA baseline or a selected FRA reference trace. For instance, a root mean square (RMS) technique can be employed to calculate the difference between two frequency response curves, i.e. a FRA reference trace and a FRA trace of interest, which can further be used to identify a winding distortion fault. A set of factors derived from RMS techniques may provide indications of winding distortion to some extent. However it is difficult to quantify a fault assessment level and further to locate a fault according to the RMS factors. In this study, a model-based approach with intelligent learning is developed to tackle the above problems.

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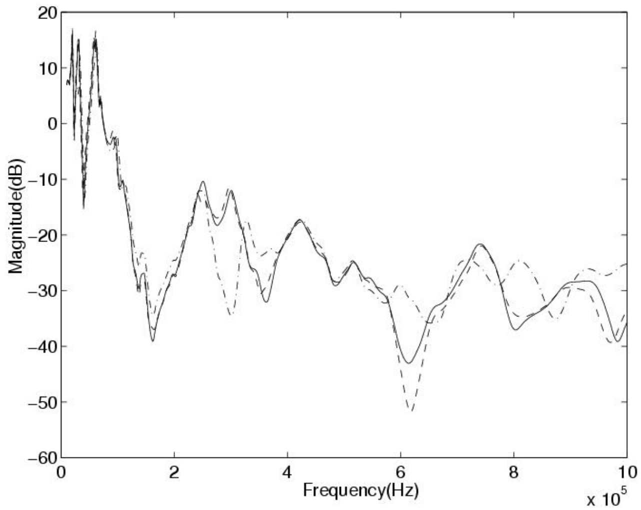

Figure 2 FRA traces of a three-phase power transformer

As known, modern model-based fault detection techniques are applied to provide continuous and unambiguous indications of transformer conditions (James *et al*. 1995). Generally speaking, a model-based system is constructed with well-understood mathematical descriptions, which can also be derived by intelligent learning. There are a variety of intelligent learning techniques, e.g. genetic algorithms (GAs), artificial neural networks, which have been utilised in a wide range of applications in power systems. For example, a GA has been successfully applied to parameter optimisation for generators (Ma *et al*. 1995) and power system dispatches (Wu *et al*. 1995). In (Tang *et al*. 2004), a simplified thermoelectric analogous model of oil-immersed power transformers has been obtained through GA learning, where a GA is utilised to seek the global solutions of the thermal parameters, based upon only a few on-site measurements instead of the experimental methods or off-line tests. A FRA test is a model-based technique, and the main problem of which is to interpret the observed frequency responses in order to identify both failures and failure tendencies for a transformer. It is considered in this study that, if variations of the distributed parameters of a transformer can be identified, a diagnosis procedure can then be implemented based on the values of the above identified parameters. Therefore, it is essential to establish a model-based approach for transformer windings, which is supported by a parameter identification technique for the purpose of frequency response analysis.

In this paper, an intelligent learning technique, i.e. a particle swarm optimiser with passive congregation (PSOPC), is employed to identify the parameters of a lumped-element model for a power transformer. The derived distributed parameters are further utilised to detect winding deformation faults. By using PSOPC, the distributed parameters of a ladder network model for a transformer can be identified based upon FRA measurements with a faster convergence rate. Simulation results and future work are also addressed.

II. Description of PSOPC

Particle swarm optimiser (PSO) was originally developed by a social-psychologist James Kennedy and an electrical engineer Russell Eberhart in 1995 and emerged from earlier experiments with algorithms that modelled the "flocking behaviour" seen in many species of birds (Kennedy *et al*. 1995, Kennedy 2001). It has been used to tackle various engineering problems (Yoshida *et al*. 2000). However, recent studies of PSO indicated that although the PSO outperforms other evolutionary algorithms in the early iterations, it does not improve the quality of the solutions as the number of generations is increased. In (He *et al*. 2004), passive congregation, a concept from biology, was introduced to the standard PSO to improve its search performance. Experimental results show that this novel hybrid PSO outperforms standard PSO on multi-model and high dimensional optimisation problems.

