Classification of Power System Disturbances Using a Fuzzy Expert System and a Fourier Linear Combiner

P. K. Dash, S. Mishra, M. M. A. Salama, and A. C. Liew

***Abstract*—This paper presents a hybrid scheme using a Fourier Linear Combiner and a fuzzy expert system for the classification of transient disturbance waveforms in a power system. The captured voltage or current waveforms are passed through a Fourier Linear Combiner block to provide normalized peak amplitude and phase at every sampling instant. The normalized peak amplitude and computed slope of the waveforms are then passed on to a diagnostic module that computes the truth value of the signal combination and determines the class to which the waveform belongs. Several numerical tests have been conducted using EMTP programs to validate the disturbance waveform classification with the help of the new hybrid approach which is much simpler than the recently postulated ANN or wavelet based approaches.**

I. Introduction

THE PROLIFICATION power electronics devices that cause harmonic voltages and currents and the widespread use of harmonics-sensitive electronic equipments are addressed by both users and suppliers of electric energy. As a result numerous power quality assessment methodologies and diagnostic equipments for the detection, measurements, and analysis are becoming commonplace in the power industry. Many of the power quality concerns are associated with the operation and design of customer facilities, concerns associated with wiring and grounding problems, switching transients, load variations and harmonic distortions of voltage and current waveforms, etc.

The power quality study involves an important step, i.e., monitoring the actual voltage and current waveforms and classify these waveforms and display them when certain thresholds are exceeded. An useftd breakdown of disturbance waveforms includes voltage sags, impulses, swells, outages,etc. These waveforms exhibit certain distinguishing characteristics and can be identified to belong to a certain waveform class. The classification scheme has to be robust and accurate to handle the noisy data collected from the transmission or distribution networks. Artificial Neural Networks (ANN) have attracted a great deal of attention because of their pattern recognition capabilities, and their ability to handle noisy data: However, it's ability to perform well is greatly influenced by the weight adaptation algorithm and the amount of noise in the data.

Past research has considered the applications of ANN's to classification of waveforms for low and high impedance faults [1], [2], magnetizing inrush [3], and power quality issues [4]. In a recent paper [5], the authors have studied both multilayered feed-forward and time-delay ANN architectures for power system disturbance waveform classification with a success rate varying from 72% to 93%. The neural network architectures suffer from large number of training cycles and computational burden. Though Wavelet transform[6] has been used as a powerful technique for disturbance waveform classification with great success recently, the computational burden is very high. The present paper, therefore, presents a computationally simple and fairly accurate approach using a Fourier linear combiner and a fuzzy expert system. The Fourier linear combiner [7] extracts the amplitude and phase of the fundamental signal and the fuzzy expert system identifies the class to which the disturbance waveform belongs. Several digital simulation results are presented to validate the procedure outlined in the paper for successful classification of power system disturbance waveforms.

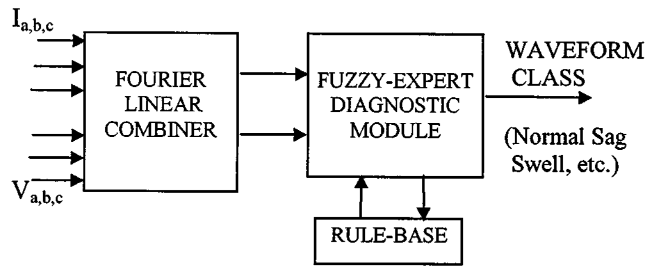

Fig. 1. Block diagram representation of waveform classifier.

II. Application of Artificial Intelligence Technologies

This section describes the development of a hybrid expert system designed to improve the knowledge of the power systems engineer in the pursuit of an accurate diagnosis of power system operating problems such as voltage sag, voltage swell, faults, harmonics, etc..

Having chosen the classes of disturbance waveforms, the next step in developing a classifier is the selection and extraction of desired features. Any successful classification scheme would depend on its ability in the presence of significant noise and harmonics to pick out these relevant features of a waveform. The expert system chosen for this purpose consists of a Fourier Linear Combiner and a fuzzy diagnostic module. Fig. 1 shows how these module are connected. The raw data in an actual system is to be captured by using a signal conditioner, a data acquisition interface, an analog-to-digital (A/D) conversion kit

Manuscript received March 18, 1998; revised August 17,1998; November 17,1998; and December 22, 1998.

