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A Wavelet-Fuzzy Logic Based System to Detect and Identify Electric Power Disturbances

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***Abstract*-In this paper a method to detect and classify typical electric power disturbances is presented. Voltage sags, swells, momentary outage and capacitor switching transient events (CSTs) are the electric disturbances considered in this work. Disturbance detection and some disturbance features are obtained by the discrete wavelet transform. These features are used in the design of a fuzzy rule classification system. Both methods, wavelet detection and the fuzzy classifier, are extensively tested on the detection and classification of several simulated electric disturbances. In particular, capacitor switching transients events (CSTs) are presented to validate the proposed methodologies. The performance of the Wavelet-Fuzzy logic system turned out to be 95% of correct identification. The performance of the fuzzy classifier outperforms a classifier based on crisp decisions also presented in this paper. This performance is acceptable compared with other methodologies reported in the literature with performances varying from 92% to 95%.**

I. Introduction

Detection and identification of electric disturbances in power lines is a paramount issue in industrial environment. Opportune detection and correct identification of electric disturbances can lead to activate adequate procedures to avoid the negative effects of them, for example damage of expensive equipment and machinery [1]. In the last decade several power quality studies have been conducted due to the increased importance of improving the quality of electric power supply. Those studies had predicted that in 1985 20% of the total electric load connected in the US was electronic. However, this electronic load was estimated to reach approximately 50-60% by the year 2000 [2]. By the end of this decade more sensitive electronic equipment is expected to proliferate even more thus jumping to 70-80% of the total US electric load. In a similar fashion, sensitive power electronic equipment will increase the electric load worldwide. As this electronic equipment helps to save energy and control industrial processes they are also especially vulnerable to electric power disturbances. Additional surveys have been shown that 80% of the electric power disturbances were originated by the industrial customer electronic loads [3].

Numerous existing approaches have proposed to analyze, detect and classify the typical power disturbances encountered within industrial facilities. However, those methods are strenuous since they are mainly based on inspecting visually the signature of the disturbance waveforms [4]. New studies applying neural networks, fuzzy logic and wavelet transform approaches have been performed before [1],[4], [5]-[9]. However the problem stays as an open problem searching for better and improved solutions.

In response to these concerns, this paper explores a new method for detecting and classifying some of the main concerning electric power disturbances affecting both, industrial customers and utility companies. The typical disturbances are termed as voltage sag, voltage swell, momentary outage and capacitor switching transient.

The approach followed in this research incorporates signal multiresolution analysis [4],[10],[11], and linguistic description computation [12]-[16]. Therefore, the paper presents original work not reported in other papers. Multiresolution analysis based on Daubechis wavelet is used to detect the occurrence of an electric disturbance to generate features used by the fuzzy classification system. The fuzzy rules evaluate the multiresolution features as well as electric characteristics to identify the disturbances.

The paper is organized as follows. Section 2 provides a description of electric disturbance generation. Characterization of the electric disturbances is presented in Section 3, and electric disturbance detection, using wavelet analysis, is described in Section 4. The classifier design is reported in Section 5. The paper concludes in Section 6.

II. Electric Disturbance Generation Using The PSIM Simulator

In this work five different electric disturbances were simulated and applied on an adjustable speed drive, ASD, system [3]. The five events are, voltage sags, swells, momentary outage and capacitor switching transient events (CSTs) both oscillatory (capacitor bank energization) and impulsive (capacitor bank de-energization) types.

The ASD system is simulated, with the PSIM simulator, under the typical electric disturbances and load conditions. The simulated ASD system consists of a line-to-line voltage, V_{LL}=220V, an output power, P_o=1 KW, a source line inductance, L_s=500µH and a three-phase capacitor bank with capacitance values varying between 50µH and 300µH. Simulation results were saved for subsequent analysis.

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III. Characterization of Electric Disturbances

In order to design a system able to detect and classify the electric disturbances, each event needs to be characterized. Event characterization corresponds to feature extraction that will be used in the detection and classification stages. In this section the process to determine the most discriminative features for each electric disturbance are described.

