

Transformer Failure Rate Prediction Based on Condition Assessment



Engineering

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ABSTRACT

Past few years several electric power companies takes a lot attention in the risk assessment transformer because average age of the transformer is increasing and large system outages caused by transformer failures. In day to day rising operating stresses from larger loads and increased bulk power transmission increase transformer failures speed. This "transformer failures" phenomenon has been difficult to estimate, as the effects of operating conditions on a transformer vary according to its family, make, model, age, and application. On the other hand, a transformer that is older than the original manufacturer's normal life estimate may be in good condition physically and can last for decades more. It is essential therefore to understand completely the condition of a fleet of transformers and to predict their failure rate to keep away from unplanned outages and catastrophic failure.

Introduction

Power transmission and distribution companies are facing challenges of higher level of reliability for lower cost. Therefore there is need to develop best way to achieve these challenges of transmission and distribution companies. Subsequently is required to develop a reliability model of transmission and distribution system. The objective of this paper is first to evaluate failure rate of transformer by using condition of transformer, second by using values of failure rate estimate reliability of power system. This will help to enhance the accuracy of the power system reliability. Condition monitoring refers to the monitoring of key parameters or indicators of equipment condition in a power system network. Condition monitoring has traditionally been done manually by the use of various diagnostic checks. Examples include the levels and types of oil condition, winding condition, insulation condition and physical condition of transformer and timing or operating checks on mechanical equipment etc. In recent years a number of technologies have become available that enable continuous on-line condition monitoring, that is, continuous, in-service monitoring that returns information about key parameters or indicators (A. Kingsmill, S. Jones, n.d.). Earlier to the 1960's, the reliability of proposed power systems was often estimated by extrapolating the experience obtained from existing systems and using rule-of-thumb methods to forecast the reliability of new systems (D.P. Gaver, F.E. Montmeat, n.d.). During the 1960's significant work was performed in the field of power system reliability and some excellent papers were published. The most significant publications were two company papers by a group of Westinghouse Electric Corporation and Public Service and Gas Company authors (C. E. Montmeat, A.D. Patton, n.d.) . These papers introduced the notion of a fluctuation environment to illustrate the failure rate of transmission system components. The methods proposed in these papers were provided results within a few percent of those obtained using more theoretical techniques, such as Markov processes. Billinton Roy, et. al., suggested the application of Markov Chains in the power system reliability. The application of Markov technique required large space in computer memory and take longer time to solve large systems. Most previous publications have focused on transmission system reliability. This research focuses on distribution system reliability. This work extends previous research (Roy Billinton, Kenneth E. Bollinger, n.d.) which demonstrated sets used in describing power system reliability calculations. System reliability models typically use average equipment failure rates. Even if these models are calibrated based on historical reliability indices, all-like components within a calibrated region remain homogeneous. Brown, R.E presented a new method of customizing failure rates using equipment inspection data. This allows available inspection information to be reflected in system models, and allows for calibration based on interruption distributions rather than mean values (Neelamkavil, J.).

Condition data of Transformer

The estimation of the state of a transformer asset is typically made using a variety of condition data. Selection of parameters

for condition assessment criteria depends upon its type, size, and application. Parameter variety to be provides considerable information about the equipment condition. Various techniques are available in the market for monitoring various condition parameters of transformer and its subsystems. Attempt here is to select the parameters which will be realistic, be more significant in representing transformer condition, and reflect the results obtained from the advanced monitoring systems.

The condition assessment criteria of transformer are broadly categorized as general condition, winding condition, oil condition and physical condition. The general conditions include so-called age of transformer, incident with transformer type and loading condition. The year of operation (age of transformer) of transformer is often defined as the time required for the mechanical strength of the insulation material to lose its mechanical strength . In practice, there are a variety of transformers of different types comprises the so-called 'nameplate' information including manufacturer, model, rated powers and voltages, manufacturer's recommended maintenance schedule. Then conclusions need to be drawn regarding the reliable operation of the transformer as per their types, rating and manufacturer. According to IEEE Std C57.12.90 the loading condition of transformer define by the highest average winding temperature rise. A sufficient number of direct reading sensors should be used at expected locations of the maximum temperature rise as indicated by prior testing or loss and heat transfer calculations. The advancement in technology fiber optic temperature detectors may be used to measure temperatures in power transformers.