A. Standard Particle Swarm Optimisation

The population of PSO is called *swarm* and each individual is called a *particle*. For the i^{th} particle at iteration k, it has the following two attributes:

1) A current position in an N-dimensional search space

$$X_i^k = (x_{i,1}^k, ..., x_{i,n}^k, ..., x_{i,N}^k)$$

where

$$x_{i,n}^k \in [l_n, u_n],\ 1 \le n \le N$$

l_n and u_n is the lower and upper bound for the n^{th} dimension, respectively.

2) A current velocity V_i^k,

$$V_i^k = (v_{1,i}^k, ..., v_{n,i}^k, ..., v_{N,i}^k)$$

which is clamped to a maximum velocity

$$V_{\max}^k = (v_{\max,1}^k, ..., v_{\max,n}^k, ..., v_{\max,N}^k)$$

At each iteration, the swarm is updated by the following equations:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) \qquad (1)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad (2)$$

where P_i is the best previous position of the i^{th} particle (also known as *pbest*) and P_g is the global best position among all the particles in the swarm (also known as *gbest*), r_1 and r_2 are elements from two uniform random sequences on the interval [0,1], and ω is inertia weight which is typically chosen in the range of [0,1]. A larger inertia weight facilitates the global exploration and a smaller inertia weight tends to facilitate the local exploration to fine-tune the current search area (Shi 1998). Therefore the inertia weight ω is critical for the PSO's convergence behaviour. A suitable value for the inertia weight ω usually provides balance between global and local exploration abilities and consequently results in a better optimum solution. c_1 and c_2 are acceleration constants, which also control how far a particle will move in a single iteration. The maximum velocity $V_{\max}$ is set to be half of the length of the search space.

B. PSO with Passive Congregation (PSOPC)

The foundation of the development of PSO is based on the hypothesis: social sharing of information among conspecifics offers an evolutionary advantage. The PSO model is on the basis of (Kennedy *et al*. 1995):

1) the autobiographical memory which remembers the best previous position of each individual (*pbest*) in the swarm and

2) the publicised knowledge which is the best solution (*gbest*) currently found by the population.

From biology point of view, the sharing of information among conspecifics is achieved by employing the publicly available information *gbest*. There is no information sharing among the individuals except that *gbest* gives out the information to the all individuals. Therefore, for the i^{th} particle, the search direction will only be affected by 3 factors as shown in Fig. 3: the inertia velocity ωV_i^k, the best previous position *pbest*, and the position of global best particle *gbest*. The population is more likely to lose diversity and confine the search around local minima. From our experimental results, the performance of standard PSO is not sufficiently good enough due to its high-dimensional and multi-model nature.

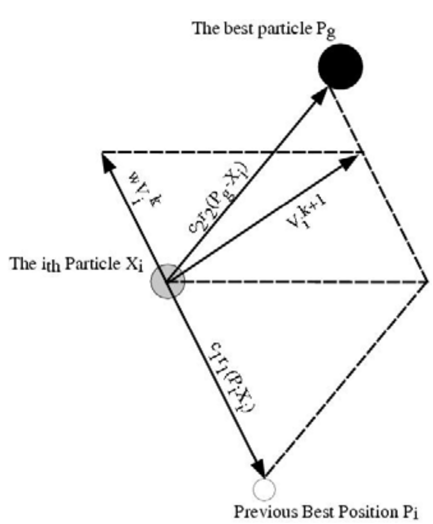

Figure 3 Search direction of the i^{th} particle in PSO

Biologists have proposed four types of biological mechanisms that allow animals to aggregate into groups: passive aggregation, active aggregation, passive congregation, and social congregation (Parrish *et al*. 1997). There are different information sharing mechanisms inside these forces. We found that the passive congregation model is suitable to be incorporated in the PSO model to improve the search performance. Passive congregation is the attraction of an individual to the entire group but does not display social behaviour. It has been discovered that in spatially well-defined congregations, such as fish schools, individuals may have low fidelity to the group because the congregations may be composed of individuals with little or no genetic relation to each other. In these congregations, information may be transferred passively rather than actively. Such asocial types of congregations can be referred as passive congregation.

