A Particle Filtering Based Approach for Transformer Winding Degradation Prognostics

Haifeng Guo, Aidong Xu, Kai Wang
Key Laboratory of Networked Control Systems, Chinese Academy of Sciences
Shenyang Institute of Automation, Chinese Academy of Sciences
Shenyang, China
guohaifeng@sia.cn, xad@sia.cn, wangkai@sia.cn

Xiongfeng Zhang
Department of Electronic Systems Engineering, Hanyang University, Ansan, 15588, Korea
xiongfeng2016@gmail.com

Haifeng Guo, Xiaojia Han, Yang Liu
University of Chinese Academy of Sciences
Beijing, China

Haifeng Guo, Decai Lv
Liaoning Institute of Science and Technology
Benxi, China
174800410@qq.com

Abstract*—When the transformer works for a long time, its winding is gradually deteriorated with time, and the fault phenomena such as winding short circuit or circuit break lead to serious power supply accidents. Under high temperature conditions, this paper analyzes the degradation process of the winding, and determines that the resonant frequency can be used as testing index of its degradation process. Therefore, the resonant frequency is used to monitor the performance degradation state of the transformer winding and realize the advance prediction, which can effectively avoid accidents. Accurate prediction of system reliability is of plenty of importance to engineering systems for accomplishing the designate function and system safety management. As the concerned system is getting complicated and more sufficient health monitoring measurement is available, the traditional reliability prediction schemes resorting to only one kind of prediction approaches, model-based or data-driven, begin to show their limitations. This paper proposes a PF prognostic method by combining traditional model approaches. The effectiveness of the proposed method is verified by thermal degradation experiments. This method improves the reliability of power system and is conducive to the rapid development of smart grid.

Keywords*—*degeneration, insulation failure, PF, resonant frequency, premature prognostic

I. INTRODUCTION

Transformer is the main equipment of electric energy conversion, which plays a very important role in the power system. While the transformer fails, it will lead to extremely serious accidents. Therefore, it is very important to find the potential fault of the transformer in time. This is an important measure to ensure the safe operation of the power system [1-5]. In the transformer assembly, winding is one of the key components of the transformer. According to literature [6-8], the transformer winding fault accounts for 70%-80% of the total number of transformer faults, and the insulation failure rate of the winding is the highest. The common dry transformer winding in the industrial system is composed of several transformer winding. The insulation fault of the winding is mainly caused by the interturn or interlayer short circuit fault of the transformer winding, and eventually leads to the transformer's fault. Therefore, it is of great significance to study the status of the transformer windings before turn to turn short circuit, and to take effective measures to evaluate the state of the transformer, which is of great significance to avoid the serious accidents of the transformer effectively [9-10].

Activities of health monitoring and life prediction are of great importance to engineered systems. Generally, the reliability prediction approaches can be categorized as [11-12]:1) model-based approaches, 2) data-driven approaches and 3) hybrid approaches. Model-based prediction technology relies on combining the operating mechanism and physical failure model [13-14]. Nevertheless, inadequate modeling information and changes in physical behavior or environmental conditions may limit its prediction accuracy [15]. Data-driven approaches, using artificial intelligence techniques to track the degradation process, improve the accuracy greatly [16-17]. However, it may result in inferior results and large variations due to the absence of complete data [18-19]. Hybrid approaches [20-22] are produced based on model-based and statistical approaches. However, the statistical technology is only used to update the physical model parameters, not for reliability prediction. In case of an inaccurate physical model, this hybrid technology will increase computational cost but un-improve the predictive accuracy. We can conclude that the limitations of these algorithms lie on: (i) the selected algorithm can't reasonably make full use of physical prior knowledge and measurement data; (ii) it can be less accurate or has poor robustness.

To address the above-mentioned problems, in this work, a new reliability prediction method is proposed by combining the superiorities of model-based approaches and data-driven approaches. The ensemble method can be structured in two phases: 1) Employing the model-based and the data-driven

2166-5656/18/$31.00 ©2018 IEEE
DOI 10.1109/PHM-Chongqing.2018.00125

technology respectively to obtain forecast data. 2) The prediction results of such methods are weighted-sum to derive the ensemble data.

