# A new method to diagnose the type and location of different disturbances in Fars power distribution system

Mojtaba Kordestani (IEEE member)
Power and Control Engineering
Dept. Shiraz University
Shiraz, Iran
mojtaba.kordestani@ shirazu.ac.ir

Ali Akbar Safavi
Power and Control Engineering
Dept. Shiraz University
Shiraz, Iran
safavi@shirazu.ac.ir

Ali Sadrzadeh
Power and Control Engineering
Dept. Shiraz University
Shiraz, Iran
ali_sadrzadeh@yahoo.com

*Abstract*— **Fault detection and diagnosis (FDD) of power systems have become important issues due to the high power quality (PQ) demands for modern systems. For this purpose, wavelet transform is invoked to extract features of different transient disturbances. Then, an artificial neural network (ANN) as a powerful intelligent method is employed to automatically classify the disturbances based on their features. The energies of the features based on Parseval's theorem are used to train the ANN. The collected data of Fars power system is considered to evaluate the proposed FDD approach. Simulation results show the approach can diagnose different fault categories and detect the fault locations.**

**Keywords- Power quality; intelligent methods; Wavelet transform; fault.**

## I. INTRODUCTION

Recently, power quality has been an issue for costumers and power suppliers. The characteristic of new devices such as computers, power rectifiers, large inductions, furnaces, invertors could highly deteriorate the power quality in the power distribution systems [1].On the other hand; the new equipments are sensitive to different disturbances. The demand for better power quality increases competition in electricity markets and thus fault detection and diagnosis would be the first steps in the power quality improvement [2].

The power quality problem is the deviations of voltage or current waveforms from their ideal forms in the power distribution systems [3] although most researchers work only with voltage waveforms. Various faults may occur in power distribution system and each of them has its especial sources. The most common faults are sags (dips), swells, harmonics, momentary interruptions, transient oscillations, notches, spikes, etc [1]. Different fault characteristics are defined in IEEE standard 1159.

Electricity companies need to monitor power quality to deliver electricity with high qualification. For this purpose, electricity waveforms are monitored using recorders in power distribution substations [4]. Processing large amount of data is time consuming and it increases error in such systems. To improve quality, automatic identification and classification methods are proposed for power quality improvement [2, 4].

Fault detection and diagnosis in power quality consist of two steps. The first step is feature extraction and the second step is classification. Fourier transform (FT), wavelet transform (WT) and S-transform (ST) are three famous methods in signal processing which are usually used for feature extraction [5].

FT is the most common method in signal processing which is suitable for analyzing stationary signals. However, non-stationary signals cannot be diagnosed by FT. To deal with this issue, short time Fourier transform (STFT) is applied to non-stationary signals by assuming a fixed window to focus on certain period of time [5]. Although it can be used for simple time varying signals but it may face some difficulties in non-stationary signals with high degree of nonlinearity or uncertainty [6]. This is due to the limitation of the fixed window. Wavelet transform (WT) is widely used in power quality for analyzing signals [2, 5, 7-13]. It provides a short window for high frequency components and long window for low frequency components [7], so it can be used for time varying signals. WT is able to consider the time and the frequency information together; therefore, it is known as a tool for time-frequency representation of signals [14]. S-transform (ST) is obtained by phase correction of WT [14] and it has the ability to detect disturbance correctly at the presence of noises [1].ST is used in the field of power quality for the feature extraction [1, 12, 14-19].

After extracting features of signals, different methods are used for classification and diagnosing of the faults. There are two main classification methods in the literature of power quality, parametric and non-parametric methods. Parametric methods like mean, variance are used when statistical distributions of faults are accessible. Unfortunately, they are not available in the most cases. On the other hand, non-parametric methods need no statistical characteristic of the signal. For example, they can be considered by a description of the signals, like, fuzzy logic (FL) [5], or data driven methods, such as, artificial neural network (ANN) [7]or kernel based methods like support vector machine (SVM) [3] . Intelligent methods are proved to be powerful in many applications in different fields like estimation [20, 21], classification [22, 23]. ANN as a famous intelligent method can effectively capture characteristics of signals, learn from data, and give a proper response for new data input.

This paper presents a new method for fault detection and diagnosis in Fars power distribution system. For this purpose, WT is applied on faulty voltage signals to extract their features. Then, an ANN as a powerful intelligent tool is used to classify the faults. The novelty of the purposed method is in its simplicity and the way it is designed. The designed system can diagnose different faults correctly. The type of faulty signal is diagnosed by its energy feature vectors. It has to be mentioned when a fault occurs at some location, it always has an influence on the other locations of the power system and the effect of the fault can be seen in different locations. This paper also introduces a new method for detecting the fault location. The original location of faulty signal can be detected by measuring energy of signal at different locations of the power system. Finally, the proposed FDD approach is robust against noise. Through a simulation study, real data of Fars power distribution system are used. Simulation results show the ability of the proposed method in diagnosing faults.

