International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization on TPE (IOTPE)

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

September 2011	Issue 8	Volume 3	Number 3	Pages 65-70

WAVELET-ANN APPROACH TO CLASSIFY CAPACITOR SWITCHING, LOAD SWITCHING AND LINE SWITCHING TRANSIENTS

M.A. Beg [1] **M.K. Khedkar** [2] **S.R. Paraskar** [1] **G.M. Dhole** [1]

1. Department of Electrical Engineering, S.S.G.M. College of Engineering Shegaon (M.S.), India, beg_m_a@rediffmail.com, srparaskar@gmail.com, gmdhole@gmail.com
2. S.G.B. Amravati University, Amravati, India, mohankhedkar@rediffmail.com

Abstract- With wide spread use of sensitive nonlinear electronic devices, electromagnetic transients are capable of degrading the quality of power. Utilities often switch the shunt capacitor banks to cope up with sagging voltage levels, thereby generating transients, which travel into the network of end users. Capacitor switching can cause over voltage, resonance and in advert tripping of Adjustable Speed Drives (ASD) and many other sensitive electronics devices. This paper presents a method to distinguish between transients arising out of isolated capacitor switching, back-to-back capacitor switching, load switching, line energization and line de-energization. The DWT of modal voltage signal is used to extract distinguishing features from the voltage waveform of these events. The detail coefficients for d_1 and d_5 level only, obtained from DWT are processed, mapped and given to Feed Forward ANN (FFANN) network, which accordingly classify the event. A real power system has been simulated in PSCAD/EMTDC with lines modeled using frequency dependant phase model.

Keywords: Transients, Discrete Wavelet Transform, Multi Resolution Analysis, Power Quality, Feed Forward ANN.

I. INTRODUCTION

Traditionally the interest in power system transients has been related to the correct operation of circuit breaker, and to over voltages due to switching of HV lines. But now day's transients are seen as a potential power quality problem. Hence transient waveforms are needed to be characterized and analyzed. Methods have to be developed to extract information on the cause of transient waveforms.

Deregulated power sector has enhanced the competition amongst various power producers leading to a need to improve the quality of electric supply. The cause of degradation of power quality must be investigated to improve the quality. The wide uses of accurate electronics devices require extremely high quality supply. Even developed economics of the world are losing billions of dollars to power quality problem.

Energization of utility shunt capacitor banks is a daily operation in the utility system. They are switched into the system in anticipation of load increase at a customer site, to correct power factor, to support voltage on the system, and so on. Some Capacitor banks are permanently connected while others are switched ON and OFF as needed.

Large capacitor switching causes many problems, such as over voltages, over current, high frequency transients, nuisance tripping of ASD, malfunction of process control and any load that cannot tolerate sub cycle over voltage transients. In [1], the adverse effects of the application of shunt capacitors on the system and sensitive loads were studied. However most utilities have very limited resources to identify their problems and correlate them with capacitor switching operations [2].

Many classifier systems using ANN were proposed earlier by extracting the features using DWT, CWT (continuous wavelet transform), Fourier transforms etc. Santose et al. extracted the features of PQ signals in terms of wavelet coefficients using the MRA as inputs to the neural network for identifying impulses, voltage sags and transient oscillations [7]. Perunicic et al in [8] used the wavelet coefficients of DWT as inputs of self organizing mapping neural network to identify dc bias, harmonics, voltage sags, and other transient disturbances.

Elmitwally et al. employed the preprocessed wavelet coefficients as inputs of the neuro-fuzzy systems for classifying the voltage swell, voltage sag, interruption, impulse, voltage flicker, harmonic, and flat topped wave [9]. Angrisani et al proposed an approach for estimating the magnitudes and durations of the disturbances using the CWT and used these two features for identifying the periodic carrier and voltage sag [10]. Santose et al. incorporated DWT and learning vector quantization Neural Network with decision-making scheme as classifiers for the power signals [11]. Mokhtari et al used a wavelet-based method for on line voltage detection [12]. Permanent continuous monitoring is gaining wide acceptance as an effective mean of assessing electrical power system quality. M.A. Beg et al proposed a simple method to categories isolated capacitor switching and back-to-back capacitor switching using wavelets [13].

