

Feature Analysis of Numerical Calculated Data from Sweep Frequency Analysis (SFRA) Traces Using Self Organizing Maps

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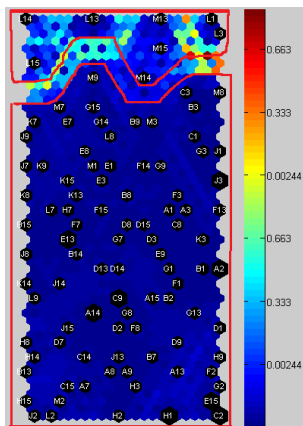
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Graphical abstract



Abstract

This paper presents a comprehensive investigation of the Self Organizing Map (SOM) classification process of good and defective power distribution transformers. Three main features were extracted from the numerical calculation method of the Sweep Frequency Response Analysis (SFRA) signals acquired from the transformers. These features are the input vectors for the SOM classification. Analysis of the results has shown the capability of the features and the SOM classification method to differentiate between good and defective transformers.

Keywords: Self Organizing Maps (SOM); power transformer; classification; SFRA

Abstrak

Dalam kertas penyelidikan ini pengkajian yang komprehensif tentang kemampuan Peta Penyusunan Kendiri (SOM) dalam mengklasifikasi alatubah kuasa pembahagian berada dalam baik atau bermasalah. Tiga ciri utama yang diekstraks dari kaedah pengiraan berangka melalui isyarat Analisis Tindak balas Frekuensi Sapuan (SFRA) yang diperolehi dari alat ubah. Ciri-ciri ini akan dijadikan sebagai vektor input untuk pengklasifikasi SOM. Hasil analisis menunjukkan yang ciri utama dan kaedah pengklasifikasi SOM mampu untuk membezakan antara alatubah yang baik dan yang bermasalah.

Kata kunci: Peta Penyusunan Kendiri (SOM); alat ubah kuasa; pengklasifikasi; SFRA

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1.0 INTRODUCTION

SOM is one type of artificial neural networks (ANNs). This methodology introduced by Kohonen in 1989.¹ Basically ANNs are mathematical models that being designed based on human brains. ANNs contain groups of interconnected neurons or nodes. ANN is widely used to find patterns or fingerprints between input and output data.²

Unsupervised learning (learning by observation) refers to the method that learns by itself according to input attributes and also applies competitive learning that made the output nodes to compete to be activated. Only one of the nodes will be activated at any one time or we called winning neuron.²⁻³ The node competition can be induced through negative feedbacks between neurons. The system is called Self Organizing Map (SOM) because all nodes are forced to be self-organized through the feedback path.

Based on neurological studies, all human sensory inputs are mapped onto certain areas at the cerebral cortex that form a map called Topographic Map.² It has two most important principals;

- At each stage of processing, every each information is reserved in its proper environment.
- Close related information nodes will be close to each other to ensure short synaptic connections.

SOM primary purpose is to transform incoming input patterns into a one or two dimensional discrete map. This process must be performing in orderly approach.

In this research, SOM is applied to classify the parameters between good and defective power distribution transformers. The SOM classification process is applied to SFRA data acquired from twelve transformers at twelve different substations.