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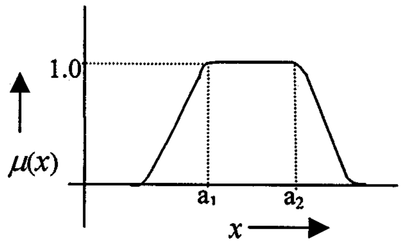
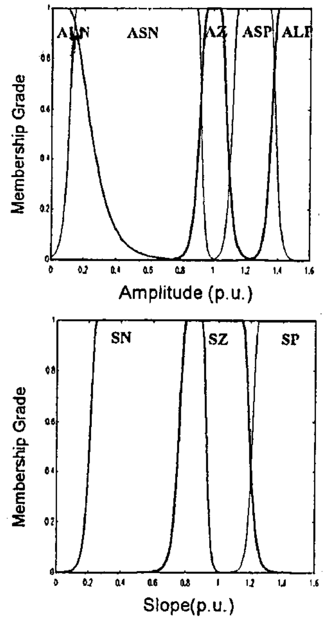
Publisher Item Identifier S 0885-8977(00)03458-0.



(a)



(b)

Fig. 2. Membership function for (a) amplitude and (b) slope of the voltage waveform.

installed in a PC. This data comprises voltage and current waveforms of a disturbed power system. A Fourier Linear Combiner (Appendix) module is then used to estimate the amplitude, phase and THD of the captured waveforms [7]. Unlike in reference[7], a least mean p-power error criterion is used to produce a robust and accurate estimate of the amplitude of the time varying power system signal.

III. Application of Fuzzy Expert System to Waveform Classification

The particular application of artificial intelligence (AI) used in the diagnostic module is called an expert system. As the power system data is highly uncertain and the power disturbance monitoring is a pattern classification problem, the fuzzy expert system approach is adopted for this problem.

For classifying the disturbance waveforms, 3 fuzzy sets are chosen for the slope designated as SN(slope negative), SZ(slope zero), SP(slope positive). In a similar way 5 fuzzy sets are chosen for the amplitude A which are designated as ALN(amplitude large negative), ASN(amplitude small negative), AZ(amplitude zero), ASP(amplitude small positive) and ALP(amplitude large positive). The membership grades for

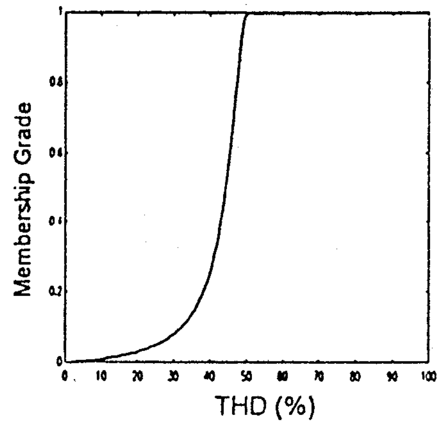


Fig. 3. Membership function of THD.

both the amplitude and slope are obtained from the following relationships (using a bell shaped function shown in Fig. 2(a)).

$$\begin{aligned}\mu(x) &= 1 \Big/ \left[1 + \frac{x - a_1}{c}\right]^{b_1}, \quad for \quad x < a_1, \\ &= 1, \quad for \quad a_1 < x < a_2 \\ &= 1 \Big/ \left[\frac{x - a_2}{c}\right]^{b_2}, \quad for \quad x > a_2 \end{aligned} \tag{1}$$

As an example, for the amplitude set ALN, the values of the constants $a_1,\ a_2,\ b_1,\ b_2$ and c are 0, 0.1, 2, 3, and 0.3, respectively. Similarly for the fuzzy set SN, the values of $a_1,\ a_2,\ b_1,\ b_2$ and c are 0.25, 0.9, 4, 8, and 0.1, respectively. Fig. 2(b) shows the membership functions of the above fuzzy sets.

