An ANFIS- Based Method for Identification Switched Capacitor Bank Location in Distribution Systems

Seyed Mohammad. Madani [1], Ramtin Sadeghi [2]

[1] Assistant Professor, Department of Electrical Engineering, Faculty of Electrical Engineering, University of Isfahan, Isfahan, Iran
madani104@yahoo.com

[2] Phd Student, Department of Electrical Engineering, Faculty of Electrical Engineering, University of Isfahan, Isfahan, Iran
r.sadeghi@eng.ui.ac.ir

Abstract :

In this paper, a new method based on Adaptive Neuro-Fuzzy Inference System (ANFIS) is proposed for locating the switched capacitor banks in distribution systems. To train the proposed ANFIS model, an index based on current transient is introduced, which is calculated either offline by using data or online by real time simulation. The proposed method uses only current transient waveforms, immediately before and after the switching instant. Since only the current signal is used which is available in several locations, the method is simple and can be applied online. The method uses wavelet to determine the capacitor switching instant, which is needed for the ANFIS model to locate the switching capacitor. The method is simulated using PSCAD. Through various simulations, it is shown that other power quality disturbances such as voltage dip, unbalances and harmonics cannot disturb the method. Moreover, the size and connection type of the capacitor bank do not affect the method accuracy. The proposed algorithm is validated by simulating the IEEE 13-bus distribution system. According to the simulation results, the method is reliable enough to be applied to real systems.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS); capacitor switching; power distribution; power quality; wavelet transforms.

1. Introduction

Capacitor banks are widely used in distribution networks to improve voltage profile, to reduce power losses and support voltage profile [1-3]. On the other hand, overvoltage transients due to capacitor switching have effect on both utility and customers. Among these effects, tripping of adjustable drives and sensitive electronic loads are important [4-6]. To minimize these consequences, the first step is to locate the switched capacitor which has caused the harmful effect. Then, by using techniques such as pre-insertion reactor or pre-insertion resistor, one can decrease the overvoltage transients to reduce these undesirable impacts of these switchings. Several studies have been done to locate the switched capacitor banks in distribution networks [4, 6]. But, most of them are not practical in real grid. Some methods are very difficult and costly to execute.

In [7], a method based on disturbance power and energy is proposed to settle the location of the switched capacitor banks. The technique assumes that the instantaneous power is constant and requires three-phase voltages and currents waveforms. [8] uses a backward Kalman filter to locate the switched capacitor bank, by estimating the voltage rise of the capacitor

However, this method is difficult to perform, because it assumes that the power system dynamic model exists. [9] Proposes a method based on changes of power factor and the signs of voltage and current waveform gradients at the switching instant. It determines the approximate location of a switched capacitor bank. However, these techniques only determine if the capacitor banks are located either at downstream or upstream, relative to monitoring location. [10] uses energy index of the disordered voltage, branch current deviation, and phase angle variations of the current. However, precise on-time measurement of the three phase current angle is difficult. [11] trains an intelligent

[1] Submission date: 30, 12, 2014
Acceptance date: 15 , 01, 2015
Corresponding author: Seyed Mohammad Madani, Electrical Engineering Department- University of Isfahan- Isfahan- Iran

system, based on energy content of some particular frequency band. [12] uses the transient current duration and its high frequency components energy to feed a decision tree (DT) and determine switched capacitor banks. But, these methods suffer from lack of accuracy since they require at least one cycle to extract the signal energy. Since power networks are very dynamic, load changes, faults and power quality disturbances can affect the signal energy. In addition, the required calculation is costly, because it depends on the wavelet transform.

[13] implements an ANFIS topology to control dc–dc converters. [14] uses a fuzzy and ANFIS to extract important features of current signal. Multi-resolution wavelets are used to obtain transmission line fault classification and location. In [15], a new technique based on wavelet and ANFIS methods, is presented to recognize and classify high-impedance ground faults of distribution feeder.

In this paper, an index based on transient current is introduced and used to train an ANFIS model to locate switched capacitors, in distribution systems. The proposed method uses only current transient waveforms, which makes it simple. Moreover, it is accurate and applicable in real systems. The method requires only the current values immediately before and after the switching instant, thus, it can be used online. Due to the high frequency nature of capacitor switching, this switching detection is not confused by other PQ disturbances. Moreover, unbalanced voltage and harmonics do not disturb the method, because of their lower frequency nature.

The description problem and its theoretical aspects are presented in section II. The definition of the applied ANFIS model is given in section III. Section IV presented the PSCAD simulation of the method on IEEE 13-bus distribution system [16-17]. The simulation results confirm the effectiveness of the proposed method.