The rest of the paper is organized as follows: Section II is devoted to describe the analysis of failure mechanism for winding insulation degradation. The proposed prognostic approach based on particle filter technique is presented in Section III. The detailed implementation for the study is described in Section IV. Finally, from this work, some conclusions are deducted and presented in the last section of the paper.

II. Analysis Of Failure Mechaniism for Winding Insulation

The wire consists of the following two parts: the conductor, which is usually copper, and insulation, which is made by a kind of polyimide (Fig 1).

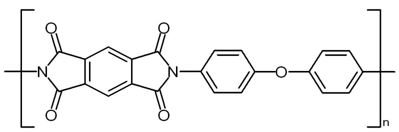

Fig 1 Chemical structure of "Kapton" polyimide

As shown in Fig. 2, the ECM of the inductor proposed in [23] is used in this paper. Considering that the windings of the transformer winding have a distributed parasitic capacitance associated with the insulation on the magnet wire, the distributed capacitance of the winding can be modeled by a lumped capacitance, C connected between the terminals of the winding.

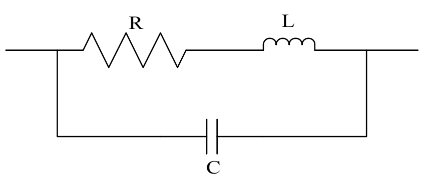

Fig. 2. ECM of the transformer winding.

According to the ECM, the winding impedance can be expressed as shown:

$$Z(w) = R(w) + jX(w) \tag{1}$$

where $j = \sqrt{-1}$ is the imaginary unit. The real part is called "resistance", and the imaginary part is called "reactance". Resistance is the opposition to the electrical current, and reactance is the opposition to a change in voltage or current due to capacitive or inductive behavior. The impedance of an ideal resistor is purely real (R), while the impedance of an ideal inductor (jwl) or capacitor $(1/jwc)$ is purely imaginary. Positive reactance is referred to as "inductive reactance," while negative reactance is referred to as "capacitive reactance." The resonance of an electrical circuit is the frequency at which the inductive reactance is exactly balanced by the capacitive reactance.

The resonant frequency is defined as the frequency at which reactance is 0, and can be obtained by splitting the impedance into its real (resistance) and imaginary (reactance) parts, then setting reactance equal to zero and solving for frequency. Thus, the resonant frequency can be expressed as shown in eq. (2).

$$\mathrm{X}_L(w_r) + \mathrm{X}_C(w_r) = 0 \qquad (w_r = 2\pi f) \tag{2}$$

The transformer winding is mainly multi turns of wire wound together, polymer insulation layer thickness of $D_p = D_0 - D_C$ (where D_0 is the transformer wire cross-section diameter including the thickness of the insulating layer, and D_C is transformer wire cross-section without including the thickness of the insulating layer). For a round conductor, the location of each elementary surface can be described by one angular coordinate, as shown in Fig. 3. As a consequence, the elementary capacitance also depends on the angular coordinate.

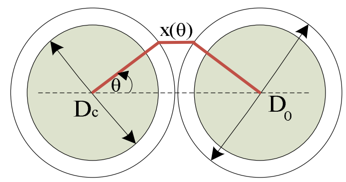

Fig. 3. Assumed path x(θ) between two adjacent turns

Due to influence of the high temperature stress, insulation layer changes thinner and thinner with increasing of aging time, until the emergence of interturn short circuit or short circuit condition between layers (Fig.4).

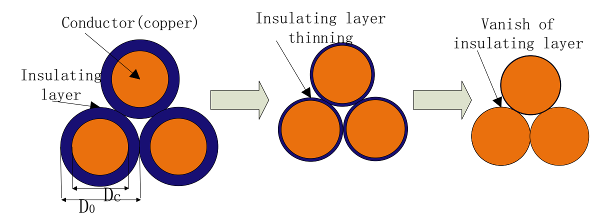

Fig. 4. Failure process of winding insulation

Li Bing [24] constructed a formula for calculating parasitic capacitance of multilayer winding：

$$C = k(C_{tt}) \tag{3}$$

k is a constant, which is related to the number of winding and the number of turns per layer; C_{tt} is the parasitic capacitance between turns (Fig. 5).