Ahmad et al [14] presented a technique for locating switched capacitors in an industrial distribution system using DWT-FFANN approach. A modal current signal was constructed by combining three phase currents. J. Liu et al [15] extracted distinguishing features from the DWT coefficients of some typical power transients using scalogram. Chung et al [16] presented a new classifier using a rule-based method and a wavelet packet-based hidden Markov model (HMM). Kaewarsa et al [17] presented a wavelet-based neural classifier integrating the discrete wavelet transform (DWT), learning vector quantization (LVQ) neural network, and decision-making scheme to become an actual power disturbance classifier.

Mario Oleskovicz et al [18], employed DWT to extract the main features of the voltage signal waveform, decomposing it until the seventh level of resolution. The resulting signal that emerged from this pre-processing stage was presented to a neural network classifier. However in the classification stage, 5 different neural networks were used to classify 5 different events. Transients, voltage sags, and harmonics are the major causes of degradation in power quality. O. Amanifar et al [19] simulated a distribution system in PSCAD to obtain the best placement of distributed generator in distribution network, together with determination of effects of distributed generation on voltage sag.

A. Sabbagh Alvani et al [20] described the construction of power quality monitoring device capable of measuring harmonics up to 121 order using FFT (fast Fourier transform). The disadvantages of FFT can be removed by using wavelet transform. The data recorded by a monitor comprising of different events including voltage transients need to be sorted. This data perhaps can be used for future analysis in determining the causes or sources of these events to assess their severity. Identifying capacitor-switching transients as described in this paper can be one of the steps in the classification process. This paper aims to propose an effective classification method for switching transients based on wavelet transform and FFANN. A modal voltage signal is constructed by a proper linear combination of three phase voltage signals. This modal signal is analyzed further using DWT. The modal voltage signal is decomposed up to five levels using bior1.3 as mother wavelet. The detailed coefficients of level 1 and 5 only, yield features that are capable of classifying type of switching action using FFANN. It is assumed that the monitoring instruments are connected to (or very close to) the switching point. This paper is organized as follows.

In section II, the DWT and multi resolution analysis is presented. The real power system on which the applicability of the proposed method is tested is presented in section III. The proposed method is discussed in detail in section IV. Simulation and results are discussed in section V. The conclusion is presented in section VI.

II. DISCRETE WAVELET TRANSFORM AND MULTI RESOLUTION ANALYSIS

WT expands a signal in terms of a wavelet, generated using translation and dilation of a fixed wavelet function called "mother wavelet". A mother wavelet is defined as

$$\Psi_{(j,k)}(t) = 2^{-j/2}\psi(2^{-j}t-k) \quad (1)$$

Wavelets analyze any signal by using an approach called the multi resolution analysis (MRA), i.e., it analyzes the signal at different frequencies with different resolutions. MRA is designed to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. Discrete wavelet transform (DWT) can be implemented using a tree-structured filter bank. An input signal x[n] is decomposed as

$$y_{high}[k] = \sum_n x[n]\cdot g[2k-n] \quad (2)$$

$$y_{low}[k] = \sum_n x[n]\cdot h[2k-n] \quad (3)$$

where, $y_{high}[k]$ and $y_{low}[k]$ are the outputs of the high pass and low pass filter at a given level, after sub-sampling by Equation (2). Here, $g[n]$ is a high pass filter, $h[n]$ is a low pass filter.

III. POWER SYSTEM MODEL

The applicability of the proposed method has been tested successfully on a simplified real power system model of a State Electricity Transmission Company Limited shown in Figure 1. It is a 132 KV network with 14 buses. The two lines between bus 10 and bus 14 are 220 KV lines and remaining are 132 KV lines. The transmissions lines have been modeled using the frequency dependent phase model in PSCAD/EMTDC. In practice two capacitors $C1$ and $C2$ of 10 MVAR and 15 MVAR are switched at bus 5 to provide the reactive power support as per the requirement. This 132 KV network is interconnected with 220 KV network.