2. Problem Description

This paper objective is to determine the location of switched capacitors using switching current transients, measured by power-quality meters (PQM). Figure 1 shows the general flowchart of the proposed algorithm. At first, the capacitor switching transient features are extracted from PQ disturbance, which can be done automatically. Then, these transients are analyzed to determine the direction and location of the switched capacitor bank.

Immediately after switching a capacitor, its branch current raises, while other branches currents fall down. The method uses this fact and employs a current Deviation Index (DI) to train the ANFIS model [18].

Fig (2,3) show current transient of a capacitor switching, in the IEEE-13 bus distribution system. At the switching instant, the capacitor current may fall down or rise up based on the system condition [18]. The sudden rise up or fall down of the current is a high frequency phenomenon, which is shown in Figures 2 and 3. Considering capacitor switching in Fig (2,3), the D_I index is defined as:

$$D_I = \frac{i(t_s^-)\, i(t_s^+)}{\left|i(t_s^-)\right|} - \left|i(t_s^-)\right| \qquad (1)$$

In the following, it is shown that at increasing or decreasing current magnitude, D_I is positive or negative, respectively, regardless of the switching instant. So, the sign and magnitude of D_I can determine if the monitoring location is on the feeding path of the capacitor bank. Moreover, the closer branch to the switched capacitor gets the greater index value. Figures 2 and 3 show two possible instants of the switching. This index is examined for capacitor switching transients shown in Fig (2,3), which validate the effectiveness of this method. The wavelet transform is used to precisely localize discontinuities, in order to determine the exact instant of switching and the current values.

The proposed D_I index calculation is very simple and easy to implement. Moreover, this calculation needs only real-time power quality data and do not require any load or line data. In other words, this calculation uses capacitor switching transients immediately after the switching instant. The other system events such as load changes, faults, and current harmonics do not decrease the method accuracy. Therefore, the D_I index is very reliable to train the ANFIS model.

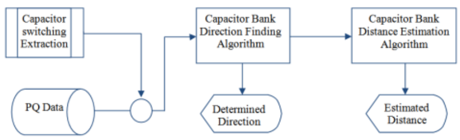
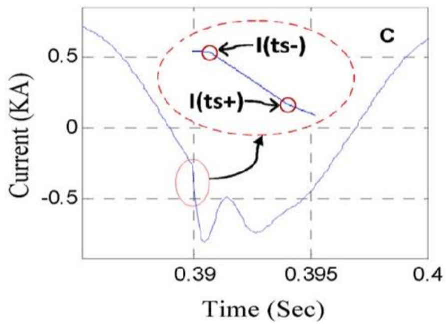


Fig (1): General diagram of the proposed algorithm

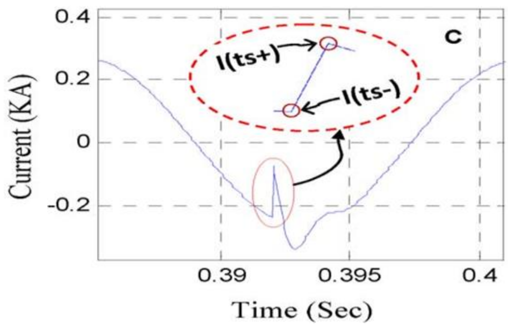
2.1. Wavelet Applications for Transient Analysis

Recently, wavelet analysis has been employed for analysis of non-stationary signals. It provides a powerful tool to characterize the. local (time dependent) characteristics of a signal The wavelet transform is described as converting signals to a short wave or set of short waves. Thus, the decomposed signals have short duration and limited energy, and their integral

