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An Independent Component Analysis Classification for Complex Power Quality Disturbances With Sparse Auto Encoder Features

XIAOYING SHI[1,2], HUI YANG[1,2], ZHIBANG XU[2], XIUJUN ZHANG[3], AND MOHAMMAD REZA FARAHANI[4]

[1]School of Mechatronics Engineering, Nanchang University, Nanchang 330031, China
[2]School of Electrical and Automatic Engineering, East China Jiaotong University, Nanchang 330013, China
[3]Key Laboratory of Pattern Recognition and Intelligent Information Processing, Institutions of Higher Education of Sichuan Province, Chengdu University, Chengdu 610106, China
[4]Department of Applied Mathematics, Iran University of Science and Technology, Tehran 16844, Iran

Corresponding author: Xiaoying Shi (sxyecjtu@163.com)

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ABSTRACT This paper introduces a method to detect multiple power quality (PQ) disturbances of power system features based on an independent component analysis (ICA) and a sparse auto encoder (SAE). Seven basic single PQ disturbances are extracted as typical features from numerous training samples of PQ disturbances by the SAE method, which can automatically gain the training features rather than manually selecting features as in the conventional approaches. An ICA is adapted to conduct basic separate signals from the blind original disturbance sources. The experimental results indicate that the proposed method has not only achieved a significant improvement for detecting single PQ disturbances but is also effective for detecting and classifying multiple PQ disturbances.

INDEX TERMS Multiple power quality disturbances (PQDs), sparse auto encoder (SAE), blind original signal, independent component analysis (ICA), complex fault diagnosis.

I. INTRODUCTION

Electricity is transmitted and distributed mainly through the public power grid. Nowadays, there is wind energy, solar energy and some kinds of the other new energy provided for electrical grid. On the other hand, more and more energy-saving electronic devices, asymmetric loads and other non-linear, impact resistance, such as electric arc furnaces, rolling mills, electric locomotives, etc., have been widely used. As a result, a large number of harmonics have been produced in the power grid. These harmonics distort the normal voltage wave forms. A great deal of non-steady power disturbances, including voltage sag, swell, flicker, harmonic distortion, notch, spike transients, etc., may bring us so many safety issues with electrical equipment, including breakdown, instability, short lifetime, fault, and so on. In order to identify the sources of disturbances and improve the power quality(PQ), it is important to PQ disturbances to be identified accurately.

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A large number of approaches have been proposed to the recognition of single PQ disturbances [1]. Although the fast Fourier transform (FFT) can accurately obtain the spectral information of the disturbance signal, it does not provide the time domain information of the signal. The short-time Fourier transform (STFT), briefing time-frequency information connected with the disturbance waveform. It divides the signal into several small time intervals, and the signals in these small intervals are analyzed by Fourier transform to determine the frequency components present in the time interval. The wavelet transform (WT) is the most commonly used time frequency domain analysis approach in power quality detection. In this method, multi-resolution analysis (MRA) decomposes the signal into different frequency bands according to different scales. Based on the methods of STFT and WT, Stockwell proposed the S-transform (ST) method [1]. Dash then introduced the ST method into the detection of power quality signals [2]–[4]. The Hilbert-Huang transform (HHT) approach posed by Norden E. Huang in 1998 could detect single type of perturbation signal, as well as mixed-type disturbances [6], [7].

The above methods mainly obtain the features of signal by the transformation in the time domain or the frequency domain. In addition to the above time domain-frequency domain transform methods, d-q transform, also known as the rotating coordinate transformation [8], [9], is often used in the detection of power system harmonics. These transform methods [2]–[11] may lose parts of the original signal important features. Deep learning methods [12]–[15] simulate human brain activity extracting the abstract features of the power quality disturbance signal. It can be expected to avoid this deficiency at a very large extent. In [16], Spare Auto Encoder (SAE) is firstly introduced into the classification of power quality disturbances (PQDs) and has an obvious improvement to classification accuracy rate.

The performance of the above approaches may appear very limited because, for substantial power networks, the disturbances usually behave simultaneously and are commonly used to refer to multiple disturbances. With respect to the classification of such multiple disturbances, Some recent outcomes have taken the occurrence of only two classes into account. In [6], ant colony optimization algorithm for disturbances classification was proposed, where four types of multiple disturbances were considered: sag or swell, flicker and interruption, each of them was combined with harmonics. In [6], in order to classify six classes of those disturbances, S-transform variant with fuzzy decision tree was proposed. For more works, please consult [7], [16]–[23].

