

Power Quality Time Series Data Mining Using S-Transform and Fuzzy Expert System

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ABSTRACT

This paper presents new approach for time series data classification using Fuzzy Expert System (FES). In the proposed study, the power disturbance signals are considered as time series data for testing the designed FES. Initially the time series data are pre-processed through the advanced signal processing tool such as S-transform and various statistical features are extracted, which are used as inputs to the FES. The FES output is optimized using Particle Swarm Optimization (PSO) to bring the output to distinct classification level. Both Gaussian and trapezoidal membership functions are selected for designing the proposed FES and the performance measure is derived by comparing the classification rates for the time series data without noise and with noise up to SNR 20 db. The proposed algorithm provides accurate classification rates even under noisy conditions compared to the existing techniques, which shows the efficacy and robustness of the proposed algorithm for time series data classification.

Keywords: - Time-series data, Fuzzy Expert System, S-transform, Particle Swarm Optimization.

I. INTRODUCTION

Data mining is one of the key area which has extensive utility in real world situations such as business, science, technology, government and academia. Data mining involves fitting models to or determining pattern from observed data. The fitted models play the role of inferred knowledge. Typically, a data-mining algorithm constitutes a model, a preference criterion, and a search algorithm. The more common model functions in data mining include classification, clustering, rule generation and knowledge discovery. The continued growth in data collection in all of these areas ensures that the fundamental problem of how does one understand and uses one's data, will continue to be of critical importance across a large number organizations. Although simple statistical techniques and machine learning for data analysis were developed long ago, advance techniques for intelligent data analysis are not yet mature [1]. Knowledge Discovery can be regarded as one of the prime function of data mining that is a new generation of information processing technology.

Electrical power disturbance signals are considered as one of the similar time series data to be studied for time series pattern classification problems. In electrical power networks, the voltage and current signals exhibit fluctuations in amplitude, phase, and frequency due to the operation of solid-state devices that are prolifically used for power control. The sudden increase and decrease in voltage signal are known as swell and sag, respectively. If the signal amplitude momentarily becomes zero, it is the condition of interruption. Apart from these steady state disturbances, transient oscillations are seen in power networks when power electronically controlled capacitors are switched across a node in an electrical power network. These transients are of large amplitude in comparison to the normal voltage or current signal and exhibit multiple frequencies ranging from 300Hz to

5000Hz. In addition to oscillatory transients, impulsive transients, multiple voltage notches due to solid-state converter switching, harmonics, and power sinusoids being modulated by low frequency signals are also observed in the electric power networks. To distinguish and finding the similarity between non-stationary disturbance signal patterns like sag, swell, oscillatory transients, impulsive transients, notch, in the normal sinusoidal signals of frequency 50Hz or 60Hz, advanced signal processing techniques along with intelligent systems approach play a very important role in generating patterns that resemble the nature of the non-stationary disturbance. Existing automatic recognition methods for time-series pattern classification need improvement in terms of their capability, reliability, and accuracy. Approaches for automated detection and classification of time-series data, proposed recently are based on wavelet analysis, artificial neural networks, hidden markov models, time frequency ambiguity planes, etc.

These techniques have been successfully employed in other pattern recognition and signal processing applications, such as speech recognition, audio processing, communications, and radar and sonar applications, where the data is found to be a non-stationary time series. Although the above mentioned techniques provide improved recognition rates, they are not yet sufficient for supporting a robust data mining algorithm.

Amongst the suitable algorithms for non-stationary time-series data such as power system disturbance signals waveform processing, the wavelet is found to be most efficient since its multiresolution decomposition contains time domain information of the signal at different scales. Although wavelets are a promising tool [2-10] for detecting and extracting relevant features of various types of non-stationary time series data, they

are still not optimal since they are a set of band pass filters with no exact cutoff frequency. Besides wavelet based methods require

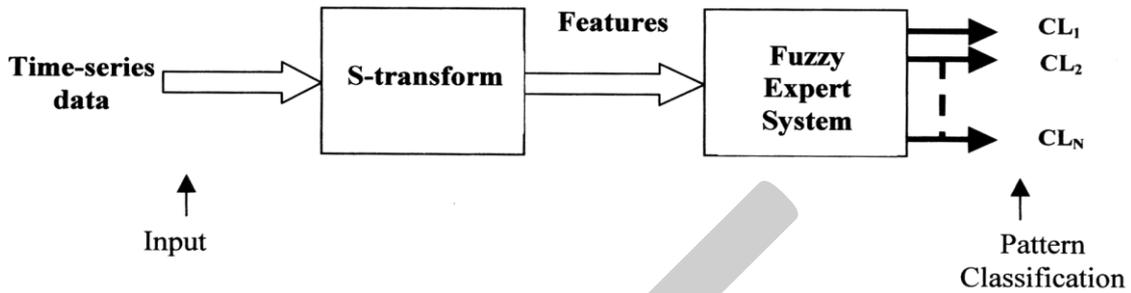


Fig.1 Proposed pattern classifier

training examples a large number of neural networks for pattern classification. The S-transform [11-13] has an advantage in that it provides multiresolution analysis while retaining the absolute phase of each frequency. This has led to its application for detection and interpretation of events in time series in a variety of disciplines. Some examples are analysis of the time variation in the amplitude and phases of sea level data in oceanography, analysis of seismic waveform and electrocardiogram data in cardiology.