The paper is organized as follows. Section II illustrates different faults in power distribution system according to IEEE standard 1159. Section III presents the basic theory of the methods used in this paper. Design methodology and simulation study are considered in Section IV. Simulation results are demonstrated in Section V. Finally, concluding remarks are given in Section VI.

## II. FAULT DESCRIPTION IN POWER QUALITY

This section illustrates different fault categories in power distribution System. Table 1 presents characteristics of power quality disturbances based on IEEE standard 1159.

**Table 1: Different fault categories based on IEEE standard 1159**

| numbers | Categories | Typical spectral content | Typical duration | Typical voltage magnitude |
|---|---|---|---|---|
| **1.0** | Transients | | | |
| **1.1** | Impulsive | | | |
| **1.1.1** | Nanosecond | 5-ns rise | <50 ns | |
| **1.1.2** | Microsecond | 1µs rise | 50 ns-1 ms | |
| **1.1.3** | Millisecond | .1-ms rise | > 1 ms | |
| **1.2** | Oscillatory | | | |
| **1.2.1** | Low frequency | <5k Hz | .3-50 ms | 0-4 pu (per unit) |
| **1.2.1** | Medium frequency | 5-500 k Hz | 20 µs | 0-8 pu |
| **1.2.3** | High frequency | .5-5 M Hz | 5 µs | 0-4 pu |
| **2.0** | Short duration variations | | | |
| **2.1** | Instantaneous | | | |
| **2.1.1** | Interruption | | .5-30 cyc | <.1 pu |
| **2.1.2** | Sag (Dip) | | .5-30 cyc | .1-.9 pu |
| **2.1.3** | Swell | | .5-30 cyc | 1.1-1.8 pu |
| **2.2** | Momentary | | | |
| **2.2.1** | Interruption | | 30 cyc-3sec | <.1 pu |
| **2.2.2** | Sag (Dip) | | 30 cyc-3sec | .1-.9 pu |
| **2.2.3** | Swell | | 30 cyc-3sec | 1.1-1.4 pu |
| **2.3** | temporary | | | |
| **2.3.1** | Interruption | | 3sec-1 min | <.1 pu |
| **2.3.2** | Sag (Dip) | | 3sec-1 min | .1-.9 pu |
| **2.3.3** | Swell | | 3sec-1 min | 1.1-1.2 pu |
| **3.0** | Long duration variations | | | |
| **3.1** | Interruption (Sustained) | | >1 min | 0.0 pu |
| **3.2** | Under voltages | | >1 min | .8-.9 pu |
| **3.3** | Over voltages | | >1 min | 1.1-1.2 pu |
| **4.0** | Voltage unbalance | | Steady state | .5-2% |
| **5.0** | Waveform distortion | | | |
| **5.1** | DC offset | | Steady state | 0-.1% |
| **5.2** | Harmonics | 0-100 k Hz | Steady state | 0-20% |
| **5.3** | Inter-harmonics | 0-6 k Hz | Steady state | 0-2% |
| **5.4** | Notching | | Steady state | |
| **5.5** | Noise | Broadband | Steady state | 0-1% |
| **6.0** | Voltage fluctuations | <25 Hz | Intermittent | .1-7% |
| **7.0** | Power frequency variations | | <10 sec | |

In Table 1, column 2 , 3, 4 and 5 present fault names, frequency characteristics, duration time and magnitude voltage, respectively. Fig. (1) shows three famous faults in power distribution system. In the following subsections, these are described in more details.

### A. *Sag (Dip) fault*

This is the most common fault in power distribution system. A typical sag fault shows in Fig. (1). In this fault, magnitude of signal declines between 0.1 and 0.9 pu. This is modeled in Table 2. It is noticed if magnitude of signal decreases to less than 0.1, this is noise, not sag. Further, if the magnitude of signal reduces to more than 0.9 it is interruption, and if time of fault takes more than one minute this is under voltage according to Table 1.

### B. *Swell fault*

This is a common fault in power distribution system. In this fault, magnitude of signal takes a level between 1.1 and 1.8 pu. This is modeled in Table 2. It is noticed if magnitude of signal increases to less than 0.1, this is noise, not swell. Besides, if time of fault takes more than one minute this is over voltage according to Table 1.