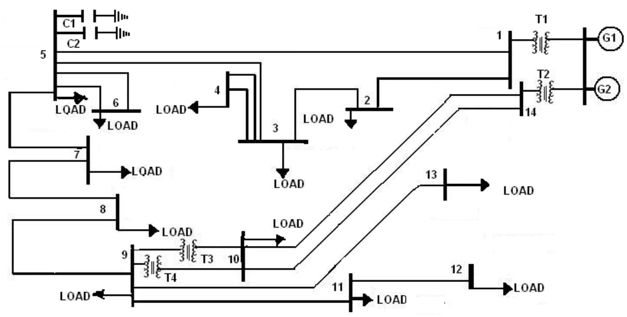

Figure 1. Single line diagram of the simplified power system

IV. PROPOSED METHOD

In the proposed scheme a modal voltage signal-

$$E_m = ME^{abc} \quad (4)$$

where, $E^{abc} = [E_a \quad E_b \quad E_c]$, E_m is modal voltage signal, E_a, E_b, E_c are three phase voltages, M is column vector of modal coefficient having 1x3 dimensions has been used.

The transients produced in individual phase voltage signal are preserved in the modal signal, when all the modal coefficients are not 1.

The preserved transients in modal signal can be extracted using wavelet transform, which provides time-frequency resolutions or localization of signal. The detection/classification capability of any Artificial Intelligence technique primarily depends on the input given to it.

Isolated capacitor switching, back-to-back, load switching and line switching cannot be discriminated merely by observing the three phase voltages or the modal voltage waveforms. Following processing of wavelet coefficients is used to extract the desired features from the modal voltage signal.

MRA of wavelet transform of modal signal provides the following information

$$\{A_n, d_1, d_2, ..., d_i, ..., d_n\} = DWT\{E_m\} \tag{5}$$

where, A_n is the set of approximate wavelet coefficients at level n, d_1, d_2, …, d_n is the set of detailed coefficients of wavelet transform at first, second, …, nth decomposition level.

Let 'i' be the level where possible discrimination is found (in this case fifth level) and corresponding wavelet coefficients are denoted by 'd_i'. The spectral energy density of d_i coefficients for level 5 can be calculated using

$$S_{xx}(n) = d_i^2(n) \tag{6}$$

Energy contained in the detail coefficients of DWT has effectively been used in the past for the characterization of PQ disturbances. However it is observed that this method does not always work particularly when analyzing voltage signals. Hence it is necessary to map the energy into another domain to extract distinguishing features. Therefore, to avoid such drawback, the spectral energy density $S_{xx}(n)$ of d_i coefficients is mapped as follows

$$S_{xx}(n) \to (0,1) \tag{7}$$

using the following membership function

$$\mu_A(n) = \frac{1}{1+S_{xx}(n)} \tag{8}$$

Equation (8) provides discrete sequence where low magnitude long duration transients acquire higher membership than the high magnitude transients. Hence, low magnitude long duration transients which are not easy to detect directly from the Wavelet coefficients are clearly visible in mapped domain.

The complement of (8), provides the information in tune with $S_{xx}(n)$ with clarity in this domain. The compliment of (8) can be obtained from (9)

$$\overline{\mu_A}(n) = 1 - \frac{1}{1+S_{xx}(n)} \tag{9}$$

In addition to this cumulative sum of complemented function is taken to calculate the transient duration and mapped energy injected due to transient. The cumulative sum of (9) is calculated using (10).

$$C_\mu(n) = \sum_{k=1}^{n} \overline{\mu_A}(n) \qquad n = 1, 2, ..., N \tag{10}$$

The sum of minimum and maximum value of the detail 1 level coefficient is calculated for each switching event and denoted as S. The difference of the cumulative sum of complimented membership function corresponding to the instant of this minimum and maximum value of the detail 1 level coefficients is determined as E_d. These are the distinguishing features and hence given to the FFANN for classification.

V. SIMULATION AND RESULTS

The simplified real power system of State Electricity Transmission Company limited shown in Figure 1 is simulated in PSCAD /EMTDC to test the applicability of the proposed method. The three phase voltages are monitored at buses 5, 3, and 2 of utility. The lines have been constructed by using frequency dependant phase model in PSCAD /EMTDC.

