COMPENSATION OF POWER QUALITY DISTURBANCES USING WAVELET WITH MULTILAYER AND MODULAR NEURAL NETWORK

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ABSTRACT

The proposed model is based upon the Wavelet Transform to extract the features of disturbance signals and is found to detect disturbance correctly even in the presence of noise. Classification of voltage disturbances such as sag, swell, interruption and harmonics is performed with multilayer and modular neural network. Modular neural network has given better classification accuracy and reduced training time by using less number of hidden layer nodes compared wavelet based traditional multilayer neural networks. Simulation and experimental results verify that W-transform based modular neural network has correctly classified and characterized the disturbances.

.keywords – *wavelet transform, neural network, faults.*

I. INTRODUCTION

In recent years, concern over the quality of electric power has been increasing rapidly since poor electric power quality causes many problems for the affected loads, such as malfunctions, instabilities, short life time and so on. Poor quality of electric power is normally caused by power line disturbances such as impulses, notches, glitches, momentary interruptions, wave faults, over voltages, under- voltages, and harmonic distortion. In order to improve electric power quality, the sources and causes of such disturbances must be known before appropriate mitigating action can be taken. However, in order to determine the causes and sources of disturbances, one must have the capability to detect and localize those disturbances and further identify (classify) the types of disturbances. Manual procedure have been developed for this purpose; however, due to the large amount of effort required, such procedures are costly and inefficient. In the commercial market, the current state of the art with respect to detecting power quality disturbances is based on a point-to-point comparison of adjacent cycles [l]. The drawback of this approach is that it fails to detect disturbances that appear periodically such as flat-top and phase controlled load wave shape disturbances. An- other approach to detect and identify disturbances is based on neural networks [2]. This approach seems appropriate in detecting and identifying a particular type of disturbance; however, due to its intrinsic nature, a specific neural net- work architecture is required to detect a particular type of disturbance. Therefore, this neural network will, in general, not be appropriate for detecting and identifying other types of disturbances. The use of continuous, wavelet transforms to analyze non- stationary harmonic distortions in power system has been envisaged in [3], although no results were presented. In this paper, we propose to utilize a dyadic orthonormal wavelet transform analysis to detect and localize various types of power quality disturbances, including harmonic distortion [4]. The key idea underlying this approach is to decompose a given disturbance signal into other signals which represent a smoothed version and a detailed version of the original signal. Our preliminary results using simulated power line disturbances were published in [4]. In this paper, we apply our proposed techniques to the detection and localization of actual power quality disturbances measured by power line monitoring devices. The proposed technique appears to be robust for detection and localization purposes. We also investigate the uniqueness of the squared wavelet transform coefficients that will ultimately lead to an automatic scheme for classifying various types of power quality disturbances.

II. WAVELET TRANSFORM ANALYSIS

The wavelet transform is a mathematical tool, much like a Fourier transform in analyzing a stationary signal, that decomposes a signal into different scales with different levels of resolution by dilating a single prototype function. The decomposition into scales is made possible by the fact that the wavelet transform is based on a square integral function and group theory representation.

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

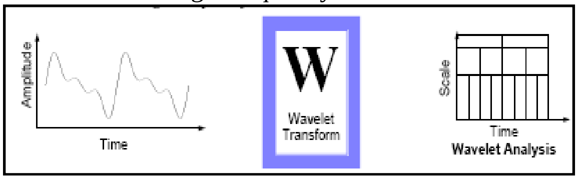


Figure 2.1 wavelet analysis

Here's what this looks like in contrast with the time-based, frequency-based, and STFT views of a signal:

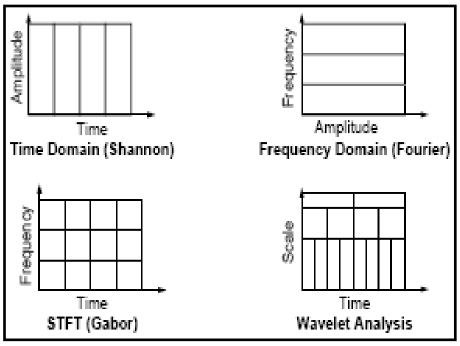


Figure 2.2 views of signals

ONE-STAGE FILTERING: APPROXIMATIONS AND DETAILS:

For many signals, the low-frequency content is the most important part. It is what gives the signal its identity. The high-frequency content on the other hand imparts flavor or nuance. Consider the human voice. If you remove the high-frequency components, the voice sounds different but you can still tell what's being said. However, if you remove enough of the low-frequency components, you hear gibberish.

In wavelet analysis, we often speak of approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components.