### C. *Harmonics fault*

This is a famous fault in power distribution systems. In harmonics distortion, the faulty signal is made by summation of the wave form with the fundamental frequency and several waveforms with integer multiple of the fundamental frequency. This is modeled in Table 2. In the most cases, this fault contains harmonic 3, 5, 7, 9, 11. Bigger harmonics can be ignored in most cases. Nevertheless, IEEE standard 1159 considers all harmonics smaller than100.

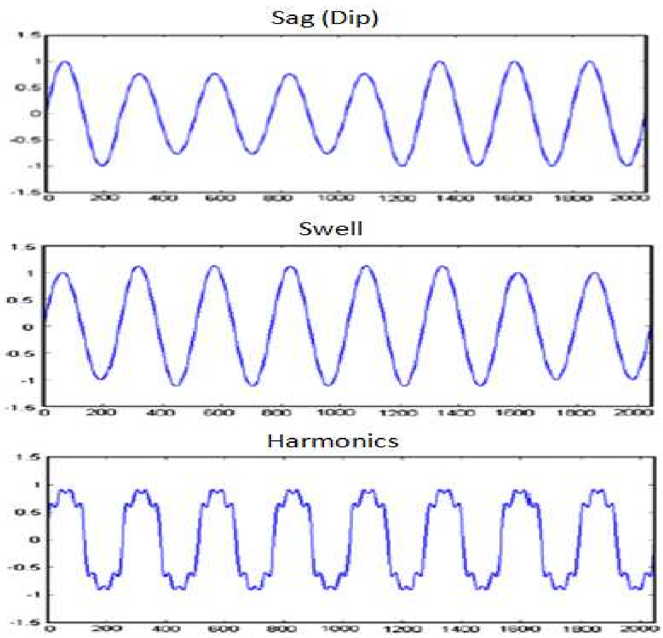


Fig. 1. Three famous faults in electricity distribution system.

**Table 2:Mathematical models of the common power quality faults**

| fault | Mathematical model |
|---|---|
| **Sag** | y(t)=A(1-α(U(t1)-U(t2)))×sin(wt) , .1<α<.9 , t1:time of beginning fault t2:time of finishing fault, T=2Π/W |
| **Swell** | y(t)=A(1+α(U(t1)-U(t2)))×sin(wt) , .1<α<.8 , t1:time of beginning fault t2:time of finishing fault, T=2π/W |
| **Harmonics** | y(t)=A($\alpha_1$×sin(wt)+$\alpha_3$×sin(3wt)+$\alpha_5$×sin(5wt)+$\alpha_7$×sin(7wt)+$\alpha_9$×sin(9wt)+$\alpha_{11}$×sin(11wt)), 0<$\alpha_n$<.9, n=1,3,5,7,9,11, T=2π/W |

## III. THE THEORY OF THE SUGGESTED METHODS

In this section, first, the basic theory of discrete wavelet transform is briefly explained. Then, some concepts on artificial neural network are considered.

### A. *Discrete wavelet transform (DWT)*

Discrete wavelet transform (DWT) presents a signal as a combination of scaling functions and their wavelets at different locations (positions) and scales (duration). Indeed, DWT is used to map a discrete signal into different resolution levels [13]. Malat builds a unique framework for discrete wavelet, known as multi-resolution analysis (MRA) [24]. The purpose of the MRA is to decompose signal f(t) ∊ $L_2$ (R). For this aim, consider f(t) as a linear combinations of scaling functions and its orthogonal wavelets as follows:

$$f(t)=\sum_{k=-\infty}^{+\infty} a_{0,k}\,\Phi_{0,k}(t)+\sum_{m=-\infty}^{0}\sum_{k=-\infty}^{+\infty} d_{m,k}\,\Psi_{m,k} \qquad (1)$$

$$\Phi_{m,k}(t)=2^{\frac{-m}{2}}\Phi(2^{-m}t-k),\quad \text{m, k} \in Z \qquad (2)$$

$$\Psi_{m,k}(t)=2^{\frac{-m}{2}}\Psi(2^{-m}t-k),\quad \text{m, k} \in Z \qquad (3)$$

Where φ(t) and ψ(t) are scaling functions and their orthogonal wavelets, and m and, k are dilation and translation factors of the scaling functions and the wavelets, respectively. It has to be noticed that $2^{\frac{-m}{2}}$ is used as an energy normalization factor.$a_{0,k}$ and $d_{m,k}$can be computed as the following:

$$a_{0,k} = <f,\Phi_{0,k}> \qquad (4)$$

$$d_{m,k} = <f,\Psi_{m,k}> \qquad (5)$$

Fig. (2) shows the decomposition of a signal based on MRA.