The pattern classification and its subsequent application to temporal data mining proposed in this paper for knowledge discovery in time series data consists of two stages. As the data comprises time varying voltage signal samples (non-stationary in nature), the first stage will process the data by using a multiresolution transform (S-transform) [11] similar to the wavelet transform to extract relevant features. The extracted features will then be used in the second stage for classification of the non-stationary time series patterns by a fuzzy expert system (FES) in form of If-Then rules. The extracted features are fuzzified and accordingly one of the rules is fired to provide the required pattern classification. The output of the FES is optimized using particle swarm optimization (PSO) technique. Both trapezoidal and gaussian membership functions are chosen to design the FES for the time series data with and without noise. To bring out the efficacy of this new approach, the well known wavelet based method combined with fuzzy logic is used for comparison for pattern classification of similar time-series data.

II. PROPOSED PATTERN CLASSIFICATION SCHEME

The proposed technique includes pre-processing the time-series data using S-transform and various statistical features are derived from the S-matrix generated from S-transformation. Basically the features are in frequency domain. The extracted features are fed to the FES driven by a set of fuzzy rules. Each feature is characterized by a fuzzy membership function and partitioned into different zones as per the features range. According to the feature value one of the fuzzy rules is fired, resulting required pattern classification. The proposed scheme is given in Figure.1

III. S-TRANSFORM BASED FEATURE EXTRACTION

The time series data generated from various kinds of disturbance signals are preprocessed through the advanced signal processing technique such as S-transform. The multiresolution S-transform originates from two-advanced signal processing tools; the Short-time Fourier transform (STFT) and the Wavelet transform [11, 12, 13]. It can be viewed as a frequency dependent STFT or a phase corrected wavelet transform. Due to the frequency dependent window used for analysis of a signal data, the multiresolution S-transform has been proven in [11] to perform better than other time-frequency transforms. Furthermore, it provides superior time-frequency localization property computing both amplitude and phase spectrum of discrete data samples. It was shown in [12] that the S-transform would be useful for classifying power signal time series disturbances. Also it is less susceptible to noise than the wavelet transform approach. The S-transform of a signal $h(t)$ is defined as

$$S(t, f) = \int_{-\infty}^{\infty} h(\tau) w^*(\tau - t, f) \cdot e^{-j2\pi f\tau} d\tau \quad (1)$$

$$\text{where } S(t, f) = \frac{|f|}{\alpha_s \sqrt{2\pi}} \cdot e^{-tf^2/2\alpha_s^2} \quad (2)$$

and * stands for complex-conjugate. The parameter sets the width of the window for a given frequency. For small, the time resolution improves and the frequency resolution deteriorates. The reverse happens when it is increased to a larger value. S-transform produces a multiresolution analysis like a bank of filters with constant relative bandwidth. The integration of S-transform over time results in the Fourier spectrum that is

$$H(f) = \int_{-\infty}^{\infty} S(t, f) dt \quad (3)$$

and for the gaussian window

$$\int_{-\infty}^{\infty} S(t, f) dt = 1 \quad (4)$$

The original signal can be obtained from S-transform as

$$h(t) = \int_{-\infty}^{\infty} \left\{ \int_{-\infty}^{\infty} s(\tau, f) d\tau \right\} e^{j2\pi ft} dt \quad (5)$$

Another way to represent S-transform is an amplitude and phase correction of the CWT (continuous wavelet transform) as

$$S(t, f) = \sqrt{|f|} / 2\pi\alpha \cdot e^{j2\pi ft} \cdot WT(t, f) \quad (6)$$

Where the wavelet transform is given by

$$WT(t, f) = \int_{-\infty}^{\infty} \frac{|f|}{\alpha} \cdot e^{-\frac{t^2 f^2}{2\alpha^2}} \cdot e^{j2\pi ft} dt \quad (7)$$

The equation(6) shows that the time-frequency resolution is distributed in the time frequency plane like wavelet transform but a direct link with Fourier transform exists

The S-transform is now expressed as

$$S(t, f) = \int_{-\infty}^{\infty} H(v, f) \cdot W^*(v, f) \cdot e^{j2\pi vt} dv \quad (8)$$

$$W(v, f) = e^{-\frac{2\pi^2 \alpha^2 v^2}{f^2}} \quad (9)$$

A discrete expression for the S-transform is obtained from equation (8) as

$$S[m, n] = \sum_{k=0}^{N-1} [n + k] \cdot e^{-2\pi^2 \alpha^2 k^2 / n^2} \cdot e^{i2\pi km} \quad (10)$$

$$\text{for } n \neq 0 \text{ and } S[m, n] = \frac{1}{N} \sum_{k=0}^{N-1} h(k) \text{ for } n = 0, \quad (11)$$

$$\text{where } H[n] = \frac{1}{N} \sum_{k=0}^{N-1} h(k) \cdot e^{-j2\pi kn} \quad (12)$$

The term H[n] is the DFT of the time series h(t) and can be computed using FFT algorithm

$$S(j, n) = \sum_{m=0}^{N-1} H[m + n] G(m, n) e^{\frac{j2\pi mn}{N}} \quad (13)$$

$$\text{where } G(m, n) = e^{-\frac{2\pi^2 m^2 \alpha^2}{n^2}} \quad (14)$$

and j, m and n = 0, 1, ..., n-1.

The computational efficiency of FFT is used to calculate the S-transform and the total number of operations is N(N+NlogN).