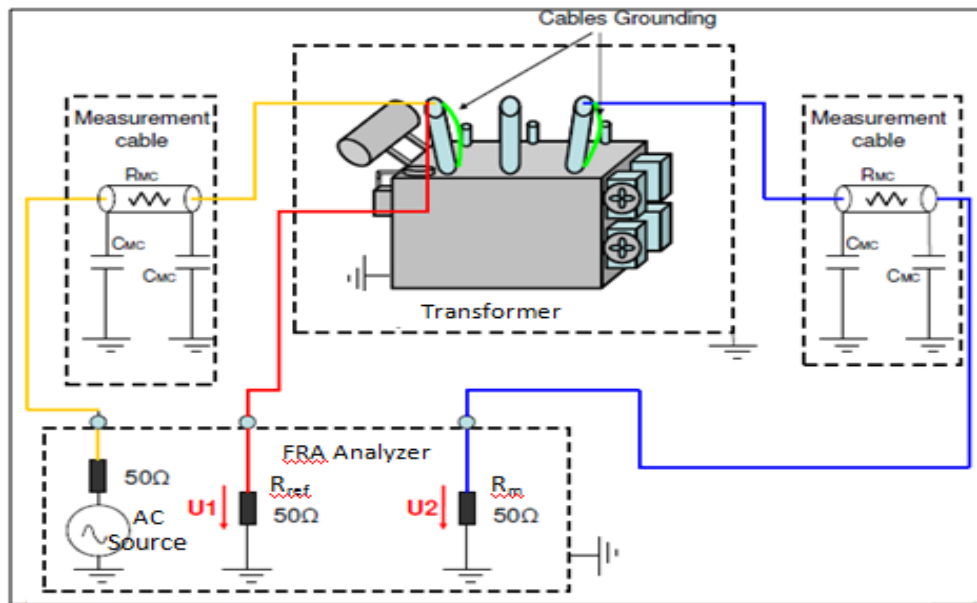


Figure 1 Test leads connection from the FRAnalyzer to a transformer⁵

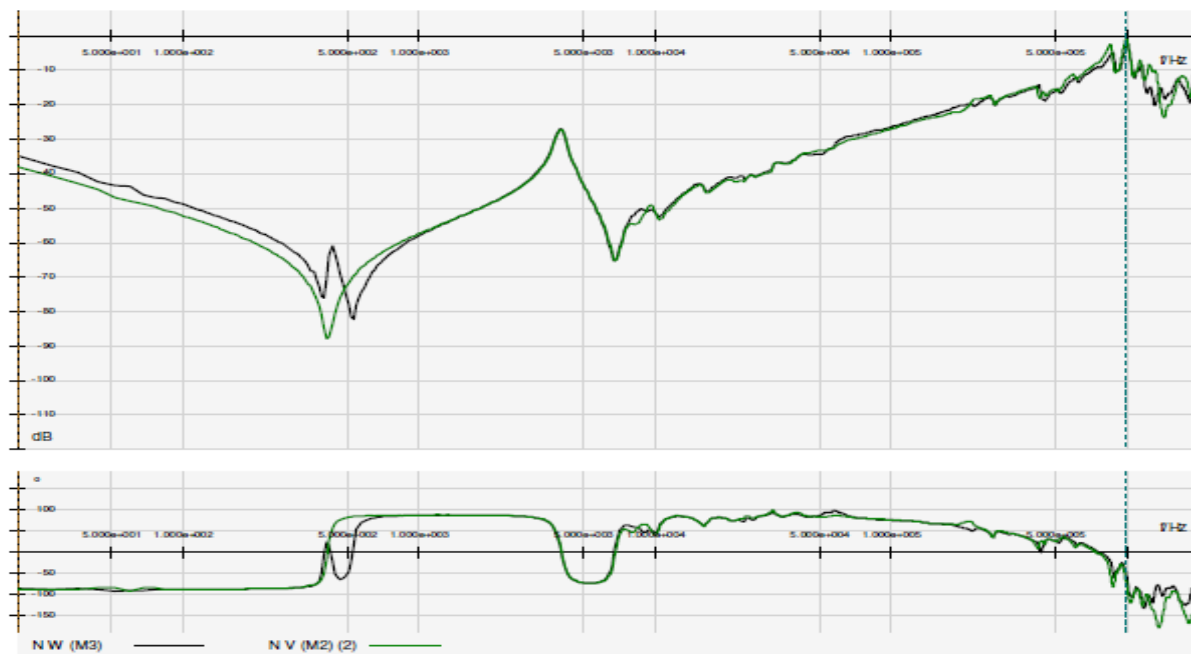


Figure 2 Graphical representation of SFRA results (y-axis: magnitude, x-axis: frequency in Hz)

