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Power System Fault Detection Using Wavelet Transform And Probability Neural Network

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Abstract*: The identification of faults in any analog circuit is highly required toensure the reliability of the circuit. Early detection of faults in a circuit can greatly assist inmaintenance of the system by avoiding possibly harmful damage borne out of the fault.*

Anovel method for establishing a power fault using Wavelet transform and probability neural network. The Circuitunder Test (CUT) is three phase single level inverter. The transform coefficients for the fault freecircuit as well as for the simulated faults of CUT are found. The Wavelet transform is applied to theoutput of CUT and Standard Deviation (SD) of the transform coefficients are extracted. Using thetransform coefficients, fault dictionary has been formed. In order to identify the type of fault, a neuralnetwork classifier has been utilized.

The compatibility of wavelet analysis with the variousclassification techniques for fault diagnosis has been illustrated in this paper. The results of the studydemonstrate the suitability and viability of wavelet analysis in fault diagnosis of power electroniccircuits.

Keywords: *Fault, Circuit, Power System, Wavelet Analysis*

I. INTRODUCTION

(Guofeng,2013)Electrical power distribution systems are responsible for supplying power todispersed residential, commercial and small industrial customers in a safe, reliable andeconomical fashion. This is achieved by maintaining a reliable voltage level, correctingthe power factor through use of reactive compensation and offering as close tocontinuous service as possible in order to meet demand. Service interruptions, althoughsometimes planned for, are to be minimized. However, it is the unplanned outage events,which are the focus of this project.

Distribution system faults are most commonly single or double phase faults. (Feng, 2006)Thesefaults occur when one or more phases come in contact with one another, the ground, or insome case both and can lead to temporary or permanent service outages. Many types ofevents including lightning flashover, animals, tree limbs and poor weather conditions,such as ice, high winds, and rain, are common causes of these service outages. Dependingon whether any conductors, towers, or other parts of the infrastructure are damagedduring such an event will determine whether a fault will cause a temporary or permanentservice outage. It is therefore advantageous to detect and identify fault events as quicklyas possible so that proper measures can be taken to restore service back to normaloperating conditions

Guo (2011) With the rapid development of scientific technology, the scale and structure of power system continue to expand and become complicated. In the process of power system operation, natural and man-made interference often occurs and the failure is difficult to avoid. Therefore, adopting effective method to diagnose the fault of power system accurately, finding out the fault components, reducing manpower, material resources and economic losses, appear particularly important. Now, with the further development of artificial intelligence, especially machine learning, data mining, etc, many theories and methods are offered to diagnose the fault. Such as expert system, optimization method, fuzzy sets theory etc. Although these theoretical researches have scored some achievements, there are still certain limitations. For example, Fourier transform has been playing an important role in data processing, but Fourier transform has some defects, on the one hand, it can only analyze stationary signals, it cannot characterize sharp-variation signals that occur during faults diagnosing. On the other hand, Fourier transform cannot localize the singularities that always symbolize some sudden faults, and its frequency and time resolutions contradict each other.

As a powerful tool of signal analysis, wavelet transform has good localization properties in time and frequency domain,Dong(2009) focus to any details of the analysis object with taking fine time or frequency step length of high frequency, express any changes existing in the object, so as to get accurate feature separation results from the measurement data with bad SNR.

By using wavelet transform to separate the feature, the key process lies in the determination of optimal decomposition levels. On the one hand, we want to separate the feature components as far as possible, on the other hand, keep the fixed errors and true value apart from the separated feature. The current methods need either manual setting threshold control or results testing with extracted trend by wavelet transform, which increase the difficulty of the application of separation methods and raise the risk of error introduced. In accordance with the above case, the project proposes a newmethod which approximates the feature with detail components of the wavelet decomposition, determines the optimal decomposition level on the frequency intervals between the feature and other components, then gets the feature directly. The method avoids the indirect error with modeling and indirect methods .