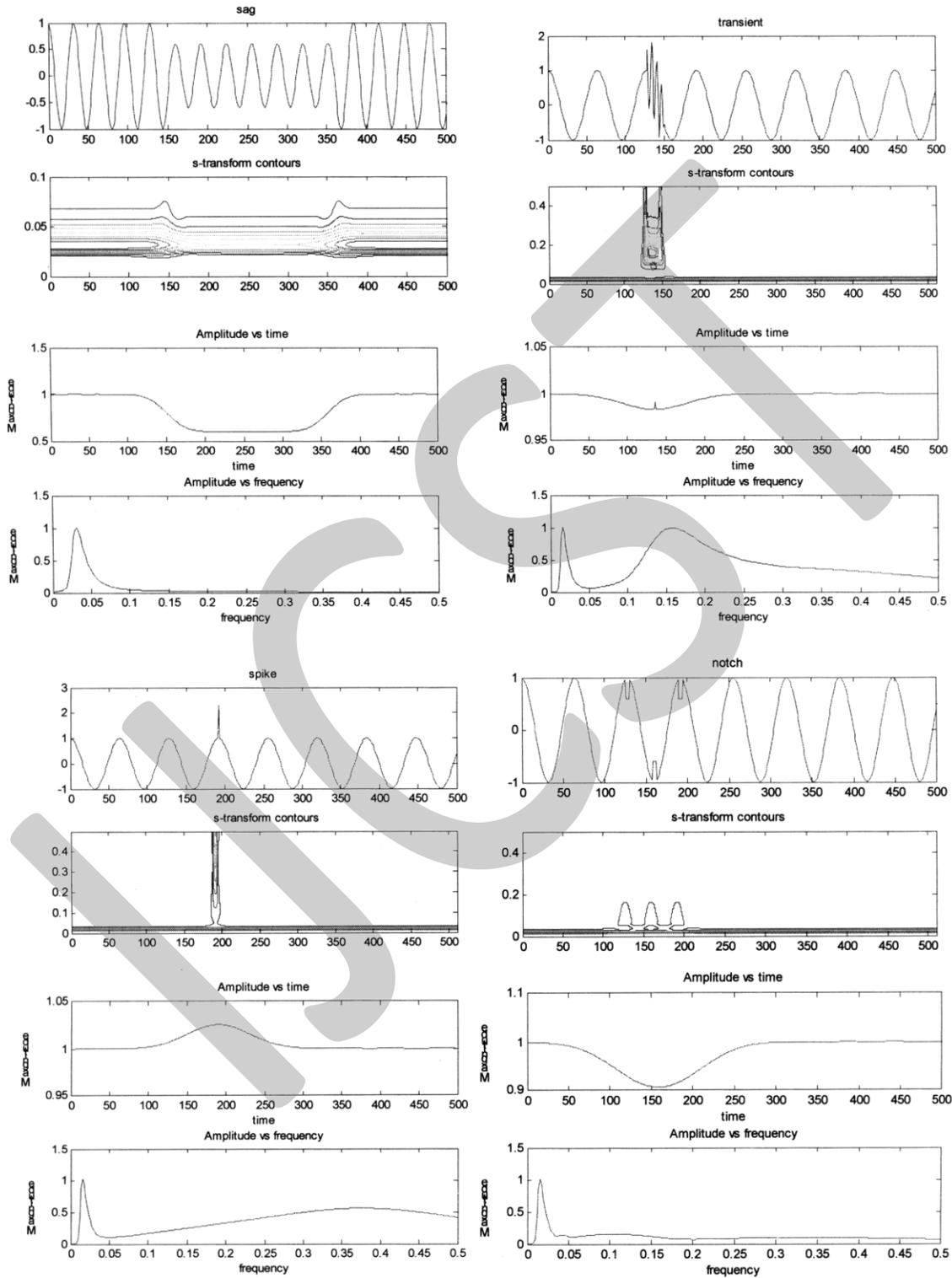
The amplitude and phase spectrum of S-transform are given by

$$A = \text{abs}(S(n, j))$$

$$\Phi(n, j) = \text{ang}(\text{Im}(|S(n, j)|) / \text{Re}(|S(n, j)|)) \quad (15)$$

IV. PRE-PROCESSING OF TIME-SERIES DATA THROUGH S-TRANSFORM

(a) Time series data and corresponding S-transform



The S-transform output shown in the figures includes the signal, S-contours, time-frequency contours, and amplitude and frequency contents. The S-contours provides the information regarding the time-localization of the time series data. As shown in the figures, the time- localization takes place in frequency domain instantly with the disturbance in the time scale. The aptitude information is also calculated for the S-matrix resulted from the S-transform. It shows the amplitude variation in the time-series data. Also the frequency content of the time-series data is calculates from the S-matrix to know the frequency content of the time-series data. As seen in the figures, the contains only one peak in the frequency characteristics while in case of transients there are two peaks with higher frequency values. This indicates sag is a low frequency phenomena which only contains one peak with other values nearly zero. But in case of transients, the more than one number of peaks indicates presence of higher harmonics in

the time-series data. This provides vital information for father analysis

V. FEATURE EXTRACTION

Four features were extracted from the S-transform output. They are:

1. $F_1 = \max(A) + \min(A) - \max(B) - \min(B)$.
where A is the amplitude versus time graph from the S-matrix under disturbance and B is the amplitude versus time graph of the S-matrix without disturbance.
2. $F_2 =$ Standard deviation of $\max(\text{abs}(s))$.
3. $F_3 =$ Energy in the S-transform output.
4. $F_4 =$ Total harmonic distortion (THD).
5. $F_5 =$ Estimated frequency hours the maximum amplitude