The filtering process at its most basic level looks like this:

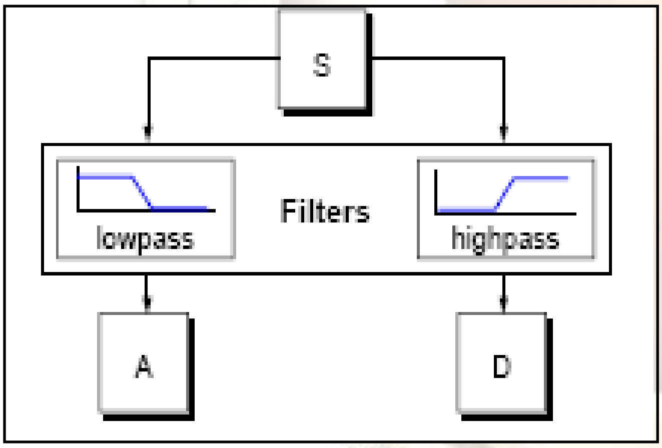


Figure2. 3 Filtering process

The original signal S passes through two complementary filters and emerges as two signals. Unfortunately, if we actually perform this operation on a real digital signal, we wind up with twice as much data as we started with. Suppose, for instance that the original signal S consists of 1000 samples of data. Then the resulting signals will each have 1000 samples, for a total of 2000. These signals A and D are interesting, but we get 2000 values instead of the 1000 we had. There exists a more subtle way to perform the decomposition using wavelets. By looking carefully at the computation, we may keep only one point out of two in each of the two 2000-length samples to get the complete information. This is the notion of own sampling. We produce two sequences called CA and CD.

RELATION OF FILTERS TO WAVELET SHAPES:

In the section "Reconstruction Filters", we spoke of the importance of choosing the right filters. In fact, the choice of filters not only determines whether perfect reconstruction is possible, it also determines the shape of the wavelet we use to perform the analysis.

To construct a wavelet of some practical utility, you seldom start by drawing a waveform. Instead, it usually makes more sense to design the appropriate quadrature mirror filters, and then use them to create the waveform. Let's see how this is done by focusing on an example.

Consider the low pass reconstruction filter (L') for the db2 wavelet.

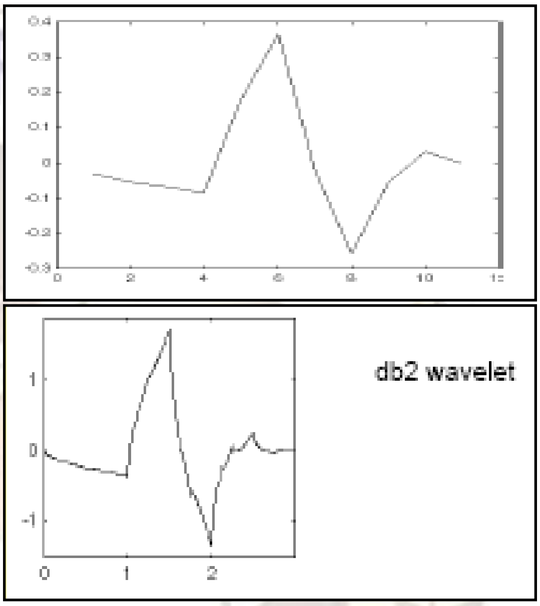


Figure 4 Wavelet function position

If we iterate this process several more times, repeatedly up sampling and convolving 0the resultant vector with the four-element filter vector L prime, a pattern begins to emerge:

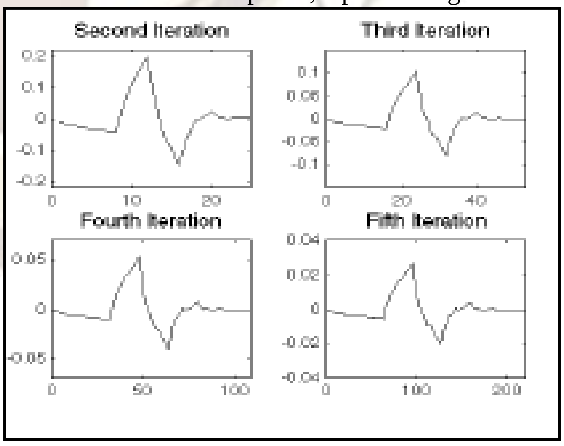


Figure 2.4 Iteration process

The curve begins to look progressively more like the db2 wavelet. This means that the wavelet's shape is determined entirely by the coefficients of the reconstruction filters. This relationship has profound implications.

It means that you cannot choose just any shape, call it a wavelet, and perform an analysis.

At least, you can't choose an arbitrary wavelet waveform if you want to be able to reconstruct the original signal accurately. You are compelled to choose a shape determined by quadrature mirror decomposition filters

WAVELET DECOMPOSITION FOR IMAGES (2-D):

Images are treated as two dimensional signals, they change horizontally and vertically, thus 2D wavelet analysis must be used for images. 2D wavelet analysis uses the same 'mother wavelets' but requires an extra step at every level of decomposition. The 1D analysis filtered out the high frequency information from the low frequency information at every level of decomposition; so only two sub signals were produced at each level.