The following switching cases at bus 5 have been presented:

i. Isolated capacitor switching:

a) Only 15 MVAR capacitor is switched ON.

b) Only 10 MVAR capacitor is switched ON.

ii. Back-to-back capacitor switching:

a) 15 MVAR capacitor in the circuit and 10 MVAR capacitor are switched ON.

b) 10 MVAR capacitor in the circuit and 15 MVAR capacitor are switched ON.

iii. Load varied from 30 MW to 80 MW

iv. Line energization and Line de-energization

Wavelet decomposition of switching transients is shown in Figure 2 to 6.

The capacitor transients are quite obvious, even when the short circuit capacity of the bus is large and their decay time is quite large compared to that of load switching. Each capacitor switching has its own reflection in the form of high frequency voltage signature which depends on size, its distance from the monitoring point and the magnitude of the load. It must be noted that, here signature does not mean that the transient voltage signature will be the same for the same capacitor under all switching conditions, but it means that the voltage transients caused by the switching operation for the same capacitor have the same properties which are different from the voltage transients caused by any other capacitor switching operation.

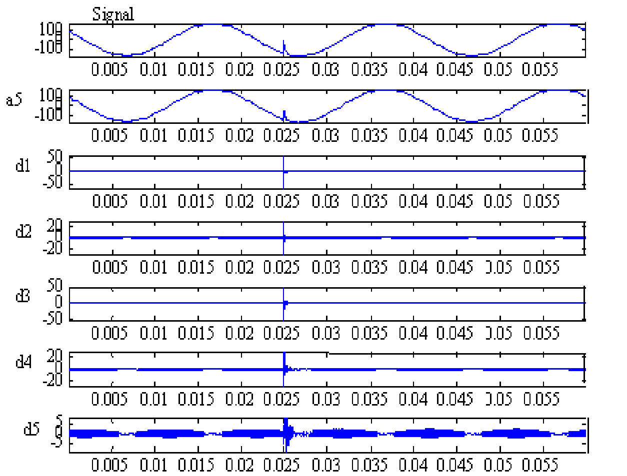

Figure 2. Wavelet decomposition of isolated capacitor switching transient

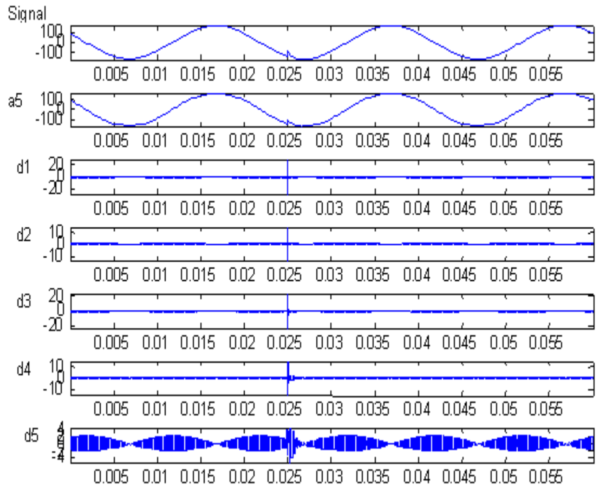

Figure 3. Wavelet decomposition of back to back capacitor switching transient

The sampling frequency is 20 KHz i.e. 400 samples per cycle for 50 Hz power frequency cycle. The DWT decomposition of the modal voltage signal is obtained up to 5th level. Based on a preliminary study on high frequency extraction capability of different wavelet transform available, it is found that, db4, sym4, bior4.4, bior1.3 and coif4 wavelets are best in high frequency extraction. Here bior1.3 is used as the mother wavelet.

The oscillations in the transients of isolated capacitor switching persist for longer duration compared to back to back switching. For training eighty percent of the total simulated cases are used and the rest of the cases as the test data set. The neural network model is trained using different learning rules, namely, Momentum (MOM), Conjugate Gradient (CG), Quick Propagation (QP), Delta Bar Delta (DBD) and Levenberg-Marquard (LM). Levenberg-Marquardt back propagation ('trainlm') algorithm is finally used for training the network. The number of neurons, momentum, number of epochs and training and testing ratio is also varied over a wide range.