A. CSTs Characterization

In this work, two types of CSTs are considered. The first type is shown in Fig. 1. From this figure we can observe that there exists an abrupt change at the starting point of the disturbance. After this abrupt change, the signal is altered by the presence of a resonant frequency. This resonant frequency and its associated energy determines the disturbance duration. After 60 milliseconds, approximately, the resonant frequency disappears. This type of CSTs behavior is defined as an oscillatory capacitor switching transient event [4]. The second type of CST is denominated as a premature opening CST or impulsive CST. This CST is characterized by the presence of two abrupt changes. One change occurs during the beginning of the event, while the second occurs at the end, as shown in Fig. 2. Under this type of disturbance the capacitor bank does not finish to discharge the energy during the previous oscillatory period, thus causing two abrupt changes during the complete event. One change is due to the closing of the capacitor bank switch (energization), and the other during the bank switch opening (de-energization).

B. Voltage Sag, Swell, And Momentary Outage Characterization

The voltage sags, swells, and momentary outage disturbances are grouped into one cluster of events. The main characteristic of these disturbances is a change on the magnitude of the signal, at the starting and ending points. This amplitude change allows us to determine the starting and ending point of the event. Some examples of these disturbances are illustrated in Figs. 3 to 5. Fig. 3 shows a voltage sag with a duration of less than one cycle, and amplitude reduction of 25% (i.e. 75% sag). Fig. 4 illustrates a case of a 40 millisecond momentary outage with a remain voltage of 6 V. Finally, Fig. 5 illustrates a simulated voltage swell case disturbance. The typical swell disturbance is shown with a half-cycle time duration with an augmented magnitude of 1.25 p.u. of nominal voltage, which corresponds approximately to a line-to-neutral peak voltage of 179 volts.

IV. Electric Disturbances Detection Using Wavelet Analysis

Contrary to the Fourier transform, the Wavelet transform generates time–scale information in a natural way. Another advantage of the wavelet transform is that it generates localized information due to discontinuities or abrupt changes presented in the signal under analysis. These two features aforementioned are characteristics of the electric disturbances under study.

In this work the discrete Wavelet transform defined in (1), [11], is used to decompose the electric disturbance signal into several levels of decomposition.

$$W_\varphi\left(j_0,k\right)=\frac{1}{\sqrt{M}}\sum_x f\left(x\right)\varphi_{j_0,k}\left(x\right) \qquad (1)$$

$$W_\psi\left(j,k\right)=\frac{1}{\sqrt{M}}\sum_x f\left(x\right)\psi_{j,k}\left(x\right)$$

where $\varphi_{j,k}\left(x\right)$ is the scaling function and $\psi_{j,k}\left(x\right)$ is the wavelet function.

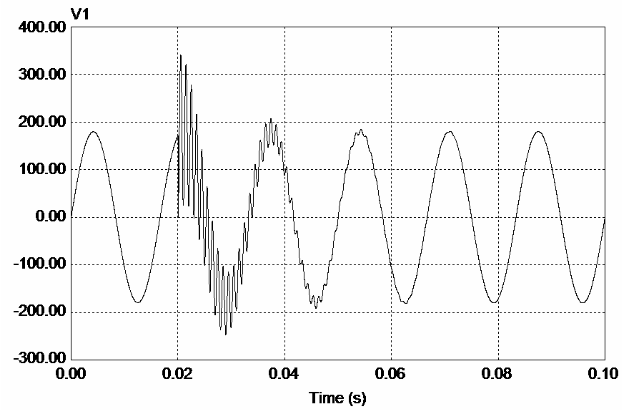

Figure 1. Simulation result of an oscillatory CST.