In 2D, the images are considered to be matrices with N rows and M columns. At every level of decomposition the horizontal data is filtered, and then the approximation and details produced from this are filtered on columns.

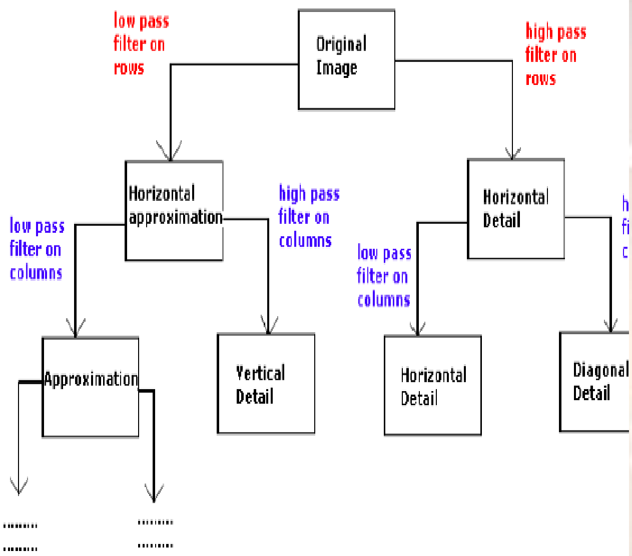


Figure 2.5approximation details

III. NEURAL NETWORK

Multi Layer Neural Network

Multilayer networks solve the classification problem for non linear sets by employing hidden layers, whose neurons are not directly connected to the output. The additional hidden layers can be interpreted geometrically as additional hyper-planes, which enhance the separation capacity of the network. This new architecture introduces a new question: how to train the hidden units for which the desired output is not known. The Back propagation algorithm offers a solution to this problem.

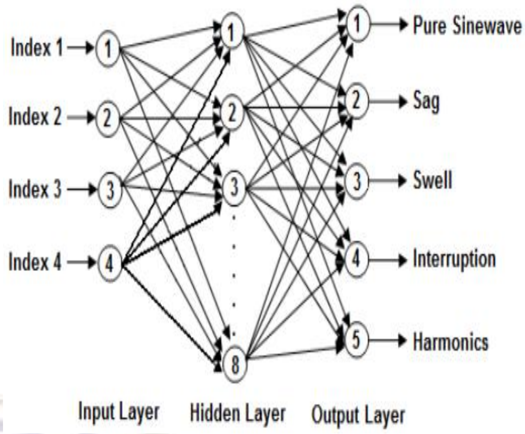


Figure 3.1 multilayer neural network

Modular Neural Network

A modular neural network is a neural network characterized by a series of independent neural networks moderated by some intermediary. Each independent neural network serves as a module and operates on separate inputs to accomplish some subtask of the task the network hopes to perform [1]. The intermediary takes the outputs of each module and processes them to produce the output of the network as a whole. The intermediary only accepts the modules' outputs—it does not respond to, nor otherwise signal, the modules. As well, the modules do not interact with each other.

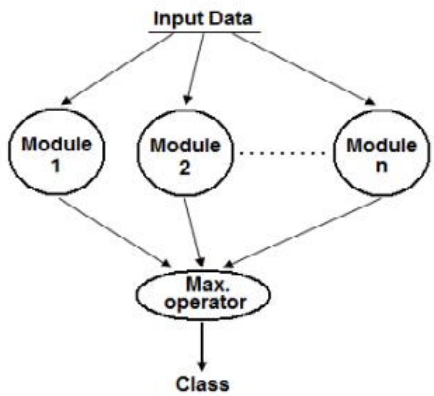
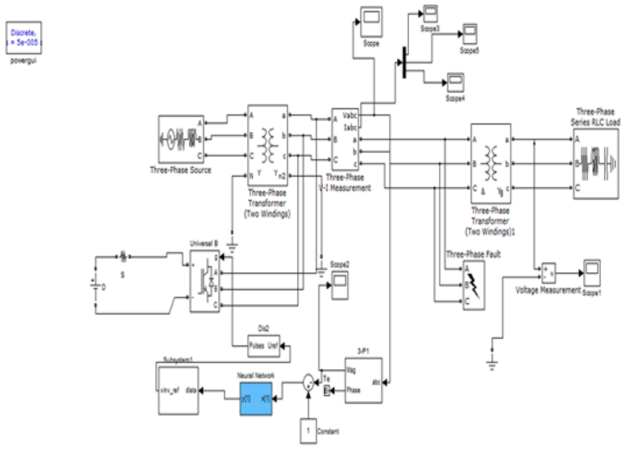


