

FAULT DETECTION FOR TRANSMISSION LINE USING POWER SYSTEM STABILIZER SIGNALS

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Abstract : It is a well known fact that power systems security is required to smooth power operation sand planning. This requires that power system operators at the control centre appropriately handle information on faults and detect these faults effectively.In this study fault detection using a Wave Transform.The MRA decomposes the signal where the components are analyzed for their energy content and characteristic and the nusedasa feature for different classes and condition of the fault. The same features are also fed to the Generalized Regression Neural Network(GRNN) and Probabilistic Neural Network(PNN)asa fault classifier and the results are compared for analyzing classification rate performance. Once the fault is classified using the above classifier, its location is sent to the lookup table using the online neuro-fuzzy control strategy the optimum value of the gain and time constant for the PSS(Power System Stabilizer) are selected and used to compensate the damping at various fault conditions.

Key words : fault detection, Multi Resolution Analysis (MRA), Generalized Regression Neural Network(GRNN), Probabilistic Neural Network(PNN), Power System Stabilizer(PSS).

1.INTRODUCTION

The main idea for this study is to propose a new method as supervised neural network fault classifier. to integrate the application of PSS (power Systems Stabilizer)as a the fault detection,.Power systems stability may be defined as“that property of a power system that enables it to remain in a state of operating equilibrium under normal operating conditions and to regain an acceptable state of equilibrium after being subjected to a disturbance”.

Power systems stabilizers have been used for many years to add damping to electromechanical oscillations.Essentially,they act through the generators excitation system in suchaway that a component of the electrical torque proportional to speed change is generated (an addition to the damping torque).

A power systems stabilizer is used to add a modulation signal to a generator’s automatic voltage regulator reference input.The k compensator to adjust the input signal to give itidea is to produce an electrical torque at the generator proportional to speed.Power systems stabilizer uses a simple lead networ the correct phase.The most simple and typical type is the Pinput type .And ,recently winput type and finput type PSS are also adopted in order to improve stability of inter-area mode due to the recent increase in power system and power re-routing.For this, an output signal of the speed deviations of each generator of the multi area multi machines system are taken as the input for wavelet analysis. The basic concept in wavelet analysis is to select a proper wavelet, called mother wavelet (analyzing wavelet or admissible),and then perform an analysis using its translated and dilated versions. In this study the only Daubechies two wavelet transform(haar, db)are used to analyze the speed deviation measured on each of the generator in the test system.

In this section Figure 4.1 shows the procedure of main steps for fault detection on transmission line using power system stabilizer,also it shows some tools like wavelet transform (WT),Generalized Regression Neural Network(GRNN) and Probabilistic Neural Network (PNN) are used to detect and classify the faults.

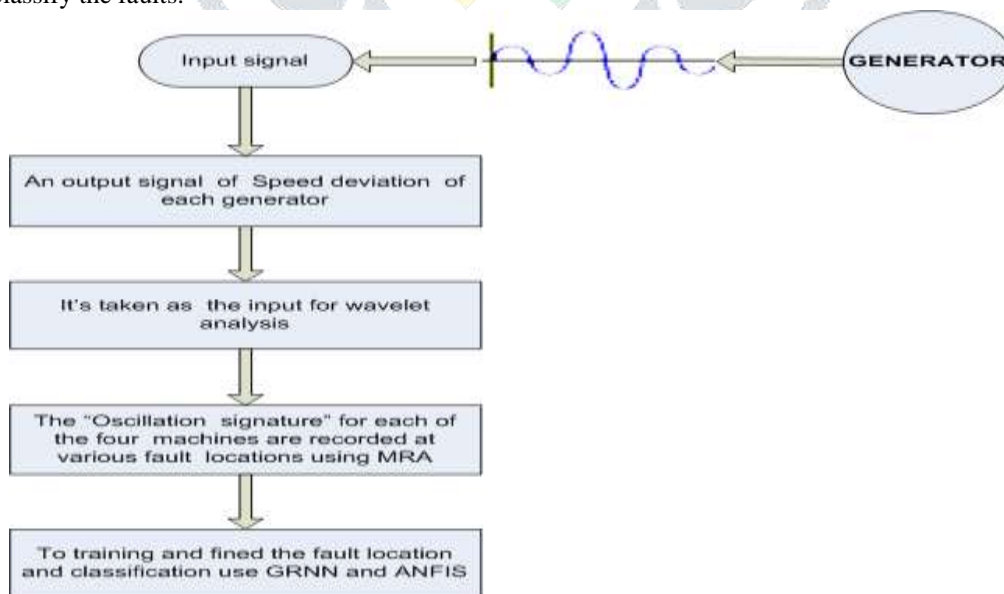


Figure1.1:Flow chart for the methodology of the project

2.TYPES OF INPUT SIGNALS USED IN POWER SYSTEM STABILIZER (PSS):

As mentioned before, a PSS detects the changing of generator output power and controls the excitation value. The type of PSS is identified by the detecting signal. The most simple and typical type is fininput type. Recently, the winput type and finput types PSS are also adopted in order to improve stability of inter-area mode due to the recent increase in power systems and power re-routing.

3.CONTROL SIGNAL :

The obvious control signal(to be used as input to the PSS) is the deviation in the deviation in the rotor velocity.However,for practical implementation,other signals such as bus frequency electrical power, acceleration power are also used.The latter signals are actually synthesized by a combination of electrical and mechanical power signals. The mechanical power signal can be obtained from the gate position in a hydraulic turbine or steam pressure in steam turbine. Never the less,it is difficult to measure mechanical power.It can be argued that if mechanical power variations are slow, then a signal derived from the electrical power approximates acceleration power. However,this can pose problem during rapid increases of generation for which PSS action leads to depression in the voltage.

