Classification of Power Signal by using S-Transform and PSO based FLANN

M .Mohanty
Centurion Institute of Technology
Bhubaneswar, India

S.Mishra
Centurion Institute of Technology
Bhubaneswar, India

M.Senapati
Centurion Institute of Technology
Bhubaneswar, India

ABSTRACT
This paper presents a novel PSO(Particle swarm optimization) based FLANN(Functional Link Artificial Neural Network)classifier for the classification of non stationary power signals. The Multilayer perceptron (MLP) neural network model with back propagation learning algorithm consumes larger computational time. When the number of layers and number of hidden nodes in the MLP model increases, the complexity of the network increases. So, it is also very difficult to finalize the number of nodes in a layer. In this paper particle swarm optimization (PSO) is used to train the weights of the functional link artificial neural network (FLANN) for power signal classification. S-Transform is used to extract the features of the power signals and fed as input to the PSO based FLANN model.

Keywords
PSO, FLANN, MLP, Power Signal

1. INTRODUCTION
Classification of power signal is the most challenging and complex task in power system. Classifying the signal indicates the class to which each instance of nonstationary power signal disturbance belongs[1]. As the power signals are nonstationary in nature the task of classification becomes complex. In classification, we are given a set of features extracted using signal processing tools and fed as input to the classifier. The aim of the classification is to build a model based upon the computational time. Researchers have shown the power signal classification using ANN as promising alternative to various conventional classification methods. The artificial neural networks (ANNs) are capable of mapping between input and the output and thus they can solve non-linear problems[3]. Along the way, there are already several artificial neural networks, each utilizing a different form of learning methods

The use of GA(Genetic Algorithm) for weight updation in ANNs[4] has already proven a sound theoretical and empirical results such as: feature selection in ANNs, and to design the structure of the network. When the dataset increases, the computational time is much more larger. In this paper, we have tried the most relevant features for functional expansion which in turns can be fed as the input of the FLANN (Functional Link Artificial Neural Network)for classification of power signals.

FLANN[4] is basically a flat network with simple learning rule and without requiring hidden layers. The functional expansion effectively increases the dimensionality of the input vector and hence the hyper-planes generated by the FLANN provide greater discriminating capability of the input patterns. Although FLANN with gradient descent gives promising results, sometimes may fall in local optimal solutions. Moreover FLANN[4] is coupled with genetic algorithm, may suffer with problems like heavy computational burdens, and large number of parameter tuning. PSO based FLANN[6] used for prediction of stock market indices, however, in this paper we propose PSO based FLANN model for the classification of power signals. The weights of FLANN model has been updated by using PSO (Particle Swarm Optimization) and compared the results with LMS(Least Mean Square) algorithm weight updation. The features of the power signal are extracted by using S-Transform[8] which uses Gaussian window.

This paper presents FLANN model in section 1, Section 2 presents the weight updation using PSO, and section 3 presents the result and conclusion followed by reference.

2. FLANN MODEL
FLANN model is a single layer, single neuron architecture, which has the capability to form complex decision regions by creating non-linear decision boundaries[2,3] shown in Fig.1. The FLANN model is different from the linear weighting of the input pattern produced by the linear links of the better known Multi Layer Perceptron (MLP). In a FLANN, each input to the network undergoes functional expansion through a set of basis functions. The functional link acts on an element or the entire pattern itself by generating a set of linearly independent functions. The inputs expanded by a set of linearly independent functions. This enables FLANN to solve complex classification problems by generating non-linear decision boundaries. In FLANN[6] model, the functional expansion block contains a set of trigonometric functions. The trigonometric polynomial basis functions used in the FLANN model is given by $\{1,\cos(\pi x),\sin(\pi x),\cos(2\pi x), \sin(2\pi x),....,$

$\cos(N\pi x), \sin(N\pi x)\}$ provide a compact representation of the function in the mean square sense. However, when the outer product terms are used along with the trigonometric polynomials for function expansion, better results were obtained in the case of learning of a two-variable function.

3. PSO ALGORITHM
The PSO algorithm [5,6] is a population based search algorithm based on social behaviour of birds within a flock. PSO requires only primitive mathematical operators and is computationally inexpensive in terms of both memory

requirements and speed. The features that drive PSO are social interaction. Individuals (particles) within the swarm learn from each other and based on the knowledge obtained move to become more similar to their better neighbours. The structure of the PSO is determined through the formation of neighbourhoods. Individuals within the neighbourhood can communicate with each other.