The winding condition includes condition of solid insulation and partial discharge test. Insulation resistance test (ANSI/IEEE Std 43-1974) is a useful indicator of condition of solid insulation on the insulation surfaces of a winding. The insulation resistance is the ratio of the dc voltage applied between the winding copper and ground, to the resultant current. A polarization or absorption current involving various molecular mechanisms in the insulation. The polarization index is a variation on the dc insulation resistance (Arvind, D.; Khushdeep, S.; Deepak, n.d.). Partial discharge is an electrical phenomenon that occurs within a transformer whenever the voltage load is sufficient to produce ionization, and partially bridges the insulation between conductors. Although the magnitude of such discharges is usually small, they cause progressive deterioration and may lead ultimately to failure (Arvind, D.; Khushdeep, S.; Deepak, n.d.).

The oil condition contain records of gas in oil, water in oil, acid in oil, and oil power factor.

The essential requirement for the oil is to maintain dielectric performance in the oil gaps and across solid surfaces, to age very slowly, and to have adequate thermal and viscosity properties to achieve factory heat run performance. Low quality oil, or one with a poor ageing rate, is often associated with low

transformer lives. The use of additives can allow a poorer oil to achieve adequate initial properties for performance. Hence, if used, the additive content must be monitored and maintained, since the loss of property values can be very rapid (Arvind, D.; Khushdeep, S.; Deepak, n.d.). Oil and oil-immersed electrical insulating materials may decompose under the influence of thermal and electrical stresses, and, in doing so, generate gaseous decomposition products of varying composition which dissolve in the oil. The nature, amount, and rate of generation of the individual component gases that are detected may be indicative of the type and degree of the abnormality responsible for the gas generation. (ANSI/IEEE Std C57.104-1978), (M. A. Khan, A. K. Sharma, n.d.).

Dielectric properties of oil-paper insulation transformer are influenced intensively by moisture; therefore, it is imperative to assess integral condition of oil-paper insulation for assuring normal operation of power transformers (J. D. Cai and T. Zhang), [22]. Low water content is necessary to obtain and maintain acceptable electrical strength and low dielectric losses in insulation systems. The influence of water content on the aging performance of natural ester-paper insulation is compared with that of mineral oil-paper insulation. Sealed stainless vessels containing copper, insulating paper with different initial water content and dielectric fluid (camellia oil based natural ester and mineral oil) were aged at 130 °C for 80 days. The degree of polymerization (DP) of paper, furfural concentration in oil and acid number in oil were measured during the aging (Junru Xiang; Jian Li, n.d.).

The acid number of oil is a measure of the amount of acidic materials present. The acidity and therefore the acid number increases as oils age in service. Used oil having a high acid number indicates that the oil is either oxidized or contaminated with materials such as varnish, paint, or other foreign matter. Dissipation factor (or oil power factor) is a measure of the dielectric losses in an oil insulation of transformer and energy dissipated as heat. A low oil power factor indicates low dielectric losses. Oil power factor may be useful as an indication of contamination and deterioration in serves of transformer. The quality of power transformer insulation system is evaluated on a routine basis by measurement of the dielectric dissipation factor and capacitance of the insulation system. The use of dielectric dissipation factor measurements at the end of the production cycle not only assures that the quality of the transformer meets the specified levels but also provides insight into the subtleties of the manufacturing process. This tool is used for many years for diagnosing the health of electrical apparatus. It is a routine test conducted at site to know the dryness of insulation in transformers. (Malpure, B.D.; Baburao, K), (M. A. Khan, A. K. Sharma, n.d.).