A recent development is to synthesize acceleration power signal from speed and electrical power signals.This is shown in Figure3.1 a similar approach is used at Ontario Hydro and the power system stabilizer(PSS) utilizing these signals are termed as Delta-P-Omega stabilizer. It is claimed that the new control signal has eliminated the problem of torsional interaction and improved reliability.

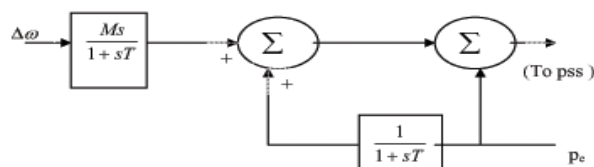


Figure3.1:Synthesis of accelerating power signal.

The choice of control signal for PSS can be based on the following criteria

The signal must be obtained from local measurements and easily synthesized.

The noise content of the signal must be minimal.Otherwise complicated filters are required which can introduce their own problems.

The PSS design based on a particular signal must be robust and reject noise. This implies that lead compensation must be kept to a minimum to avoid amplifying the noise.All the control signals considered-rotorspeed, frequency,electrical power are locally available.The speed signal can be obtained from a transducer using a tooth wheel mounted on the shaft. Alternately it can be obtained from the angle of the internal voltage which can be synthesized. The bus frequency signal can be obtained from a Hall Effect transducer.

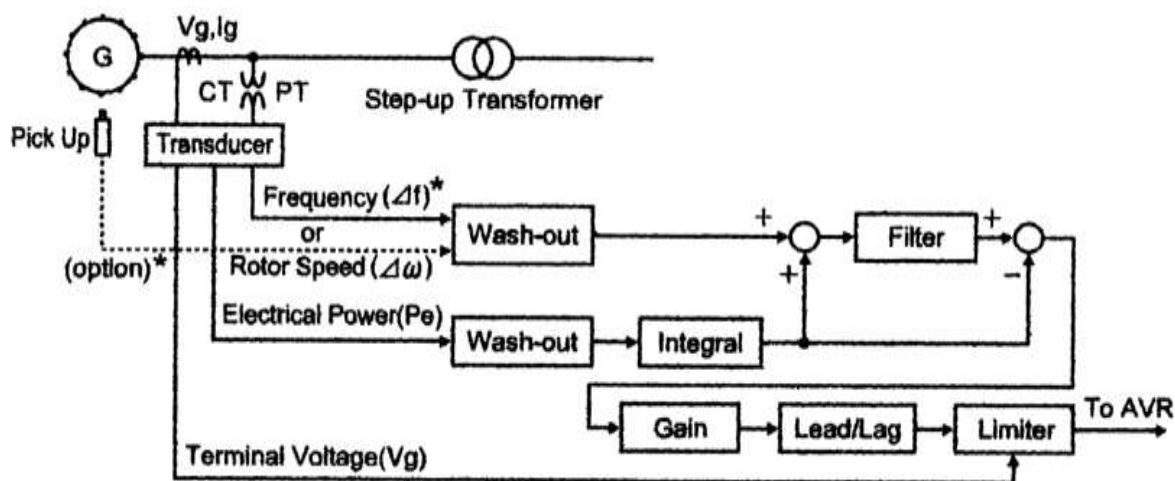


Figure : 3.2 Structure and Tuning Of PSS

The block diagram of the PSS used in industry is shown In Figure3.3. It consists of a washout circuit,dynamic compensator, torsional filter and limiter.The function of each of the complements of PSS with guidelines for the selection of parameters(tuning) are given next. It is to be noted that the major objective of providing PSS is to

increase the power transfer in the network, which would otherwise be limited by oscillatory instability.

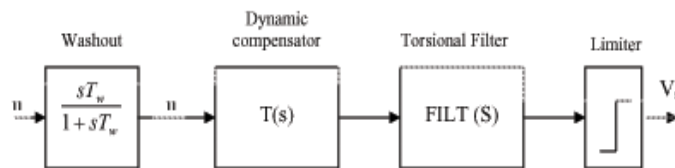


Figure 3.3:Block diagram of PSS

(a) washout circuit

The washout circuit is provided to eliminate steady-state bias in the output of PSS which will modify the generator terminal voltage.The PSS is expected to respond only to transient variations in the input signal (say rotor speed) and not to the dc offsets in the signal. This is achieved by subtracting from it the low frequency components of the signal obtained by passing the signal through a low pass filter.

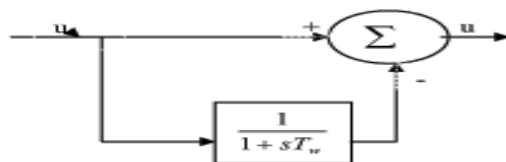


Figure3.4:washout circuit.

The washout circuit acts essentially as a high pass filter and it must pass all frequencies that are of interest. If only the local modes are of interest, the time constant T_w can be chosen in the range of 1 to 2. However, if inter-area modes are also to be damped, then T_w must be chosen in the range of 10 to 20. A recent study has shown that a value of $T_w = 10$ is necessary to improve damping of the inter-area modes. There is also a noticeable improvement in the first swing stability when T_w is increased from 1.5 to 10. The value of T_w also improved the over all terminal voltage response during system is landing conditions.