In this paper, a method combining an independent component analysis (ICA) and an SAE is posed to analyze and classify PQ events with multiple complex disturbances. First, ICA is applied to separate the blind original disturbance sources, which are acquired by voltage signal from different supervised spots. To effectively address the subject connected with detection and classification of single PQ events, an approach based on the combination of an SAE and soft max classifier is adopted. As a useful tool to apply the sparse auto encoder, the SAE is applied to hierarchically collect the features for classification, which can be considered as a highly sparse format without omitting any information from the original data so as to represent the initial data. The features of the single PQ disturbances are extracted automatically through an SAE rather than by manual selection, which is used in conventional approaches for the identification of PQ disturbances. An average classification accuracy of above 98.6% is achieved for single disturbances based on the SAE, which indicates that there is a significant improvement compared to existing detection and classification methods. In order to effectively validate the proposed classification approach, variances of signals and an ICA algorithm are adopted to perform the classification of multiple complex PQDs. The simulation results show that an ICA is effective for multiple PQ disturbances, mainly including double disturbances and quadruple disturbances.

II. SAE AND SOFT-MAX REGRESSION

A stacked auto encoder is a neural network consisting of multiple layers in which the outputs of each layer are wired to the inputs of the successive layer [9], [10]. To effectively address the issues related to detection and classification of complex PQ events, a classification method based on the spare auto encoder and soft max classifier is adopted.

A. SPARSE AUTO ENCODER

The sparse auto encoder usually attempts to learn an approximation function under some conditions of constraints, such as by restricting the number of hidden units and placing a sparsity constraint on the hidden units, so that the number of output units y is infinitely close (equal) to the number of input units x.

$$\begin{aligned} Z_j^{(l)} &= \sum_{j=1}^{n} W_{ij}^{(l-1)} y_j^{(l-1)} + b_i^{(l)} = h_{W,b}(y_j^{l-1}), \\ y_j^{(l)} &= f(z_j^{(l)}). \end{aligned} \tag{1}$$

The minimize cost function can be described as follows:

$$\begin{aligned} J(W,b) = [\frac{1}{m}\sum_{i=1}^{m}(\frac{1}{2}\|a^{(3)(i)} - x^{(i)}\|^2)] \\ + \frac{\lambda}{2}\sum_{l=1}^{n_l-1}\sum_{i=1}^{s_l}\sum_{j=1}^{s_{l+1}}(W_{ji}^{(l)})^2. \end{aligned} \tag{2}$$

In (2), the first term reflects the distance between the inputs and outputs, and the second term is a regularization that tends to cut down the weights, and is used to prevent over-fit; the parameter λ controls the weights between the two terms.

To ensure the features bear a desired sparsity in the hidden layer, a sparsity constraint, used for controlling the learning process, is introduced into the cost function. This sparsity constraint makes the hidden units be inactive as much as it can. The corresponding average activation of the j-th hidden unit is given by:

$$\hat{\rho}_j = \frac{1}{m}\sum_{i=1}^{m}(a_j^{(2)} x^{(i)}). \tag{3}$$

To make $\hat{\rho}_j$ become a very small value ρ, the sparsity penalty term is given based on the Kullback-Leibler (KL) divergence scheme:

$$KL(\rho\|\hat{\rho}_j) = \rho \log\frac{\rho}{\hat{\rho}_j} + (1-\rho)\log\frac{1-\rho}{1-\hat{\rho}_j}. \tag{4}$$

Thus, this sparsity penalty term is considered as the following cost function:

$$J_{sparse}(W,b) = J(W,b) + \beta\sum_j KL(\rho\|\hat{\rho}_j), \tag{5}$$

where β is the weight of the sparsity penalty term.

B. SOFT-MAX CLASSIFIER

A soft-max classifier generalizes to solve classification problems according to logistic regression where the class label can take on more than two possible values. In a training set $(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), \ldots, (x^{(m)}, y^{(m)})$ of m labeled examples, we know that $y^{(j)} \in \{1, 2, \ldots k\}$. For a given test input X, we will estimate the probability of the class label on each possible value among the k different ones. Thus the hypothesis $h_\theta(x)$ has the form:

$$h_\theta\left(x^{(i)}\right) = \begin{bmatrix} p\left(y^{(i)} = 1 \left| x^{(i)} ; \theta\right.\right) \\ p\left(y^{(i)} = 2 \left| x^{(i)} ; \theta\right.\right) \\ \ldots \\ p\left(y^{(i)} = k \left| x^{(i)} ; \theta\right.\right) \end{bmatrix} \tag{6}$$