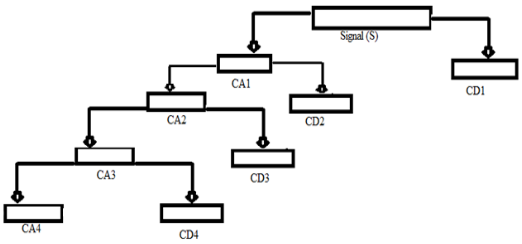


Fig. 2. The decomposition of a signal based on MRA.

The energy of the signal $f(t)$ based on Parseval's theorem can be formulated as follows:

$$E_{signal}=\int_0^T |f(t)|^2 dt=\sum_{n=0}^{N}|F[n]|^2 \qquad (6)$$

Where T and N are time period and length of the signal, respectively.

### B. *Artificial neural network (ANN)*

Ability of artificial neural networks (ANNs) to learn complex nonlinear functions motivates their applications in different fields. The layered topology of neurons provides a learning capability to imitate a general nonlinear function. Therefore, multi layered perceptron (MLP) represents the most famous class of neural networks, consisting of multiple layers of artificial neurons in a feed forward structure as shown in Fig.3 for one hidden layer configuration. It potentially provides a generic model representation for nonlinear black box systems which can be adapted with experimental input output data [20, 25, 26]. The procedure of training an MLP neural network to learn a desired dynamic representation conceptually regarded as system identification. Error back propagation (BP) algorithm presents an promising scheme to recursively train the MLP network. [26].

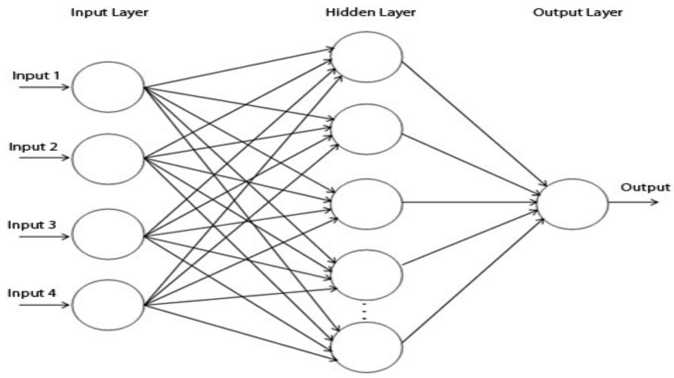


Fig. 3. MLP structure.

## IV. DESIGN METHODOLOGY AND SIMULATION STUDY FOR THE SYSTEM

In this section, first, wavelet transforms of faults introduced in Section II are analyzed and proper features are selected. Then, An MLP network is tuned to classify the purposed faults.

### A. *Feature extraction with wavelet transform*

Feature extraction is an important task in pattern reorganization, classification, machine learning and data mining [3]. Feature extraction is used to find the common properties among a group of signals. This has a high effect on the accuracy of classifiers. On the other hand, wavelet transform is a powerful method for analyzing non-stationary signals, because of this; it is widely used in power quality problems [2,5].

This section presents the suggested feature extraction method based on wavelet transform. For this purpose, the faulty signals are decomposed by MRA method to obtain decomposition levels known as details. To have a successful feature extraction and classify different faults, it is important to choose level of decomposition and type of wavelet properly. For this reason, decomposition of sag signal is made by different types of wavelet to evaluate which wavelet is more efficient for the suggested design methodology. Haar, Daubechies 3 (db3) and Daubechies 5 (db5) are used as the mother wavelets. The level of decomposition is chosen to be 4. Fig. 4 shows the sage signal and its decomposition levels for the mentioned mother wavelets. The vertical axis is per unit and the horizontal axis is the sampling time. Each sampling time lasts 0.00146.

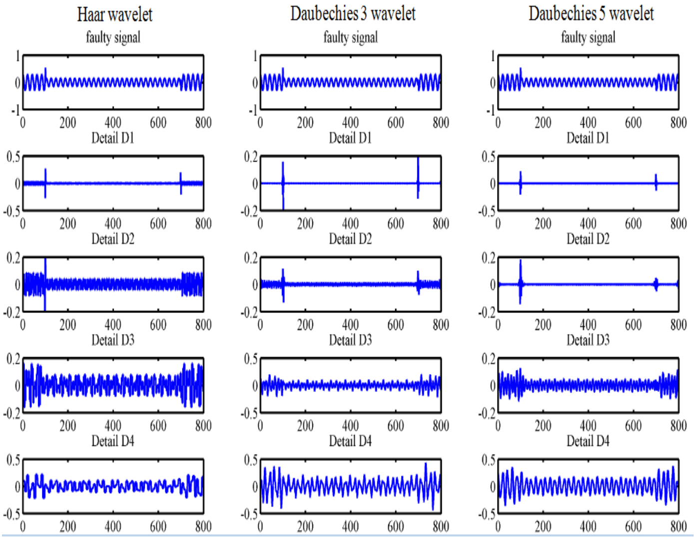

Fig. 4. Sage signal and its decomposition levels for Haar, db3 and db5 wavelets.