The slope S of a waveform is obtained from the relationship

$$S(k) = [A(k) - A(k-1)]/\Delta T \tag{2}$$

$\Delta T =$ sampling interval

$k =$ iteration count

$A(k),\ A(k-1) =$ normalized peak amplitudes of the waveform at the instants k and $(k-1)$, respectively.

The rule base for the fuzzy decision support system is listed below as:

Rule 1: IF A is ASP AND S is SP THEN the waveform is Swell;

Rule 2: IF A is ALP AND S is SP THEN the waveform is Surge;

Rule 3: IF A is ASN AND S is SN THEN the waveform is Sag;

Rule 4: IF A is AZ AND S is SZ THEN the waveform is Normal;

Rule 5: IF A is ALN AND S is SN THEN the waveform is Surge;

Rule 6: IF A is ASP AND S is SZ TBEN the waveform is Swell;

Rule 7: IF A is ALN AND S is SN THEN the waveform is Surge;

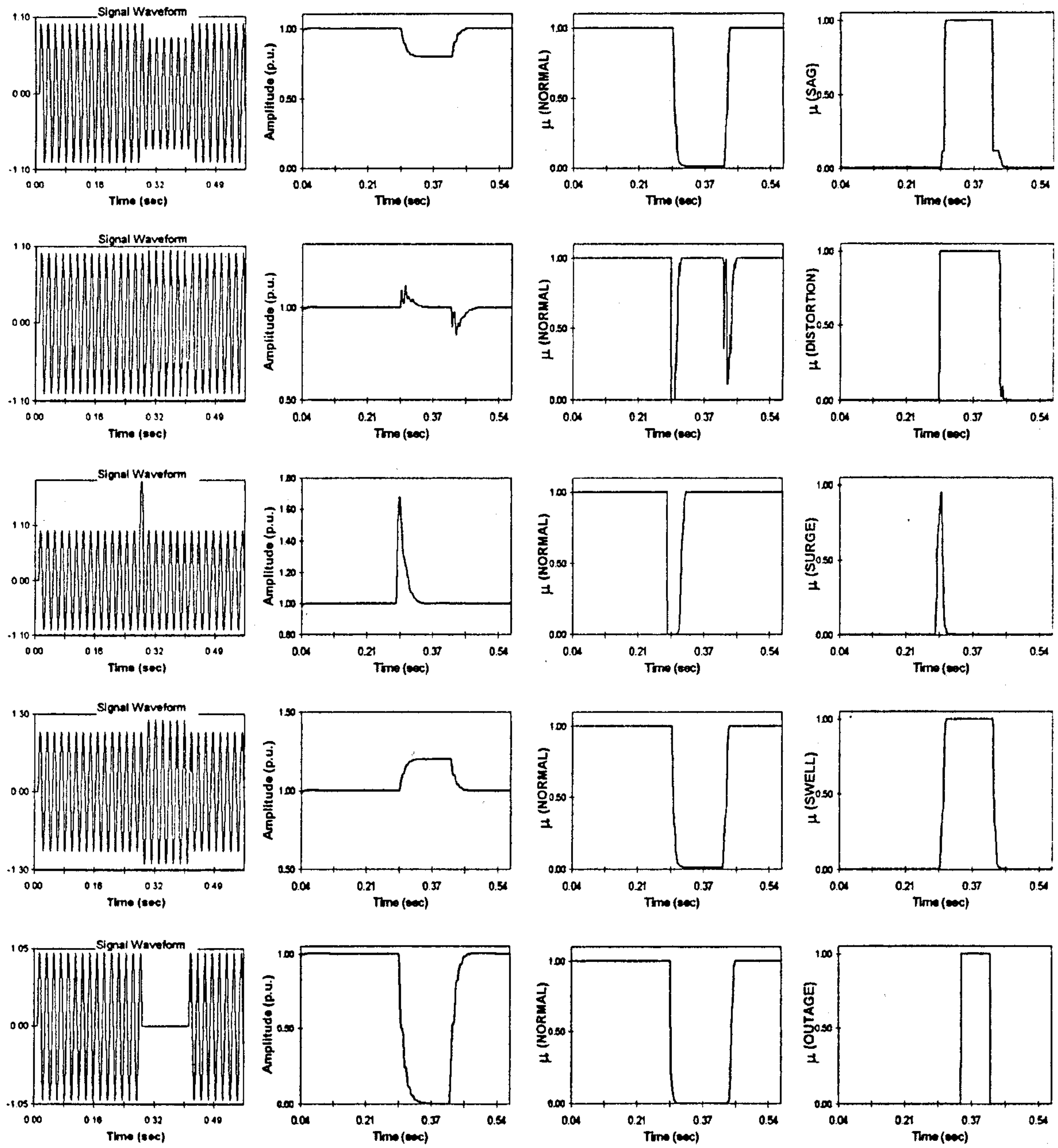


Fig. 4. Training results of the Classifier for differen waveform types.

Rule 8: IF A is ALP AND S is SZ THEN the waveform is Sag;

Rule 9: IF A is ALN AND S is SZ THEN the waveform is Outage;

Rule 10: IF A is ALN AND S is SP THEN the waveform is Outage.

The fuzzy inferencing is done using the maximum product compositional rule of inference. If $\alpha_1, \alpha_2, \ldots\ldots \alpha_5$ are the firing strength of the rule base for each category of the transient power system disturbance (Swell, Surge, Sag, Outage and Normal), the output is obtained as

$$\begin{aligned}\mu_0 &= \alpha_1 \quad OR \quad \alpha_2 \quad OR \quad \alpha_3 \quad OR \quad \alpha_5 \\ &= \max(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5)\end{aligned} \tag{3}$$

An uncertainty index λ is incorporated to the computation process to yield the final value of the output from the fuzzy decision block as

$$\mu_{of}(k) = \lambda\mu_0(k) + (1-\lambda)\cdot\mu_0(k-1). \tag{4}$$

This index λ is used to take into account the time lag between the measured value and actual value. The severity of this problem arises when the magnitude of the voltage phasor changes is accompanied by a change in the phase angle as is observed in the case of transformer switching and starting of induction motors. The value of λ is chosen to lie between 0.7 and 0.9.