(b) the ability of the wavelet analysis

One major advantage afforded by wavelets as shown in Figure3.8 is the ability to perform local analysis that is, to analyze a localized area of a larger signal. Consider a sinusoidal signal with a small discontinuity one so tiny as to be barely visible. Such a signal could easily be generated in the real world, perhaps by a power fluctuation or a noisy switch.

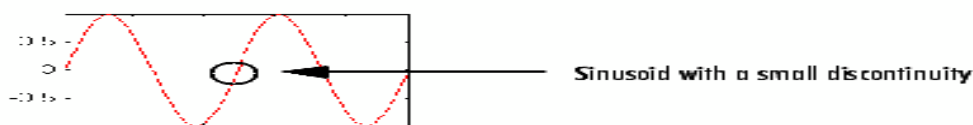


Figure3.5:ability the Wavelet to perform local analysis

A plot of the Fourier coefficients (as provided by the fft command) of this signal shows nothing particularly interesting a flat spectrum with two peaks representing a single frequency. However, a plot of wavelet coefficients clearly shows the exact location in time of the discontinuity. as shown in the Figure 3.6.

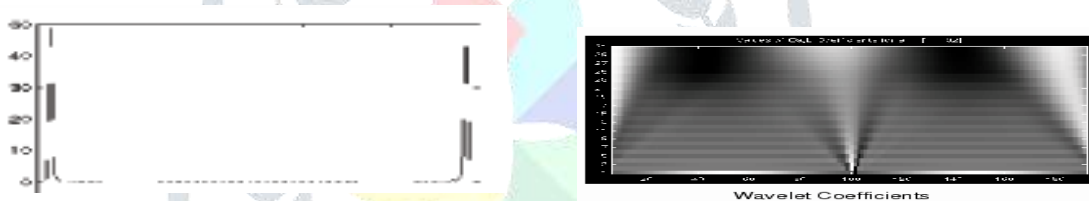


Figure3.6:Difference between Fourier and Wavelet Coefficients

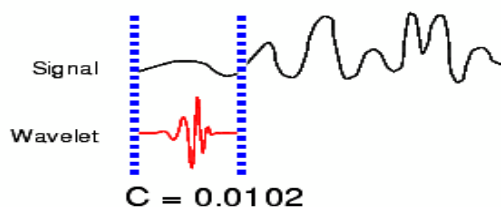
As show above the Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques miss, aspects like trends, break down points, discontinuities in higher derivatives, and self-similarity. Furthermore, because it affords a different view of data than those presented by traditional techniques, wavelet analysis can often compress or de-noise a signal without appreciable degradation.

(c) easy steps to a continuous wavelet transform

The continuous wavelet transform is the sum overall time of the signal multiplied by scaled, shifted versions of the wavelet. This process produces wavelet coefficients that area function of scale and position. It is really a very simple process. In fact, here are the five steps of an easy recipe for creating a CWT:

Take a wavelet and compare it to a section at the start of the original signal.

Calculate a number, C, that represent show closely correlated the wavelet is with this section of the signal. The higher C is, the more the similarity. More precisely, if the signal energy and the wavelet energy are equal to one, C may be interpreted as a



Correlation coefficient. Note that the results will depend on the shape of the wavelet you choose.

C. Shift the wavelet to the right and repeat steps 1 and 2 until you have covered the whole signal.



Figure 3.7: Steps of the Continuous Wavelet Transform

d. Scale (stretch) the wavelet and repeat steps 1 through 3.

e. Repeat steps 1 through 4 for all scales. When you are done, you will have the coefficients produced at different scales by different sections of the signal. The coefficients constitute the results of a regression of the original signal performed on the wavelets. How to make sense of all these coefficients? You could make a plot on which the x-axis represents positional on g the signal (time), the y-axis represents scale, and the color at each x-y point represents the magnitude of the wavelet coefficient C . These are the coefficient plots generated by the graphical tools. These coefficient plots resemble a bumpy surface viewed from above. If you could look at the same surface from the side, you might see something like this. The continuous wavelet transform coefficient plots are precisely the time-scale view of the signal we referred to earlier. It is a different view of signal data from the time-frequency Fourier view, but it is not unrelated.

It is the properties of being irregular in shape and compactly supported that make wavelets an ideal tool for analyzing signals of an on-stationary nature. Their irregular shape lends them to analyze signals with discontinuity or sharp changes, while their compactly supported nature enables temporal localization of a signal's features. When analyzing signals of an on-stationary nature, it is often beneficial to be able to acquire a correlation between the time and frequency domains of a signal. The Fourier transform provides information about the frequency domain, however time localized information is essentially lost in the process. The problem with this is the inability to associate features in the frequency domain with their location in time, as an alteration in the frequency spectrum will result in changes throughout the time domain. In contrast to the Fourier transform, the wavelet transform allows exceptional localization in both the time domain via translations of the mother wavelet, and in the scale (frequency) domain via dilations (Vida, 1991). It should be noted that the process examined here is the Discrete Wavelet Transform (DWT), where the signal is broken into dyadic blocks (shifting and scaling is based on a power of 2). The continuous wavelet transform (CWT) still uses discretely sampled data, however the shifting process is a smooth operation across the length of the sampled data, and the scaling can be defined from the minimum (original signal scale) to a maximum chosen by the user, thus giving a much finer resolution. The trade-off for this improved resolution is an increased computational time and memory required to calculate the wavelet coefficients. A comparison of the DWT and CWT representations of a signal is shown below in Figure 3.8.

