A Data Mining Approach for on-line Monitoring of Transformer Bushings
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Abstract: Power transformers are one of the most important components of electric networks. These devices are very expensive and therefore diagnosis and monitoring systems will be valuable for preventing damage to these transformers. Statistical studies have shown that failures of bushings are one of the primary reasons for long duration outages of transformers. The use of data mining can improve the reliability and provide facilities to analysis of data that obtained from special sensor installed on power apparatus. It can also be used to extract information and knowledge that is not available and not visible from the data directly. Finding peculiarity data as a data mining technique will be useful to discover the possible change in bushing’s status. In this contribution, we describe an application of peculiarity oriented mining approach for analyzing of data that obtained from special sensor installed around the bushing’s surface. We propose a procedure for monitoring of transformers bushings using a measure of peculiarity, which is called peculiarity factor. A monitoring and diagnosis system was developed and the usefulness of this system is verified by experimental results.

Key Words: Monitoring; Data mining; Peculiarity analysis; Diagnosis; Bushing

INTRODUCTION

On-line monitoring systems are of benefit to predict fault conditions and maintenance of the high voltage transformers. There are some sensors and measuring devices that can be installed on each transformer to collect measured data about the transformer’s conditions. The whole task of monitoring and fault diagnosis of high voltage power transformers is a time consuming and complex task. Different technologies such as soft computing, and information processing, etc., are involved in this system. A modular framework will be suitable for monitoring and diagnosis system of power transformers.

BUSHING MONITORING AND DIAGNOSIS

Bushings’ tap connections and non-invasive capacitive sensors were used for monitoring and diagnostics of power transformers by some researchers especially for PD analysis. For this reason, we decided to perform this method to on-line monitoring and diagnostics of transformer bushings. For this purpose, two capacitive sensors are designed and installed on the surface of each high voltage distribution transformer bushing. The detail of these sensors was described in [1]. The first sensor forms a capacitor with high voltage conductor. This sensor is used to obtain the bushing condition. In this article this sensor will be referred as bushing sensor and corresponding signal of this sensor will be referred as bushing signal. The second sensor forms an air gap capacitor with high voltage conductor. This sensor can be used as a normal capacitor in Schering’s bridge and as a reference for the voltage. This sensor will be referred to as reference sensor and corresponding signal of this sensor will be called reference signal. Fig. 1 shows these two sensors that were installed on the bushing of a 10kV/380V, 200kVA oil-immersed distribution transformer.

Fig. 1 Reference & bushing sensors installed on a transformer

THE STRUCTURE OF BUSHING MONITORING AND DIAGNOSIS SYSTEM

Monitoring and fault diagnosis of high voltage power transformer is a complex task and according to complexity, it should be divided into different logical groups of tasks or modules. Data acquisition can be performed in low level and monitoring and diagnosis can be performed in higher levels. The modular structure of our bushing monitoring and diagnosis system is shown in Fig. 2.

Fig. 2 Structure of monitoring and diagnosis system for transformer bushings
Data Acquisition Subsystem

Data acquisition is the basis for building monitoring and diagnosis system. This subsystem is used to gather appropriate information and condition measurements from power transformer bushings via bushing sensor and reference sensor. Each sensor has some data vectors and the data obtained from all three bushings will be stored in these data vectors in the data acquisition stage. Using data processing techniques these huge amounts of data will be processed to extract some useful and appropriate data.

Data pre-processing: Collected raw data (data collected by sensors and other source of data) usually contain redundant and erroneous data. Missing values and noisy data are typically kind of erroneous data. The acquired data should be consistent and as much as possible noise-free. In our system, the obtained data that was stored in data vectors contain noise as shown in Fig. 3.

![Fig. 3 The noisy signal from reference sensor](image)

In this subsystem all data will be denoised using appropriate software filter. The denoised data are the input for the feature selection stage.

Feature selection: The huge amount of data obtained from sensors in data acquisition stage was stored in temporary data vectors. The useful information was extracted from these temporary data vectors and these features will be the fields of our databases in monitoring system used in other diagnostic and data processing modules. As an example we have proposed some features for each obtained sensor’s signal as follow:

- **Amplitude of signal**: the amplitude of each single sine signal.
- **Zero crossing**: the time point on each signal where it crosses zero.
- **Date and time**: the date and time of sampled data.