2.0 THE TEST SETUP

The SFRA results utilized in the study were obtained from twelve 33/11kV transformers with ten transformers in good condition and two transformers were in defective condition. The SFRA measurement was conducted on HV winding. The whole experiment was setup at twelve different air insulated substation (AIS) and gas insulated substation (GIS). SFRA measurement has the ability to determine abnormality happen at transformer winding.⁸⁻⁹

There are four different types of SFRA measurement setup. These measurements can be defined as end to end open circuit,

end to end short circuit, capacitive and inductive interwinding measurement.⁴⁻⁵ The test configuration used in this test is the end to end open circuit. Test leads connection between FRAnalyzer and transformer as depicted (Figure 1).

The measured data can be compared to other measurement results (history, pair, twin or phase data) to determine variations or differences.⁴ The most ideal method is to compare the measured results with the health of same units (twin or pair transformer).⁴ In case of unavailability of same transformer, we often compare with twin or sister unit, phase to phase end to end open or short circuit measurement. In this research work, phase to phase comparisons are employed as in Table 1. Each

measurement will produce SFRA traces that are manipulated as an input in SOM clustering process. Each traces produced data in both magnitude and phase value (Figure 2).

Table 1 Transformer winding configuration and phase to phase comparison method

Winding	Data Description	
	Transformer Winding Code	Phase to Phase Comparison
HV	H1H2 phase (red phase)	H1H2 to H2H3 phase
	H2H3 phase (yellow phase)	H1H2 to H3H1 phase
	H3H1 phase (blue phase)	H2H3 to H3H1 phase

3.0 SELF ORGANIZING MAPS METHODOLOGY

3.1 Architecture of SOM Network

A typical SOM structure built from two main layers; input and output layer that array in two-dimensional preposition is shown in Figure 3. SOM algorithms resemble Learning Vector Quantization (LVQ). In LVQ all neurons are arranged on a grid together with selected neurons whereas SOM has a feed-forward structure with a single computational layer arranged in rows and columns. Each neuron is fully connected to all the source nodes in the input layer. Neighbouring nodes will be updated to perform neurons order. This indicates that SOM as a multidimensional scaling method from input space to two-dimensional output space. Visual format of SOM help researcher to define clusters, relations and structures in complex input database.

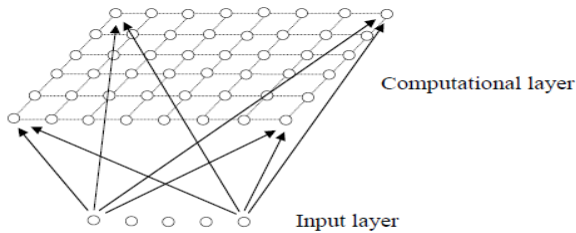


Figure 3 SOM basic architecture

3.2 Best Matching Unit (BMU)

Number of neuron may vary from a few dozen up to several thousands. Each neuron is represented by a d -dimensional weight vector (prototype vector, codebook vector) $m = [m_1, \dots, m_d]$, where d is dimension of input vectors. Neurons connected to the adjacent neurons through neighbourhood relation that dictates its topology.

SOM is then subjected to iteration for training the network. Each iteration has one sample vector s from the input data will be selected randomly, and the distances between all the nodes are then calculated by particular distance measures. The neurons that have closest weight vector to the selected sample s is called best matching unit (BMU) (Fig. 2) and denoted by c

$$\|s - m_c\| = \min_i \|s - m_i\| \quad (1)$$

where c is referred to Euclidean distance measure.²

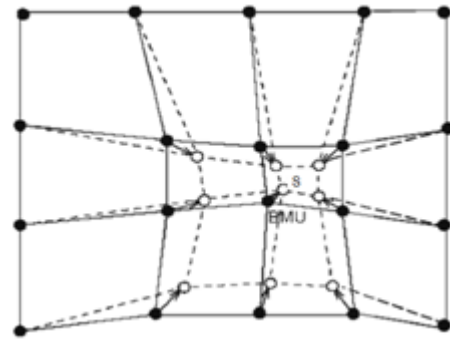


Figure 4 Updated the BMU and its neighbourhood. Input sample marked as s . Solid line referring to origin situation and dashed line represent updated condition³