Although the power system disturbance waveform belongs to five categories like the Sag, Swell, Surge, Outage and Normal,

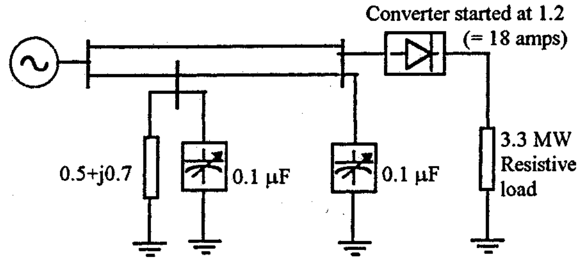


Fig. 5. System configuration of the model used for testing.

the harmonic distortion can be present in each of them. The classification of a distorted waveform can be carried out by defining a membership grade for the THD as

$$\mu(THD) = 1 \Bigg/ \left(1 + \frac{THD - 5}{50}\right)^{0.2} \tag{5}$$

where THD is expressed in percentage. From the figure, the rule for assessing THD is obtained as:

If THD is <5% then the waveform is normal and if 5% $<$ THD $<$ 50%, the waveform is distorted. At 50%, the membership grade for THD is 1.The membership function for THD is shown in Fig. 3.

IV. Simulation Results

Computer simulated waveforms for various transient disturbances of a power system are generated using MATLAB. The sampling rate of 16 based on a 50Hz waveform is used for testing the effectiveness of the new algorithm in classifying disturbance waveforms. A SGN function is used for updating the weight vector of the neural estimator which is initialized using a set of random weights.

The value of initial step size μ_i is chosen as 0.8 and the limit $\mu_{\max}$ and $\mu_{\min}$ are kept between 1.2 and 0.6, respectively.

Fig. 4 shows the category of the simulated waveforms like Sag or Swell and the corresponding output from the Fourier Linear Combiner and the integrated neural fuzzy diagnostic system. The training of the hybrid monitoring system for different class of waveforms is essential for tuning the parameters of the various modules. From the figure it is observed that each category of waveform is successfully classified as the output from the hybrid model shows a truth value of the particular class that suddenly rises from zero to 100% in most cases in comparison to the normal waveform.