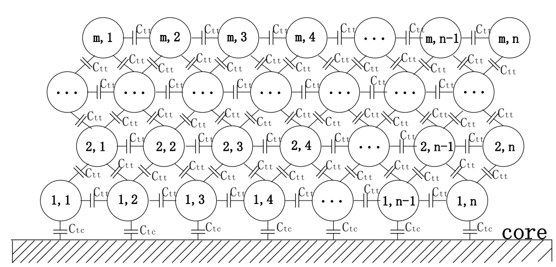

Fig. 5. Coil parasitic capacitance network

The total capacitance of the basic cell equals the parallel combination of the capacitances of the parts into which the basic cell has been subdivided

$$C_{tt} = \varepsilon_0 \, l_t \, [(\frac{\varepsilon_r \, \theta^*}{\ln D_0/D_c} + \cot(\frac{\theta^*}{2}) - \cot(\frac{\pi}{12})] \quad (4)$$

where θ^* is given by (3)

$$\theta^* = \arccos(1 - \frac{\ln D_0/D_c}{\varepsilon_r}) \quad (5)$$

Where ε_0 is Vacuum dielectric constant, and ε_r is Relative dielectric constant.

According to the winding insulation failure mechanism analysis, and with the winding aging, the relative displacement of the winding conductor and insulation will change, due to the loss of the insulation material between the conductor and insulation. These causes will lead to capacitance change and, consequently, resonant frequency change. Therefore, the resonant frequency be used as the health indicator for online health monitoring of the winding insulation considering that it can be measured in situ by injecting high-frequency signals into the winding. According to the winding insulation failure mechanism analysis in this section, the resonant frequency can be used as the health indicator for health monitoring of the winding insulation.

III. Particle Filter Prognostic Approach

To estimate and predict winding's health state, particle filter (PF) method is herein selected thanks to its ability to efficiently solve a wide range of estimation and prediction problems(non-linear, non-gaussian problems). Another advantage of PF is that it allows to easily online update the model parameters as observations become available. In the following subsection, the basic idea of PF is briefly recalled.

A. Principle of Particle Filter

PF is a statistical filtering method based on Bayesian Monte Carlo framework. It uses Monte Carlo method to solve integral computing in Bayesian estimation, the Monte Carlo method is based on the law of large numbers. The basic idea of PF is: first, a set of random samples are generated in state space according to the empirical conditional distribution. These random samples are called particles. Then, particle weights are adjusted according to the observation value, these adjusted particles information can correct initial empirical conditional distribution. When the number of samples is large, the Monte Carlo method approaches to the real posterior probability density function of state variables.

The dynamic state space model is generally used to describe the winding degradation trend over time. The dynamic state space model consists of state model and observation model:

$$x_k = f(x_{k-1}) + u_{k-1} \quad (6)$$

$$y_k = h(x_k) + v_k \quad (7)$$

x_k and y_k are state variable and observation variable of current moment of system. u_{k-1} and v_k are process noise and observation noise with zero mean. They are independent with each other. It is generally assumed that state transition process follows the first-order Markov model, it means the state of current moment x_k is only related to the state at the previous moment x_{k-1}.

Bayes filtering contains two phases: prediction phase and update phase. In the prediction phase, state model is used to predict prior probability density $p(x_k|y_{k-1})$. In the update phase, the prior probability density is corrected with knowledge of observation value and the posterior probability density $p(x_k|y_k)$ is obtained. For convenience, $X_k = x_{0:k} = \{x_0, x_1, \ldots, x_k\}$ and $Y_k = y_{0:k} = \{y_0, y_1, \ldots, y_k\}$ respectively represent state values and observation values from the beginning to the k moments.