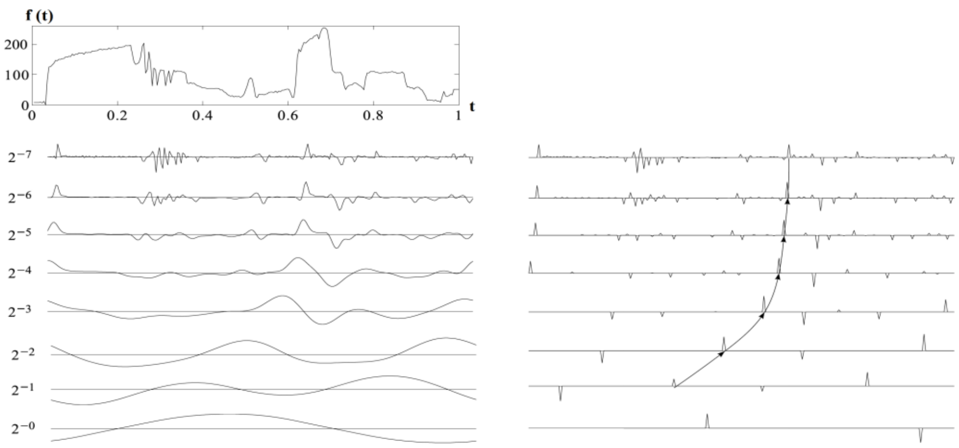
over their time interval equals zero [19].
Edge detection is a typical problem. Thus, many edge detectors have designed for signals. Derivative methods are used in some special methods. Usually, these methods are limited to the first and second derivative terms. An edge is a non-smooth term in a relatively smooth neighborhood. Therefore, compared to the surrounding derivative, the first and second derivatives give a higher response. For the first-derivative, it is maximum and for the second derivative, a zero-crossing is surrounded by a maximum and a minimum. The Canny edge detector [20] and the Marr-Hildreth [21, 22] are the two most famous designs which use the first and second derivatives, respectively. These methods proved that based on the criteria of localization, signal-to-noise ratio (SNR) (response on edge) and a unique response on one edge, the edge detectors are optimal for step-edges. However, the criteria of localization and SNR cannot simultaneously be optimized due to the uncertainty principle. Thus, a choice between good localization and a good response on an edge needs to be made. Wavelet theory proposes a solution. Rather than analyzing with an edge detector, it becomes wider. It is done on multiple scales changing the uncertainty between localization and response just like time and frequency with the Daubechies wavelet. In this way, it is possible to detect edges with more certainty where the edge occurred and still get a high response. This is done through the so called maxima-chaining and zero-crossing chaining. In fact, every classic edge detector is used in the wavelet setting, also wavelets with a few vanishing moments are popular to choose (db2 and even db3). The in general best working edge detectors are based on the Canny and Marr-Hildreth edge detectors. In DWT, edge detectors need to be designed. This is done using B-splines, which can approximate these functions quite well using scaling and wavelet filters. Almost, an Additional DWT filter bank is used, which means that down sampling is ignored. This gives a higher resolution but also the number of operations increase. In [23], it is expressed and derived that by chaining the maxima we can find back the edge when it is unique in its singularity. An example of such an algorithm is used in [24], it is shown in fig (4).



Fig(2): Typical feeder current after a capacitor is switched on and its current decreases



Fig(3):Typical feeder current after a capacitor is switched on and its current increases



Fig(4): Discrete wavelet transform computed at several scales with the quadratic wavelet (left) Modulus maxima of the Discrete wavelet transform (right)

Many maxima still exist in the scale 2^{-7}, therefore it is difficulties to classify which belongs to the bigger edges. Because of the noise, in many applications this is even more difficult. However, the maxima become small if the scales move up and on a certain moment only the big edges remain. These maxima have become very uncertain and can drift far away from the real edge. Thus, by chaining them back, the location of the original edge can be found.

Although, it is more difficult to chain the zero-crossings, there are actually three lines that are chained, namely the maxima, the minima and zero-crossings. This idea of chaining is the wavelet analysis of edges. However, the method of chaining changes, for example, they are chained using fuzzy-logic whereby some maxima are given more importance than others [25, 26].

For a discrete function *f*(*n*) the DWT is given by:

$$DWT_{\Psi x}(m,k) = k\sum_{n\in Z} X(t)\Psi_{m,k}(n) \tag{2}$$

$$\Psi_{m,n}(n) = 2^{\frac{J}{2}}\Psi(2^{-j}n-k) \tag{3}$$

Where, $\Psi_{m,n}(n)$ presents a discrete mother wavelet and, m and k are,

$$m = 2^J \tag{4}$$

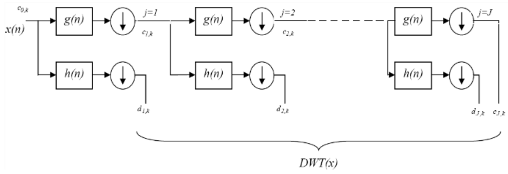
$$k = 2^J n \tag{5}$$

In Discrete Wavelet Transform (DWT), as shown in figure 5 the signal is passed through a series of high-pass and low-pass filters (h[n], g [n]) to extract its high and low frequency components, which are called detailed and approximate signal, respectively [27]. For each decomposition level j, L and H filters are followed by down-sampling operator ↓ which can be expressed as (X↓)[n]=X[n]), what is in fact the reduction of sampling rate by 2. Thus, the outputs $g_j(n)$ and $h_j(n)$ from one decomposition level, in the first case, j=1, are given by:

$$g_1(n) = \sum_i L[i]X[2n+i] \tag{6}$$

$$h_1(n) = \sum_i H[i]X[2n+i] \tag{7}$$

where *n* and *i* denote discrete time coefficients and *X* stands for the given signal. In the second decomposition level the $g_1[n]$ plays a role of $x[n]$ and so on.