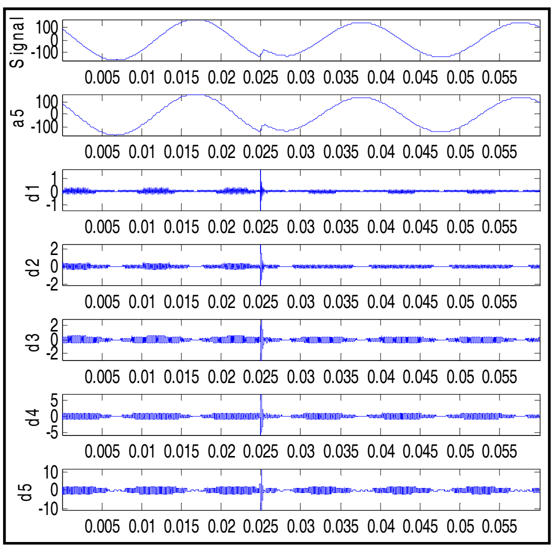

Figure 4. Wavelet decomposition of load switching transient

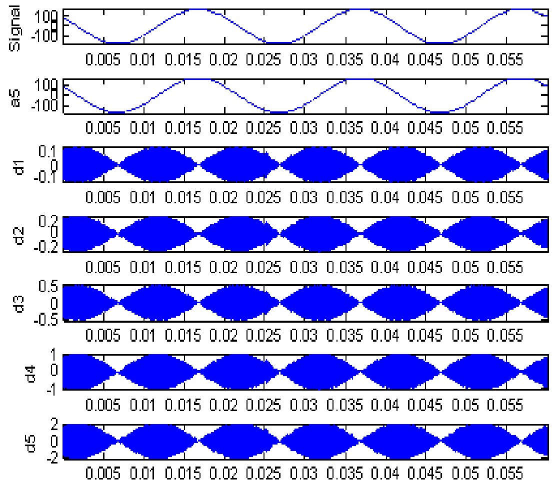

Figure 5. Wavelet decomposition of line energizing transient

The best trained MLP network for classification of non fault transients is shown in figure 7.It consists of one input layer, two hidden layers and one output layer. The input layer has three neurons. First hidden layer has 20 neurons with tansigmoid as the transfer function and second layer has 12 neurons with tansigmoid transfer function. There are 9 neurons in the output layer with tansigmoid as transfer function.