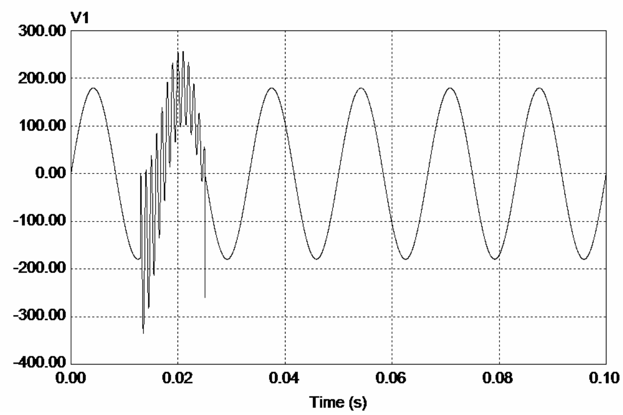

Figure 2 Simulation result of a premature opening (impulsive) CST.

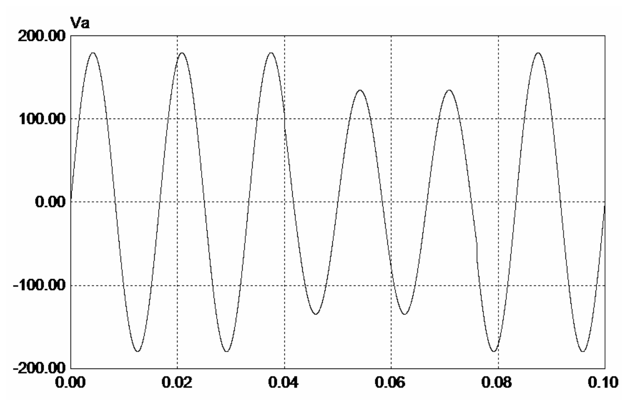

Figure 3. Simulation result of a voltage sag event.

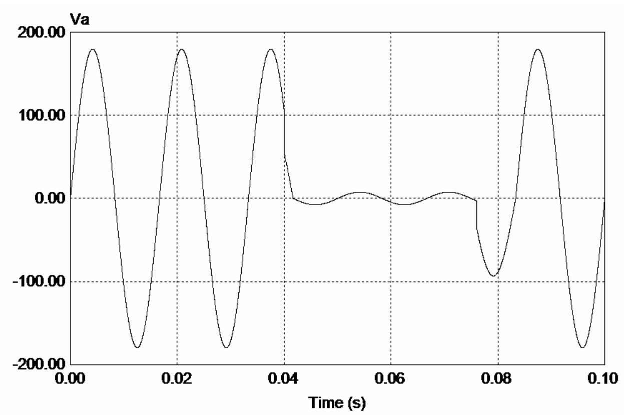

Figure 4. Simulation result of a momentary outage event.

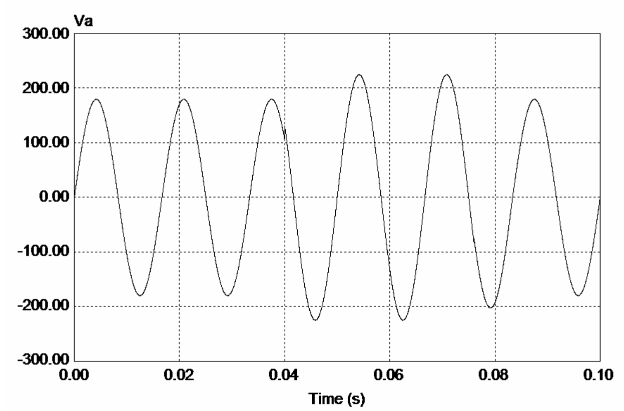

Figure 5. Simulation result of a voltage swell.

After analysis of a set of electric disturbance signals it was found that details 1 and 4, generated by the order one Daubechies wavelet, extract enough information of the electric signal to achieve the detection stage of the electric disturbances. The block diagram of the detection system is illustrated in Fig. 6. In this figure, *db1* and *db4* stand for details 1 and 4 of the Daubechies wavelet transform. Fig. 6 also shows that *db1* is enough to detect and identify the oscillatory CST disturbance. The *db4* decomposition is used to generate the multiclass group that encompasses the premature opening of a CST, sag, swell, and momentary outage disturbances. Identification of the oscillatory CST is possible with *db1* because these wavelet coefficients present a specific behavior within the oscillatory CST that not other events present. The characteristic of the coefficients of the oscillatory CST is that there exists a large value and then an exponential decay. The coefficients decrease until they reach a value that corresponds approximately to the value observed before the starting point of the disturbance. An average of this reached value is used to find the ending point of the disturbance.