Also, biologists have discovered that group members in an aggregation can react without direct detection of incoming signals from the environment, because they can get necessary information from their neighbours (Parrish *et al*. 1997). Individuals need to monitor both environment and their immediate surroundings such as the bearing and speed of their neighbours (Parrish *et al*. 1997). Therefore each individual in an aggregation has a multitude of potential information from other group members which may minimise the chance of missed detection and incorrect interpretations (Parrish *et al*. 1997). Such information transfer can be employed in the model of passive congregation. Inspired by this result, and to keep the model simple and uniform with the PSO, a hybrid PSO with passive congregation (PSOPC) has been developed as the following:

$$V_i^{k+1} = \omega V_i^k + c_1 r_1 (P_i^k - X_i^k) + c_2 r_2 (P_g^k - X_i^k) + c_3 r_3 (R_i^k - X_i^k) \qquad (3)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \qquad (4)$$

where R_i is a particle randomly selected from the swarm, c_3 the passive congregation coefficient and r_3 a uniform random sequence in the range of [0,1]. The interactions between individuals of PSOPC are shown in Fig. 4 and the pseudo code for the PSOPC is listed in Table I.

III. Ladder Network Model for Frequency Response Analysis

It is well known that, there is a direct relationship between the geometric configuration of the winding and core within a transformer and the distributed network of resistances, inductances and capacitances that make it up. In a wide range of frequency domain (2kHz < f < 2MHz), a transformer winding behaves as a complex ladder type network consisting of a series of inductances, capacitances, resistances and conductances. For a transformer winding with n sections, a simplified equivalent circuit, which was first proposed by (Dick *et al*. 1978), is shown in Fig. 5, where L_n denotes winding inductance per section, C_n ground capacitance per section, C_b bushing capacitance, K_n series capacitance per section, R_i input impedance, R_o output impedance and V_s lower voltage source signal. In theory, the distributed parameters of a ladder RLC network can then be determined based upon its frequency dependent responses.

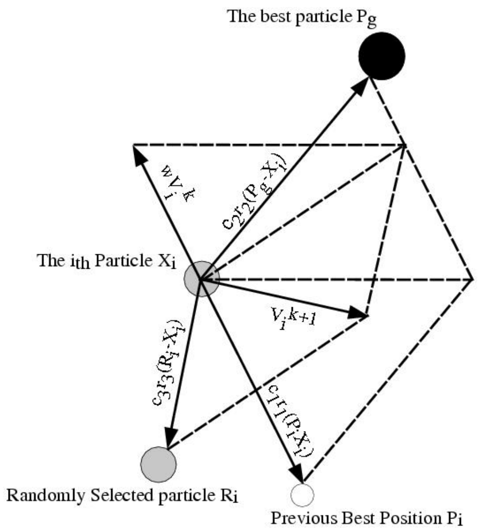

Figure 4 Search direction of the i^{th} particle in PSOPC

Set $k = 0$;
Randomly initialise positions;
Randomly initialise velocity;
WHILE (the termination conditions are not met)
FOR (each particle i in the swarm)

Check feasibility:	Check the feasibility of the current particle. If X_i^k is outside the feasible region, then reset X_i to the previous position X_i^{k-1} ;
Calculate fitness:	Calculate the fitness value $f(X_i)$ of current particle;
Update *pbest*:	Compare the fitness value of *pbest* with $f(Xi)$. If $f(X_i)$ is better than the fitness value of *pbest*, then set *pbest* to the current position X_i;
Update *gbest*:	Find the global best position of the swarm. If the $f(X_i)$ is better than the fitness value of *gbest*, then *gbest* is set to the position of the current particle X_i;
Update *Ri*:	Randomly select a particle from the swarm as R_i;
Update velocities:	Calculate velocities V_i using equation (5);
Update positions:	Calculate positions X_i using equation (6);