A swarm consists of a set of ‘N’ particles where each particle represents a potential solution. Particles are then flown through the hyperspace, where the position of each particle is changed according to its own experience and that of its neighbours. In the original formulation of PSO[7] , each particle is defined as a potential solution to the problem in a D- dimensional space. The particle i is represented in a D dimensional space as

$$x_i = (x_{i1}, x_{i2}, x_{i3}, \ldots\ldots, x_{iD}) \qquad (1)$$

and each particle maintains a memory of its previous best position. The best previous position of the i^{th} particle can be represented *as*

and each particle maintains a memory of its previous best position. The best previous position of the i^{th} particle can be represented *as*

$$P_i = (p_{i1}, p_{i2}, p_{i3}, \ldots\ldots, p_{iD}) \qquad (2)$$

and the velocity for the i^{th} particle is represented as

$$V_i = (v_{i1}, v_{i2}, v_{i3}, \ldots\ldots, v_{iD}) \qquad (3)$$

The particle position with the highest fitness value for the entire run is called the global best. The global best particle among all the particles in the population is represented by

$$P_g = (P_{g1}, P_{g2}, P_{g3}, \ldots\ldots P_{gD}) \qquad (4)$$

At each iteration the velocity vector of every particle is adjusted based on its best solution and the best solution of its neighbours. The position of the velocity adjustment made by the particle’s previous best position is called the cognition component and the position of the velocity adjustments using the global best is called the social component. The updated PSO equations described in [4] are

$$v_{id}(t+1) = \omega v_{id(t)} + \eta_1 * rand() * (p_{id}(t) - x_{id}(t)) + \eta_2 * rand() * (p_{gd}(t) - x_{gd}(t)) \qquad (5)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t) \qquad (6)$$

where ω is the inertia weight, η_1 and η_2 are positive acceleration constants. The velocity vector drives the optimization process and reflects socially exchanged information.

3.1 S-Transform

The fixed resolution of the STFT and the absence of the phase information in wavelet transform led to the development of the S-Transform [10,11].

Given a time series x (t), the local spectrum at time $t = \tau$ can be determined by multiplying $x(t)$ with a Gaussian window located at $t = \tau$ and taking the Fourier transform of the product. This defines the S-Transform as follows:

$$S(t, f, \sigma) = \int_{-\infty}^{\infty} x(\tau) g(t-\tau, \sigma) e^{-j2\pi f\tau} d\tau \qquad (7)$$

The original ST uses $g(t-\tau,\sigma)$ as the scaled Gaussian Window whose midpoint is $\tau = t$

At any time t and frequency f ,the ST can be seen as a set of localized Fourier coefficients, obtained by considering only the portion of the primary function lying within a few cycles on either side of $\tau = t$.The scaled contraction $g(t-\tau,\sigma)$ causes the relevant range of τ to become more localized around t as f increases.

$$g(t-\tau,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-(t-\tau)^2}{2\sigma^2}} \qquad (8)$$

Let us assume $\sigma = \frac{1}{|f|}$, so the above equation becomes

$$g(t-\tau, \frac{1}{f}) = \frac{|f|}{\sqrt{2\pi}\sigma} e^{\frac{-(t-\tau)^2 f^2}{2}} \qquad (9)$$

Taking Fourier Transform of above equation with respect to τ becomes

$$G(v, f) = e^{\frac{-2\pi^2 v^2}{f^2}} \qquad (10)$$

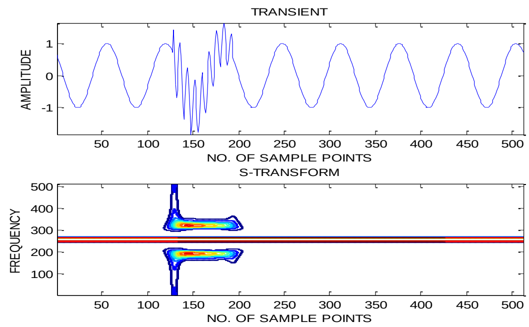

Fig.2 Transient power signal disturbance and its S-Transform.

3.2 Weight updation of FLANN mosel using PSO and LMS algorithm

1. Initialize the weights (swarm) $P(t)$, such that the position $X_i(t)$ of each particle $P_i \in P(t)$ is random within the hyperspace, with $t = 0$.
2. Evaluate the performance $F(X_i(t))$ of each particle, using its current position $X_i(t)$

3. Compare the performance of each individual to its best performance thus far:
if $F(X_i(t)) < p_{id}$ then
(a) $p_{id} = F(X_i(t))$
(b) $P_i = X_i(t)$
4. Compare the performance of each particle to the global best particle if $F(X_i(t)) < p_{gd}$ then
(a) $p_{gd} = F(X_i(t))$
(b) $P_g = X_i(t)$
5. Change the velocity vector for each:

$$v_{id}(t+1) = \omega v_{id(t)} + \eta_1 * rand() * (p_{id}(t) - \mathrm{x}_{id}(t))$$
$$+ \eta_2 * rand()(p_{gd}(t) - \mathrm{x}_{gd}(t))$$

where the second term above is referred to as the cognitive component, while the last term is the social component.
6. Move each particle to a new position.
(a) $x_{id(t+1)} = x_{id(t)} + v_{id(t)}$
(b) $t = t + 1$

7. Go to step 2 and repeat until convergence.

The network weight is updated by using Widrow Hoff's Least Mean Square algorithm as:

$$w(n+1) = w(n) + \eta x^T e$$

Where η= learning parameter, e= error, x= input features

4. Results and conclusion

The different power signals are used for classification are Voltage Swell, Transient, Sag with harmonic, Swell harmonic, Flicker harmonic, Voltage Notch, Harmonic, Voltage Spike.