V. Classifiers Design

A. Electric Disturbance Features

In this section we present the disturbance features considered to design the classifier. These features must have

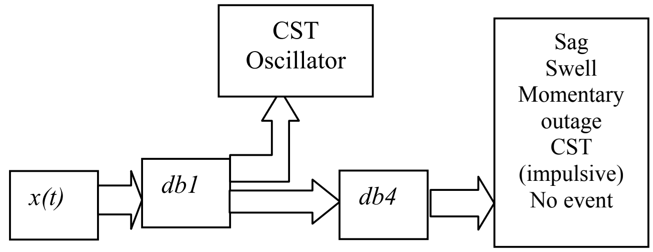

Figure 6. Disturbance detection system based on wavelet analysis.

the maximum discriminative power to assure the best identification rate possible, and their computational cost must be low in order to guarantee that they can be used in a real time application. These features are listed below.

The feature of the voltage sag is that it presents an amplitude attenuation in the range of 10% to 90% of the nominal value. The voltage swell has an amplitude increment in the range of 10% to 40% of the nominal value. The momentary outage is defined as the voltage drop in the range of 90% to 100% of the nominal value. Another important characteristic of a CST event is that it presents a resonant frequency. This resonant frequency is a function of the capacitor bank and the system inductance, which is part of the utility distribution system.

Considering the previous disturbance features, we can group those features into two categories, that is, time features and frequency features. Features of the voltage sag, voltage swell and momentary outage correspond to time features, whereas the CST events contain frequency features. The time features can be defined through the RMS value of the signal obtained by

$$V_{rms} = \sqrt{\frac{\sum_{n=1}^{M} \left(x(n)\right)^2}{M}} \tag{2}$$

where $x(n)$ is the disturbance signal of length M.

Frequency features can be used to analyze the impulsive CST disturbance by the discrete Fourier transform

$$X(k) = \sum_{n=0}^{N} x(n) e^{-\frac{j\omega nk}{n}} \tag{3}$$

B. Crisp Classifier System

The RMS values and the frequency features are used to design a crisp based classifier. The complete system, detection and classification scheme is shown in Fig. 7. From Fig. 7 we can observe that *db1* has the discriminative power to identify the oscillatory CST. In the next stage the impulsive CST is discriminated from the sag, swell and momentary outage disturbances by means of the Fourier analysis. Finally, the RMS value is computed to discriminate among the sag, swell and momentary outage. The performance of the system is shown in Table I. In Table I two types of capacitor bank de-