$$= \frac{1}{\sum_{j=1}^{k} e^{\theta_j^T x^{(i)}}} \begin{bmatrix} e^{\theta_1^T x^{(i)}} \\ e^{\theta_2^T x^{(i)}} \\ \ldots \\ e^{\theta_k^T x^{(i)}} \end{bmatrix}, \tag{7}$$

where θ is the parameter set of the model and the term $\sum_{j=1}^{k} e^{\theta_j^T x^{(i)}}$ normalizes the distribution such that it sums to one. The cost function is

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{j=1}^{k} 1\left\{y^{(i)} = j\right\} \log \frac{e^{\theta_j^T x^{(i)}}}{\sum_{l=1}^{k} e^{\theta_l^T x^{(i)}}}\right] + \frac{\lambda_s}{2}\sum_{i=1}^{k}\sum_{j=1}^{n}\theta_{ij}^2. \tag{8}$$

In (8), 1{.} is considered as the indicator function, for which 1{a true statement}=1 and 1{a false statement}=0; the second part presents the weight decay term, which is used to penalize some values of the parameters.

Fig.1 shows the structure of a sparse auto-encoder with soft-max regression. Among which, a stacked one is a type of neural network containing multiple layers of sparse auto encoders where the outputs of each layer are connected to the inputs of the successive layer [9], [10].

III. ICA STRATIGY FOR COMPLEX PQDS

The multiple-labels classification is a complex classification, different from the single label one, is a complex classification. It can process the data with multiple categories, and the ICA is a widely used blind source separation technique and has been applied in substantial fields [12] . Although the components separated from multiple complex PQDs may be disordered and the amplitude of these waveforms is changed, it does not affect the classification accuracy rate for multiple-label complex PQDs.

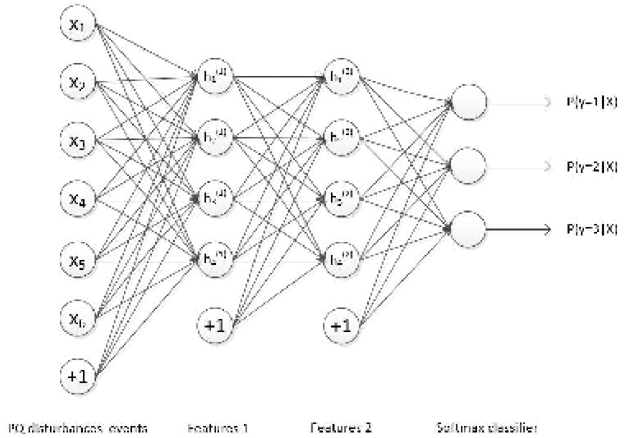

FIGURE 1. The structure of auto-encoder with a soft-max regression.

A. PRINCIPLE COMPONENT ANALYSIS

Adopting SVD (singular value decomposition) to covariance matrix X,

$$C_X = XX^T = U\sum V^T V \sum U^T = U\Lambda U^T. \tag{9}$$

The principle components do not have correlation, and the principle components should be ordered in accordance with the magnitude of the energy ($\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_n$). Using Principal Component Analysis (PCA), we could obtain the main components effectively of the original vector and reduce the original vector dimensions greatly.

B. INDEPENDENT COMPONENT ANALYSIS

Independent Component Analysis is based on the theory of instantaneous linear aliasing blind signal separation. The output of the approximate independent source signals are statistically independent of each other. Currently, ICA-based blind separation algorithms include Bell-Sejnowski's Maximum Information method, Amari's Natural Gradient method, and Cardoso's Change Adaptive method.

In addition these gradient optimization algorithms, there are the matrix eigenvalue decomposition method and the fast Independent Component Analysis (FastICA) algorithm. The FastICA algorithm based on the criterion of non-Gaussian maximization, which uses a fixed-point recursive algorithm to find the optimal value of the cost function and makes the separated signals to have the best mutually independent. In 1997, Finnish scholar Hyvarinen et al first proposed a fixed-point algorithm based on kurtosis, and then proposed a fixed-point algorithm based on negative entropy.