These features are used for each signal and should be calculated from continuous sampled signals that have taken from each bushing of the power transformer. We need additional information called phase difference, which represents the phase shift between the obtained signals from bushing sensor and reference sensor and can be considered as power factor of the bushing.

The mentioned features form a database for each bushing. The important fields for database are as follow:

- Bushing amplitude: the amplitude of the signals from bushing sensor.
- Reference amplitude: the amplitude of the signal from reference sensor.
- Phase difference: the phase difference between the signals from bushing sensor and corresponding signal from reference sensor.
- Date and time: the date and time of sampled data.

Data Mining Subsystem

Data mining is a powerful new technology with great potential to help companies, industries and researchers to discover new knowledge from databases. Data mining algorithms and tasks refer to the procedure where different methods are applied to extract useful information, hidden knowledge, unexpected patterns and new rules from data. The data mining technique that will be used in our proposed monitoring system is a peculiarity oriented mining.

Peculiarity oriented mining: The main task of peculiarity oriented mining is the identification of peculiar data. It is used to specify the difference between one data object from other similar data objects and is proposed by Zhong et al. [2].

**Finding Peculiar Data**

The peculiarity factor is given by:

\[
PF(x_{ij}) = \sum_{k=1}^{n} \sqrt{N(x_{ij}, x_{kj})}
\]

Where \(x_{ij}\) and \(x_{kj}\) are attribute values, \(n\) is the number of different attribute values, and \(N(x_{ij}, x_{kj})\) is the conceptual distance between \(x_{ij}\) and \(x_{kj}\). The conceptual difference is given by:

\[
N(x_{ij}, x_{kj}) = |x_{ij} - x_{kj}|
\]

Selection of peculiar data is performed by using a threshold value. An attribute value is peculiar if its peculiarity factor is above threshold \(p\), namely, \(PF(x_{ij}) \geq p\). The threshold value \(p\) will be represented by the sum of mean value plus the standard deviation multiplied by \(\beta\).

The user can change the parameter \(\beta\) to adjust threshold value. If \(PF(x_{ij})\) is over the threshold value, \(x_{ij}\) is a peculiar data.

**Peculiarity oriented mining algorithm**

For on-line monitoring of transformer bushings, two parameters are important. One parameter is variation of signal level of bushings and the other is determination of difference between zero crossing of bushing sensor signal and zero crossing of reference sensor signal.
Three extracted data fields in the feature selection phase will be stored in three different circular buffers and the peculiarity procedure will be carried out on them repeatedly after capturing each sample from sensors. These parameters are bushing amplitude, reference amplitude, and phase difference vectors. The peculiarity oriented mining will be performed on these data vectors for each bushing simultaneously. The peculiarity factor will be determined by using a sliding window method. The length of the window is 25 and sliding length is 1. As shown in Fig. 4 the peculiarity oriented mining algorithm consists of two procedures. The first procedure calculates peculiarity factor for each of three mentioned data vectors of two sensors of a bushing (bushing sensor and reference sensor). Peculiarity factor will be calculated for a data length of window size. The second procedure calculates threshold value for this range of data and determines that ith sample is peculiar or not. In case of any peculiar data this procedure returns a true flag for each three vectors.

DIAGNOSIS

Diagnostics contains interpretation of data to determine the current condition of the transformer bushings. The diagnostic task has an important influence on the overall maintenance cost as well as on reliability and availability. Artificial neural networks (ANN) are frequently used in the development of computer-aided diagnosis systems. Comparative analysis has shown that the back-propagation algorithm has the ability to predict with greater accuracy than other neural networks algorithms and has low complexity and sufficient performance to produce good results [3]. A feed-forward back-propagation artificial neural network is used for the diagnosis subsystem and was trained to evaluate the status of each bushing. Input-output pairs are presented to the network, and weights are adjusted to minimize the error between the network output and the actual value. Fig. 6 shows the used back-propagation model which has three layers of neurons: an input layer, a hidden layer, and an output layer.