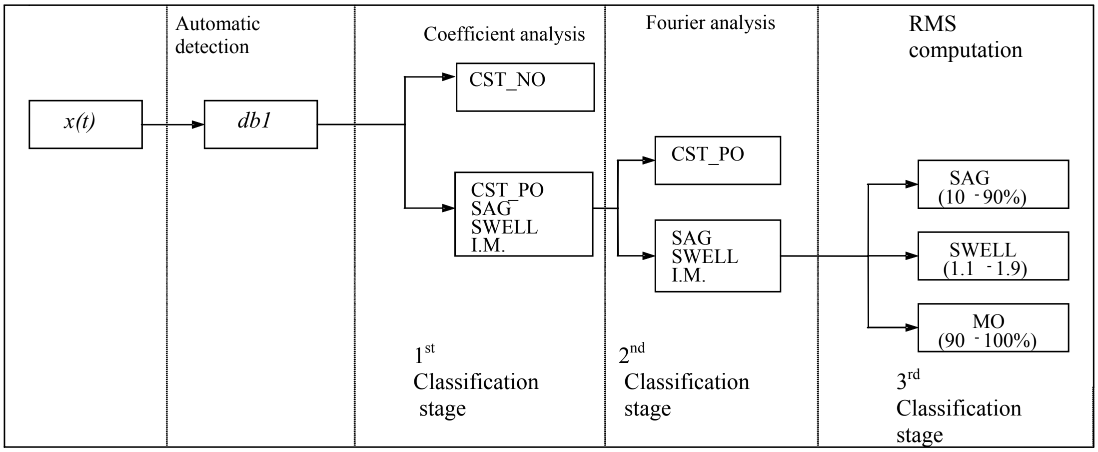

Figure 7. Detection and classification system based on crisp decisions.

energization (impulsive CSTs) are considered, one is defined as a normal opening

TABLE I
CRISP CLASSIFICATION PERFORMANCE

	Sag	Swell	CST_NO	CST_PO	M.O.	No event	Errors
Sag	15	0	0	0	0	3	3
Swell	0	21	0	0	0	0	0
CST_NO	0	0	14	0	0	2	2
CST_PO	1	0	0	18	0	1	2
M.O.	0	0	0	0	3	0	0
No event	2	0	0	0	0	8	2
Performance 89.77%.							

(CST_NO) and the other as premature opening (CST_PO). According to the results shown in Table I, the crisp classifier performance is 89.77%.

C. *Fuzzy Classifier*

The fuzzy classification system involves four linguistic variables that define four concepts, the wavelet coefficients *db1*, variable CDB1, and *db4*, variable CDB4, the resonant frequency value, Fr, and the RMS value, VRMS. The fuzzy classifier is based on Mamdani type rules to evaluate the information provided by the linguistic variable inputs. Fig. 8 illustrates the scheme of the fuzzy classifier.

A complete description of the input variables and the output variable is provided next.

The universe of discourse for the variable CDB1 is [0,10], and its possible values are CDB1L, low and CDB1H high, defined by the trapezoidal fuzzy sets shown in Fig. 9.

The universe of discourse for the variable CDB4 is [0,100], and its possible values are CDB4L, low, and CDB4H, high, defined by the fuzzy sets shown in Fig. 10, in this case represented by a trapezoidal and S functions.

The Fr variable is defined within the range [0,500] with possible values LOW_Fr, and HIGH_Fr, defined by S functions as shown in Fig. 11.

The universe of discourse of the input VRMS, Fig. 12, is [0, 250], and it could take the values, VLRMS, very low, LOWRMS, low, MIDRMS, medium, HIGHRMS, high, and VHRMS, very high.

With respect to the output of the system, the possible values are SAG, SWEL, MO, CST_NO, and CST_ PO, defined by the fuzzy set shown in Fig. 13.

The membership function shapes shown in Figs. 9 to 13 were selected to better represent the meaning of the variable information and their expected values. For example in Fig. 9 the variable CDB1 is classified low and high in the intervals shown according to the behavior found in the wavelet coefficients. The interval of definition of the variable Fr is determined by the expected values of this variable, the same occurs for the RMS variable. The same criterion is considered to generate non overlapping membership functions.

The fuzzy rules are of the form

If condition 1 and condition n THEN event is

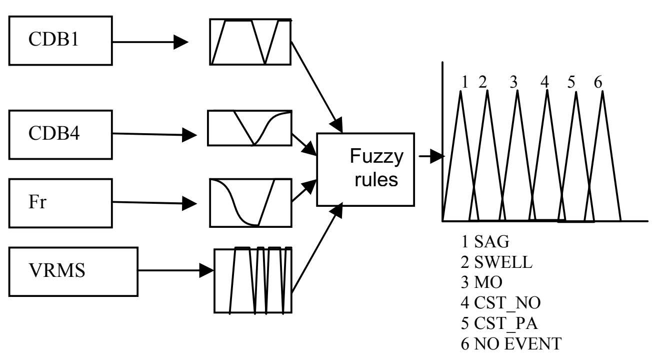

Figure 8. Fuzzy classification scheme.