In the prediction phase, the probability density function $p(x_{k-1}|Y_{k-1})$ in $k-1$ moment is assumed to be known, and the prior probability density is obtained from $p(x_{k-1}|Y_{k-1})$ by Bayesian filtering with the knowledge of Y_{k-1} and x_{k-1}:

$$p(x_k|Y_{k-1}) = \int p(x_k|x_{k-1}) p(x_{k-1}|Y_{k-1}) \, dx_{k-1} \quad (8)$$

After obtaining the latest observation value y_k, the prior probability density is updated by Bayes formula to obtain the posterior probability density:

$$p(x_k|Y_k) = \frac{p(y_k|x_k) p(x_k|Y_{k-1})}{p(y_k|Y_{k-1})} \quad (9)$$

$p(y_k|Y_{k-1})$ is normalization constant that $p(y_k|Y_{k-1}) = \int p(y_k|x_k) p(x_k|Y_{k-1}) \, dx_k$ .The conditional mean of the posterior probability density will be used as estimation value of system state.

$$x_k = E[f(x_k)|Y_k] = \int f(x_k) p(x_k|Y_k) \, dx_k \quad (10)$$

Bayesian filtering is a complete state estimation process. However, except for some special system models (such as linear and Gaussian), integral operation in Bayesian filter is difficult to obtain the closed-form solution of posterior probability for the general nonlinear and non-Gaussian systems. Therefore, only suboptimal solutions can be found and Monte Carlo simulation is an effective method for obtaining suboptimal solutions.

The core idea of Monte Carlo simulation is to use a large number of sample points to approximate the posterior probability distribution of variables to be estimated. Independent and identically distributed random samples $x_k^{(i)} (i = 1,2, \ldots, N)$ are extracted from posterior probability density function and posterior probability density function $p(x_k|Y_k)$ is approximated as:

$$p(x_k|Y_k) \approx \frac{1}{N} \sum_{i=1}^{N} \delta\left(x_k - x_k^{(i)}\right) \quad (11)$$

$\delta(x - x_k)$ is drac function, when $x \neq x_k$, $\delta(x - x_k) = 0$ and $\int \delta(x) dx = 1$. Sum is used to estimate system state value instead of integral:

$$x_k = E[f(x_k)|Y_k] = \int f(x_k)p(x_k|Y_k)\,dx_k = \frac{1}{N}\sum f\left(x_k^{(i)}\right) \quad (12)$$

In practice, because the specific form of posterior probability density can't be known, it's impossible to sample directly from posterior probability density. A easy sampling importance density function. And $q(x_k|Y_k)$ is introduced in PF algorithm. With the increasement of particle number, the sum of random samples weights gradually approach the real posterior probability density. The estimation of system state is:

$$E[f(x_k)|Y_k] = \frac{1}{N}\sum_{i=1}^{N} f(x_k^{(i)})\frac{p(x_k^{(i)}|Y_k)}{q(x_k^{(i)}|Y_k)} = \frac{1}{N}\sum_{i=1}^{N} f(x_k^{(i)})w_k^{(i)} \quad (13)$$

The recurrence form of weight of particle i is:

$$w_k^{(i)} = w_{k-1}^{(i)}\frac{p(y_k|x_k^{(i)})p(x_k^{(i)}|x_{k-1}^{(i)})}{q(x_k^{(i)}|X_{k-1}^{(i)},Y_k)} \quad (14)$$

The state transition probability density function $p(x_k|x_{k-1})$ is used as the importance probability density function and the form of weight is:

$$w_k^{(i)} = w_{k-1}^{(i)}\ p\left(y_k\middle|x_k^{(i)}\right) \quad (15)$$

The weights of particles should be normalized:

$$\overline{w_k}^{(i)} = \frac{w_k^{(i)}}{\sum_{i=1}^{N} w_k^{(i)}} \quad (16)$$

The estimation of state at time k is:

$$x_k = \sum_{i=1}^{N} x_k^{(i)}\overline{w_k}^{(i)} \quad (17)$$

B. Particle Filter – Based Prognostic Approach

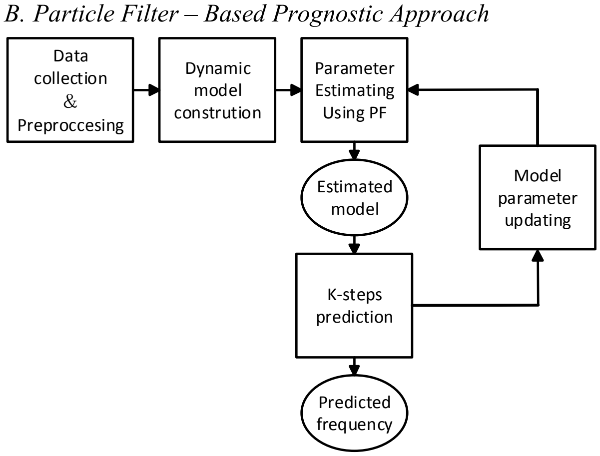

Fig. 6. ECM of the transformer winding.