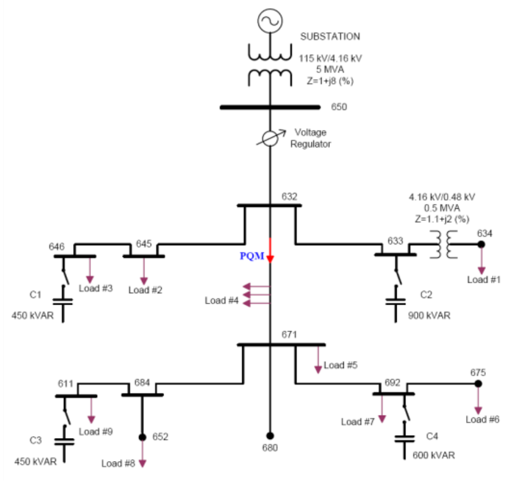


Fig(5): Achieving the discrete wavelet time

Various wavelet families like Daubechies (dbN), Haar, and biorthogonal wavelets exist. This paper uses 'db3' mother wavelet from Daubechies family [28]. The presented simulation result in [28] shows its effectiveness for system transient issues. This is done by choosing the right mother wavelet and scales for detecting the current rising and falling edges of the current such as switching detection. Unlike other mentioned events, switching capacitor current edges clearly appear in the highest frequency details.

The proposed method is as follow. First, the D_I index is calculated for various load conditions of the IEEE 13-bus distribution system (figure 6), simulated in PSCAD. The specifications of the system are given in the Appendix. In this system, there are four switched capacitor banks with different sizes. The D_I index versus load changes is calculated and depicted in figure 7. As shown in this figure, the D_I index differs for every capacitor bank and system load conditions. Therefore, this paper implements an intelligent system and trains it to locate the switched capacitor bank.

The standard fuzzy membership functions are employed to depict the uncertain parameters. Fuzzy logic explains the feasibility as a range rather than a point, which is like human thinking.

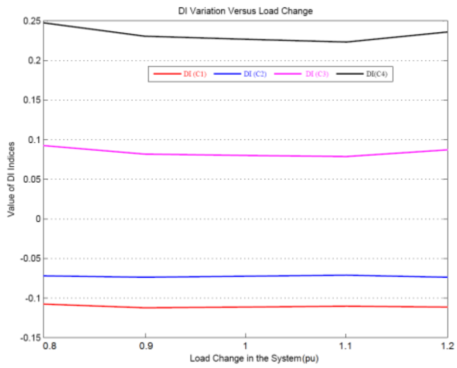


Fig(6): The IEEE 13-bus distribution system

The main structure of Fuzzy Inference System

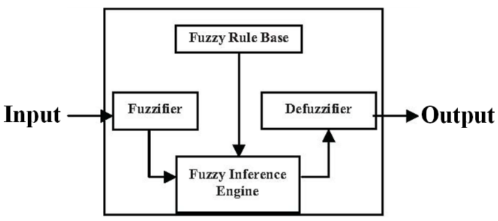
(FIS) is shown in figure 8. Fuzzy inference can be employed to model systems which is user's explanation from variables predetermine rules [29].

The parallel characteristics (i.e. computation and learning abilities) of neural networks can be combined with characteristics (i.e. the human-like knowledge representation and explanative abilities) of fuzzy systems by ANFIS [30, 31].