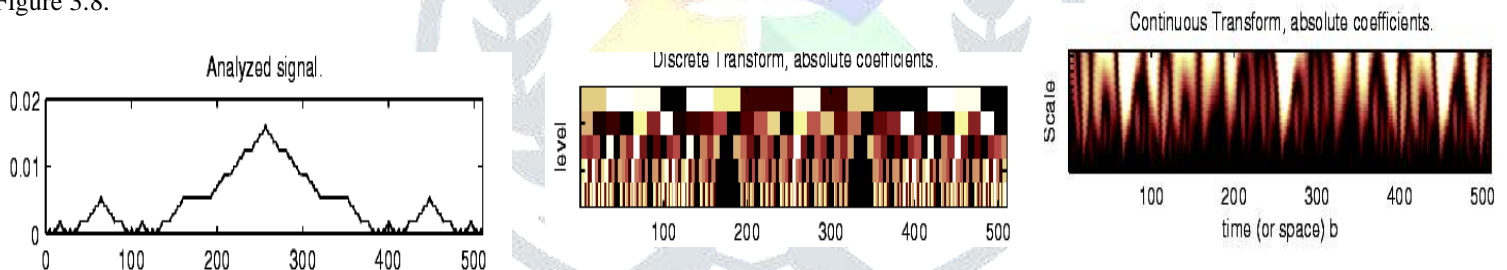


Figure 3.8: A comparison of the DWT and CWT representations of a signal

(d) the suitable selecting for the wavelet algorithms

There are a wide variety of popular wavelet algorithms, but our concern will only be for only two strategies of wavelet transform (Haar, db), including Daubechies wavelets, Mexican Hat wavelets and Morlet wavelets. These wavelet algorithms have the advantage of better resolution for smoothly changing time series. However, they have the disadvantage of being more expensive to calculate than the Haar wavelets. The higher resolution provided by these wavelets is not worth the cost for financial time series, which are characterized by jagged transitions. The wavelet literature covers a wide variety of wavelet algorithms, which are drawn from an infinite set of wavelet algorithms. When I first started studying wavelets, one of the many questions had was "How does one decide which wavelet algorithm to use?" There is no absolute answer to this question. The choice of the wavelet algorithm depends on the application. The Haar wavelet algorithm has the advantage of being simple to compute and easier to understand. The Daubechies D4 algorithm has a slightly higher computational overhead and is conceptually more complex. As the matrix forms of the Daubechies D4 algorithm above show, there is an overlap between iterations in the Daubechies D4 transform step. This overlap allows the Daubechies D4 algorithm to pick up detail that is missed by the Haar wavelet

As shown in the Figure 3.10 the red line in the plot below shows a signal with large changes between even and odd elements. The pink line plots the largest band of Haar wavelet coefficients. The green line plots the largest band of Daubechies wavelet coefficients. The coefficient bands contain information on the change in the signal at a particular resolution. In this version of the Haar transform, the coefficients show the average change between odd and even elements of the signal. Since the large changes fall between even and odd elements in this sample, these changes are missed in this wavelet coefficient spectrum. These changes would be picked up by lower frequency (smaller) Haar wavelet coefficient bands.

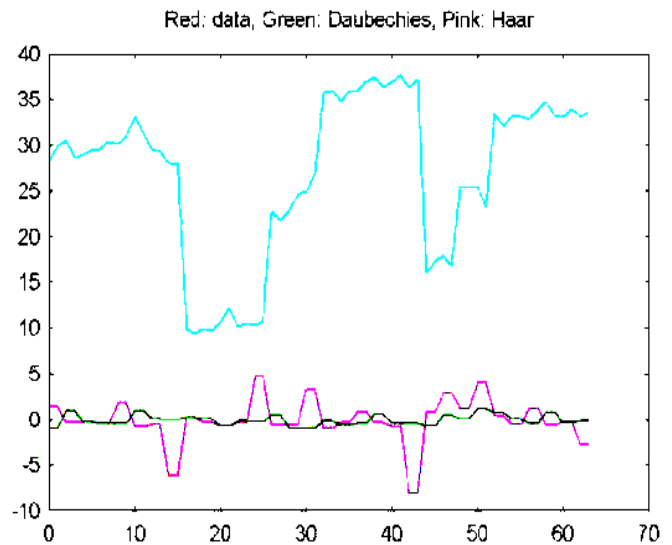
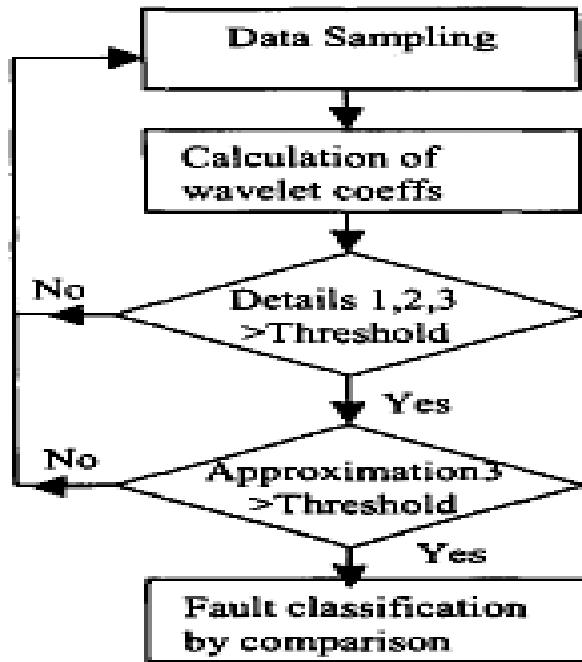


Figure3.9:Flow chart for wavelet algorithm

Figure3.10:Difference between Haar and Daubechies for the same Data.