Table I.Features Extracted From S-Transform

Disturbances	F1	F2	F3	F4	F5
Normal	1.002				
Sag (60%)	0.593	0.053	0.031	0.0312	50.0
Swell (50%)	1.50	0.0129	0.076	0.015	50.00
Momentary Interruption (MI) (5%)	0.0724	0.035	0.019	0.0350	50.00
Harmonics (0% 3 rd + 10% 5 th)	1.0	0.0339	0.0556	0.141	50.00
Sag with Harmonic (60%)	0.601	.0228	0.0408	0.1139	50.00
Swell with Harmonic (50%)	1.5	.0219	0.079	0.1155	50.00
Flicker (5 Hz, 4%)	0.987	.0168	0.026	0.0186	55.00
Notch + harmonics	0.939	0.131	0.0529	0.136	56.25
Spike + harmonics	1.065	0.141	0.0627	0.1308	56.25
Transient (low frequency)	0.493	0.138	0.0163	0.01	705.00
Transient (high frequency)		0.149	0.014	0.043	2520.00

Table II. Features Extracted From S-transform with SNR 20DB

Disturbances	F1	F2	F3	F4	F5
Normal	0.9963	0.001	0.052	0.028	50.00
Sag (60%)	0.591	0.022	0.039	0.027	50.00
Swell (50%)	1.503	0.012	0.076	0.029	50.00
Momentary Interruption (MI)	0.070	0.0387	0.0323	0.044	50.00
Harmonics	1.032	0.050	0.064	0.25	50.00

Sag with Harmonic (60%)	0.601	0.0228	0.0408	0.1139	50.00
Swell with Harmonic (50%)	1.500	0.0219	0.079	0.1155	50.00
Flicker (4%, 5 Hz)	0.998	0.0209	0.027	0.1159	55.00
Notch + harmonics	0.940	0.1275	0.0531	0.198	50.00
Spike + harmonics	1.072	0.141	0.066	0.204	50.00
Transient (low frequency)	1.000	0.1473	0.0148	0.0566	440.00
Transient (high frequency)	1.0384	0.155	0.014	0.068	3315.00

Two nonstationary time series databases like sag and transient which occur very frequently in power networks are given in a separate table to highlight the variations in the feature values for the same event:

VI. FUZZY EXPERT SYSTEM (FES)

A Fuzzy Expert System has two key elements, (i) fuzzy sets and (ii) fuzzy rule base. A fuzzy set can be fully defined by its membership functions. Fuzzy rules offer human-like reasoning capabilities and provide transparent interface mechanism. In the proposed pattern classification technique, the features extracted from S-transform, are fed to the FES with trapezoidal and gaussian membership functions. A fuzzy rule base is developed for exact classification of the time-series data for 12 classes. The following sections deal with the membership function (MF) and fuzzy rule base. In classical fuzzy expert system the knowledge base constitute a set of rules derived from the statistical knowledge pre-processing the time-series data. The knowledge base, however, needs to be adapted with changes in the operating conditions, addition of spurious disturbances, and noise that might be superimposed over the data. This requires addition of new rules if necessary and a correct choice of membership functions to analyze the data.

The fuzzy if-then rules are in the following form for the n-dimensional pattern recognition problem:

Rule R_i: If X₁ is A₂₁ and X_n is A_{in}

The consequent Class C_i with classification factor CF_i, where R_i is the ith rule of the fuzzy rule base, x = (X₁, X₂,X_n.) is n-dimensional pattern vector and A_i is an antecedent fuzzy set, C_i the consequent class out of N classes, and classification factor CF_i in the interval [0, 1] is the certainty factor also termed as rule weight. In data mining problem, two measures known as confidence and support are used for finding the association rule in the form

$$A_i \rightarrow C_i \text{ with } A_i = [A_{i1}, A_{i2}, \dots, A_{in}] \quad (16)$$

The confidence c and support of each fuzzy rule R_i is written as

$$c = \frac{[\sum_p \mu_{A_i}(x_p)]}{[\sum_{p=1}^m \mu_{A_i}(x_p)]} \quad (17)$$

where p denotes the pth pattern and m is the total number of patterns used for classification.

The compatibility grade $\mu_{A_i}(x_p)$ of the pth pattern is obtained as

$$\mu_{A_i}(x_p) = \min\{\mu_{A_{i1}}(x_{p1}), \mu_{A_{i2}}(x_{p2}), \dots, \mu_{A_{in}}(x_{pn})\} \quad (18)$$

and $\mu_{A_i}(x_p)$ is the membership value of the x_p to the set A_i, p ∈ class C_i.

The support s of a fuzzy rule indicates the grade of coverage by (A_i → C_i)

(consequent) is given by $s = \frac{\sum_{p \in \text{class } C_i} \mu_{A_i}(x_p)}{m}$

To obtain the consequent class C_i from the fuzzy rule base R_i, the confidence measure is obtained from the antecedent fuzzy sets as

$$c_i = \max(c_1, c_2, \dots, c_N) \quad (19)$$

where c₁, c₂, c_N denotes the recognized classes of non-stationary time-series data.

The expression for support s is obtained in the same way as

$$s_1, s_2, \dots, s_N \quad (20)$$

For finding the classification performance of the fuzzy rule base, it is envisaged to use a single winner rule methods.