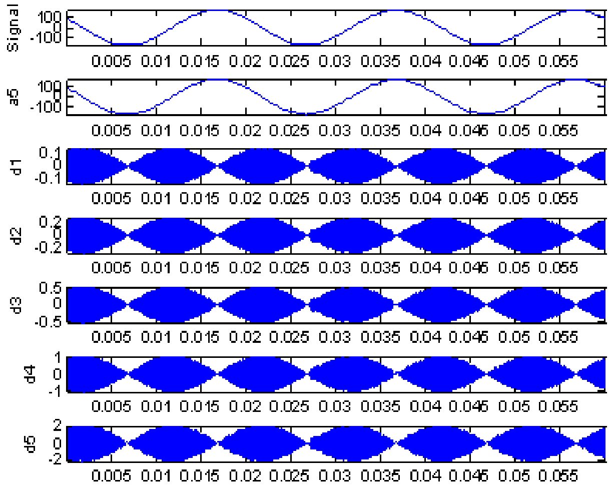

Figure 6. Wavelet decomposition of line de- energizing transient

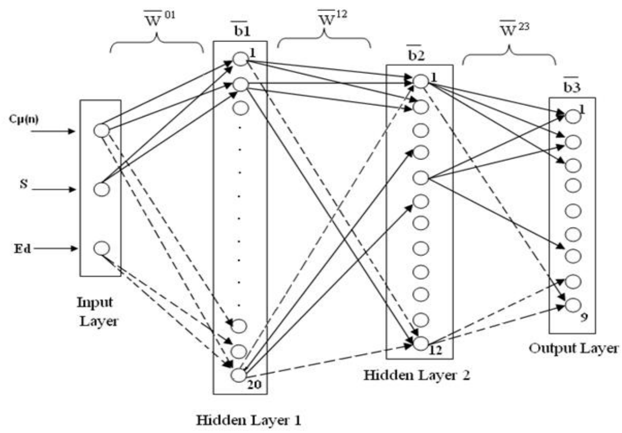

Figure 7. The structure of used FFANN

Y_1, Y_2, Y_3 are the outputs of hidden layers 1, 2 and 3, respectively

$$Y_1 = \varphi\left[\overline{w}^{01} x + \overline{b}_1\right] \quad (11)$$

$$Y_2 = \varphi\left[\overline{w}^{12} x + \overline{b}_2\right] \quad (12)$$

$$Y_3 = \varphi\left[\overline{w}^{23} Y_2 + \overline{b}_2\right] \quad (13)$$

$$x = \left[C_\mu(n) \quad S \quad E_d\right]^T \quad (14)$$

where, $\overline{w}^{01}$ is weight matrix between layer input layer 0 to hidden layer 1, $\overline{w}^{12}$ is weight matrix between layer hidden layer 1 to hidden layer 2, $\overline{w}^{23}$ is weight matrix between layer hidden layer 2 to output layer 3 and $\overline{b}_1, \overline{b}_2, \overline{b}_3$ are bias matrix for hidden layer 1, hidden layer 2 and output layer, respectively

This network gave an overall classification accuracy of 96% for switching transients. Eighty percent data is given for training. The learning rate is 0.7 momentum is 0.6 and iterations are 1500.The classification accuracy is given in Table 1.

Table 1. Correct classification accuracy

Event	Classification accuracy (%)
Isolated	95
Back to back	96
Load	100
Line energization	94
Line de-energization	95

VI. CONCLUSIONS

A novel method using DWT and multi layer FFANN for classification of capacitor, load and transmission line switching transients has been proposed. A simple membership function, its compliment, and the cumulative sum of this complemented function, obtained from detail coefficients of level 5 of the DWT of modal voltage signal have been successfully used to extract distinguishing features. A single modal voltage signal which is a linear combination of three phase voltages is used as an input signal, thereby eliminating the need to analyze all the three phase voltages. The validity of this method is exhaustively tested by simulating the switching events on a real power system modeled in PSCAD / EMTDC. The overall accuracy of classification of the events is 96%.

REFERENCES

[1] A.A. Girgis, et al, "Harmonics and Transient Over Voltages due to Capacitor Switching", IEEE Transactions on Industrial Applications, Vol. 29, No. 6, pp. 1184-1188, Nov./Dec. 1993.

[2] T.E. Grebe, "Application of Distribution System Capacitor Banks and their Impacts on Power Quality", IEEE Transactions Power delivery, Vol. 6, No. 4, pp. 1623-1628, 1991.

[3] G.T. Heydt, "Power Quality Engineering", Proceedings of IEEE Power Engineering Review, Vol. 21, No. 9, pp. 5-7, Sept. 2001.

[4] J. Kim, et al, "A Frequency Domain Procedure for Locating Switched Capacitors in Power Distribution Systems", Proceedings of IEEE Power Engineering Society Summer Meeting, Vol. 2, pp. 945-950, July 16-20, 2001.

[5] J. Kim, et al, "A Time Domain Procedure for Locating Switched Capacitors in Power Distribution Systems", IEEE Trans. Power Delivery, Vol. 17, No. 4, pp. 1044-1049, Oct. 2002.

[6] A.C. Parsons, et al, "Rules for Locating the Sources of Capacitor Switching Disturbances", Proceedings of IEEE Power Engineering Society Summer Meeting, Vol. 2, No. 18-22, pp. 794-799, July 1999.

[7] S. Santoso, et al, "Power Quality Assessment via Wavelet Transform Analysis", IEEE Trans. Power Delivery, Vol. 11, No. 2, pp. 924-930, April 1996.

[8] B. Perunicic, et al, "Power Quality Disturbance Detection and Classification using Wavelets and Artificial Neural Networks", Proc. 8th Int. Conf. Harmonics and Quality of Power, pp. 77-82, Oct. 1998.

[9] A. Elmitwally, et al, "Proposed Wavelet-Neuro-Fuzzy Combined System for Power Quality Violations Detection and Diagnosis", Proc. Inst. Elect. Gen., Trans., Distrib., Vol. 148, No. 1, pp. 15-20, Jan. 2001.

[10] L. Angrisani, et al, "A Measurement Method based on the Wavelet Transform for Power Quality Analysis", IEEE Transactions Power Delivery, Vol. 13, No. 4, pp. 990-998, Oct. 1998.