We propose here in Fig.6 a procedure to deal with the problem of unknown models. The main idea of the proposed procedure is to establish dynamic models (models with unknown parameters) based on the dependence and expert opinion analysis, and then use Particle Filter as a tool for testing different dynamic models, estimating the unknown parameters of the dynamic models, updating estimated parameters, estimating and predicting the temperature.

For more detail, the procedure contains the following steps:

·Step 1:Data collection and Preprocessing. This step is devoted to removing all unexpected phenomena that can lead to an incorrect identification of the system models.

·Step 2: Dynamic model construction. The objective is to identify all factors that influence the state and observation process. This could be done by using different dependence analysis techniques such as Pearson dependence coefficient, non-linear dependence coefficient, principle component analysis, expert opinions, etc. The models are then designed as functions of influence factors with unknown parameters.

·Step 3: Parameter and Temperature estimating using Particle Filter. The PF is used to estimate the unknown parameters of the designed dynamic models. The temperature is then can be estimated thanks to the estimated models. To improve the performance of particle filter in estimating the unknown parameters of the models, a combination of Auxiliary Particle Filter (APF) and Regularized Particle Filter (RPF) named Regularized PF is chosen.

·Step 4: K-steps prediction and parameter updating. The designed models and their estimated parameters are then tested and used to predict the temperature within the horizon of K-steps ahead. The parameters can be updated or re-estimated during the prediction horizon or at its ending.

We will explain clearly step by step the application of the proposed process to our case study in the following sections.

IV. Applition To Voltage Transformer Winding Degradation

A. Experimental platform

The experimental and measurement setups for the experiments presented in this paper are given in this section. The setups are meant to elicit the degradation of the insulation and provide winding impedance measurements that correspond to insulation degradation by thermal aging failure mechanism due to exposure high temperature environment.

The transformer winding used was primary winding of transformer with polyester-imide-based enamel. The dc resistance of magnet wire was about 72.1Ω.

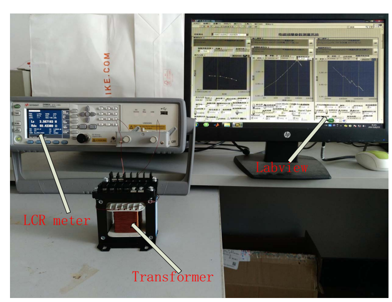

Fig. 7. ECM of the transformer winding.

The winding terminals were connected to an Agilent E4980A LCR(inductance–capacitance–resistance) meter, which is capable of take impedance measurements at frequencies ranging from 100 Hz to 1MHz. The connection was made using the Agilent 16047E four-terminal fixture. A schematic of this connection is shown in Fig. 7. The LCR meter was controlled externally and reactance was measured at 1001 distinct frequencies over its entire spectral range, equally spaced in the base-1000 domain, with a signal amplitude of 500mv rms.

The degradation reactance data can be represented as a vector of measurement times and a matrix of reactance values that are time (t) and frequency (f = ω/2π) dependent.

$$t = [t_0 \ t_1 \ t_2 \cdots t_T] \tag{18}$$

$$X = \begin{bmatrix} X(t_0, f_1) \, X(t_1, f_1) \dots X(t_T, f_1) \\ X(t_0, f_1) \, X(t_0, f_1) \cdots X(t_0, f_1) \\ \vdots \quad \vdots \quad \vdots \quad \vdots \\ X(t_0, f_N) \ (t_1, f_N) \cdots X(t_T, f_N) \end{bmatrix} \tag{19}$$

In (19), T is the total number of spectra measured (degenerate cycle number), and N is the total number of frequencies at which reactance is measured (501 in these experiments). With the aid of formulas (19) and (5), the resonant frequency of the transformer winding is obtained.