It can be indicated from Fig. 4 that the start time and the end time of the fault can be identified by different mother wavelets at 100 and 700, respectively. It is important to note that the start time and end time of the fault can be identified with the Daubechies wavelet. However, when the length of wavelet increases, the decomposition levels have less amount of information about the faulty signal, so Daubechies wavelet with big length is not suitable for feature extraction. To have a proper feature extraction and to identify the start time and end time of the fault, a compromise has to be made and db3 is chosen to be the mother wavelet. Fig 5 and 6 show swell and harmonics faults and their decomposition levels with db3 wavelets.

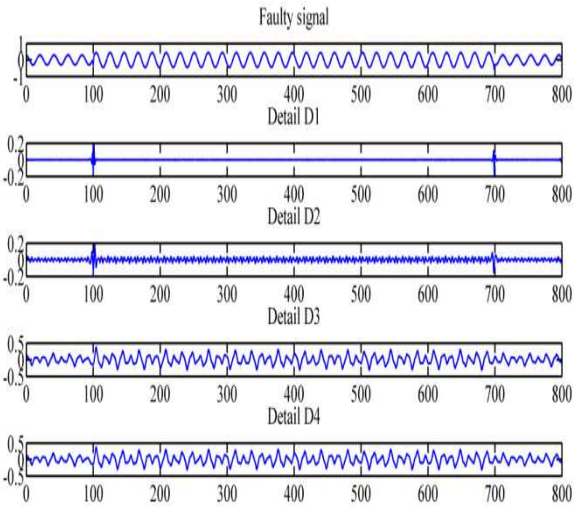

Fig. 5. Swell fault and its decomposition levels with db3 wavelets.

In this paper, the energies of decomposition levels D2, D3 and D4 are computed by Eq. (6) and they are used for feature extraction. It should be mentioned that D1 does not have much information and it only contains the noise and fast changes of the faulty signal, so it is not suitable for identifying different types of faults. It is only used for detecting the start time and end time of the fault.

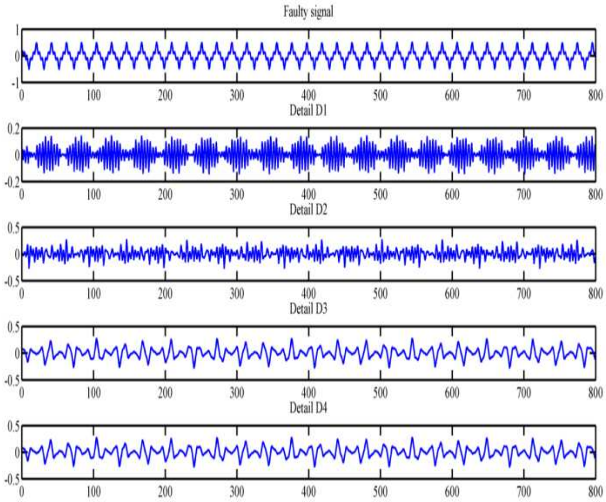

Fig. 6. Harmonics fault and its decomposition levels with db3 wavelets.

In real implementation, the characteristics of sag and swell signals are the same as they have the same slow frequency manner, because of this, the magnitude of the faulty signal per healthy signal is taken as an extra parameter to distinguish between these two faults. This parameter is named A1. A new vector is taken as a feature in the following:

$$\text{Feature vector} = [\text{A1 D2 D3 D4}] \quad (7)$$

### B. Classification with MLP network

This subsection presents the structure of the suggested MLP network for classification of different faults.

The aim is to design an MLP network to receive the feature vector in Eq. (7) and classify the faulty signal correctly. For this purpose, a three layered MLP network with four inputs, eight neurons in the hidden layer and one output is designed. Logsig (Log-sigmoid) and linear functions are used in the hidden and output layers, respectively. The dedicated MLP network is tuned by BP algorithm to classify different faults.

Real data (healthy and faulty) of the far distribution company is used for training the suggested MLP network. Different output level ranges are considered in the MLP to indicate different faulty cases. For this purpose, output levels in the ranges of -0.5 to +0.5 is considered as a healthy case and 0.5 to 1.5, 1.5 to 2.5, 2.5 to 3.5 are allocated to the sag, swell and harmonic cases, respectively. A white noise, having 5% of real data are added to input data to make the suggested MLP network robust against uncertainty and increase plausibility of the classifier.