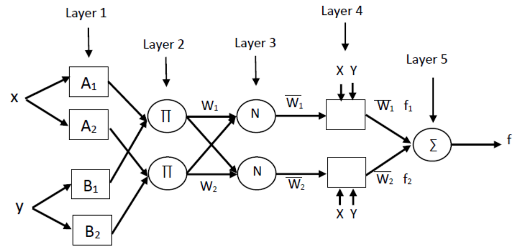
Fig(7): The values of D_I indices for each capacitor bank under different load conditions

In this section, an Adaptive Neuro-Fuzzy Interface System (ANFIS) is designed. The ANFIS input (which are DI indices) and its knowledge of the underlying system are available. Then, the Neuro-Fuzzy is used to create an exact system model. ANFIS is a hybrid Neuro-Fuzzy Inference expert systems that employs Takagi-Sugeno-type Fuzzy Inference System (FIS), developed by Jang [29]. In this method hybrid learning algorithm is applied to identify parameters of Sugeno-type fuzzy inference systems. A combination of the least-squares and the back-propagation gradient descent methods is used to recognize FIS membership function parameters and optimize the Sugeno system signals by ANFIS. The main ANFIS structure of a first-order Sugeno fuzzy model with two inputs and two rules is shown in figure 9, which are:



Fig(8): Main structure of the Fuzzy Inference System

Rule 1: if (x is A_1) and (y is B_1) then ($f_1=p_1x+q_1y+r_1$)



Fig(9): Structure of an ANFIS equivalent to a first-order Sugeno fuzzy model with two inputs and two rules [29].

Rule 2: if (x is A_2) and (y is B_2) then ($f_2=p_2x+q_2y+r_2$)

Where A_1, A_2, B_1, and B_2 are nonlinear parameters and p_1, p_2, q_1, q_2, r_1, and r_2 are linear parameters.

The ANFIS structure comprises of five layers, in which all nodes in each layer have a similar function. Based on premise signals, layer 1 comprises of adaptive nodes generating membership grades of linguistic labels, using suitable parameterized membership function expressed as (2) and (3).

where $O_{1,i}$, $O_{1,j}$ are the membership grade for x and y and mainly express the output functions. The nodes in layer 2 are fixed nodes intended Π, which stand for the firing strength of each rule. As shown in (4), the output of each node is the fuzzy AND (product or MIN) of all the input signals.

Where $O_{2,i}$ expresses the output of layer 2.

The outputs of layer 3 are the normalized firing strengths. As shown in (5), this layer includes fixed nodes which are tagged as N that computes the ratio of weighting strength of the rules.

The rule outputs based upon consequent parameters using the function are calculated by the adaptive nodes in layer 4, as shown in (6).

Where (p_i, q_i, r_i) is the consequent parameter set of the node, and $\overline{w}_i$ is a normalized firing strength from layer

Eventually, the fifth layer is the total output layer, whose node is tagged as Σ. There is a single node here which computes the overall ANFIS output from sum of the node inputs as shown in (7).

Where O5, i expresses the output of layer 5.

3.1. ANFIS Design and Training

Generally, fuzzy rules depend on the control objectives and the type of the controller. Simultaneously, three objects must be regarded to execute an adaptive fuzzy system: dynamic characteristics of a plant, self-selection of the performance index, and self-tuning of the controller parameters, respectively. The structure of the designed ANFIS model contains one input and one output with 5 membership functions.

Usually, to set a particular weight, for adjusting the main fuzzy system, Weights Adjusting Method (WAM) is used. In this section, the WAM is applied to determine an adaptive gain and to tune the estimated output, by Tuning Fuzzy System (TFS) laws. The designed TFS membership functions are shown in figure 10. The TFS input membership function parameters are set, based on the knowledge of the D_I indices. To estimate the model output, Output membership function parameters are set to guarantee precise tuning. After a feedback signal is achieved through the TFS, to tune the estimation consequences, the adjusting method is applied to the next estimation iterations. Based on the D_I indices of the System, the rule based system has also been developed.

The model is trained by 80 samples out of 160. The remaining 80 samples are applied to test the trained ANFIS model, to verify the accuracy of the output.

The ANFIS model with different membership function types results in slightly different values respective to least squares error. Table I shows that the results are in accordance with the different membership function type.

The best membership function based on the Mean Square Error is “pimf” with an error of 2.0156 E-7, as shown in table I. Figure 11 shows the training error for 50 epochs. Figures 12 and 13 show the initial and final membership functions extracted by applying the pi membership function training.

4. Simulation Results

In this section, two case studies are presented to locate the switched capacitor banks in the IEEE 13-bus distribution system. The results approve the effectiveness of the proposed method.