(e) comparison between haar and daubechies

As we have clearly seen,there are some differences between the two types of the Wavelet(Haar and Daubechies),Table3.1 shown below will explain some other differences.

	HaarWavelets	DaubechiesWavelets
Generalcharacteristics	Compactly supported	Compactly supported
Family	Haar	Daubechies
Shortname	Haar	Db
Examples	Haaris the same as db1	db1or haar, db4, db15
DWT	Possible	Possible
CWT	Possible	Possible
Orthogonal	Yes	Yes
Biorthogonal	Yes	Yes
Compact support	Yes	Yes
Supportwidth	1	2N-1
Filters length	2	2N
Regularity	Haaris not continuous	about0.2 N for large N
Symmetry	Yes	Farfrom

Table3.11:Comparison between Haar and Daubechies

(f) wavelet transforms

In mathematics, wavelets, wavelet analysis, and the wavelet transform refers to the representation of a signal in terms of a finite length or fast decaying oscillating wave form(known as the mother wavelet).This wave form is scaled and translated to match the inputsignal.The translation and dilation operations applied to the mother wavelet are performed to calculate the wavelet coefficients,which represent the correlation between the wavelet and a localized section of the signal.The wavelet coefficients are calculated for each wavelet segment,giving a time-scale function relating the wavelets correlation to the signal.This process of translation and dilation of the mother wavelet is depicted in Figure 3.12.

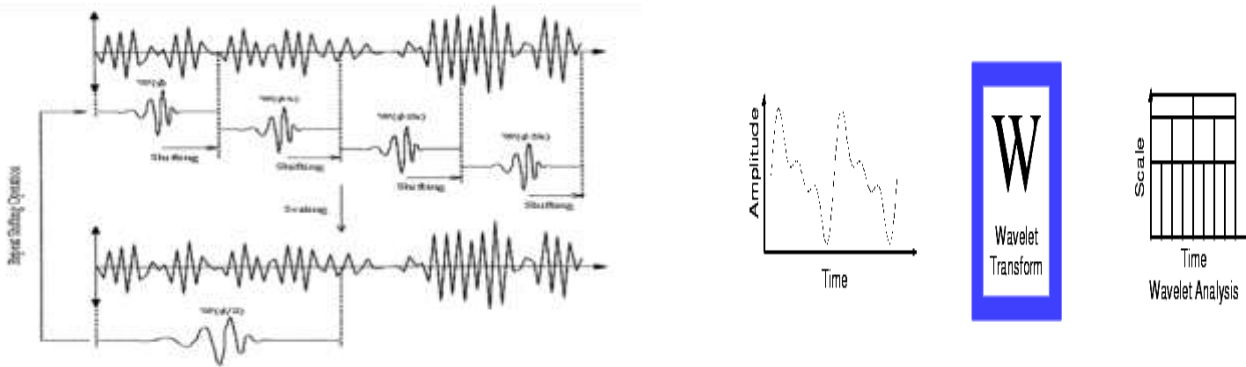


Figure3.12:The mother wavelet

Figure3.13:Wavelet analysis

There are a large number of wavelet transforms each suitable for different applications. For a full list see list of wavelet related transforms but the common ones are listed below:

- Continuous wavelet transforms(CWT).
- Discrete wavelet transforms (DWT).
- Fast wavelet transforms (FWT).
- Wavelet packet decomposition(WPD).
- Stationary wavelet transform(SWT)

As a technique,Wavelet transform has a special feature of variable time-frequency location which is different from the windowed Fourier transform.The wavelet transform is often compared with the Fourier transform,in which signals are represented as a sum of sinusoids.The main difference is that the wavelets are localized in both time and frequency here as the standard Fourier transform is only localized in frequency.The Short time Fourier transform(STFT) is also time and frequency localized but the reae issues with the frequency time resolution and the wavelet softengivea better signal representation using Multi resolution analysis,as we know,the Fourier analysis has a serious drawback.When a signal is transformed in to the frequency domain, time information is lost.However If you are mainly concerned with stationary signals,signals that do not change much over time,this drawback is not very important.

The Short-Time Fourier Transform(STFT) maps a signal in to a 2-Dfunction of time and frequency.However,the time and frequency information can only be obtained with limited precision. The precision is determined by the size of the window used to analyze the signal.

4. FAULT DETECTION

As a frame work of security control,fault detection is one of the important tasks. Specifically, it requires that power system operators at control centers appropriately handle information on faults and detect faults effectively.In other words,more sophisticated fault detection techniques are necessary to maintain secure power systems.

In this project study,a method is proposed for fault detection and classification.A novel technique, called optimal feature selection in the wavelet domain and supervised neural network-fault classifier is developed.An output signal of the speed deviations of each generator of the multi area multi machines system are taken as the input for the wavelet analysis which are then fed to the Generalized Regression Neural Network (GRNN) and Probabilistic Neural Network (PNN) to give the location and classification of the fault.