## V. SIMULATION TESTS AND RESULTS

In this section, real faulty signals from Fars power distribution system are considered to evaluate the FDD system. For this purpose, data of four power stations including Ghaemieh, Neiriz, Kazeroon and Lar power station are used for test study. Figs 7, 8, 9 and 10 show three phase faulty signals of the above power stations, respectively. It can be indicated that the power stations of Ghaemieh and Neiriz are 400kw and the power stations of Kazeroon and Lar are 230kw. To use these power station datasets, first, they have to be normalized. Then the feature vectors for all three phases of the power station are obtained. Finally they apply to the MLP network to classify the signals.

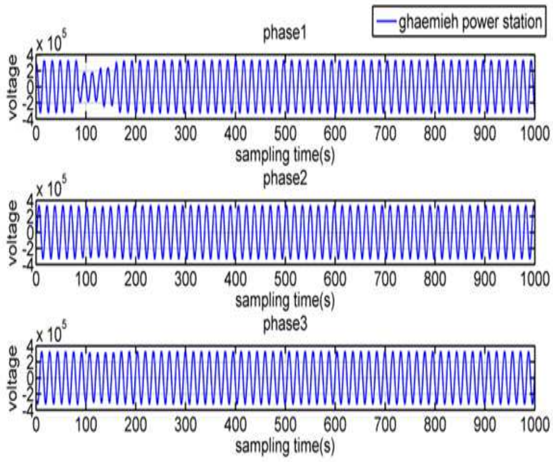


Fig. 7. Data of Ghaemieh power station

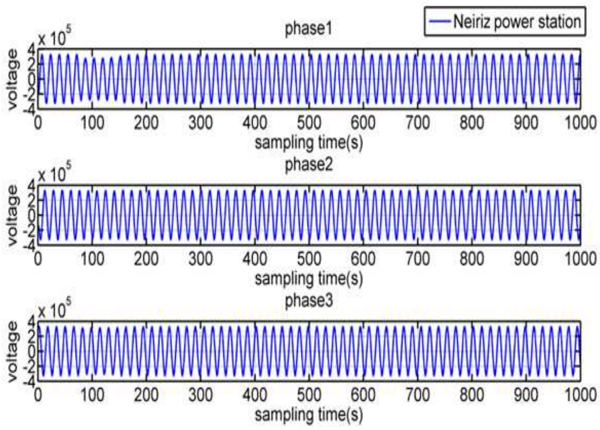


Fig. 8. Data of Neiriz power station

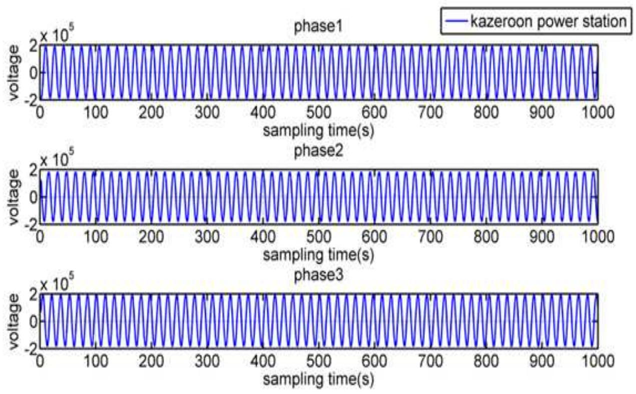


Fig. 9. Data of Kazeroon power station

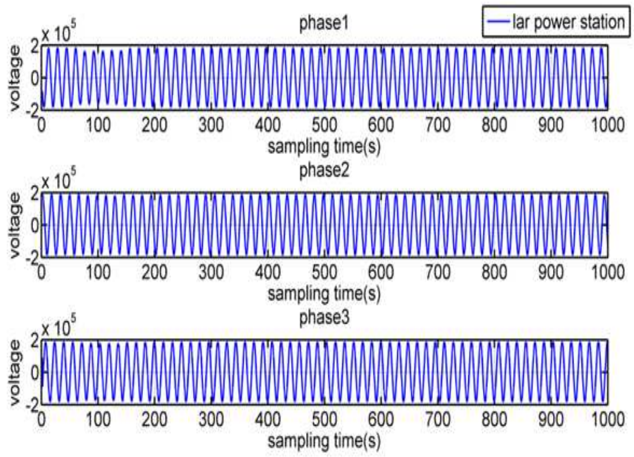


Fig. 10. Data of Lar power station

It can be seen from Fig. 9 that a sag fault occurs in phase 1 of Ghaemieh power station and it has an effect on phase 1 of Neiriz power station too.

Fig.11shows phase 1 of the four power stations and their decomposition levels.