The example taken for study is a generator supplying a power network which comprises short transmission line section and resistive and constant impedance loads. The system configuration is shown in Fig. 5. The resistive load (3.3 MW) is supplied through a power converter (rectifier) and the initial current is 18 amps when the converter is started. Variable static capacitors are installed at the load bus and the converter bus to improve the load power factor and provide VAR support to the buses. The power converter is started at $t = 0.043$ s and an outage at the generator end is initiated at $t = 0.49$ s. The outage persists for 0.04 s (2 cycles based on 50Hz; supply). The power network

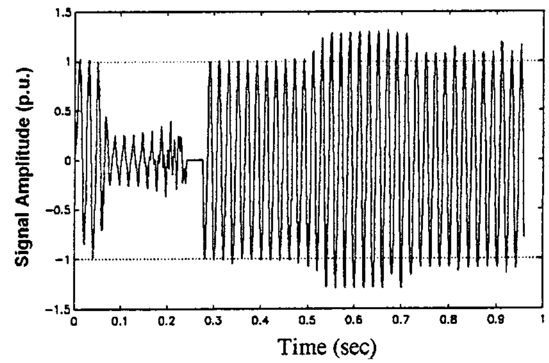


Fig. 6. Converter bus voltage (Ph. A).

is simulated using EMTP software package and Fig. 6 presents the instantaneous converter bus voltage waveform (one phase only). The classification results are presented in Fig. 7. From the figure it can be seen that the classification of the transient power quality disturbance waveform is done very successfully. For the particular type of disturbance, membership grade will become unity and for other nonoccuring types, membership grades will be very small.

The above results reveal that the proposed approach is computationally simple in comparison to the ANN based approaches [7] and yeilds classification in less than a cycle (.02 sec) based on a 50 Hz fundamental waveform. However, if the signal is highly distorted or there is frequency variation at the time of disturbance, the time required for the calculation of peak amplitude and slope will be completed within 2 cycles (.04 secs). Thus the total classification time for the computation and fuzzy logic based classification will be slightly higher than 1 or 2 cycles (.02 or .04 sec) depending on the level of distortion of the power system signal.

The ANN based approach uses Discrete Fourier Transform technique for peak or rms value extraction which produces large error in the presence harmonics, decaying dc and noise. This results in an incorrect classification of transient disturbances in nearly 25% of the cases taken for study and larger classification time. The wavelet transform, on the other hand, yields more accurate results than the ANN approach, although it is computationally intensive and requires nearly 3 cycles of the fundamental waveform to yield a disturbance classification. An on-line simulation study for voltage sag and harmonic distortion has been carried out to confirm the simplicity and validity of the approach.

V. Conclusions

The paper presents a new approach for the classification of power system disturbance waveforms using a Fourier linear combiner and a fuzzy expert system. A Fourier linear combiner is used to estimate the normalized peak amplitude of the voltage signal and its rate of change which become the inputs to the fuzzy expert system for classification of the waveforms. The fuzzy expert system yields a robust and accurate classification scheme for a variety of simulated waveforms containing harmonic distortions and noise. The approach is found to be computationally much simpler than the ANN and Wavelet