[11] S. Santoso, et al, "Power Quality Disturbance Waveform Recognition using Wavelet based Neural Classifier - Parts 1 & 2: Theoretical Foundation", IEEE Trans. Power Delivery, Vol. 15, No. 1, pp. 222-235, Jan. 2000.

[12] H. Mokhtari, et al, "Experimental Performance Evaluation of a Wavelet based Online Voltage Detection Method for Power Quality Applications", IEEE Trans. Power Delivery, Vol. 17, No. 1, pp. 161-172, Jan. 2002.

[13] M.A. Beg, et al, "Wavelet based Categorization of Capacitor Switching Transients", 7th International Conference on Technical and Physical Problems of Power Engineering (ICTPE-2011), No. 5, pp. 20-24, 7-9 July 2011.

[14] A.E.B. Abu-Elanien, et al, "A Wavelet-ANN Technique for Locating Switched Capacitors in Distribution Systems", IEEE Trans. Power Delivery, Vol. 24, No. 1, pp. 400-409, Jan. 2009.

[15] J. Liu, et al, "Wavelet Analysis of Power Systems Transients using Scalograms and Multiresolution Analysis", Electric Power Components and Systems, Vol. 27, Issue 12, pp. 1331-1341, Nov. 1999.

[16] J. Chung, et al, "Power Distribution Classifier using a Rule based Method and Wavelet Package-based Hidden Markov Model", IEEE Trans. Power Delivery, Vol. 17, No. 1, pp. 233-241, 2002.

[17] S. Kaewarsa, et al, "A Wavelet - base Neural Network for Power Quality Disturbance Recognition and

Classification", Aust. J. Electr. Eng. Vol. 3, No. 1, pp. 67-76, 2006.
[18] M. Oleskovicz, et al, "Power Quality Analysis Applying a Hybrid Methodology with Wavelet Transforms and Neural Networks", Electrical Power and Energy Systems, No. 31, pp. 206-212, 2009.
[19] O. Amanifar, et al, "The Effect of Placement of Distributed Generation on Mitigating Voltage Sag in Distribution Network", 7th International Conference on Technical and Physical Problems of Power Engineering (ICTPE-2011), No. 53, pp. 257-262, 7-9 July 2011.
[20] A. Sabbagh Alvani, et al, "Design and Construction Monitoring System Parameters of Power Quality", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 7, Vol. 3, No. 2, pp. 92-99, June 2011.

BIOGRAPHIES

Mirza Ansar Beg received his B.E. and M.E. degrees from the S.G.B. Amravati University, Amravati, India in 1988 and 1999, respectively in Electrical Power System Engineering and currently pursuing his Ph.D. from the S.G.B. University of Amravati, in Power Quality. He is IACSIT and ISTE members. He is working as Assistant Professor of Electrical Engineering in S.S.G.M. College of Engineering Shegaon, India. His present research interest includes power quality monitoring, power system protection and signal processing techniques in power systems.

Mohan Krishnarao Khedkar received the B.E., M.Tech. and Ph.D. degrees in Electrical Engineering from Visvesvaraya National Institute of Technology (VRCE), Nagpur, India. He is currently vice chancellor of S.G.B. Amravati University, Amravati, India. He has published more than 100 research papers in different international and national journals and conference proceedings. His main research interest includes power system planning, operation and control, and energy management.

Sudhir Ramdas Paraskar received his B.E. and M.E. degrees from the S.G.B. University of Amravati, India in 1992 and 2001, respectively in Electrical Power system Engineering and pursuing his Ph.D. degree from the S.G.B. University of Amravati, India, in Transformer Protection. He is IEEE, IACSIT and ISTE members. In 1995, he joined S.S.G.M. College of Engineering Shegaon, India, where he is a faculty in Electrical Engineering Department. His present research interest includes digital protection of transformer, FACTS, and power quality.

Gajanan Madhukar Dhole received M.Tech. degree from Visvesvaraya National Institute of Technology, Nagpur, India and Ph.D. degree in Electrical Engineering from Amravati University, India. He is IEEE, IACSIT, IE and ISTE members. He has published more than 50 research papers in different international and national journals and conference proceedings. His main research interest includes power system planning, operation and control, intelligent methods and its applications in power system.