END FOR
Set $k = k + 1$;
END WHILE

Table I Pseudo code for the PSOPC

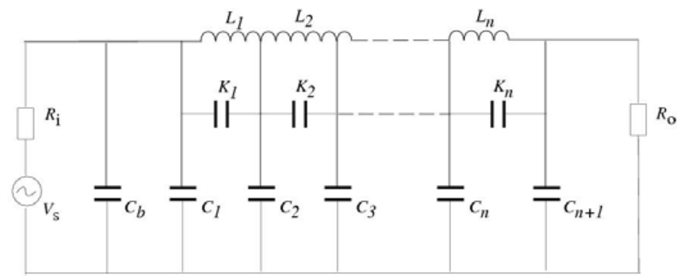

Figure 5 Ladder network model for single transformer winding

In industrial practice, a sweep frequency response analysis (SFRA) method measures the frequency responses of a winding at each frequency point of interest. An excitation source, i.e. V_s, generates a sinusoidal waveform at a constant magnitude, which is applied to the test terminals of a winding. Since the source is constant and can be maintained for a specified amount of time, designated digitisers have ample time to adjust their gain settings, resulting in higher dynamic range performance. As mentioned above, FRA is generally applied to a complex network of passive elements, which is depicted in Fig. 5. In order to calculate frequency responses of the lumped-element circuit in Fig. 5, the ladder network model is transferred into a circuit nodal graph in Fig. 5. The derived nodal graph contains n+1 nodes and m branches (m=3n+1), which is directly mapped to a winding with n sections with respect to the RLC circuit in Fig. 5.

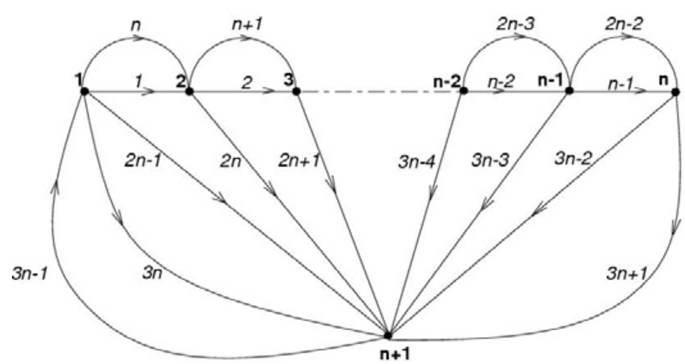

Figure 6 Circuit nodal graph of ladder network model

By applying circuit nodal analysis principles, the voltage of each node in Fig. 5 is calculated with the following equation:

$$U = G_n^{-1} I \qquad (5)$$

where U is the node voltage vector; G_n is the node conductance matrix; and I is the node current-excitation vector, i.e. $I = [-V_s/R_i,0,\ldots,0]^T$. It is obvious that the lumped-element winding model is the foundation for transformer FRA simulations, rule base extractions, distortion location analysis and other relevant research regarding transformer windings. The structure and the number of winding sections of the RLC circuit model can be varied to mimic a real transformer through MATLAB programming. On the basis of equation (5), the established ladder network model is employed to simulate high frequency responses of a transformer in the next section.

IV. Model-based Approach with Intelligent Learning

A. Derivation of Frequency Response

The goal of FRA is to measure the impedance model $Z(j\omega)$ of the test transformer, where $j\omega$ denotes the presence of a frequency dependent function and ω equals $2\pi f$. Since a FRA test method uses an impedance R_o to match measuring system, the output impedance R_i must be incorporated into the calculation of frequency response $H(j\omega)$. The relationship between $Z(j\omega)$ and $H(j\omega)$ is shown in equation (6):

$$H(j\omega) = \frac{V_{output}}{V_{input}} = \frac{R_o}{Z(j\omega)+R_o} \qquad (6)$$

The preferred method of engineers is to use the Bode Diagram, which plots the magnitude as $20\log_{10}^{H(j\omega)}$. Therefore, the unit of the derived frequency responses is decibel (dB), which is the form of lumped-element model outputs for model optimisation in the next subsection.