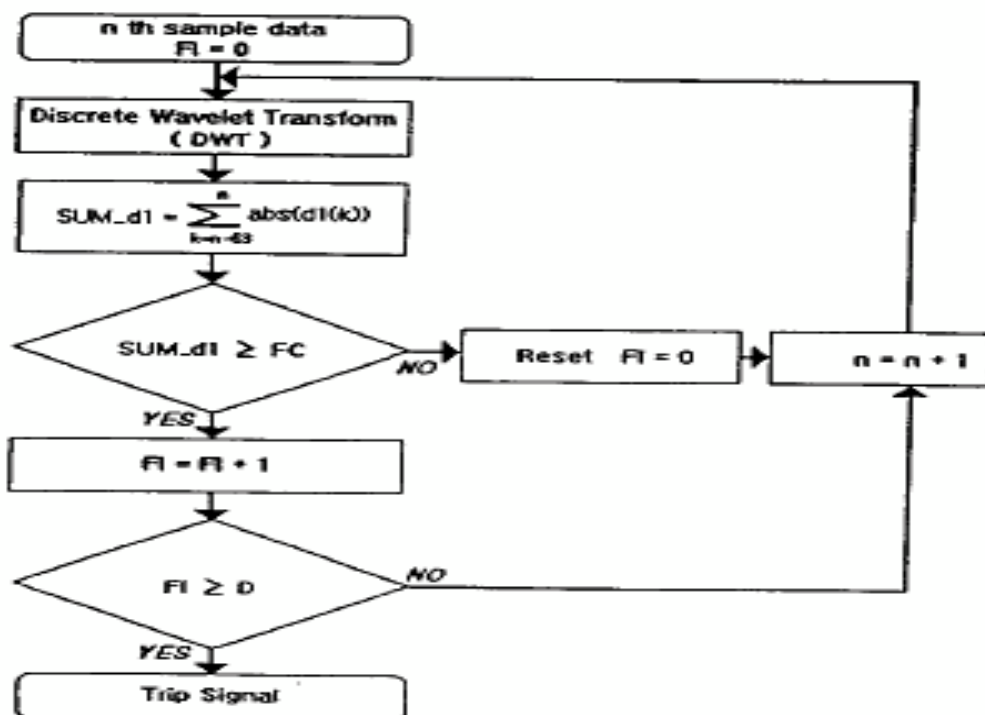


Figure4.1:A block diagramof the fault detection technique

(a) fault classification

Several algorithms have been reported for fault detection in transmission lines. They are based on either artificial neural networks (ANNs) or wavelets transform(WT).Most of them have been developed for relaying purposes and may only distinguish a fault from the normal steady-state power system operation.

Fault classification algorithms based on ANN have been proposed in this project.The WT has also used to get best features for the coefficients.Further more, combined techniques have already been used,such as ANN and WT as a fault detection,both fault detection and classification algorithms found in the project have been developed from simulated data obtained using a MATLAB Program.

This project proposes an ovel method for fault detection and classification in transmission lines by using transient stability program and record the speed deviation of every generator.Both fault signals are then fed to the wavelet program to extract the features for fault classification using neural network.

(b) using grnn as fault classifier and detector

Generalized Regression Network Networks(GRNN)has been developed by Donald Specht and works as a multi-layer feed-forward network.GRNN is based on localized basis function NN which uses the probability density functions and is quite similar in principle to the RBFNN. The term general regression simply that the regression surface is not restricted to be linear. In control engineering, neural network models are often used as dynamic plants emulators for controller design and also as configurations when they estimate the future values of variables.In many previous applications of the GRNN, the sigma (δ)which is referred to as the smoothing factor in the GRNN algorithm is usually fixed and thus not applicable in a dynamic environment.To date,there has not been much work on the application of GRNN for online prediction and classification.

(c) using pnn as a faultclassifier and detector

Probabilistic Neural Networks(PNN) is feed forward network swhich are built with three layers.They estimate the probability density function for each class based on the training samples using either Parzen window or similar probability density function which are calculated for each test vector.as it attention before that, Probabilistic Neural Networks(PNN) are feedforward networks which are built with three layers,one pass,learning network that uses sums of Gaussian distribution to estimate the class probability functions as learned from training vector sets Consequently,the PNN is able to make a classification decision in accordance with the Bayes strategy for decision rules and to provide probability and reliability measures for each classification, Learning involves choosing a single suitable smoothing factor which is thecommon standard deviation for all the Gaussian.The PNN uses one of a class of probability density function estimators which asymptotically approaches the underlying parent density provided that it is smooth andcontinuous.The network is tolerant of erroneous straining vectors and sparse data samples can be adequate for optimal performance.It is both easy to use and fast for moderately sized databases.The major disadvantage of the PNN is that all training vectors must be stored and used to classify new vectors, thus requiring large memories for many practical problems.This is not a severe disadvantage if the PNN is implemented in a parallel hardware structure where memory is relatively inexpensive.Among the advantages offered by PNN are that they train faster(more than five times faster than back propagation),they converge to a Bayes classifier if enough training example examples are provided, they enable a fast incremental training and are robust to noisy example.

5. RESULTS

The two-area four machine system with a double circuit transmission lines between two areas is modified to include a fictitious bus for the study.This system is well-known and its data and analysis can be foundin(Rogers,2000),(seeFigure5.1).

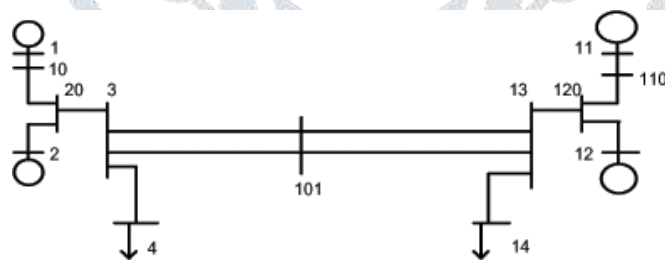


Figure5.1:Single Line Diagramof Two-Area system.