Among the above mentioned specific parameters physical condition contains records of condition of cooling system, tap-changer, busing, and tank. Cooling system and tap changer assembly are vital. Transformer cooling system consists of fans, oil pumps, valves, and other control devices. They must be inspected, cleaned, and maintained regularly. There are other auxiliary components, like bushings, pressure relief valves, breathers and transformer tank, which require to be inspected for reliable operation.

Condition Data mapping in ANFIS

Condition histories are comprised of measurements providing information about the state of the transformer with respect to one or more failure modes. Common condition data information for a transformer includes that coming from condition assessment criteria of transformer are categorized as general condition, winding condition, oil condition and physical condition. All of this data can be collected either manually via inspections/laboratory testing or using continuous monitoring sensors. All these data modeling situations cannot discern what the membership functions should look like simply from looking at data. Rather than choosing the parameters associated with a given membership function arbitrarily, these parameters could be chosen so as to tailor the membership functions to the input/output data in order to account for these types of variations in the data values. In such cases, the neuro-adaptive learning

techniques incorporated. Neuro-adaptive learning techniques provide a method for the fuzzy modeling procedure to learn information about a data set. The membership function parameters that best allocate the associated fuzzy inference system to track specify input/output data. There are two learning techniques for adaptive neuro-fuzzy inference system i.e. ANFIS using specify input/output data set, which employs for updating membership function parameters. (A. Kablan). (1) back-propagation algorithm is an application of gradient descent algorithm originally for multilayer perceptron network. (E. Ardil, E. Uçar, n.d.). (2) back-propagation algorithm combination with a least squares type of method in which the interpretation of the fuzzy rule-base in terms of a neural network. In such way the fuzzy sets can be interpreted as weights, and the rules, input variables, and output variables can be represented as neurons. The learning algorithm results, like in neural networks, in a change of the architecture, i.e. in an adaption of the weights, and/or in creating or deleting connections. These changes can be interpreted both in terms of a neural net and in terms of a fuzzy controller [18, 21]. After we generated the fuzzy systems to learn from the transformer condition assessment data they are modeling. A network-type structure which maps inputs through transformer condition data membership functions and associated parameters, and then through transformer failure rate membership functions and associated parameters to outputs i.e. transformer failure rate, can be used to interpret the transformer condition data / transformer failure rate map. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the transformer condition data / transformer failure rate for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs. The modeling transformer assessment data approach first, hypothesizes a parameterized model organization (relating inputs to membership functions to rules to outputs to membership functions, and so on). Next, collected transformer condition assessment data for input and failure rate for output data that will be utilizable by ANFIS model for training. The training data presented to it by modifying the membership function parameters according to a chosen error criterion. In general, this type of modeling works well if the training data presented to model for training membership function parameters is fully representative of the features of the data that the trained FIS is intended to model.

In some cases however, transformer data is collected using noisy measurements, because in real life situations, the related data sources maintained by different institutions often differ in structure, organization and query capabilities (P. Gruber and J. Wills). In these unavoidably assumptions training data cannot be representative of all the features of the data that will be presented to the model. Model validation is the process by which the input vectors from input/output data sets on which the model was not trained, are presented to the trained model, to see how well the model predicts the corresponding data set output values.

The testing data set let's check the generalization capability of the resulting fuzzy inference system. The inspiration after using a checking data set for model validation is that after a certain point in the training, the model begins overfitting the training data set. In principle, the model error for the checking data set tends to decrease as the training takes place up to the point that overfitting begins, and then the model error for the checking data suddenly increases. Overfitting is accounted for by testing the model trained on the training data against the checking data, and choosing the membership function parameters to be those associated with the minimum checking error tile these errors indicate model overfitting.