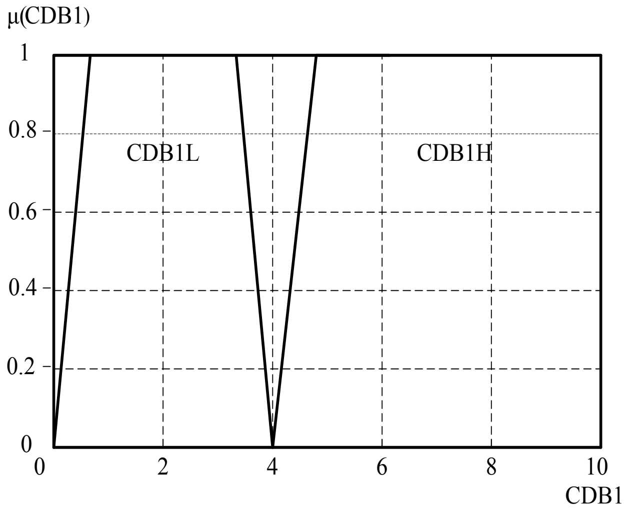

Figure 9. Definition of the variable CDB1.

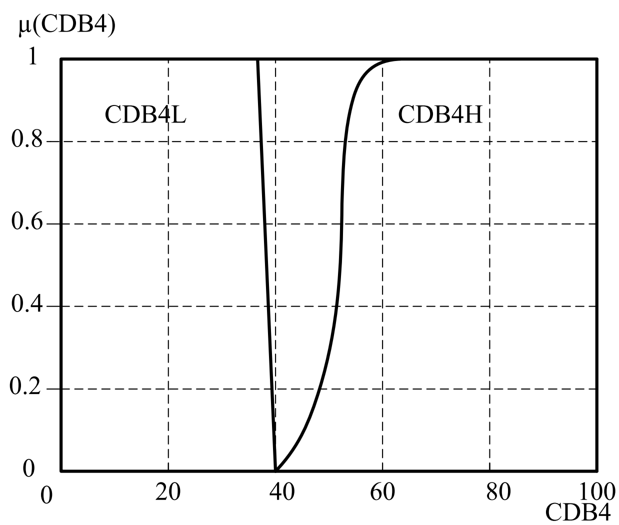

Figure 10. Definition of the variable CDB4.

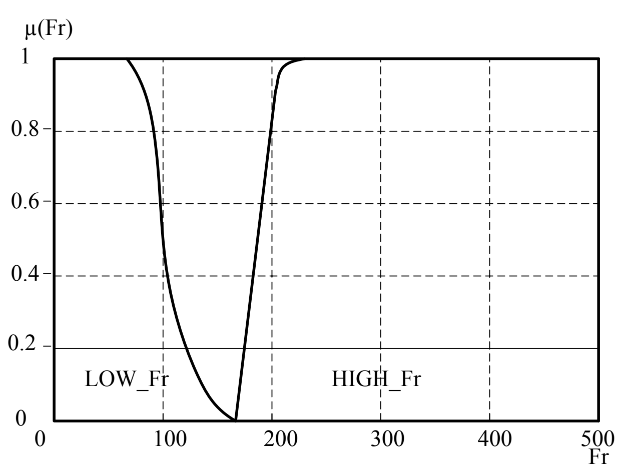

Figure 11. Definition of the variable Fr.