Since the majority of works utilize simulated data or smaller sets of actual data wherenetwork conditions may or may not have been known, this work seeks to address thispotential shortcoming by the development of a hardware/software platform. In addition,since state-of-the-art fault detection techniques utilize thresholding from a singlemeasurement point (substation), this work seeks to investigate the impacts of meterlocations on fault detection techniques in multiphase distribution power systems using wavelet transform and probability neural network

II. REVIEW OF RELATED WORKS

To improve the EPQ of the power system supply, the PQDsshould be detected and classified precisely so that correctmitigation measures could be applied. This requiresmonitoring, recognition and classification of disturbancesthat is often an inconvenient task involving a broad rangeof disturbance categories from low-frequency dc offsetsto high-frequency transients. In the literature (Wang,2006), variousmethods based on WT, FL (Fuzzy Logic), NN (NeuralNetwork) and GA (Genetic Algorithm) have been proposedand implemented for PQ recognition and classification.

Different approaches based on WT and waveletpacket for EPQDs recognition are presented. The

combination of FFT (Fourier Transform) and FL isintroduced for classification of PQDs , new techniques based on fuzzy reasoning with WT havebeen suggested. A rule-based technique with a waveletpacket-based hidden Markov model for recognition andclassification of PQDs is presented .

ANN detection schemes are carried out in (Fushun, 1994). In hybrid schemes combined with NNs as classifier and WTfor feature extractions are suggested. For identifying andclassifying PQDs, neural-fuzzy technique is utilized withthe decomposition procedure of WT in .Applicationof ANN combined with GA in power quality signalsdisturbances classification is suggested in (Song, 2010).

From this survey it is favored to extract signal features byadvanced analytical tools, replace of signal time domainvalues for adaptation of AI (Artificial Intelligence) tools,because of improved efficiency. Thus, monitoring EPQhas become essential for fast recognition and correctionof EPQ problems(Yousheng,1996). The survey of DSP (Digital SignalProcessing) techniques for EPQDs analysis suggests thedifferent methods like: Park's Vector Approach, Kalmanfilters and most popular time-frequency analysis methodssuch as FT, STFT (Short Time Fourier Transform), WT,and ST. The conventional methodologies for monitoringEPQ are expensive and incompetent. In literature over theyears, a variety of techniques for automatic detection andclassification of EPQDs like voltage swell, sag, harmonics,notch, flicker and transients employ DSP techniques withelectrical power systems knowledge and AI.

Xia(2006) As PQDs are non-stationary signal, so time-frequencytools such as WT are more practical than FFT that mapssignal to frequency domain, without any time information.FT determines the time-averaged spectral components ofa signal which does not provide the changes of magnitude,frequency and phase difference with time. Hence, the timefrequencyinformation of the signals can easily be analyzedwith advanced techniques of STFT, WT and ST.

(Zhou,2008) As PQDs are non-stationary signal, and the frequency content varies with time. Due to the limitation of affixedwindow width, and fixed resolution over time frequency,STFT can not distinguish the signal characteristics properly. This has been proved in (Xiuyun,2013) that WT isincapable of identifying the accurate results when noiseis present in the signal.

As a powerful tool of signal analysis, wavelet transform has good localization properties in time and frequency domain,Dong(2009) focus to any details of the analysis object with taking fine time or frequency step length of high frequency, express any changes existing in the object, so as to get accurate feature separation results from the measurement data with bad SNR.

By using wavelet transform to separate the feature, the key process lies in the determination of optimal decomposition levels. On the one hand, we want to separate the feature components as far as possible, on the other hand, keep the fixed errors and true value apart from the separated feature. The current methods need either manual setting threshold control or results testing with extracted trend by wavelet transform, which increase the difficulty of the application of separation methods and raise the risk of error introduced. In accordance with the above case, the project proposes a newmethod which approximates the feature with detail

components of the wavelet decomposition, determines the optimal decomposition level on the frequency intervals between the feature and other components, then gets the feature directly. The method avoids the indirect error with modeling and indirect methods .

The uncertainty of power system operation, the diversity, complexity and associated level-oriented of gathering information, cause detection randomness and uncertainty. Wavelet is a new developing signal processing means. It is localized both in time and frequency domains. So it is possible to characterize the local singularities based on the coefficients in a wavelet orthonormal basis expansion. Combining model theory and statistical knowledge, wavelet provides a method to describe causal relationship between variables. Using probability theory to handle the uncertainty between different knowledge for conditions related, so it thus becomes one of the models in the field of uncertain knowledge representation and reasoning. Applying the neural network to power system fault diagnosis, can solve incomplete and uncertainty. Using the neural network structurelearning algorithm to obtain a precise power system fault diagnosis model in qualitative, using the wavelet parameters learning algorithm to obtain the table of conditional probability and reflect the link degree between components in quantitative. Through reasoning algorithm further achieve the power system fault diagnosis under the uncertainty and incomplete information (Friswell,1997).