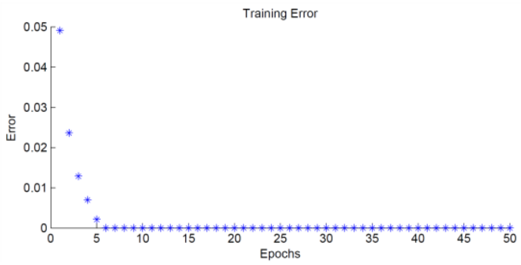
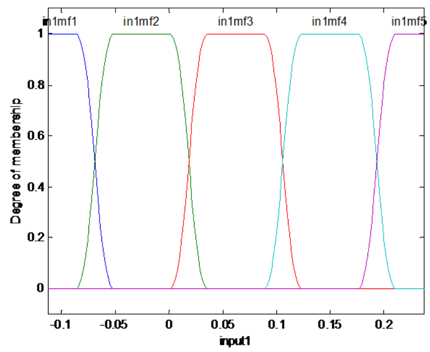
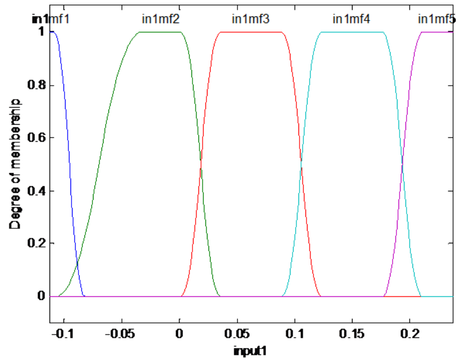


Fig (11): The training error



Fig(12): Initial membership function



Fig(13): Final membership function

4.1. Case under Small Changing of Loads in the System

In this section, a case study will be done under small load changing in the system. A system load changes about 20% and then that load capacitor is switched on to compensate the load power factor. The switched capacitor transients are different for each capacitor bank. The ANFIS model defined in the previous section is used to classify the transients related to each capacitor bank.

A Power Quality Meter (PQM) is located in the branch near bus 632, which its branch current is measured, in the direction shown in figure 6. The switching instant of current transient waveform is detected by wavelet 'db3'. The value of D_I is calculated for this branch. The values of the index for 80 switching cases under different load conditions are used to train the ANFIS model defined in section III. Then, the 80 more switching cases are used to test the network. Table II shows the test results.

Table II shows the results that are conclusive. In fact, these results show that the proposed index D_I and the ANFIS create a very accurate intelligent system, to locate switched capacitor banks. The exact results shown in Table (2) are predictable, since the indices are very distinct for each capacitor bank, as shown in fig(7). Thus, the ANFIS model can exactly discriminate the capacitor banks.

4.2. Case under large load changes in the system

In this section, a case study is done under large load changes in the system. This means that system load is changed for each switching cases in a range of about 40 percent of the total load. The ANFIS model defined in the previous section is used to classify the four switched capacitor bank. The same as case A, the values of the index for 80 switching cases under different load conditions are used to train the ANFIS model. Then, 80 more switching cases are used to test the model. Table (3) shows the test results.

Table (1): Mean square errors with different membership function types

ANFIS MF Type	Mean Square Error
trimf	0.0094792
trapmf	0.0097323
gbellmf	0.0071247
gaussmf	0.0036382
pimf	2.0156 E-7
dsigmf	0.0061367
psigmf	0.0061367

Table (2): Test results for case 4-3

	C1	C2	C3	C4	Total Cases
C1	80				80
C2		80			80
C3			80		80
C4				80	80

The results on Table (3) are also conclusive. The maximum error in detecting the switched capacitor bank is 3 cases over 80 (or 3.75%), which is quite acceptable. Compare to the previous case, this is a negligible error for such a large system load changes. However, the simulation results of two cases are acceptable.

This technique is tested through different simulations and the results are conclusive. Simulation results shows that other conditions such as different capacitor size, location, and type do not affect the result accuracy. Also, through various simulations, it is shown that other power quality disturbances such as voltage dip, unbalances and harmonics cannot disturb the method [32-35]. For implementing the proposed method on a real power system, it is trained through the simulations. But, it must be applied on other real networks and solve its problem that may occur.

5. Conclusions

This paper proposes a new method for locating switched capacitor in distribution systems. The method is based on an ANFIS model and trained by a new index, D_I. The index is only based on the measurement of instantaneous current waveforms and does not require any system or loading data. The index can be calculated with an existing power quality database or a real-time power quality data as used in web-based monitoring services. The hypothesis of the method is mentioned and then simulation results confirmed the feasibility and accuracy of the proposed method.

6. Appendix

In this section, load data of the IEEE 13-bus distribution system (figure 5) is given [17]. Spot and distributed load data of the system are shown in Table IV and Table V. Other specifications of the system are given in [17].

Table (3): Test results for case 4-2

	C1	C2	C3	C4	Total Cases
C1	78	2			80
C2		79		1	80
C3		2	77	1	80
C4	1		1	78	80

Table (4): Spot load data of the system shown in fig(2).