The distortion level of a winding distortion fault should be carefully assessed before removing a transformer from service to avoid an outage. Currently, there is not an effective method to scale and locate a winding distortion fault. It is considered that if prior-fault and post-fault parameters of a transformer model are known, the position and degree of a distortion fault may then be determined. Therefore, the proposed technique is used to search the optimal parameters by minimising the difference (i.e. fitness) between original frequency responses and simulated model outputs with PSOPC.

B. Fitness Function Used by PSOPC Optimisation

A PSOPC is employed to optimise the model parameters to achieve the minimum fitness, hence the outputs of the simplified circuit model have satisfactory agreements with the original frequency responses. Before implementing PSOPC and searching optimal parameters for a lumped-element model, a fitness function and other relevant arguments of a PSOPC programme should be defined. In this particular task, the errors between the original responses and the model outputs are defined as fitness. Thereby, for each individual (particle) of a population in PSOPC, its total fitness value is given as follows:

$$\min \sum_{i=1}^{N} \| u_{o_i} - a(G_n)^{-1} I \| \qquad (7)$$

where $u_{oi} \in R^1$ is the original frequency responses; $a \in R^{1xn}$ is a vector, i.e. $a = [0,\ldots,0,1]$; and N is the number of original frequency responses involved for PSOPC optimisation.

V. Simulation and Discussions

In order to verify the proposed approach to determine the parameters of a lumped-element model with PSOPC learning, simulations and optimisations are implemented in MATLAB environment. Firstly, a simulated FRA test is carried out to generate the frequency responses of a lumped-element model. The distributed parameters of the lumped-element model are predefined for illustrative purposes. Then, the parameters of the lumped-element model are identified using PSOPC based upon the simulated frequency responses. Results and future work are addressed in the end of this section.

A. The Simulations of FRA Test

When a transformer is subjected to an actual FRA test, the leads are configured in such a manner that four terminals are used. These four terminals can be divided into two unique pairs, one pair for the input and the other pair for the output. These terminals can be modelled in a two-terminal pair or a two-port network configuration. The following procedures are employed to simulate an actual FRA test:

1. According to the knowledge of a real transformer, the parameters of a lumped-element circuit are pre-set as L_n=10^5mH, K_n=100µF and C_n=100µF for each section of a winding. The number of winding sections is selected as 10 for simulation purposes.

2. After the pre-definition of model parameters and its structure, a sinusoidal waveform at a constant magnitude 1.0 is applied to the simplified circuit as input source at frequencies varying from 20Hz to 1MHz. Then, the generated frequency responses are recorded as dataset 1 using equations (7) and (8), which is employed as training targets for PSOPC optimisation.

B. Parameter Identification with PSOPC

Based upon dataset 1, the PSOPC technique is utilised to derive a set of parameters, which can represent a lumped-element transformer model with frequency responses close to dataset 1. The generation of PSOPC is set as 50 and its fitness function is defined as equation (7). The following steps describe the implemented PSOPC optimisation procedures:

1. By feeding frequency response dataset 1 through a RLC circuit model with 10 sections representing a winding, the parameters of such a model can then be determined with PSOPC optimisation.

2. The optimisation procedures follow the algorithms listed in Table I.

3. When the optimisation termination criterion is reached, the model outputs and dataset 1 are compared to verify the effectiveness of the proposed approach.

C. Results and Discussions

In Fig.7, the original frequency response trend and the calculated frequency response trend using the parameters found by PSOPC are displayed for comparison. Because the fitness did not decrease after 50 generations, there are still deviations between the two trends at the lowest peak point and the final fitness is 430 with respect to 400 sets of data. It is noted that, the simulated frequency response curve using the parameters identified by PSOPC learning is very close to the original responses of dataset 1. The identified parameters with PSOPC optimisation are $L_n = 0.939\text{x}10^5$mH, $K_n = 97.5\mu$F and $C_n = 96.5\mu$F, which are fairly close to the pre-set values. The results demonstrate that the proposed approach can find an accurate solution from a simulated FRA dataset.