Below are the steps and procedures for fault detection and classification using the proposed new techniques.DatafileProgram-The original data file is modified to include the factious transmission line which acts as the bus bar in the nearest line where the fault occurs. Busbar 376 is introduced between bus 3 and bus 101 and the various calculations of the line distance are obtained.The Load low program calculates the new reference bus voltage and its magnitude automatically.

(a) run the base program

The transient simulation program is run with the three-phase fault occurring on the transmission line between bus 376 and bus 101.All output programs are saved in a Matfile.The main output data for the feature extraction is the speed deviation.The program is run for different lengths of the transmission line distance i.e. 1%, 5%, 25%, 50%, 75%, 95% and 100%.A single drive, svm_mgen, for small signal stability is provided. It is organized similar to the transient stability simulation drivers_simu.New model can be designed to work satisfactory in either driver.Generally,if a model is satisfactory in s_simu, it will be satisfactory in svm_mgen.Figure5.2 shows the generator speed deviation for each generator G1, G2, G3 and G4 by doing some change in the delinevary.mto apply a three phase to ground fault at 5% of transmission line between bus 376 and bus 101.

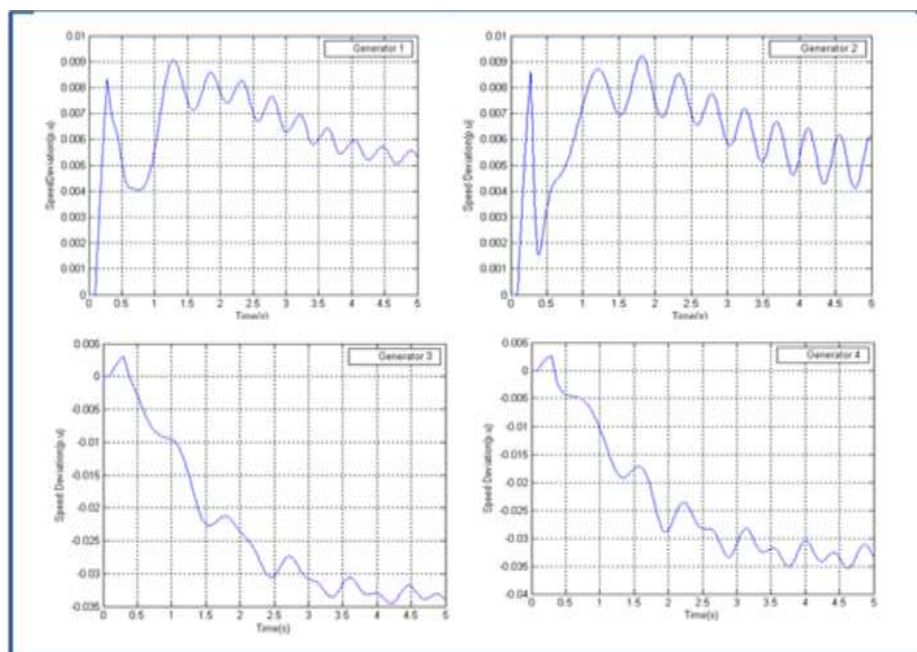


Figure5.2:The Generator Speed Deviation following a three phase fault at 5%of Transmission line between bus 376 and bus 101.

Figure5.3shows the Wavelet coefficient d2, d3 of the speed generator deviation for the generator G1 as an output of the small program ezd5_33.m,which is programmed to produce all the coefficients for db5,level3.when three phase fault and line to line to ground fault occurs at variety percentage of the transmission line between bus 376 and bus 101.

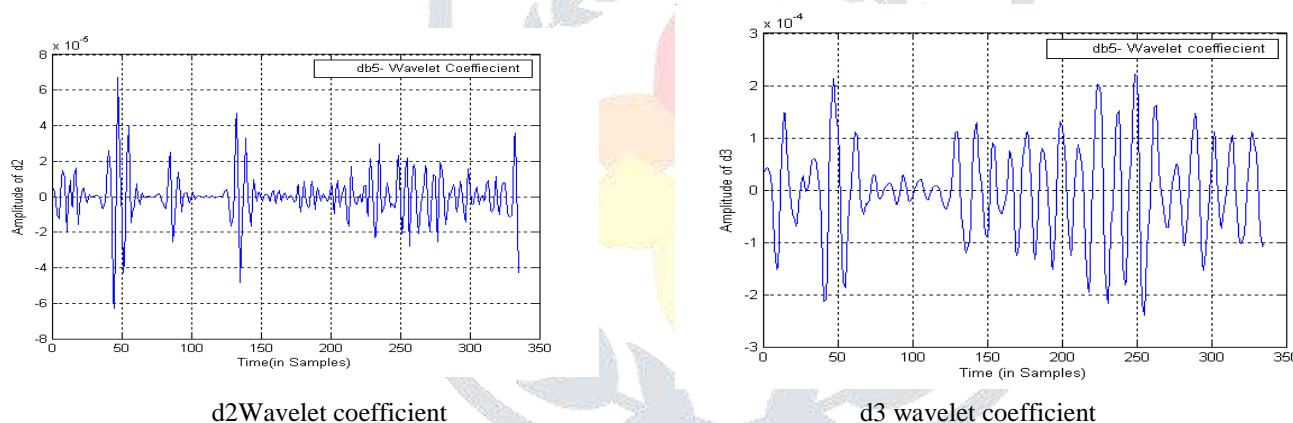


Figure5.3:The DWT of a Speed Deviation of Generator number1 as an out put of the ezd5_33 program.