B. Data collection and processing

According to the experimental platform, the reactance data is obtained from the transformer winding every 18 hours a period, and using the formula (2), obtain the resonant frequency of the corresponding aging time, as shown in Table 1. And Fig.8 show the resonant frequency from transformer winding insulation degradation.

TABLE I AGING TIME AND RESONANT FREQUENCY

Aging time	Resonant frequency	Health index	Aging time	Resonant frequency	Health index
0h	722015.4196	1	396h	691215.387	0.953401
18h	714109.3696	0.984978	414h	690902.237	0.952969
36h	707676.0263	0.976105	432h	691952.487	0.954417
54h	706419.8827	0.974372	450h	691967.043	0.954437
72h	707317.9662	0.975611	468h	691956.214	0.954422
90h	707302.8484	0.97559	486h	692186.627	0.95474
108h	706174.6776	0.974034	504h	691452.51	0.953728
126h	704590.7754	0.971849	522h	691401.866	0.953658
144h	700716.4098	0.966505	540h	692118.335	0.954646
162h	701173.9685	0.967137	558h	692404.953	0.955041
180h	697036.8755	0.96143	576h	686714.824	0.947193
198h	698045.1556	0.962821	594h	689418.647	0.950922
216h	696359.6202	0.960496	612h	690830.427	0.95287
234h	695689.9508	0.959572	630h	689808.588	0.95146
252h	695493.8333	0.959302	648h	686516.568	0.946919
270h	693680.4388	0.956801	666h	686741.711	0.94723
288h	695843.7683	0.959785	684h	685805.105	0.945938
306h	691297.8578	0.953514	702h	687810.77	0.948705
324h	691883.7229	0.954322	720h	685331.212	0.945284
342h	692751.0959	0.955519	738h	684741.768	0.944471
360h	692571.6967	0.955271	756h	683983.583	0.943426
378h	692934.0513	0.955771	774h	685528.01	0.945556

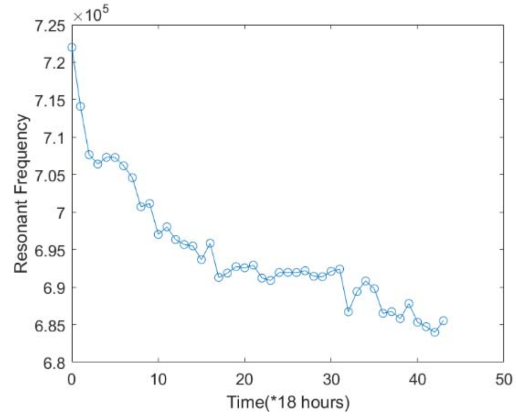

Fig. 8. Resonant frequency from winding insulation degradation

In order to directly reflect the degradation degree of translator, the health index (0-1) is introduced as an indicator of the health of the winding. Therefore, Resonant frequency is normalized, as shown in Table 1.

C. Prediction of resonant frequency using PF

In this paper, the state equations and observational equations of the following (20) formula are obtained by combining historical data and empirical models.

$$\begin{cases} f_{k+1} = f_k + \beta_1 exp\left(-\frac{\beta_2}{T\Delta t_k}\right) + u_k \\ HI_k = \frac{f_k}{f_1} + v_k \end{cases} \tag{20}$$

u_k and v_k are process noise, f_k and f_{k+1} is resonant frequency of k and $k+1$ aging period, β_1 and β_2 model parameters, and *HI* is health index. T is the accelerating aging temperature.

The data of 360 hours aging time is used as historical data to predict the degenerate state of the winding. As shown in Figure 9, the particle filter can basically track the degenerate path of the winding. And as shown in table □, the accuracy relative error of the prediction result is within a reasonable range, and with the increase of data, the accuracy of prediction is also improved.