Negative entropy is used as a measure of non-Gaussian signal, and its convergence effect is better than kurtosis. But it is difficult to calculate the theoretical value of negative entropy in practice. An optimal algorithm proposed by Hyvarinen solves the approximate maximum value of negative entropy. The Newton iterative algorithm finds the optimal separation matrix JW_{max} by batch processing to continuously update the weight W, so that the negative entropy reaches the maximum.

Choose the number of iterations p and the number of the component needed to estimate m, the steps of Fast-ICA algorithm are as follows:
(1) Centralize the observed data X, for which the expected mean is zero; and whiten the data so that Z replaces X.
(2) For estimating m, choose the number of the component needed, and set the number of iterations p.
(3) Choose a random initial phase W_p, and order
$W_p = E\{Z_g\,(W/Z)\} - E\{g'(W/Z)\}W$.
(4) By applying the Newton iterative method, we get, $p - I$
$W_p = W_p - L(W_p^T W_j)W_j$.
(5) Carry out regularization: If W_p dose not convergence, return to step (3) and set $p = p + 1$. If $P < m$, return to step(2).

IV. ICA STRATIGY FOR COMPLEX PQDs

As shown in Fig. 2, there are seven kinds of basic single PQDs signals, including voltage sag (S1), voltage swell (S2), voltage interruption (S3), oscillation transient (S4), pulse transient (S5), flicker signal (S6), and harmonic signal (S7). These seven disturbances should be divided into four classes by the corresponding definitions and characteristics, e.g. S1–S3 belong to the first class (denoted as CLASS1), S4 and S5 belong to the (denoted as CLASS2), S6 belongs to the third (denoted as CLASS3), S7 belongs to the fourth (denoted as CLASS 4).
There are three types of compositions for these classes of PQ disturbances, and they are listed as follows:
1) Double disturbances: There are 17 random combinations of two disturbances in CLASS1–CLASS4.
2) Triple disturbances: There are 17 random combinations of three disturbances in CLASS1–CLASS4.
3) Quadruple disturbances: There are 6 random combinations of four disturbances in CLASS1–CLASS4.

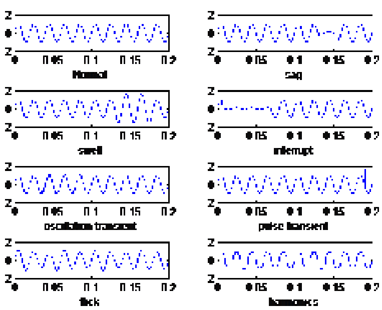

FIGURE 2. The waveforms of seven basic single PQDs.

V. SIMULATION AND RESULTS

A. THE WAVEFORMS OF BASIC SINGLE PQ DISTURBANCES

We randomly produced a normal signal and the seven basic single PQDs signals (voltage sag, voltage swell, voltage interruption, impulsive transient, oscillation transient, harmonic,

TABLE 1. The seven kinds of single PQDs classification results based on SAE.

Single PQDs	sag	Swell	Interruption	Oscillation Transients	Pulse Transients	Flicker	Harmonics	Total
Classify results	99%	95%	100%	99%	96%	99%	100%	98.61%

and flicker). The parameters of the voltage waveforms during power quality events were statistically different from those that were calculated during an event-free time period (see Fig.2).

To effectively detection and classification of single PQ signals separated by ICA from complex PQDs, the method based on the combination of spare auto encoder and soft max classifier is adopted.

First, we learned the primary features of the raw input by trained a sparse auto encoder on the raw inputs. Then, we fed the raw input into this trained sparse auto encoder to obtain the primary feature activations for each of the inputs. Next, we used these primary features as the "raw input" to another sparse auto encoder to learn the secondary features on these primary ones. By doing so, we fed the primary features into the second sparse auto encoder to obtain the secondary feature activations for each of the primary features. The sparsity parameter ρ of the SAE was 0.05, and it controlled the average activation of the hidden units; the weight decay parameter term λ of SAE was $3e - 8$. The structure of *NN* based on SAE was 640-196-196-7 by train samples of $7 \times 2000 = 14000$.

The features of the single PQ disturbances were automatically extracted through sparse auto encoder rather than by manually selecting compared to conventional approaches for the identification of PQ disturbances. The image of the hidden weights is shown in Fig.3.

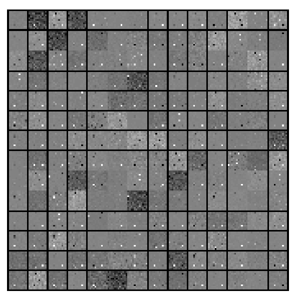

FIGURE 3. The image of hidden weights of SAE network for single PQDs.