Node	Load	Ph-1	Ph-1	Ph-2	Ph-2	Ph-3	Ph-3
	Model	kW	kVAr	kW	kVAr	kW	kVAr
634	Y- P, Q Constant	160	110	120	90	120	90
645	Y- P, Q Constant	0	0	170	125	0	0
646	D- Z Constant	0	0	230	132	0	0
652	Y- Z Constant	128	86	0	0	0	0
671	D- P, Q Constant	385	220	385	220	385	220
675	Y- P, Q Constant	485	190	68	60	290	212
692	D- I Constant	0	0	0	0	170	151
611	Y- I Constant	0	0	0	0	170	80
	TOTAL	1158	606	973	627	1135	753

References

[1] M. El Arini, “Optimal capacitor placement incorporating voltage stability and system security,” EUROPEAN TRANSACTIONS ON ELECTRICAL POWER, Vol. 10, pp. 319-325, 2000.

[2] At. Saric, Ms. Calovic, Mb. Djukanovic, “Advanced voltage dependent dynamic programming algorithm for the optimization of shunt capacitors in radial distribution systems,” EUROPEAN TRANSACTIONS ON ELECTRICAL POWER, Vol. 11, pp. 257-265, 2001.

[3] R. Hooshmand, “Application of a genetic algorithm in the reduction of loss and control of the voltage of distribution networks using the real optimization of fixed and switched capacitors,” EUROPEAN TRANSACTIONS ON ELECTRICAL POWER, Vol. 15, pp. 425-442, 2005.

[4] lon, C. P. Rubino, and R. C. Catoe, “Harmonics and Transients Overvoltages Due to Capacitor Switching,” IEEE Trans. Industry Applications, Vol. 29, pp. 1184-1188, 1993.

[5] T. E. Grebe, “Application of Distribution System Capacitor Banks and Their Impact on Power Quality,” IEEE Trans. Industry Applications, Vol. 32, pp. 714-719, 1996.

[6] R. A. Adams, S. W. Middlekauff, “Solving Customer Power Quality Problems Due to Voltage Magnification,” IEEE Trans. Power Delivery, vol. 13, pp. 1515-1520, October 1998.

[7] A. C. Parsons, W. M. Grady, E. J. Powers, and J. C. Soward, “A Direction Finder for Power Quality Disturbances Based upon Disturbance Power and Energy,” IEEE Trans. Power Delivery, vol. 15, pp. 1081-1086, Jul. 2000.

[8] J. Kim, W. M. Grady, A. Arapostathis, J. C. Soward, and S. C. Bhatt, “A Time-Domain Procedure for Locating Switched Capacitors in Power Distribution Systems,” IEEE Trans. Power Delivery, Vol. 17, pp. 1044 – 1049, 2002.

[9] K. Hur, and S. Santoso, “On Two Fundamental Signatures for Determining the Relative Location of Switched Capacitor Banks”, IEEE Trans. Power Delivery, Vol. 23, pp. 1105-1112, 2008.

[10] G. W. Chang, J. Chao, H. M. Huang, C. Chen, and S. Chu, “On Tracking the Source Location of Voltage Sags and Utility Shunt Capacitor Switching Transients,” IEEE Trans. Power Delivery, Vol. 23, pp. 2124 – 2131, 2008.

[11] Zhu, H.Y., Chen, S., “Identification of Capacitor Switching Transients with Consideration of Uncertain System and Component Parameters," *Power Delivery, IEEE Transactions on*, Vol.23, No.1, pp.213-220, 2008.

[12] Abu-Elanien, A.E.B., Salama, M.M.A., “A Wavelet-ANN Technique for Locating Switched Capacitors in Distribution Systems,” Power Delivery, IEEE Transactions on, Vol.24, No.1, pp.400-409, Jan. 2009.

[13] Ahmed Rubaai, Abdul R. Ofoli, Legand Burge, and Moses Garuba, “Hardware Implementation of an Adaptive Network-Based Fuzzy Controller for DC–DC Converters,” IEEE TRANSACTIONS ON INDUSTRY APPLICATIONS, Vol. 41, No. 6, pp. 1557–1565, 2005.

[14] M.J., Reddy, and D.K., Mohanta, “Adaptive-neuro-fuzzy inference system approach for transmission line fault classification and location incorporating effects of power swings,” IET Gener. Transm. Distrib, Vol. 2, No. 2, pp. 235–244, 2008.