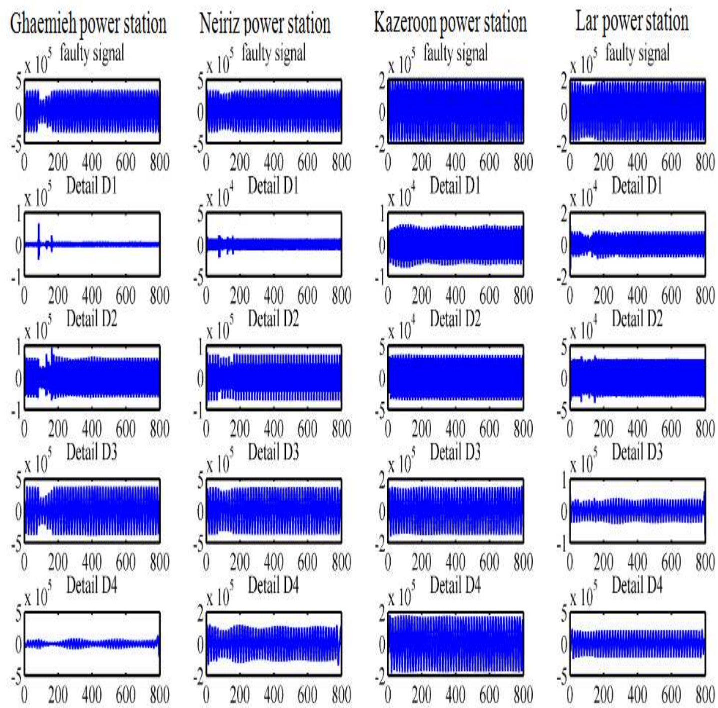


Fig. 11. Data and its decomposition levels with db3 wavelets of the four Fars power stations

It can be indicated from Fig. 11, D1 waveforms that a fault occurs in Ghaemieh and Neiriz power station, also, the start time of the faults in Ghaemieh and Neiriz power station is identified by D1 at 90 . Besides the output of MLP classifier for Ghaemieh, Neiriz, Kazeroon and Lar show 0.8966, 0.8037, 0.1770 and 0.4068, respectively. Therefore the FDD show sag fault inGhaemieh and Neiriz power station correctly. Finally, the energy of the normalized phase1 in Ghaemieh and Nieriz power station are computed by Eq. (6). They are 259.1250 and 262.6750. Because the type of fault is sag, the location of the fault belongs to the signal with smaller energy. Thus, the original location of fault is in Ghaemieh power station.

## VI . CONCLUSION

This paper presented a new FDD approach for Fars power distribution system using feature extraction and intelligent methods. For this purpose, first, different types of faults in power quality system based on IEEE standard 1159 were introduced. Then, wavelet transform was applied for feature extraction of the considered faulty signals. Using decomposition levels of the signals, their energies were computed. The energy and an extra input are fed into the MLP network to classify faulty signals. To increase robustness of the system a 5% white noise was added to the inputs. The suggested approach could successfully diagnosis types of faults and their original locations. Simulation test showed the ability of the FDD approach on real data of Fars power distribution system.


## ACKNOWLEDGMENT

The authors would like to thank Fars Power Company for their guidance and permission to use real power quality data.


## REFERENCES


[1] C.N. Bhende, S. Mishra, B.K. Panigrahi." Detection and classification of power quality disturbances using S-transform and modular neural network", electric power systems research 78 (2008) 122–128.

[2] H. Dehghani , B. Vahidi , R.A. Naghizadeh , S.H. Hosseinian," Power quality disturbance classification using a statistical and wavelet-based hidden Markov model with Dempster–Shafer algorithm", Electrical power and energy systems 47 (2013) 368–377.

[3] H. Eristi, O. Yıldırım, B. Eristi, Y. Demir." Optimal feature selection for classification of the power quality events using wavelet transform and least squares support vector machines", Electrical Power and Energy Systems 49 (2013) 95–103.

[4] S. M. Kumar, K. Rajiv. " Classification of power quality events – areview". Int J Electr Power Energy Syst 2012;43:11–9.

[5] S.K. Meher, A.K. Pradhan," Fuzzy classifiers for power quality events analysis", Electric Power Systems Research 80 (2010) 71–76.

[6] R. Zolfaghari, Y. Shrivastava, V.G. Agelidis," Evaluation of windowed ESPRIT virtual instrument for estimating Power Quality Indices" Electric Power Systems Research 83 (2012) 58– 65.

[7] S. Kaewarsa, K.Attakitmongcol, T. Kulworawanichpong," Recognition of power quality events by using multi-wavelet-based neural networks" Electrical Power and Energy Systems 30 (2008) 254–260.