Based on analyzing the incompleteness and uncertainty of information existing in power system fault diagnosis, a new fault diagnosis method based on wavelet transform and neural network is proposed. The wavelet transform is used to pre-process data and extract feature vectors. The neural network is used to identify fault types. Diagnostic results of instance proved the effectiveness and superiority of the proposed method (Hansen et al, 1997).

The discrete wavelet transform has been recently implemented for power qualityanalysis and fault detection. For fault detection, most work focuses on balanced powersystems using per phase analysis. This thesis proposes a wavelet-based fault detectionand identification algorithm capable of detecting and identifying faults within ¼ cycle of a 60Hz signal in unbalanced radial distribution systems. Fault experiments under a widerange of load distributions and loading levels have been performed in order to design andvalidate the algorithm’s performance. In addition, studies have been performed on meterplacement, sensitivity and detection error with respect to various fault types andlocations, in order to further increase the algorithm’s reliability

III. METHODOLOGY

3.1 Designing an RL Equivalent Motor Load

The load types currently available for experimentation in RDAC include R and RLloads, both of which are passive elements. It is of strong interest to however to integrate amotor load in order to observe the voltage and current dynamics during system faults.Before an actual induction motor can be connected ,an RLequivalent needed to be designed to model steady-state operation.

One RDAC inductor cart was available for use in the design of the motor load. Theindividual inductors were tested rigorously in at various current levels. In order tochoose the proper inductor cart for the motor load, a per-phase value of currentmagnitude was required at a desired rating of 208V and 4-hp (3.1). The value 745.7 is theconversion factor between W and hp.

$$|I| = \frac{P_{motor}(745.7)}{\sqrt{3}V_{LL}pf} = \frac{4(745.7)}{\sqrt{3}(208)(0.85)} = 9.7404A$$

where:

motor P: real power rating of the motor in hp,

LL V : line-to-line voltage,*pf*: desired power factor

3.2 Load Distribution For An Unbalanced Radial Distribution System

Distribution systems are inherently unbalanced; servicing dispersed 1Φ, 2Φ and 3Φ loads. Although this can lead to a slightly large imbalance at individual buses, systemsare planned for and attempt to maintain a balanced overall load at the feeder bus. Theload distributions used during experimentation were conducted such that a voltage of 110±1 V was maintained at the feeder bus.

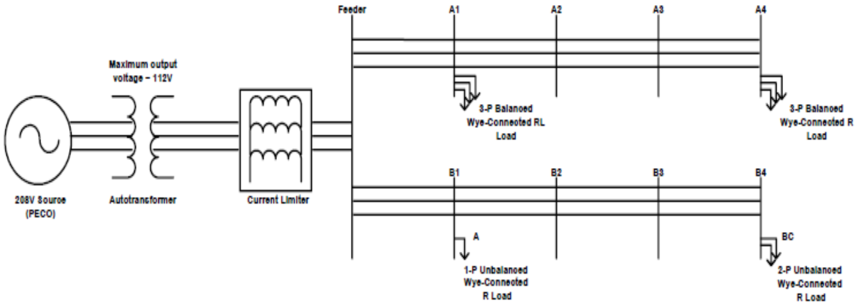

Figure 1: Schematic of a sample load distribution in RDAC, incorporating 1Φ, 2Φ and 3Φ R loads, aswell as a 3Φ RL load.

In order to properly capture the effects of different loading configurations throughoutthe system on fault detection, 21 different load distributions were tested, varying faultand measurement locations. This involved moving different loads closer and farther awayfrom the feeder bus, as well as changing the individual phases being serviced by 1Φ and2Φ loads. One particular load distribution seen commonly in distribution systems is shown in Figure 3.2. One lateral was loaded with 1Φ, 2Φ and 3Φ loads, simulatingresidential and commercial customers, while the other lateral was loaded to a much lesserdegree using the RL equivalent induction motors. These RL loads symbolize an industrialcustomer, which is generally serviced on a separate feeder.