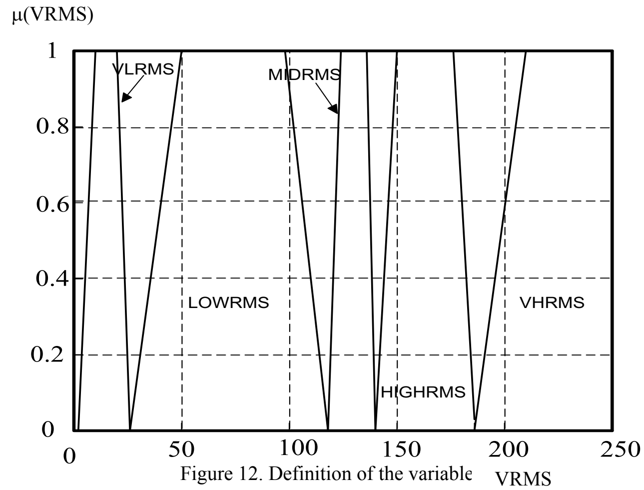

Figure 12. Definition of the variable

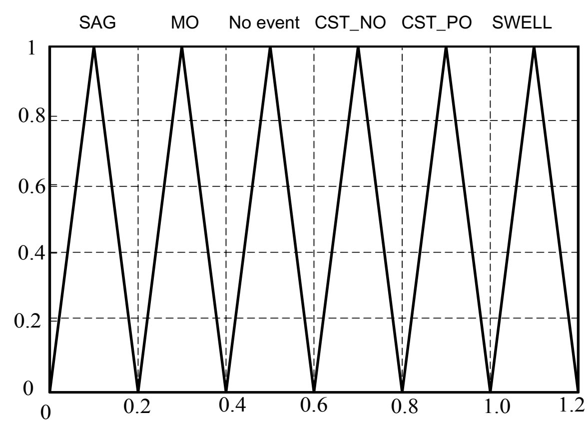

Figure 13. Output of the fuzzy system.

The system includes the following 8 fuzzy rules:

1. If (CDB1 is CDB1L) and(CDB4 is CDB4L) then Event is No event
2. If (CDB1 is CDB1L) and (F_r is LOWF_r) and (V_RMS is VLRMS) and (CDB4 is CDB4H) then Event is MO
3. If (CDB1 is CDB1L) and (F_r is LOWF_r) and (V_RMS is LowRMS) and (CDB4 is CDB4H) then Event is Sag
4. If (CDB1 is CDB1L) and (F_r is LOWF_r) and (V_RMS is MedRMS) and (CDB4 is CDB4H) then Event is No event
5. If (CDB1 is CDB1L) and (F_r is LOWF_r) and (V_RMS is HRMS) and (CDB4 is CDB4H) then Event is Swell
6. If (CDB1 is CDB1L) and (F_r is LOWF_r) and (V_RMS is VHRMS) and (CDB4 is CDB4H) then Event is Swell
7. If (CDB1 is CDB1L) and (F_r is HIGHF_r) and (CDB4 is CDB4H) then Event is CST_PO
8. If (CDB1 is CDB1H)) then Event is CST_NO

The implication operator incorporated in the fuzzy rules is the Mamdani implication operator defined by

$$\phi\ [\mu_A(x), \mu_B(y)] \equiv \mu_A(x) \wedge \mu_B(y) \qquad (4)$$

The detection and classification system was tested with 108 electric disturbances generated with the simulator PSIM. The performance achieved by the system was 95% of correct classification. Table II presents the details of the evaluation by means of a confusion matrix. From this table it can be noticed that most of the misclassification errors are related to the Sag event. This is a consequence of incorrect evaluation of the *db1* and *db4* wavelet coefficients according to the fuzzy rule 1.

TABLE II
PERFORMANCE CONFUSION MATRIX OF THE FUZZY CLASSIFIER

	Sag	Swell	CST_NO	CST_PO	M.O.	No event	Errors
Sag	20	0	0	0	0	3	3
Swell	0	21	0	0	0	0	0
CST_NO	1	0	16	0	0	0	1
CST_PO	0	0	0	19	0	1	1
M.O.	0	0	0	0	15	0	0
No event	0	0	0	0	0	11	0
Performance 95%							

VI. RESULTS AND CONCLUSIONS

Results in this work indicate that the *db1* and *db4* coefficients of the Daubechies wavelet turned out to be efficient to detect the starting and ending points of electric disturbances in most of the cases. Besides the *db1* wavelet coefficient have the discriminative power to identify the oscillatory CST. These findings have proved the contribution of multiresolution analysis in the detection and classification of electric disturbances.