MONITORING

Monitoring subsystem is used to give clear information to the operator and expert about all stages from data acquisition to diagnosis. Using monitoring, faults can be detected before they lead to a catastrophic failure. In the developed software, the amplitude from bushing and reference signal and phase difference of them will be displayed. Peculiarity analysis routine will be run after each sampling period and each peculiarity in each of these three data series will be displayed with black color in graphical screen. Fig. 5 shows the prepared software for this system.
Three extracted data fields in feature selection phase which are bushing amplitude, reference amplitude and phase difference are the inputs of neural network. The output node in output layer shows the status of bushing a normal condition or fault.

SOFTWARE SYSTEM

The software window is displayed in Fig. 5. Data acquisition module acquires data from sensors. After denoising, the appropriate features will be extracted. Data mining module apply peculiarity procedure and all features and peculiarity flags will be stored in database and the results will be displayed in main window as graphs and values. The diagnosing module will display the status of bushing using a trained neural network. The peculiarity analysis module and neural network module were developed using c++ as two dll (dynamic link library) files.

As shown in Fig. 7, a visual basic module also is developed to view the stored data in database. The user can select different type of stored data (bushing signal, reference signal and phase difference) and see the values and probably occurred change (peculiar data) with a red cross.

Fig. 7 Database viewer tool

As shown in Fig. 5, the software has three graphs in the middle of window and a graph in the right side. The first graph in the middle displays both signals from bushing and reference sensor. The second and third graph show the calculated amplitude of bushing and reference signal respectively. The graph in the right side of window gives the values of phase difference of these two signals. The occurrence of peculiarity will be displayed as a black line in these three graphs to inform user about changes.

EXPERIMENTAL RESULTS

For evaluating the ability of this method, measurements were performed on a 10kV/380V, 200kVA oil-immersed distribution transformer and an oil-pressboard capacitor. Fig. 5 shows the running of software for the oil immersed distribution transformer. The system indicates the normal condition of bushing and no changes in the obtained data.

As a model for a transformer bushing a five layers oil-pressboard capacitor was designed, shown in Fig. 8. Each layer of capacitor has a connection, therefore short circuiting of layers is possible to simulate faults in the model.

As shown in Fig. 8, applying voltage to the five layers oil-pressboard capacitor and short circuiting one layer, the amplitude of the bushing signal will change. According to Fig. 6 the neural network has three input values and an output value. Five different cases are carried out for training the neural network. For each case, 100 data is entered to the ANN input and the network is trained with 500 input data to show 5 different cases. The first case is the operating in normal state with no short circuit in capacitor layers. The second case is with short circuit of one layer of capacitor. The third, fourth and fifth cases are with short circuit of two, three and four layers respectively. The ANN output should have a value to show one of these five situations.

After training process, the software is used for monitoring and diagnosis of the oil-pressboard capacitor. Each five case were tested to evaluate the software system. It means that normal condition and short circuit of different number of layers are performed to test the software. The software has distinguished all five cases successfully. Fig. 9 shows the result of
running software after these five cases. There are five different data range for bushing signal (second graph in the middle of window). The first range is for normal condition. The second range shows the amplitude of bushing signal after short circuiting one layer. The peculiarity process will show this rapid change in data with a black line in the graph. The other three data ranges are the result of short circuiting two, three and four layers. After each short circuiting, a peculiarity occurred and is displayed as a black line in graph. The ANN process will send a message to notify the user about short circuiting of a layer. For example after short circuiting the fourth layer the ANN module displays the “five layers are short circuit” message to user.

It is obvious that in these four changes, the amplitude of reference signal does not change. There is only a little change in phase value and therefore the peculiarity module does not show any peculiarity in phase values. To make peculiarity algorithm more sensitive the $\beta$ parameter can be adjusted.

**CONCLUSIONS**

Monitoring and diagnosis for power transformers is a complex task, because different technologies are involved in this process. It is necessary to define an appropriate database for each diagnostic component/technique of power transformer. These databases will help to perform more data processing and data mining techniques on data and extracting useful information that is not visible from data directly. Peculiarity analysis as a data mining technique was used to recognize any change of bushing status automatically. ANN can be a good method for diagnosis. To train proposed ANN for a power transformer bushing, simulation can be used to generate faulty signals after short circuit of capacitive layers.

**REFERENCES**