Figure 3.2 modular neural network

IV. SIMULATION RESULTS

Simulink Block Diagram for Compensation of Power Quality Disturbances Using Wavelet Based Multilayer and Modular Neural Network



CONTROLLER DESIGN

PROGRAM FOR WAVELET DECOMPOSITION

```
save Ia
load Ia
for  i=0:99
Iat (: , i+1) = i
[ca, la]=wavedec (Iat (:,i+1),1,'db1');
da (:,i+1) = detcoef (ca,la,1);
nda (i+1) = sqrt (sum (abs (da (:,i+1))))/100;
end
```

MULTILAYER NEURAL NETWORK

```
P = [0.2003 0.2048 0.2048 0.2049 0.2049 0.2065 0.2391 0.2573 0.3099 0.3116 0.3152 0.3167 0.3170 0.3246 0.3246 0.3246];
T = [0.9947 0.9215 0.9200 0.9198 0.9183 0.8681 0.6635 0.6635 0.6635 0.7662 0.8503 0.8934 0.9013 0.9947 0.9948 0.9949];
net = network;
net = newff (minmax (P),[7 1],{'tansig' 'purelin'},'traingdx','learngdm','sse');
net.trainParam.lr=1.0;
net.trainParam.epochs=1000;
net.trainParam.sse=1e-2;
[net,tr] = train (net,P,T);
gensim (net)
```

MODULAR NEURAL NETWORK

```
P = [0.2003 0.2048 0.2048 0.2049 0.2049 0.2065 0.2391 0.2573 0.3099 0.3116 0.3152 0.3167 0.3170 0.3246 0.3246 0.3246];
 %p=p';
O = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1];
net.numInputs=2;
net.numLayers=1;
net = newff ([0.4 0.6],[20,1],{'tansig','poslin'},'traingdm');
net.trainparam.lr=0.02;
net.trainparam.epochs=500;
net.trainparam.goal=0.0;
net.trainParam.min_grad=1e-40;
net = train (net,p,o);
%net = newlind (p,o);
gensim (net,-1)
```

OUTPUT GRAPHS

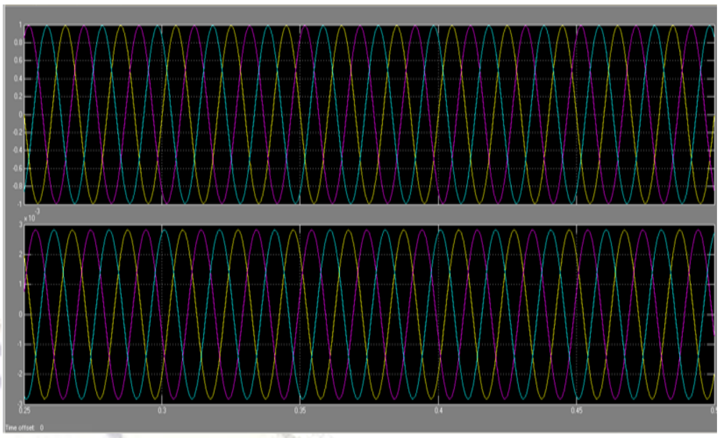


Figure 4.1 three phase sinusoidal wave under no fault condition

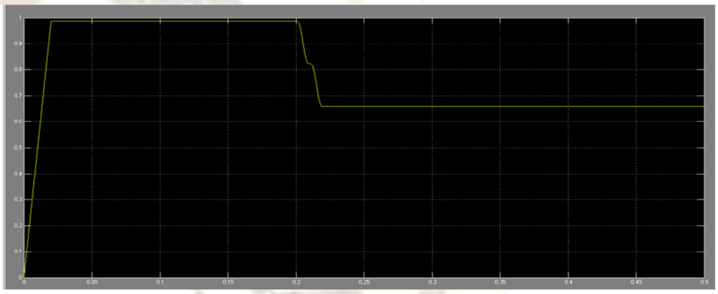


Figure 4.2 voltage magnitude during fault condition

OUTPUT TABLE

SIGNAL	TEST SET Vrms (pu)	WMLNN Vrms (pu)	WMNN Vrms (pu)
SAG Rated voltage(25e3)	0.09948	0.03444	0.03463
10% of rated voltage(25e2)	0.9948	0.3444	0.3463

V. CONCLUSION:

Wavelet transform is used in this paper to extract the features of disturbance signals and is found to detect disturbance correctly even in the presence of noise. Classification of voltage disturbances of sag with modular neural network. Modular neural network has given better classification accuracy and reduced training time by using less number of hidden layer nodes compared to wavelet transform based traditional multilayer neural network. Simulation and experimental results verify that wavelet transform based modular neural network has correctly classified and characterized the disturbances.

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