[8] J. Huang, M. Negnevitsky, D. T. Nguyen, " A neural-fuzzy classifier for recognition ofpower quality disturbances", IEEE transactions on power delivery, VOL. 17, NO. 2, APRIL 2002.

[9] M.V. Ribeiro, J. M. T. Romano, C. A. Duque, " An improved method for signal processing and compression in power quality evaluation" IEEE transactions on power delivery, VOL. 19, NO. 2, April 2004.

[10] U. D. Dwivedi, S. N. Singh, " Denoising Techniques With Change-Point Approach for Wavelet-Based Power-Quality Monitoring" IEEE transactions on power delivery, VOL. 24, NO. 3, JULY 17-19, 2009.

[11] M.B.I. Reaz, F. Choong, M. S. Sulaiman, F. Mohd-Yasin, M. Kamada," Expert System for Power Quality Disturbance Classifier", IEEE transactions on power delivery, VOL. 22, NO. 3, JULY 2007 1979

[12] A. M. Gargoom, N.Ertugrul, . L. Soong," Investigation of Effective Automatic Recognition Systems of Power-Quality Events" IEEE transactions on power delivery, VOL. 22, NO. 4, October 2007 2319.

[13] A.M. Gaouda ,M.M.A. Salaina, M.K. Sultan, A.Y. Cliildiaoi,"Power Quality Detection and Classification Using Wavelet-Multi-resolution Signal Decomposition". IEEE Transactions on Power Delivery, Vol. 14, No. 4, October 1999 1469

[14] T. Nguyen, Y. Liao," Power quality disturbance classification utilizing S-transformand binary feature matrix method", Electric Power Systems Research 79 (2009) 569–575.

[15] M. Faisal, A. Mohamed , H. Shareef, A. Hussain," Power quality diagnosis using time frequency analysis and rule based techniques", Expert Systems with Applications 38 (2011) 12592–12598.

[16] A. Rodriguez, J.A. Aguado, F. Martin, J.J. Lóopez, F. Munoz, J.E. Ruiz," Rule-based classification of power quality disturbances using S-transform" Electric Power Systems Research 86 (2012) 113– 121.

[17] M.F. Faisal, A. Mohamed." A new technique for power quality based condition monitoring" 20th International Conference on Electricity Distribution Prague, 8-11 June 2009,Paper 0062.

[18] A. M. Gargoom, N. Ertugrul, W.L. Soong, " Automatic Classification and Characterizationof Power Quality Events" IEEE transactions on power delivery, VOL. 23, NO. 4, OCTOBER 2008.

[19] T. Weiqing, Y. Shaoge, D. Ming, L. Chuanjian, Y. Nanhua, B. Xiaofei, C. Hongguang, G. Jinnan," Classification of Power Quality Disturbance Signals Based on S-Transform and HHT"IEEE conference,26-28July,2013.12.16

[20] K. Salahshoor, M. Kordestani, M. S. Khoshro, IEEE Members, "Design of online soft sensors based on combined adaptive PCA and DMLP neural networks," Chinese Control and Decision Conference (CCDC ), 17-19 June 2009, page(s): 3481-3486, IEEE

[21] K. Salahshoor, M. Kordestani, M. S. Khoshro, "Design of online soft sensors based on combined adaptive PCA and RBF neural networks design," Computational intelligence in control and automation, USA, March 30 2009-April 2 2009, page(s): 89-95, IEEE

[22] K. Salahshoor, M. Kordestani, M. S. Khoshro, "Fault detection and diagnosis of an industrial steam turbine using fusion of SVM (support vector machine) and ANFIS (adaptive euro-fuzzy inference system) classifiers," Energy 35 (2010) 5472-5482.

[23] K. Salahshoor, M. S. Khoshro ,M. Kordestani , "Fault detection and diagnosis of an industrial steam turbine using a distributedconfiguration of adaptive neuro-fuzzy inference systems," Simulation Modelling Practice and Theory 19 (2011) 1280–1293

[24] S. G. Mallat, "A theory for multiresolution signal decomposition: the wavelet representation". IEEE Transactions on Pattern Analysis and Mach. Int., 11(7), 674-693, 1989.

[25] Q. Guo, Q. Tang. " Data mining based on improved neural network and its application in fault diagnosis of steam turbine". In: Congress on intelligent control and automation. IEEE; 2008.

[26] Z. Tian, H. Zhang, Y. Wang. " Failure diagnosis of steam turbine-generator set based on genetic algorithm and BP network. In: Conference on intelligent systems design and applications (ISDA' 06). IEEE; 2006. 0-7695-2528-8/06.