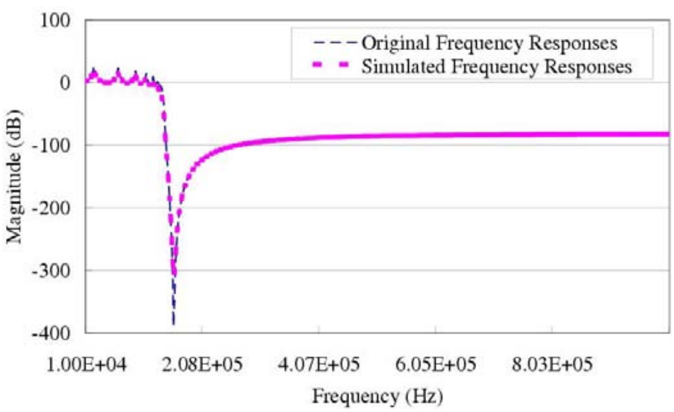

Figure 7 Comparison between the frequency responses (dataset 1) and the model outputs with PSOPC learning

In parallel, a GA technique is also utilised to identify the distributed parameters of the simulated winding model in accordance with dataset 1. However, the obtained results are not satisfactory regarding the difference between the original dataset 1 and the model outputs with GA learning. It is deduced that, PSOPC has comparable or even superior search performance for some hard optimisation problems with faster convergence rates (He *et al*. 2004), compared with other stochastic optimisation methods, such as GAs. In a PSOPC system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience and the experience of a neighbouring particle. The actions taken by each particle make use of the best position encountered by itself and its neighbour. Thus, a PSOPC system can combine local search methods with global search methods, which attempts to balance exploration and exploitation. In this research, after a comparison study between the PSOPC learning and the GA simulation, the following results have been derived:

1. An advantage of PSOPC is that, GAs have at least 4 parameters, i.e. mutation probability, crossover probability, selection probability and maximum generations, to be tuned; in comparison, PSOPC has only 2 parameters to adjust, i.e. inertia weight and maximum generations, that makes it particularly attractive from a practitioner's point of view.

2. Experiments have been carried out with both the GA learning and the PSOPC modelling, which have involved the same fitness function in Section IV-B and the same data extracted from dataset 1. With regard to a predefined fitness, PSOPC has shown a faster convergence rate than GAs in this particular task.

D. Future work

In the current study, only simulations are involved to determine the parameters of a lumped-element transformer model. In the next stage, actual FRA datasets with different time stamps will be used for parameter identification and comparison. Hence, by comparing the evolution of the obtained parameters after optimisation, the interpretation of a certain fault can be deployed for winding distortion problems.

- Theoretically speaking, a frequency width for FRA tests should be from zero to infinite for parameter identification, which is difficult to achieve in a practical situation. In this study, an appropriate frequency width is obtained through simulation regarding the proposed transformer model.

- In the next stage, the proposed model and the developed software packages will be used to analyse frequency responses for real on-site power transformers. In parallel, several modifications may be made to enhance the functions of the developed approach, e.g. choose different topologies of the simplified circuit model with respect to a wide frequency bandwidth.

VI. CONCLUSIONS

In summary, a new approach is proposed to determine the parameters of a lumped-element transformer model with PSOPC learning. A circuit nodal analysis technique has been applied to develop a general model for different types of transformers with variant winding sections. The PSOPC learning has delivered a satisfactory performance during optimisation based upon original FRA targets. Compared with other parameter estimation techniques, the proposed PSOPC has the advantages of less parameters to adjust, faster convergence rate and more local searches. There is a slight difference between the identified parameters and the preset parameters, which is negligible in a practical sense. It can also be deduced that the proposed approach is applicable and practical, which can be utilised for fault identification and trend analysis aiming at winding distortion problems. Additionally, as the method has a simple form and a clear physical meaning, it holds significant potential for condition assessment of power transformers.

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