A single winner rule is selected from the set of classifying

$$x_p = (s_{p1}, s_{p2}, \dots, s_{pn}) \text{ as } \mu_{A_q}(x_p) \cdot CF_q$$

$$\max \{ \mu_{A_q}(x_p) \cdot CF_q | R_q \in S \}$$

The single winner rule posses the highest compatibility index in comparison to other rules in the rule base.

However, if two rules have the same compatibility index, the pattern is not classified.

The certainty factor or the rule weight is found as

$$CF_q = c - \bar{c} \quad (21)$$

where c is given by equation (17)

$$\text{and } \bar{c} = \frac{1}{N-1} \sum_{j=1}^N C(A_j \rightarrow \text{class } j) \quad (22)$$

VII. MEMBERSHIP FUNCTIONS

For generating fuzzy rules, two types of membership functions namely trapezoidal and gaussian are used for classification.

(i) Trapezoidal MF :

$$\mu_A(x_i) = 0 \quad x \leq a$$

$$\frac{x-a}{b-a} \quad a \leq x \leq b$$

$$1 \quad b \leq x \leq c$$

$$\frac{c-x}{d-c} \quad c \leq x \leq d$$

$$0 \quad d \leq x$$

where a, b, c, d are parameters that need to be optimized.

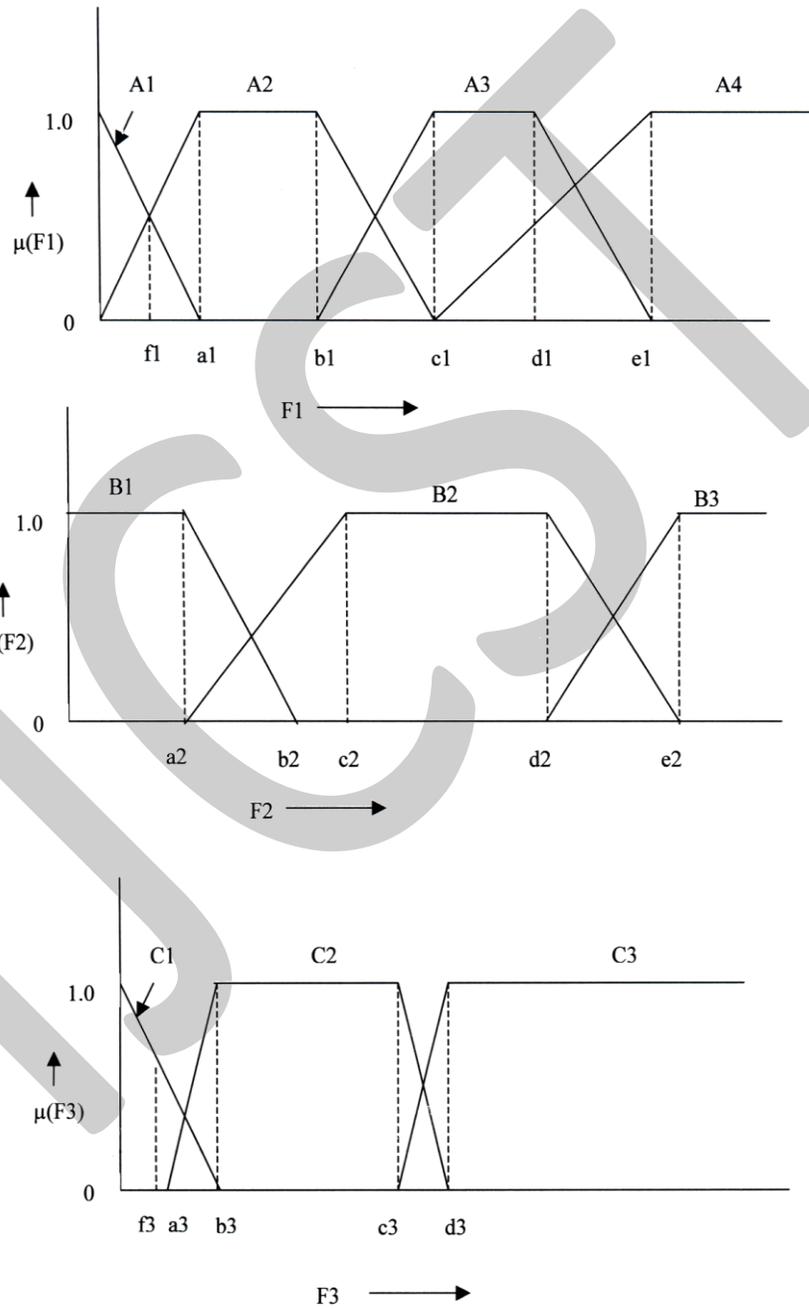


Figure 1

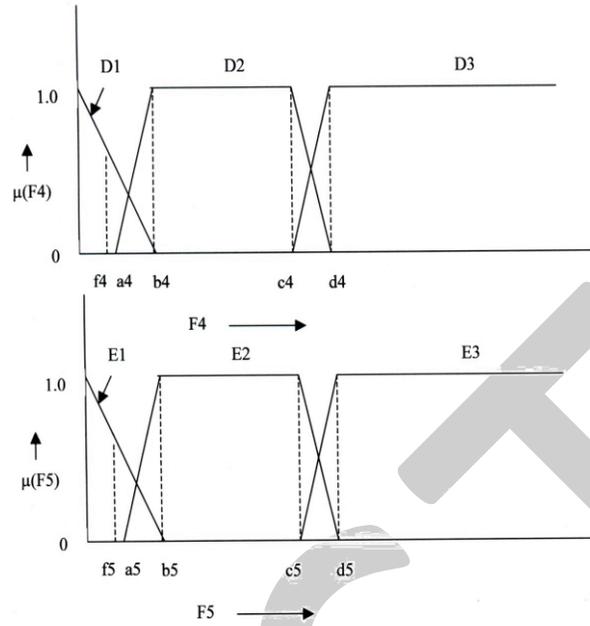


Figure2

VIII. Gaussian MF

In a similar way, the Gaussian membership function is defined as

$$\mu_{Ai}(xi) = \exp \left\{ -\frac{x_i - a_i}{\sigma_i} \right\}^2 \tag{23}$$

where a_i is the mean of the i th attribute value of x_{pi} , of class c patterns and σ_i is the standard deviation •