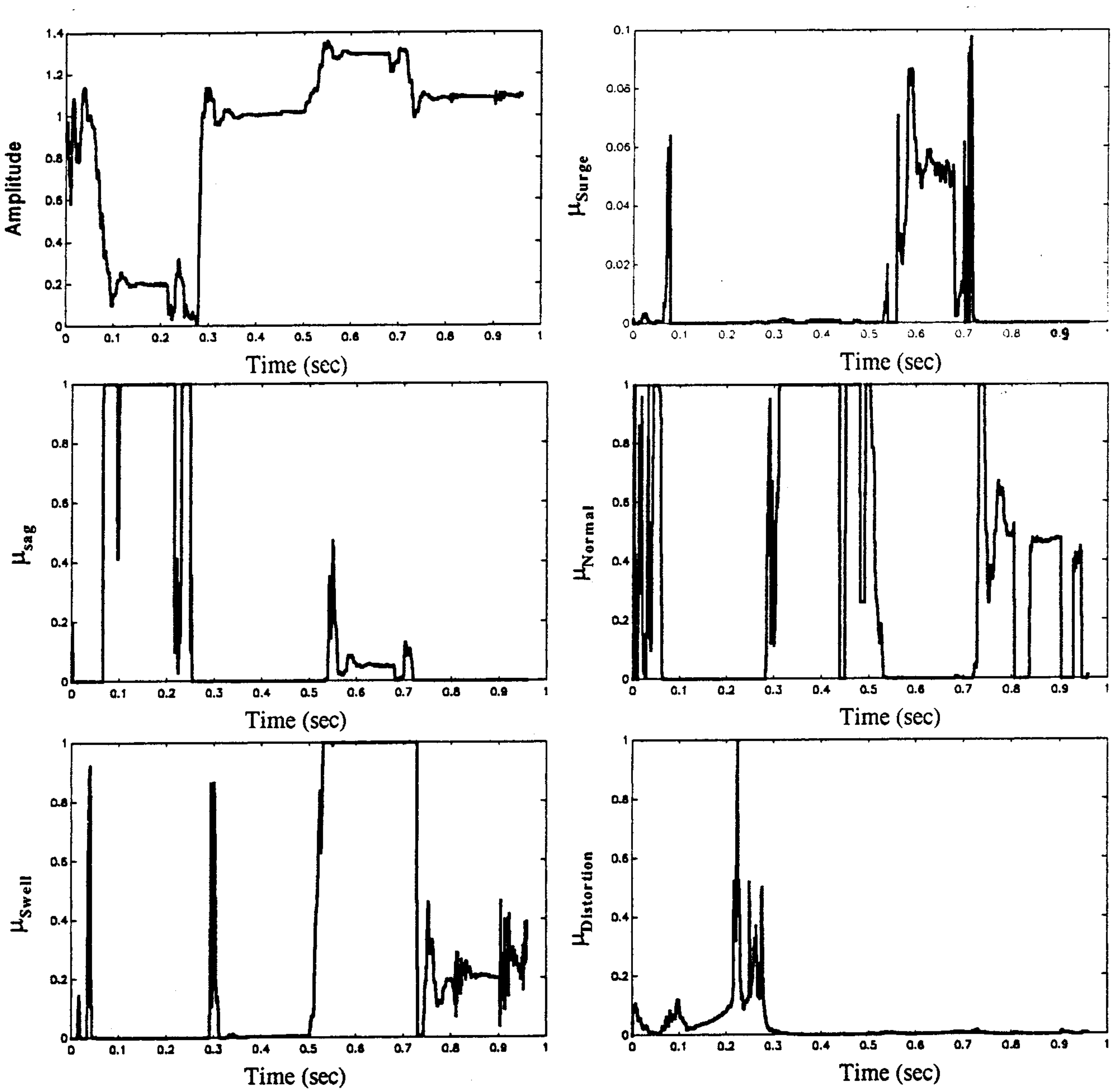


Fig. 7. Output of fuzzy expert module for the test waveform.

approaches which are currently used for transient disturbance classification.

Appendix
Fourier Linear Combiner

The voltage or current signal of a power network is expressed in the discrete form at the kth sampling instant as

$$y(k) = s(k) + (k) \tag{A1}$$

where

$$s(k) = \sum_{i=1}^{N} (a_i \cos i\omega\, k\Delta\, T + b_i \sin i\omega\, k\Delta\, T) \tag{A2}$$

where ω is the frequency of the fundamental component of the power system signal and is known apriori ; N is the order of the highest harmonic in the signal and $\Delta\, T =$ sampling interval. In the above formulation $v(k)$ is the additive white Gaussian noise with zero mean and variance σ_v^2 which has no correlation with the signal $s(k)$. A decaying dc component can also be added to the signal model given in (A2).