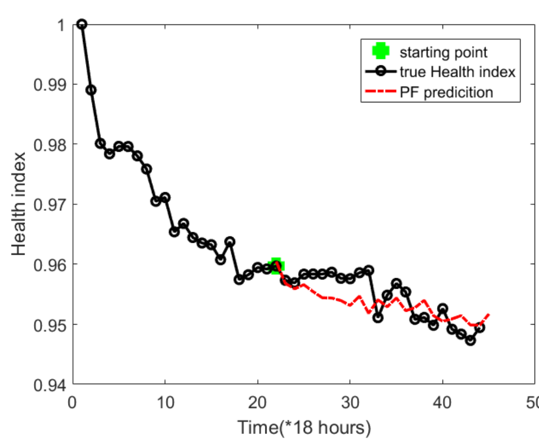

Fig. 9. Particle file prediction from winding insulation degradation

TABLE ERROR ANALYSIS OF PARTICLE FILTER PREDICTION

Aging time(hour)	Actual value	Predictive value	Relative error (%)
378h	0.95577	0.95948	0.37077
396h	0.9534	0.9582	0.479801832
414h	0.95297	0.95548	0.250966667
432h	0.95442	0.96313	0.870952629
450h	0.95444	0.95602	0.158195314
468h	0.95442	0.95607	0.164891909
486h	0.95474	0.95899	0.425422229
504h	0.95373	0.95892	0.519502795
522h	0.95366	0.95719	0.353131851
540h	0.95465	0.96131	0.666827552
558h	0.95504	0.95606	0.101459829
576h	0.95472	0.95347	0.627644701
594h	0.95092	0.95114	0.021489
612h	0.95287	0.95244	0.042912922
630h	0.95146	0.95457	0.310956623
648h	0.94692	0.94743	0.051148722
666h	0.94723	0.94929	0.206492996
684h	0.94594	0.94462	0.131341296
702h	0.9487	0.94983	0.112125897
720h	0.94528	0.94575	0.04649834
738h	0.952	0.94479	0.03223709
756h	0.95279	0.94443	0.1005281
774h	0.95075	0.94549	0.006100007

V. CONCLUTION

This paper presents a particle filter method to predict the performance degradation of transformer winding. The first step of this paper is to establish the performance degradation mechanism model of transformer winding. The resonant frequency of transformer winding is determined as health monitoring parameter, and the thermal acceleration degradation is realized. Based on normalization, the resonant frequency is used as a health index, and particle filter is used to verify its effectiveness in predicting the performance degradation of the transformer winding. The validity of the selected health monitoring parameters is verified by the test and data fitting technique. It lays the theoretical and experimental basis for the final realization of the "self-cognition" state monitoring of the transformer winding. This method improves the reliability of power system and is conducive to the rapid development of smart grid. However, in accelerated aging tests, some data are affected by external factors. In this paper, due to the lack of de-noising of the data, the prediction of particle filter has a certain deviation. Therefore, the future work needs to improve the accuracy of particle filter prediction.

ACKNOWLEDGMENT

This work is supported by the Natural Science Foundation of China under contract 71661147005 and Ministry of industry and information technology of the People’s Republic of china “Research and verification on the standards of operation management and equipment interconnection and interoperability in digital workshop of robot manufacturing”

REFERENCES

[1] KULKARNI S V, KHAPAEDE S A. Transformer Engineering: Design, Technology and Diagnostics [M]. Boca Raton: CRC Press, 2012.

[2] Liao Ruijin, Yang Lijun, Zheng Hanbo. Reviews on Oil-Paper Insulation Thermal Aging in Power Transformers[J]. Transactions of China Electrotechnical Society, 2012, 27(05): 1-12.

[3] Guo Chuangxin, Wang Yue, etal. Time-varying outage model for transformers representing internal latent fault[J].Proceedings of the CSEE,2013, 33(01) : 63-69(in Chinese)

[4] Zhu Yongli ,Yin Jinliang . Study on application of multi-kernel learning relevance vector machines in fault diagnosis of power transformers[J].Proceedings of the CSEE,2013,33(22) : 68-74(in Chinese).

[5] BAI Cuifen, GAO Wensheng, CHENG Jianwei, Tusongjia Kari, LIU Tong, MA Yi. Failure Rate Analysis of Transformers Based on Semi-Markov Process[J]. High Voltage Engineering, 2015,41(12) : 3916-3921.