B. THE ICA SIMULATIONS FOR COMPLEX PQ DISTURBANCE

Triple disturbances could be effectively extracted single disturbance components by ICA, such as harmonic, voltage swell, and oscillation transient in Fig.4.

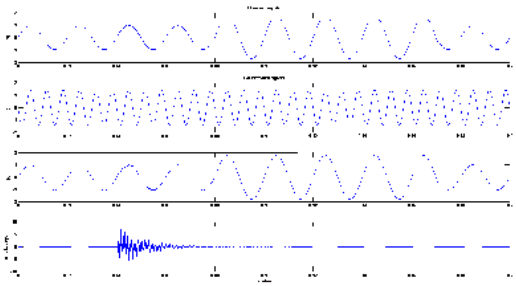

FIGURE 4. The observed signal of Triple disturbances and ICA extracted signals (3 channels) Harmonic + Swell + Osillation.

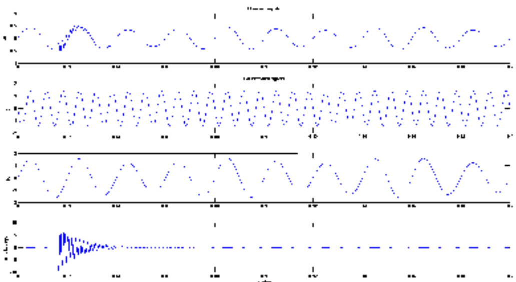

FIGURE 5. The observed signal of Triple disturbances and ICA extracted signals (3 channels) Harmonic + Flick + Osillation.

Harmonic, voltage fluctuation, and voltage oscillation transient hybrid multiple-labels signals is effectively decomposed by ICA in Fig.5, as well as the most double disturbances.

The features of the single PQ disturbances were automatically extracted through sparse auto encoder rather than by manually selecting compared to conventional approaches for the identification of PQ disturbances. An average classification accuracy of above 98.6% is achieved for single disturbances based on SAE, which indicates that there is a significant improvement compared to existing detection and classification methods. The seven kinds of single PQDs classify results based on SAE are showed in Table1.

To sufficiently validate the effectiveness of the proposed classification scheme, variances of signals and ICA algorithm are applied to assist classification of the multiple complex PQDs. The simulation results show that ICA for multiple PQ disturbances mainly including double disturbances or triple linear aliasing disturbances is effective.

VI. CONCLUSION

The main contribution of this paper is the proposal of a new classification approach for PQ complex disturbances combining with ICA and SAE. For extracting the characteristic value of a single disturbance, we adopt an SAE instead of a WT method or other approaches. Moreover, for the multiple-label PQ disturbances, we propose to adopt an ICA mainly for double disturbances and quadruple disturbances. The simulation and experimental results show that an ICA can effectively extract the independent components of complex disturbances of different double and quadruple types. The classification performance of single disturbances based on the SAE is better than other methods, including ranking loss, hamming loss, coverage, one-error and average precision.

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XIAOYING SHI received the M.S. degree in engineering from the Wuhan University of Technology, in 2004. She is currently pursuing the Ph.D. degree with Nanchang University. She has been a Teacher with East China Jiaotong University, since 2004. Her research interests include signal detection, pattern recognition, and intelligent optimization.

HUI YANG received the M.S. degree in engineering from the Northeastern Institute of Technology, in 1988, and the Ph.D. degree in control theory and control engineering from Northeastern University, in 2004. He is currently a Professor with East China Jiaotong University. His current research interests include complex system modeling control and optimization, and mechatronics online detection system's theory, technology, and applications.

ZHIBANG XU received the B.S. degree in power electronics and electric traction from Southwest Jiaotong University, in 1995, and the M.S. degree in engineering from the Wuhan University of Technology, in 2005. He has been an Associate Professor with East China Jiaotong University, since 2008. His current research interests include pattern recognition and intelligent optimization.

XIUJUN ZHANG received the M.S. degree in engineering from Zhejiang University, in 2003. He is currently an Associate Professor of computer science with Chengdu University. His research interests include graph theory, combinatorial optimization, and algorithm design.

MOHAMMAD REZA FARAHANI received the bachelor's degree in applied mathematics from the Iran University of Science and Technology, in 2010, as best department student, where he is currently a Researcher in applied mathematics. He works with faculties of this department, in applied mathematics, operation research, mathematics chemistry, and graph theory.