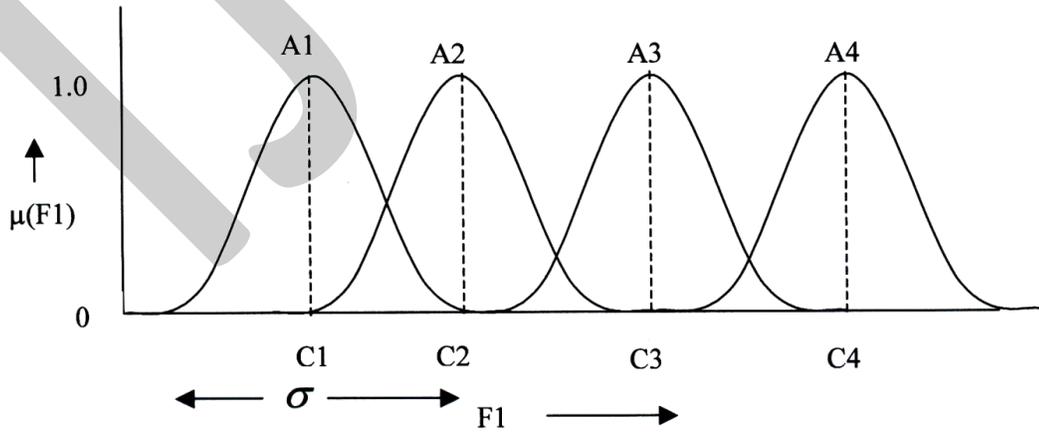


Figure3

IX. THE FOLLOWING FUZZY IF-THEN RULES ARE USED FOR BUILDING THE FUZZY RULE BASE LEADING TO A FUZZY EXPERT SYSTEM

Fuzzy Rule Base:

- Rule-1 If F1 is A3 and F2 is B1 and F3 is C2 and F4 is D2, then CL1 with CF1
- Rule-2 If F1 is A1 and F2 is B1 and F4 is D2, then CL2 with CF2.
- Rule-3 If F1 is A4 and F2 is B1 and F4 is D2, then CL3 with CF3
- Rule-4 If F1 is A1 and F2 is B1, then CL4 with CF4
- Rule-5 If F1 is A3 and F2 is B2 and F4 is D3, then CL5 with CF5.
- Rule-6 If F1 is A2 and F2 is B1 and F4 is D3 and F5 is E2, then CL6 with CF6
- Rule-7 If F1 is A4 and F2 is B1 and F4 is D3 and F5 is E2, then CL7 with CF7
- Rule-8 If F1 is A1 and F2 is B1 and F4 is D3, then CL8 with CF8
- Rule-9 If F2 is B2 and F3 is C1 and F4 is D2 and F5 is E3, then CL9 with CF9
- Rule-10 If F1 is A3 and F3 is C2, then CL 10 with CF 10
- Rule-11 If F1 is A2 and F2 is B2 and F3 is C2, then CL 11 with CF 11
- Rule-12 If F1 is A3 and F2 is B1 and F3 is C1 and F4 is D3 and F5 is E2, then CL12 with CF12

X. OUTPUT FROM FUZZY INFERENCE SYSTEM

- Rule- 1 output $\alpha_1 = \min(\mu_{f1a3}, \mu_{f2b1}, \mu_{f3c2}, \mu_{f4d2})$
- Rule-2 output $\alpha_2 = \min(\mu_{f1a1}, \mu_{f2b1}, \mu_{f4d2})$
- Rule-3 output $\alpha_3 = \min(\mu_{f1a4}, \mu_{f2b1}, \mu_{f4d2})$
- Rule-4 output $\alpha_4 = \min(\mu_{f1a1}, \mu_{f2b1}, \mu_{f3c1})$
- Rule-5 output $\alpha_5 = \min(\mu_{f1a3}, \mu_{f2b2}, \mu_{f4d3})$
- Rule-6 output $\alpha_6 = \min(\mu_{f1a2}, \mu_{f2b1}, \mu_{f4d3}, \mu_{f5e2})$
- Rule-7 output $\alpha_7 = \min(\mu_{f1a2}, \mu_{f2b1}, \mu_{f4d3}, \mu_{f5e2})$
- Rule-8 output $\alpha_8 = \min(\mu_{f1a1}, \mu_{f2b1}, \mu_{f4d2})$
- Rule-9 output $\alpha_9 = \min(\mu_{f2b2}, \mu_{f3c1}, \mu_{f4d2}, \mu_{f5e3})$
- Rule- 10 output $\alpha_{10} = \min(\mu_{f1a3}, \mu_{f3c2})$
- Rule- 11 output $\alpha_{11} = \min(\mu_{f1a2}, \mu_{f2b2}, \mu_{f3c2})$
- Rule- 12 output $\alpha_{12} = \min(\mu_{f1a3}, \mu_{f3c1}, \mu_{f4d3}, \mu_{f5e2})$