[6] Yao Qinglin, LIU Xing, LI Ruisheng. New Nertral Transverse Differential Protection of Furnace Transformer with One Core[J], Automation of Electric Power Systems, ,2013,07:99-101.

[7] Wang Nan, Yang Hong, Liu Baocheng. Analysis of Interturn Short Circuit Fault in 35kV Transformer[J]. TRANSFORMER, 2013,10:60-64.

[8] Huang Dengfeng, Yu Weiyong. A Fuzzy SET Theory Based Protection Algorithm for Turn to Turn Fault of Power Transformer and ITS Simulation[J]. Power System Technology,2002,01:11-14

[9] P.A.A.F.Wouters, A.van Schijndel, and J.M.Wetzer. Remaining lifetime modeling of power transformers: individual assets and fleets[J]. IEEE Electrical Insulation Magazine, 2011, 27(3): 45-51.

[10] Wang Cheng, Huang Honghua. Analysis and Treatment of Turn-to-turn Short-circuit Fault in Transformer[J], Electric Power Science and Engineering, 2012, 01:46-49.

[11] G.W. Vogl, A.B. Weiss and M. Helu, “A review of diagnostic and prognostic capabilities and best practices for manufacturing[J].” Journal of Intelligent Manufacturing, pp.1-17, 2016.

[12] V George, L. Frank, R. Michael, H. Andrew and W. Biqing, “Intelligent fault diagnosis and prognosis for engineering systems[J].” John Wiley&Sons, Beiqing, 2006.

[13] HU Changhua, SHI Quan, SI Xiaosheng, ZHANG Zhengxin.Data-driven life Prediction and Health Management:State of the Art[J]. Information and Control,2017, 46(1): 72-82.

[14] P Baraldi, M. Compare, S. Sauco and E. Zio, “Ensemble neural network-based particle filtering for prognostics[J].” Mechanical Systems and Signal Processing, vol. 41, no. 1, pp. 288-300, 2013.

[15] E. Zio and G. Peloni, “Particle filtering prognostic estimation of the remaining useful life of nonlinear components[J].”Reliability Engineering&System Safety, vol. 96, no. 3, pp. 403-409, 2011.

[16] M. Jouin, R. Gouriveau, D. Hissel, M. Pra and N. Zerhouni, “Particle filter-based prognostics:Review, discussion and perspectives,” Mechanical Systems and Signal Processing, vol. 72, pp. 2-31, 2016.

[17] M.S. Arulampalam, S. Maskell, N. Gordon andT.Clapp, “A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking[J].” IEEE Transactions on signal processing, vol. 50, no. 2, pp. 174-188, 2002.

[18] E Gustafsson, “Particle filter theory and practice with positioning applications[J].” IEEE Aerospace and Electronic Systems Magazine, vol. 25, no. 7, pp. 53-82, 2010.

[19] D. An, J.H. Choi and N.H. Kim, “Prognostics 101: A tutorial for particle filter-based prognostics algorithm using Matlab[J].” Reliability Engineering&System Safety, vol.115, pp161-169, 2013.

[20] M. Dalal, J. Ma and D. He, “Lithium-ion battery life prognostic health management system using particle filtering framework[J].” Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, vol. 225, no. 1, pp. 81-90, 2011.

[21] S. Butler, F. O'Connor, D. Farren and J.V. Ringwood, “A feasibility study into prognostics for the main bearing of a wind turbine[J].” IEEE International Conference on Control Applications, pp.1092-1097, 2012.

[22] S. Butler and J. Ringwood, “Particle filters for remaining useful life estimation of abatement equipment used in semiconductor manufacturing[J].” IEEE Conference on in Control and Fault-Tolerant Systems, pp.436-441,2010.

[23] WANG Kai, GUO Haifeng, XU Aidong. Degradation Monitoring Method of Electromagnetic Coil Insulation for Smart Manufacturing[J]. Information and Control,2017, 46(4): 469-473.

[24] Li B, Yang W Y, Zhou X, Zhai G F. Study on Extraction of parasitic parameters of multilayer coil for electromagnetic relay [J]. Low voltage apparatus, 12, 2011:8-12.