3.3 Wavelet Based Fault Detector Algorithm

3.3.1 Design of the Power System

The system shown in Figure 3.2 represents a 36-bus radial unbalanced distribution system with 4 feeder busesand 8 lateral feeders. The line segments of each lateral have the same impedances ratings,although due to slight differences in manufacturing, create a slight unbalance betweenphases. Four solid-state voltage relays act as normally closed switches and can becontrolled remotely. Measurements are acquired from Hall-Effect Devices (HED) onthree phases as well as the neutral wire and can be taken at any four buses at one time.

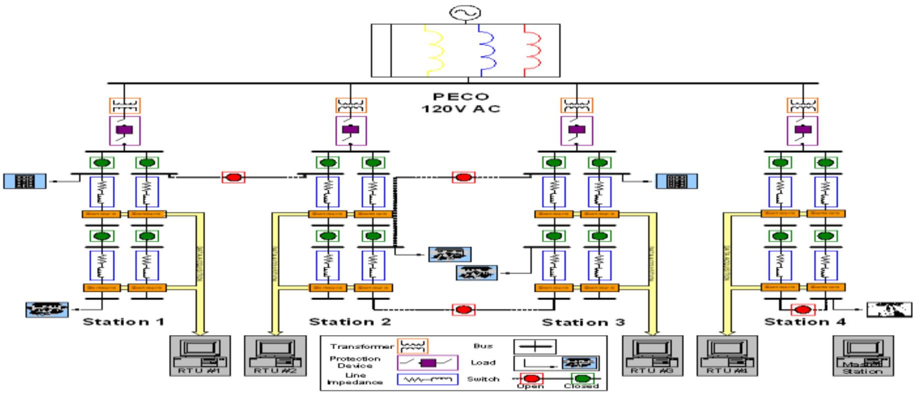

Figure 2 : One line diagram of power system including current limiting protection device

Thiscurrent limiting device was connected between the variable autotransformer and thedistribution feeder box. The device utilized two 40mH inductors connected in parallel perphase and limited the current to 15A, approximately 5A below the maximum currentrating of the system components. Another inductor box was also created in order to testRL loads, which contained two 40mH inductors per phase that could be connected inseries or parallel.

Incorporating motors loads into the fault experiments would further add to voltage andcurrent dynamics during fault conditions and was therefore of special interest. Although,four 5-hp induction motors were available in the adjacent laboratory it was uncertainwhether they could be safely connected because of their electrical characteristics.

Therefore, before an actual induction motor could be connected to the system, an RLequivalent circuit model of an induction motor during steady-state operation was requiredto be proposed and tested.The upper three relays are responsible forswitching phases A, B and C to ground, whereas the lower three connect phases A to B,B to C and C to A respectively. Several relays can be used in unison to create 11combinations of LG, LL, LLG and three-phase faults.

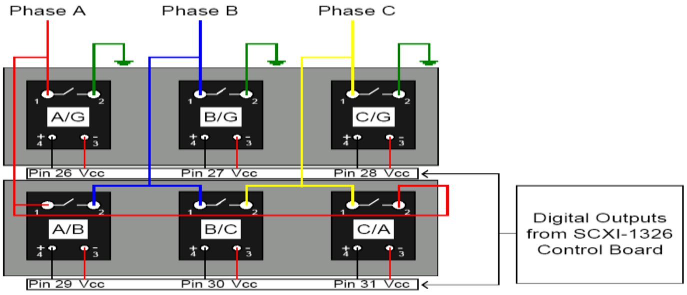

Figure 3*:* Over-voltage relays used for faultcreation .

IV. CONCLUSION

This paper presented a study of the power system fault detection in 120kV electrical distribution systems based on discretewavelet transform and probability neural network. The study involved computer simulationof power systems, discrete wavelet transform and neural network. The electrical faults including HIFs andcommon faults are stochastic in nature, and depend onfactors such as fault location, fault impedance, fault inceptionangle, other electrical loads, etc. A statistical analysiswas performed, and this determined the error probabilityof classification between the fault cases and normal operation.

The statistical data was incorporated into the computersimulation, and the classification results identifiedboth the fault cases and normal operation. The differenceof frequency characteristics between high impedance faultsand normal capacitor bank switching operation simulatedby MATLAB can be recognized by the classifier usingnearest neighbor rule method. It is concluded wavelet transform gives lesser percentage of error than probability neural network

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