One of the main causes of misclassification is related to false alarms in the detection of the starting and ending points of the disturbance. This point needs to be considered in future work in order to increase the classification performance.

The work has also illustrated not only the capability of fuzzy logic to model physical system but also to outperform models based on classical logic. Comparing the results of the crisp classifier with the fuzzy logic approach, 89.77% and 95% respectively, it is clear the better performance of the fuzzy approach. The fuzzy system performance is also comparable with other systems reported in the literature [6],[7] with performances around 92% to 95%.

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REFERENCES

[1] M. V. Chilukuri and P. K. Dash, “Multiresolution S–transform- based fuzzy recognition system for power quality events,” *IEEE Trans. on Power Delivery*, vol. 19, no. 1, pp. 323-330, January 2004.

[2] S. Santoso, W. M. Grady, E. J. Powers, J. Lamoree, and S.C. Bhatt, “Characterization of distribution power quality events with Fourier and wavelet transforms,” *IEEE Trans. on Power Delivery*, vol. 15, no. 1, pp. 247-254, January 2000.

[3] J.L. Durán-Gómez and P.N. Enjeti, “A new approach to mitigate nuisance tripping of PWM ASDs due to utility capacitor switching transients (CSTs),” *IEEE Trans. on Power Electronics*, vol. 17, no. 5, pp. 799-806, September 2002.

[4] S. Santoso, E.J. Powers, W.M. Grady and A.C. Parsons, “Power quality disturbance waveform recognition using wavelet-based neural classifier—Part 1: Teoretical Foundation,” *IEEE Trans. on Power Delivery*, vol. 15, no. 1, pp. 222-228-, January 2000.

[5] Lefteri H. Tsoukalas and Robert E. Uhrig, *Fuzzy and neural approaches in engineering*, New York, A Wiley – Interscience Publication, , pp. 77-125, 1996.

[6] D. J. Sogajic, “Artificial neural-net based dynamic security assessment for electric power systems,” *IEEE Trans. on Power Systems,* vol. 4, no. 1, pp. 220-228, February 1989.

[7] A. K. Ghosh and D. L. Lubkeman, “The classification of Power System Disturbance waveforms using a neural network approach,” *IEEE Trans. On Power Systems*, vol. 10 no. 1, January 1995.

[8] S. R. Shah Baki, M. Z. Abdullah and A. F. Abidin, “Combination wavelets and artificial intelligent for classification and detection transient overvoltage,” *IEEE Student Conference on Research and Development Proceedings*, Shah Alam, Malaysia, pp. 177-180, 2002.

[9] J. Chung, E.J. Powers, W.M. Grady and S.C. Bhat,”Power distribution classifier using a rule based method and wavelet packet based hidden Markov model,” *IEEE Trans. on Power Delivery*, vol. 17, pp 233-241, January 2002.

[10] G. Strang, “Wavelets,” *American Scientist*, vol. 82, pp 250-255, May 1994.

[11] S. Mallat, *A Wavelet Tour of Signal Processing*, Academic Press, 1999.

[12] L. Zadeh, "Fuzzy logic = computing with words," *IEEE Trans. on Fuzzy Systems*, vol 4, no. 2, pp 103-111, May 1996.

[13] J. Mendel, "Fuzzy logic systems for engineering: a tutorial," *Proceedings of the IEEE*, vol. 83, no. 3, pp 345-377, March 1996.

[14] H. Roubos, M. Setnes and J. Abonyi. “Learning fuzzy classification rules from data”. *Inf. Sci*. 150(1-2) pp 77-93, 2003.

[15] S. Singh, “Updating a priori Information in Fuzzy Pattern Recognition to Improve Classification Performance”, *Journal of Intelligent and Fuzzy Systems*, vol. 9, pp. 235-250, 2000.

[16] G. Ramirez, *Study of Pattern Recognition Methods Based on Artificial Neural Networks and Fuzzy Logic Applied to Wood Defect Recognition*, M.Sc. Thesis, Chihuahua Institute of Technology, November 2004.