To obtain the Fourier coefficients a_i and b_i of the signal, we propose the use of an adaptive estimator in the form of a linear combiner shown in Fig. 8. The input to the linear combiner is the vector $[\cos k\omega\Delta T,\, \sin k\omega\Delta T,\, \cdots,\, \cos k\omega N\Delta T,\, \sin k\omega N\Delta T]^T$ and the weight vector W_i comprises the parameters a_i and b_i, which are the Fourier coefficients of the signal. A performance index of the form $J(k) = E[|\, e(k)|^p]$ is minimized to obtain the parameters a_i and b_i. Here E is the expectation of the quantity and $e(k)$ is the error between the desired signal $y(k)$ and estimated signal $\hat{y}(k)$; p is an index varying between 1

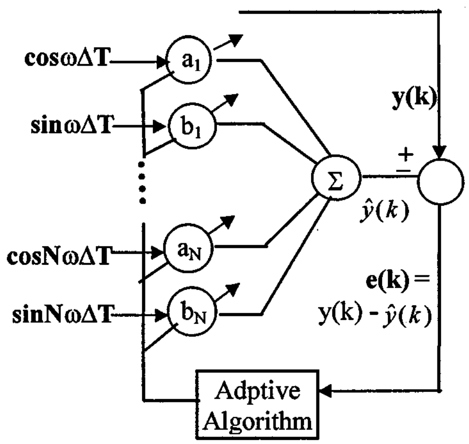


Fig. 8. Fourier Linear Combiner.

and 5. Using the steepest descent algorithm, the weight vector W_i is updated as

$$W_i(k+1) = W_i + \mu e^{p-1}(k) x_i(k) \tag{A1}$$

$i = 1, 2, \cdots\cdots, N$ for even p ; and

$$W_i(k+1) = W_i + \mu \cdot \text{sgn}(e(k)) e^{p-1}(k) x_i(k) \tag{A2}$$

$i = 1, 2 \cdots\cdots, N$ for odd p; where

$$x_i(k) = [\cos i\omega k\Delta T \sin i\omega k\Delta T]^T \tag{A3}$$

$W_i = [a_i(k) b_i(k)]^T$ μ is the step size parameter and sgn(.) is the sign function. Thus for $p = 3$, the parameter W is updated as

$$W_i(k+1) = W_i(k) + \mu e^2(k) \text{sgn}\{e(k) x_i(k)\} \tag{A4}$$

For the value of p greater than 5, the simulations exhibit performance deterioration of the algorithm for tracking power system sinusoids corrupted with noise. Also for $p = 1$, and 2, the performance of the standard LMS algorithm is obtained. For optimum results, the step size μ can also be varied. A suitable value of μ lies between 0.2 and 2. The peak amplitude and phase of the fundamental component are obtained as

$$A = \sqrt{a_1^2 + b_1^2}, \qquad \phi^{-1}(b_1/a_1).$$

The normalized peak amplitude is computed in per unit.

References

[1] S. Ebron, D. Lubkeman, and M. White, “A Neural Network Power Distribution Feeders,” *IEEE Transactions on Power Delivery*, vol. 5, no. 2, pp. 905–914, April 1990.

[2] A. F. Sultan, G. W. Swift, and D. J. Fedirchu, “Detection of High Impedance Arcing Faults Using A Multi-Layer Perceptron,” *IEEE Transactions on Power Delivery*, vol. 7, no. 4, pp. 1871–1877, Oct. 1992.

[3] L. G. Perez, A. J. Flechsig, J. L. Meador, and Z. Obradovic, “Training An Artificial Neural Network To Discriminate Between Magnetizing Inrush And Internal Faults,” in *IEEE Winter Power Meeting*, 1993, paper no.WM037-2, PWRD.

[4] R. Daniels, “Power Quality Monitoring Using Neural Networks,” in *Proceedings of the First International Forum on Application of Neural Networks to Power Systems*, pp. 195–197.

[5] A. K. Ghosh and D. L. Lubkeman, “The classification of Power System Disturbance Waveforms Using A Neural Approach,” *IEEE Transactions on Power Delivery*, vol. 10, no. 1, pp. 109–115, January 1995.

[6] S. Santoso, E. J. Power, W. M. Grady, and P. Hofmann, “Tower quality assessment via wavelet transform analysis,” *IEEE Trans. on Power Delivery*, vol. 11, no. 2, pp. 924–930, 1996.

[7] P. K. Dash, D. P. Swain, A. C. Liew, and S. Rahman, “An adaptive Linear Combiner For On-line Tracking of Power System Harmonics,” *IEEE Trans. on Power Systems*, vol. 11, no. 4, pp. 1730–1736, 1996.

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