The above rule outputs for p-numbers of patterns are used along with equation to identify the classes of the time series events. The Fuzzy Expert System provides the output for corresponding class with some absolute value. But there may be possibility of small variations in the absolute value of the output which create confusion for the automatic recognition system to take proper decision with respect to the class and no-class. Generally the one output among 12 values should be higher showing the corresponding class while others should be comparatively low. But the absolute values of the other 11 outputs (may be little bit higher) may create problem for drawing a decision boundary for class

and no-class. Thus in the proposed system, the corresponding outputs from FES are optimized using Particle Swarm Optimization technique which results nearly '1' for the class and nearly '0' no-class. This makes the designed automatic system more reliable and accurate to decide for classification of time-series data. The algorithm maintains a population of particles, where each particle represents a potential solution to the optimization problem. Each particle finds a position in the 'N' dimensional feature space and moves in the multidimensional feature space to find the best optimized result. The position of the particle is decided as follows:

$x_i =$ The current position of the ith particle

$v_i =$ The current velocity of the ith particle

$Y_i =$ The personal best position of the ith particle

Then the particle position is adjusted as

$$V_{i,k}(t+1) = W V_{i,k}(t) + C_1 r_{1,k}(t)(Y_{i,k}(t) - X_{i,k}(t)) + C_2 r_{2,k}(t) - X_{i,k}(t)$$

$$x_i(t+1) = x_i(t) + V_i(t+1)$$

$$y(t+1) = \begin{cases} y(t) & \text{if } f(x_i(t+1)) \geq f(y(t)) \\ x_i(t+1) & \text{if } f(x_i(t+1)) < f(y(t)) \end{cases}$$

where 'i' is the particle and $k = 1, \dots, N$. 'w' is the inertia weight, c_1 and c_2 are the acceleration constants.

The velocity based on the following

- (i) Fraction of the previous velocity
- (ii) Distance of the particle from the personal best position (p-best).
- (iii) Distance of the particle from best particle found (g-best).

XI. SIMULATION RESULTS

Different disturbances with corresponding classes are given as follows

CL ₁	→	Normal
CL ₂	→	Sag
CL ₃	→	Swell
CL ₄	→	Momentary Interruption (MI)
CL ₅	→	Harmonics
CL ₆	→	Sag with Harmonic
CL ₇	→	Swell with Harmonic
CL ₈	→	Flicker
CL ₉	→	Notch + Harmonics
CL ₁₀	→	Spike + Harmonics
CL ₁₁	→	Transient (low frequency)
CL ₁₂	→	Transient (high frequency)

The simulation results for class and certainty factor are depicted in Table.III and Table.IV respectively. The classes are defined against the time series data as mentioned above. For CL₁ (Normal), the classification results obtained from FES (CL1) is 0.85. But for other patterns the class results are less than 0.3. Similarly for CL₂ (Sag), the FES result (CL2) is 0.9, while other results are comparatively very low

indicating non-class. For momentary interruptions the CL4 is 0.8 and for flicker CL8 is 0.75, which indicates classification. Similar observations are made with transient (high frequency) and transient (low frequency). Another index derived known as Certainty Factor (Table.IV), which is also a measure of the classification results. For sag, the CF₁ is 0.7 and for other patterns CF is less than even -0.2. For sag and swell, the CF₂ and CF₃ are 0.75 and 0.7 respectively. Similar observations are made with other time-series data where the Certainty Factors are highly +ve for classification and -ve for no-class. Table.V provides the support values which is the average classification value over 100 cases for each time series disturbances. For sag and swell, the support values are 0.85 (CL₁), and 0.8 (CL₂)

respectively. For other disturbances the support values are depicted as in Table.V. Thus the support value provides the robustness of the FES system considering all possible conditions of the time series disturbances.

Table.VI provides the Class and Certainty Factors obtained from FES for trapezoidal and Gaussian membership functions respectively. The Class obtained sag is 0.85 for Gaussian MF, while for trapezoidal is 0.80. Similarly the Certainty Factor obtained form Gaussian MF is 0.7, while form trapezoidal MF is 0.65. It is observed that the Gaussian MF provides better Class and Certainty Factors compared to trapezoidal MF. Table.VII provides the Particle Swarm Optimization (PSO) for the optimizing the class for different time-series data.

TableIII. Classification Factors for Different Classes

Time Series Data	CL1	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9	CL10	CL11	CL12
CF ₁	0.85	0.1	0.17	0.2	0.22	0.18	0.31	0.13	0.02	0.11	0.18	0.21
CF ₂	0.1	0.9	0.3	0.2	0.11	0.13	0.15	0.10	0.22	0.21	0.07	0
CF ₃	0.11	0.2	0.89	0.1	0.2	0.3	0.14	0.15	0.21	0.22	0.23	0.19
CF ₄	0.12	0.1	0.14	0.8	0.15	0.18	0.19	0.12	0.09	0.11	0.14	0.13
CF ₅	0.15	0.08	0.17	0.2	0.91	0.3	0.18	0.21	0.3	0.33	0.18	0.17
CF ₆	0.2	0.09	0.32	0.31	0.27	0.95	0.23	0.22	0.01	0.09	0.3	0.1
CF ₇	0.3	0.11	0.16	0.19	0.21	0.17	0.99	0.1	0.2	0.3	0.33	0.34
CF ₈	0.32	0.32	0.17	0.16	0.22	0.18	0.1	0.75	0.11	0.12	0.17	0.19
CF ₉	0.33	0.31	0.19	0.34	0.23	0.19	0.14	0.27	0.83	0.3	0.2	0.21
CF ₁₀	0.1	0.24	0.21	0.33	0.19	0.2	0.3	0.25	0.19	0.97	0.15	0.21
CF ₁₁	0.2	0.23	0.22	0.32	0.33	0.22	0.2	0.23	0.18	0.34	0.9	0.23
CF ₁₂	0.17	0.22	0.33	0.31	0.14	0.25	0.16	0.22	0.17	0.33	0.3	0.97