6. CONCLUSION:

A method for classification and fault detection of a transmission line using intelligent technique is proposed in this study.The use of Multi Resolution Analysis (MRA) Wavelet transform is expected to be very efficient in extracting relevant features from the signal,which produced by the generator The MRA decomposition components were analyzed for their energy content classes and locations of the fault to be classified.

A wavelet based approach is presented in this project,which can be used for detecting and classifying faults on transmission line when three phase and line to line to ground fault occurs.After detailed analysis of the properties of different mother wavelets of Haarand db5 analysis to select best features of the coefficients,which presented in the d2 and d3 to enter it as an input to the PNN and GRNN to training for classification and detection the faults.After training the information it is found that db5 is better than Haarin both detectors PNN and GRNN.It is also found that db5 is more accurate than Haar.

A neural network is very popular as classifiers and has proved efficient; however,they need a large number of data to be effective.But using GRNN and PNN with small amounts of data give quite a good classification rate.The result shows that for the training data the algorithm succeeds in obtaining 100% accuracy. For testing an unseen data of a small variation in the original signal,a noise of 0.01% is added to the signal,thus the simulation ran again for the whole location.The result of correct classification is 100%.From all the previous results,which shown in theTables 5-9,5-10,5-11 and 5-12 during both types of fault three phases and line to line to ground fault can conclude that,theclassification and detection fault for the transmission line by using the best features of the signal at coefficient d2 was better than using coefficient d3. Hence,this study found an ovelway of detecting,classifying and locating the transmission line fault using intelligent technique based on PSS inputsignals as compared to the traditional method such as the traveling wave and the impedance methods which are alreadyestablished

7. REFERENCES

- [1] Kundur, P., "Power System Stability and Control", McGraw-Hill, 1994, ISBN 0-07-035958-X.
- [2] Graham Rogers, "Power System Oscillations", New York: Kluwer, 2000.
- [3] Padiyar, K. R., "Power System Dynamics: Stability and Control", printed in the Republic of Singapore, 1996, ISBN: 0-471-19002-0
- [4] M. F. Othman, M. Mahfouf, and D. A. Linkens, "Transmission Lines fault detection, classification and location using power system stabilizer", IEEE. International conference on Electric utility Deregulation, Restructuring and power technologies, April 2004, Hong Kong.
- [5] Mohd Fauzi Othman, "A Hybrid System Approach to Control and Fault Detection and Accommodation in Power Systems", Department of Automatic Control and Systems Engineering University of Sheffield, March 2004, UK.
- [6] Graham J. Rogers, "The Application of Power System Stabilizers to multi generator Plant", IEEE *Transaction On Power Systems*, vol. 15, no. 1, February 2000.
- [7] Lakmeharan & M. L. Coker, "Optimal Placement and Tuning of Power System Stabilisers", IEEE Technology Group, 1999, pp 40175, South Africa.
- [8] Xiaomeng Li, Student Member, "A Neural Network Based Wide Area Monitor for a Power system", IEEE 2005.
- [9] K. M. Silva, Student Member, IEEE, B. A. Souza, Senior Member, IEEE, and N. S. D. Brito, "Fault Detection and Classification in Transmission Lines Based on Wavelet Transform and ANN" IEEE Transactions On Power Delivery, vol. 21, no. 4, October 2006
- [10] K. Harish Kashyap and U. Jayachandra Shenoy, "Classification of Power System Faults Using Wavelet Transforms and Probabilistic Neural Networks", IEEE, Department of Electrical Engineering.
- [11] M. Solanki, Y. H. Song, S. Potts and A. Perks, "Transient Protection of Transmission Line Using Wavelet Transform" IEEE, Developments in Power System Protection, Conference Publication No. 479 0, 2001.
- [12] C. H. Kim, H. Kim and R. K. Aggarwal, A. T. Johns, "Wavelet Transform In The Accurate Detection of High Impedance Arcing Faults In High Voltage Transmission Lines" IEEE, Developments in Power System Protection, Conference Publication No. 479 0, 2001.
- [13] Marek Michalik, Waldemar Rebizant, Miroslaw Lukowicz, and Sang-Hee Kang, "High-Impedance Fault Detection in Distribution Networks With Use of Wavelet-Based Algorithm" IEEE Transactions On Power Delivery, vol. 21, no. 4, October 2006
- [14] Ali-Reza Sedighi, Mahmood-Reza Haghifam, and Mohammad-Hassan Ghassemian "High Impedance Fault Detection Based on Wavelet Transform and Statistical Pattern Recognition" IEEE Transactions On Power Delivery, vol. 20, no. 4, October 2005.
- [15] Joe-Air Jiang, Ping-Lin Fan, Ching-Shan Chen, Chi-Shan Yu, and Jin-Yi Sheu "A Fault Detection and Faulted-Phase Selection Approach for Transmission Lines with Haar Wavelet Transform" IEEE 0-7803-8 1 10-6/03/\$17.00, 2003.
- [16] M. Solanki and Y. H. Song "Transient Protection of EHV Transmission Line Using Discrete Wavelet Analysis" IEEE, 0-7803-7989-6/03/\$17.00 2003.
- [17] Shyh-Jier Huang, Cheng-Tao Hsieh and Ching-Lien Huang, "Application of Morlet Wavelets to Supervise Power System Disturbances" IEEE, Transactions on Power Delivery, Vol. 14, No. 1, January 1999.
- [18] MITUBISHI Corporation, Power System Stabilizer (PSS). <http://www.powersystemstabilizer.com>