[15] A.H. Etemadi and M. Sanaye-Pasand, “High-impedance fault detection using multi-resolution signal decomposition and adaptive neural fuzzy inference system,” IET Gener. Transm. Distrib, Vol. 2, No. 1, pp. 110–118, 2008.

[16] “Fuzzy Logic Toolbox User's Guide”. Retrieved. May 28, 2009, from The MathWorks: Accelerating the pace of engineering and science, Web Site: http://www.mathworks.com/access/helpdesk/help/pdf_doc/fuzzy/fuzzy.pdf

[17] PES Distribution Systems Analysis Subcommittee, [Online]. Available: http://ewh.ieee.org/soc/pes/dsacom/testfeeders.html, Radial Test Feeders, IEEE.

[18] Khani, H., Moallem, M., Sadri, S., Dolatshahi, M., “A New Method for Online Determination of the Location of Switched Capacitor Banks in Distribution Systems,” *Power Delivery, IEEE Transactions on*, Vol.26, No.1, pp.341-351, 2011.

[19] Angrisani L, Daponte P, Apuzzo MD, Testa A, “A measurement method based on the wavelet transform for power quality analysis,” IEEE Trans. Power Deliv., 13, pp. 990-998, 1998.

[20] J. Canny. A computational approach to edge detection. Readings in Computer Vision: Issues, Problems, Principles and Paradigms, pp 184-203.

[21] D. Marr and E. Hildreth. Theory of edge detection. Proceedings of the Royal Society of London. Series B, Biological Sciences, pp 187-217, 1980.

[22] C. Christopoulos, A. Skodras, and T. Ebrahimi. The jpeg2000 still image coding: An overview. IEEE Transactions on Consumer Electronics, 46:1103, 1127, 2000.

[23] S. Mallat and S. Zhong. Characterization of signals from multiscale edges. IEEE Transactions on pattern analysis and machine intelligence, Vol.14, No.7, pp.710-732, 1992.

[24] Stephane Mallat. A wavelet tour of signal processing; The sparse way. Academic Press, London, 3th edition, 2009.

[25] A.S. Akbari and JJ Soraghan. Fuzzy-based multiscale edge detection. Electronics letters, 39:30, 2003.

[26] SK Setarehdan and JJ Soraghan. Fuzzy multiscale edge detection (FMED) applied to automatic leftventricle boundary extraction. 2, 1999.

[27] Santoso S, Powers EJ, Grady WM, Hofmann P, “Power quality assessment via wavelet transform analysis,” IEEE Trans. Power Deliv., 11, pp. 924-930, 1996.

[28] Candido MR, Zanetta LC, “A Wavelet-Based algorithm for power quality detection in electric arc furnace,” Transmission and Distribution Conference and Exposition, T&D, IEEE/PES, pp. 1-6, 2008.

[29] J.S. R Jang, “ANFIS: Adaptive network-based fuzzy inference system,” IEEE Trans. Syst., Man, Cybern., Vol. 23, No. 3, pp. 665-685, 1993.

[30] Taghipour M, ShamsiNejad M, Razavi S, Farshad M, Faraji I, Ghahramani H., “Determining Inter-Turn stator winding Fault Percent of Permanent Magnet Synchronous Motor Using Fuzzy Logic,” ISEE; Vol.2, No. 2, pp.12-24, 2011.

[31] Shariatinasab R, Akafi M, Farshad M., “Estimation of Switching Overvoltages on Transmission Lines Using Neuro-Fuzzy Method,” ISEE,; Vol.3, No. 3, pp55-66, 2012.

[32] Zwe-Lee Gaing, "Wavelet-based neural network for power disturbance recognition and classification," in IEEE Transactions on Power Delivery, vol. 19, no. 4, pp. 1560-1568, Oct. 2004.

[33] T. X. Zhu, S. K. Tso and K. L. Lo, "Wavelet-based fuzzy reasoning approach to power-quality disturbance recognition," in IEEE Transactions on Power Delivery, vol. 19, no. 4, pp. 1928-1935, Oct. 2004.

[34] H. Eristi and Y. Demir, "Automatic classification of power quality events and disturbances using wavelet transform and support vector machines," in IET Generation, Transmission & Distribution, vol. 6, no. 10, pp. 968-976, October 2012.

[35] Chen Wei, Hao Xiaohong and Lin Jie, "Interference Source of Voltage Sag in Distribution System Automatic Identification and Classification Using Wavelet and Neural Network," 2006 6th World Congress on Intelligent Control and Automation, Dalian, 2006, pp. 7508-7512.