Failure rate model

The average age of transformer has improved considerably during the past years. As a result, the electrical power companies

increased condition monitoring of transformer and many of them now maintaining extended condition histories. There has also been significant work in developing diagnostics, mainly in the form of rules that we call deterioration functions, used to operate on condition measurements and identify the state of transformer with respect to a particular failure mode. But there has not been subsequent efforts to transform condition data into a format that can be used in system level decision tools. Such tools like maintenance selection and scheduling and transmission reliability evaluation. The standard representation for transformer state in such tools is via a probabilistic failure index such as failure rate, failure probability, or time to failure. Consequently, to make use of the key information that is embedded in the gradually more available condition histories, it is essential to share the condition data into such probabilistic failure indices. A few works in the direction of this area has been incorporate (L. Bertling, and R. Allan,n.d.), (L. Fangxing and R. Brown).

ANFIS based models are desirable because they are inherently suited to model multi state process such as equipment deterioration as computed from deterioration functions from operating on condition measurement. Transformer condition collecting and recording inspection results from various processes is classified into rank their relative condition. Further, suppose that each inspection item result is normalized so that values correspond to the best inspection outcome, average inspection outcome, worst inspection outcome. After each transformer is assigned a condition rank and using the same inspection can be ranked and prioritized for maintenance. This approach has been successfully applied to several transformers. Although useful for prioritizing maintenance activities, relative equipment condition ranking is less useful for rigorous reliability analysis. Since reliability assessment models require transformer failure rates, inspection results would ideally be mapped into a failure rate through a closed-form ANFIS derived from regression models. At a minimum, interpolation requires failure rates corresponding to the worst and best condition rank. The model is tested for assumption violations of multiple regressions. Plotting the condition rank versus the predicted failure rate is a basic method of identifying failure rate. Figure-1 gives the condition rank versus the predicted failure rate plots and as can be seen the specified model does not violate the core assumptions of multiple regression. After exploring a variety of mapping functions, the authors have empirically found that an exponential model best describes the relationship between the normalized transformer condition and failure rates.

Table 1
condition DATA and Measuring data (case 1)

Sr. No.	Condition assessment type	Measuring data
1	age of transformer (in year)	
2	nameplate rating (MVA, KVH/KVL)	
3	loading condition [% loss of insulation life]	
4	measure temperatures (in oC)	
5	polarization index	
6	Partial discharge (in pC)	
7	gas in oil [TDCG] (in ppm)	

8	Percent Water Content in Oil (in ppm)	
9	acid in oil (Neutralization number)	
10	Dissipation factor (% oil power factor)	
11	condition of cooling system	
12	condition of tap-changer	
13	condition of busing	
14	Condition of tank.	

Conclusion

Transformer failures data are collected from various local electrical companies. Compare failure rates estimated by proposed condition based failure rate model with transformer based on a normal distribution. After we generated the fuzzy systems to learn from the transformer condition assessment data they are modeling.

Table 2
Predicted failure rate with various condition data of transformer

Transformer Case No.	Failure rate
Case 1	0.0844
Case 2	0.0782
Case 3	0.1386
Case 4	0.0119
Case 5	0.0497
Case 6	0.0046
Case 7	0.0540
Case 8	0.0838

A network-type structure which maps inputs through transformer condition data membership functions and associated parameters, and then through transformer failure rate membership functions and associated parameters to outputs i.e. transformer failure rate, can be used to interpret the transformer condition data / transformer failure rate map. The parameters associated with the membership functions changes through the learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector. This gradient vector provides a measure of how well the fuzzy inference system is modeling the transformer condition data / transformer failure rate for a given set of parameters. When the gradient vector is obtained, any of several optimization routines can be applied in order to adjust the parameters to reduce some error measure. This error measure is usually defined by the sum of the squared difference between actual and desired outputs The modeling transformer assessment data approach first, hypothesizes a parameterized model organization.

The shape of the estimated histogram is similar to the historical histogram, but the predicted histogram retains a slightly smaller variance. These tools must go beyond expected values, and must be able to assess the variation in reliability due to condition and/or monitoring of transformer. To make these tools as accurate as possible, it is critical that utilities maintain very good historical reliability data records. Table (2) shows predicted failure rate with various condition data of transformer.

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