Upon determining BMU, SOM weight vectors are updated so that the BMU will be closer to the input vector in input space. This adaptation process will stretch the BMU and its topological neighbours towards the sample vector (Figure 4).

The SOM update rule for the weight vector m of unit i is

$$m_i(t + 1) = m_i(t) + \alpha(t)h_{ci}(t)[s(t) - m_i(t)] \quad (2)$$

where t denotes times, $s(t)$ is random selected input vector from set of input data at time t , $h_{ci}(t)$ the neighbourhood kernel around winner c , and $\alpha(t)$ the learning rate at time t . The neighbourhood kernel defines the region of influence that the input sample has on the SOM.

4.0 FEATURE EXTRACTION

In this research work, the measurement results from SFRA traces are converted into CSV 2.0 format. The retrieved raw data are then used to calculate the numerical parameters. There are three type of parameters as shown in Table 2 that are selected for feature extraction of the SFRA data which are the Cross-Correlation Coefficient Function (CCF), Standard Deviation (SD) and Absolute Sum Logarithmic Error (ASLE).⁶⁻⁷

Table 2 Numerical parameters and its equations⁷

No	Table Column Head	
	Numerical Parameters	Equations
1.	Cross-Correlation Coefficient Function (CCF)	$CCF_{(x,y)} = \frac{\sum_{i=1}^N (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^N (X_i - \bar{X})^2 (Y_i - \bar{Y})^2}}$
2.	Standard Deviation (SD)	$SD_{(x,y)} = \sqrt{\frac{\sum_{i=1}^N (Y_i - X_i)^2}{N}}$
3.	Absolute Sum of Logarithmic Error (ASLE)	$ASLE_{(x,y)} = \frac{\sum_{i=1}^N (20 \log_{10} Y_i - 20 \log_{10} X_i)}{N}$

The related formula for numerical calculation of X_i and Y_i refer to SFRA measurement data of the reference phase and adjacent phase respectively. N is number of frequency samples

used in the measurement. Only the magnitude response data from SFRA measurements are used to compute the numerical features. These features are used as the input vectors for the SOM classification.

5.0 RESULTS AND DISCUSSION

Four sets of SOM parameters (normalization methods and number of neurons) need to be applied and optimized for SOM classification of the numerical features. Below, the results are presented and discussed.

5.1 SOM Parameters Optimization

Each simulation consists of the combination between various normalization method ('var', 'range', 'log', or 'logistic') and optimum number of neurons (from 120 to 340 neurons). For 'var' data input, it will be normalized to unity and means to zero while 'range' input data will be normalized between zero and one. For 'log', natural logarithm as in the equation below is applied.

$$X_{new} = \log(X-m+1); m = \min X \quad (3)$$

while 'logistic' or softmax transformation scales all possible values between zero and one.³

Data normalization is very vital in forming the maps to present higher values to dominate map topology and hide other components. Table 3, 4, 5 and 6 used the same data inputs from SFRA numerical calculated features which are CCF, SD and ASLE with different types of normalization method for SOM classification. All tables have shown that all normalization methods achieve very small quantization and topographic error using 340 neurons except for Table 5 ('log' normalization method) that manage to reach low value using only 300 neurons. Low quantization and topographic indicates that good and smooth classification is achieved through hexagonal lattice for all normalization method.

Training time for all classification is achieved by less than or equal five second. Short training time referred to good mapping capability and quality especially for classification process. Upon comparing the least value of quantization and topographic error and also training time, Table 6 or 'range' normalization is the best selection. Therefore, for the SOM classification map, 'range' normalization with 340 neurons is selected.