Table.IV Certainty Factors for Different Classes

Time-series data	CL1	CL2	CL3	CL4	CL5	CL6	CL7	CL8	CL9	CL10	CL11	CL12
CF ₁	0.7	-0.13	-0.05	-0.02	-0.003	-0.04	0.1	-0.1	-0.22	-0.12	-0.04	-0.01
CF ₂	-0.11	0.75	0.1	-0.008	-0.1	-0.08	-0.06	-0.11	-0.01	0.002	-0.15	-0.22
CF ₃	-0.14	-0.04	0.7	-0.15	-0.04	0.06	-0.11	-0.1	-0.03	-0.036	-0.01	-0.06

CF ₄	-0.07	-0.095	-0.05	0.668	-0.045	-0.008	-0.019	-0.07	-0.1	-0.08	-0.13	-0.06
CF ₅	-0.125	-0.2	-0.1	-0.07	0.7	0.03	-0.09	-0.06	0.03	0.07	-0.09	-0.1
CF ₆	-0.06	-0.018	0.06	0.05	0.01	0.75	-0.03	-0.04	-0.27	-0.18	0.04	-0.1
CF ₇	0.01	-0.18	-0.13	-0.1	-0.08	-0.1	0.7	-0.2	-0.09	0.01	0.05	0.06
CF ₈	0.09	0.09	-0.07	-0.08	-0.01	-0.05	-0.14	0.56	-0.13	-0.12	-0.07	-0.04
CF ₉	0.03	0.01	-0.11	0.04	-0.07	-0.11	-0.1	-0.02	0.58	0.005	-0.1	-0.09
CF ₁₀	-0.19	-0.04	-0.07	0.05	-0.09	-0.08	0.02	-0.03	-0.09	0.75	-0.14	-0.07
CF ₁₁	-0.1	-0.07	-0.08	0.02	0.03	-0.08	-0.1	-0.07	-0.13	0.04	0.65	-0.7
CF ₁₂	-0.13	-0.07	-0.06	0.02	-0.16	-0.04	-0.14	-0.07	-0.13	0.04	0.01	0.74

Table.V Support Values for Different(classes (100 cases each))

Time-series data	Support values
CF ₁	0.81
CF ₂	0.85
CF ₃	0.8
CF ₄	0.75
CF ₅	0.83
CF ₆	0.9
CF ₇	0.9
CF ₈	0.7
CF ₉	0.79
CF ₁₀	0.77
CF ₁₁	0.81
CF ₁₂	0.8

Table.VI Compression between Trapezoidal and Gaussian MF

Time-series data	Gaussian MF		Trapezoidal MF	
	CL	CF	CL	CF
CF ₁	0.85	0.7	0.80	0.65
CF ₂	0.9	0.75	0.85	0.69
CF ₃	0.89	0.7	0.81	0.62
CF ₄	0.8	0.668	0.74	0.60
CF ₅	0.91	0.7	0.82	0.62

CF ₆	0.95	0.75	0.85	0.68
CF ₇	0.99	0.7	0.88	0.64
CF ₈	0.75	0.56	0.69	0.51
CF ₉	0.83	0.58	0.75	0.52
CF ₁₀	0.97	0.75	0.87	0.68
CF ₁₁	0.9	0.65	0.79	0.59
CF ₁₂	0.97	0.74	0.89	0.71

Table.VII Results and Comparison from PSO Based Optimization

Time-series data	Gaussian MF PSO optimization		Gaussian MF Without optimization	
	CL	CF	CL	CF
CL ₁	0.97	0.95	0.859	0.75
CL ₂	1	0.93	0.95	0.8
CL ₃	1	0.93	0.95	0.75
CL ₄	0.98	0.97	0.877	0.73
CL ₅	1	0.91	0.97	0.75
CL ₆	1	0.97	0.95	0.77
CL ₇	1	0.92	0.99	0.70
CL ₈	0.97	0.91	0.8	0.76
CL ₉	0.99	0.95	0.95	0.7
CL ₁₀	1	0.99	0.98	0.8
CL ₁₁	1	0.899	0.93	0.79
CL ₁₂	1	0.93	0.99	0.79

XII. CONCLUSION

A novel approach for time series data classification using Fuzzy Expert System (FES) is presented in this paper. The power disturbance signals are considered as time-series data for the proposed study. The time-series data is pre-processed through the advanced signal processing technique such as S-transform and the features obtained are fed to the designed FES for classification. Other indices for accurate classification such as certainty factors and support values are derived and the obtained results shows the robustness of the propose technique. Also the FES outputs are optimized using PSO for further enhancement of the

classification results. The proposed technique is also tested for features obtained from noisy environment. Thus a robust and accurate FES system is developed for classification of time-series data in data mining.

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