Table 3 Result from MATLAB simulation using hexagonal topology and 'var' normalization method

No. of Neurons	Simulation Result			
	Map Size	Quantization error	Topographic Error	Training Time (sec)
120	[17, 7]	0.157	0.046	1
140	[18, 8]	0.126	0.028	1
160	[18, 9]	0.117	0.028	1
180	[20, 9]	0.109	0.009	1
200	[20, 10]	0.108	0.009	1
220	[22, 10]	0.097	0.009	1
240	[24, 10]	0.085	0.028	2
260	[24, 11]	0.083	0.028	3

No. of Neurons	Simulation Result			
	Map Size	Quantization error	Topographic Error	Training Time (sec)
280	[25, 11]	0.075	0.028	2
300	[25, 12]	0.072	0.019	2
320	[27, 12]	0.066	0.000	3
340	[28, 12]	0.063	0.000	3

Table 4 Result from MATLAB simulation using hexagonal topology and 'range' normalization method

No. of Neurons	Simulation Result			
	Map Size	Quantization error	Topographic Error	Training Time (sec)
120	[17, 7]	0.020	0.037	0
140	[18, 8]	0.018	0.028	0
160	[20, 8]	0.017	0.019	1
180	[20, 9]	0.015	0.009	1
200	[22, 9]	0.014	0.028	2
220	[22, 10]	0.013	0.009	1
240	[24, 10]	0.012	0.019	2
260	[24, 11]	0.011	0.037	2
280	[25, 11]	0.010	0.028	2
300	[27, 11]	0.010	0.037	2
320	[27, 12]	0.009	0.019	2
340	[28, 12]	0.009	0.009	4

Table 5 Result from MATLAB simulation using hexagonal topology and 'log' normalization method

No. of Neurons	Simulation Result			
	Map Size	Quantization error	Topographic Error	Training Time (sec)
120	[17, 7]	0.043	0.056	1
140	[20, 7]	0.039	0.056	0
160	[20, 8]	0.035	0.019	1
180	[23, 8]	0.030	0.056	1
200	[22, 9]	0.028	0.046	1
220	[24, 9]	0.027	0.056	3
240	[27, 9]	0.022	0.037	1
260	[26, 10]	0.023	0.065	2
280	[28, 10]	0.021	0.037	2
300	[27, 11]	0.018	0.009	3
320	[29, 11]	0.017	0.028	10
340	[31, 11]	0.017	0.037	3

Table 6 Result from MATLAB simulation using hexagonal topology and 'logistic' normalization method

No. of Neurons	Simulation Result			Training Time (sec)
	Map Size	Quantization error	Topographic Error	
120	[20, 6]	0.034	0.065	2
140	[20, 7]	0.030	0.037	1
160	[23, 7]	0.028	0.019	1
180	[23, 8]	0.025	0.037	1
200	[25, 8]	0.023	0.019	1
220	[24, 9]	0.021	0.009	2
240	[27, 9]	0.020	0.009	2
260	[29, 9]	0.018	0.009	2
280	[28, 10]	0.017	0.019	2
300	[30, 10]	0.015	0.009	4
320	[32, 10]	0.014	0.009	2
340	[31, 11]	0.014	0.000	5

5.2 The U Matrix Classification

For U Matrix classification map, hexagonal topology was chosen to get higher resolution and faster result because rectangular topology needed lesser number of neurons to achieve low quantization and topographic error. The U Matrix result (Figure 5) from the selected SOM parameters. The accuracy of classification via BMUs in the U Matrix is considered as almost precise and produces good and smooth mapping quality.

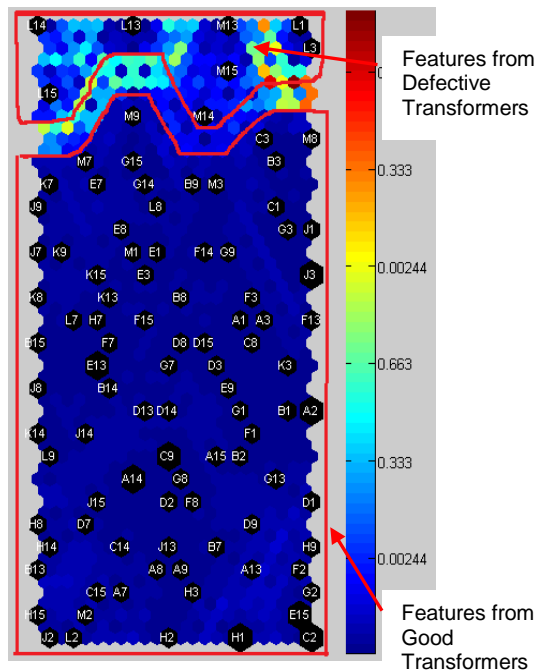


Figure 5 The U Matrix for the 'range' normalization for the classification, using Hexagon lattice, with 340 neurons. Both quantization error and topographic error are at 0.009

In the map units or neurons of the U Matrix (Figure 5) shown are labeled by their respective substation with alphabetical order from A to M where each neuron is represented by the vectors of the numerical features. Clearly, the clustering process is achieved by inspecting the data components that are grouped together and place inside a lighter color border that that signifies higher distances and inside darker color border for shorter distances.

It is proven that from the U Matrix visualization, abnormality that happen in a transformer can be analyzed through SOM. Numerical calculated data produced from SFRA signal raw data can be used as an input in clustering to separate between normal (good transformer) and abnormal (defective transformer) data.

5.3 Analysis of Extracted Feature

Component plane representation (Figure 6) for the U Matrix (Figure 5) is presented. Observe that, there are three main component planes that represent the numerical calculated features such as CCF, ASLE, and SD that are being used as the SOM classification input data. Each plane portrays the values and patterns of the respective numerical features from the lowest to the highest values as indicated by the indicator on the right of every component plane. The darkest colour corresponds to the lowest values while the lightest colour corresponds to the highest values.

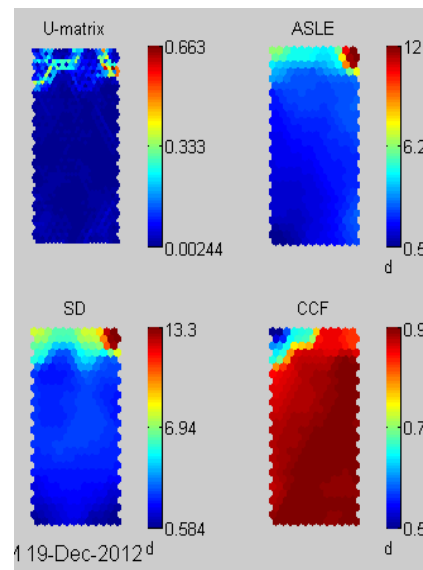


Figure 6 The Plane Representation Showing Data Contribution of Three Numerical Calculated Data for the SOM Classification

The plane representation in Figure 6 also demonstrated that each component projects different pattern and no uniform distribution are found throughout the plane. Hence each plane is unique and all the three numerical features are very important features to contribute to the classification process through the U Matrix classification in Figure 5 and none of the features is needed to be removed.

6.0 CONCLUSION

SFRA raw traces from twelve power distribution transformers are manipulated using three numerical parameters (CCF, SD and ASLE) as an input data for SOM clustering to separate defect data

from normal data. SOM visualizations depicted that data that have the same characteristics or conditions are mapped close together. Hence, the numerical features from the good transformers are separated from the defective transformers in the SOM U-Matrix classification. The analysis signifies that the methodology carried out in this research work is an effective way to evaluate the transformer condition from the SFRA traces.

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