TABLE I

Sl. No.	Power signals	Accuracy in %		
		Input Data	LMS Training	PSO Training
1	Transient	100	98	99
2	Sag with harmonic	100	99	100
3	Swell harmonic	100	86	96
4	Flicker harmonic	100	88	100
5	Voltage Notch	100	100	100
6	Harmonic	100	86	92
7	Voltage Spike	100	100	100
8	Voltage Swell	100	100	100
%Average Accuracy			94.62	98.37

It is found from the table that PSO training gives better accuracy than LMS training of the FLANN network. In the case of harmonic the accuracy is not better in comparison to the other power signals.

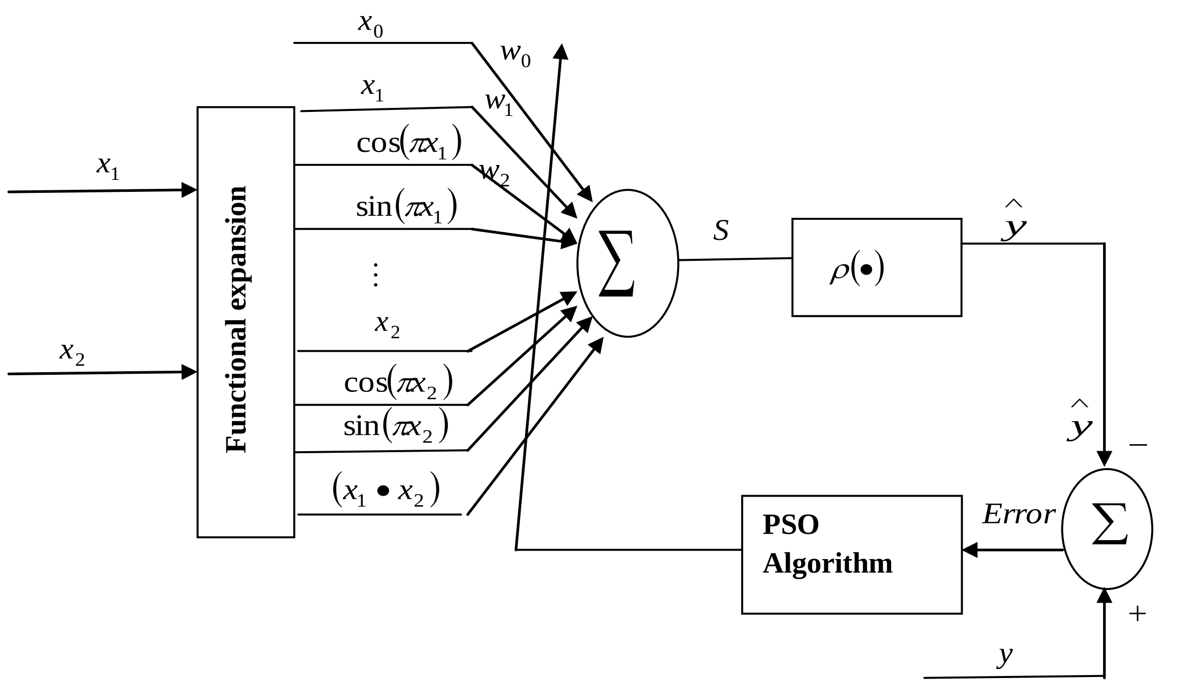

Fig.1 FLANN model

5. CONCLUSION

The proposed FLANN model with PSO training is quite simple and to design the architecture. It consumes very less time to optimize the weights as compared to that of conventional MLP. It can be noted that the proposed FLANN model with PSO training uses a very few number of nodes as compared to MLP. The average accuracy in classification in the case of FLANN model with PSO training is better than FLANN model with LMS training.

6. REFERENCES

[1] H. Zang, P. Liu and O.P. Malik, "Detection And Classification Of Power Quality Disturbances In Noisy Conditions", *IEE Proc. Gener. Transm. Distrib*, Vol 150, No.5, pp. 567-572, Sept. 2003.

[2] T. McConaghy, H. Lung, E. Bosse, V. Vardan, "Classification Of Audio Radar Signals Using Radial Basis Function Neural Network", *IEEE Transactions on Inst .And Measurement*, Vol. 52, No.6, pp.1771-17779, Dec. 2003.

[3] J.C. Patra, R.N. Pal, B.N. Chatterji, G. Panda, "Identification of non-linear & dynamic system using functional link artificial neural network ", IEEE Transactions on System, Man & Cybernetics – Part B; Cybernetics, Vol. 29, No. 2, April 1999.

[4] S. Dehuri, Sung-Bae Cho "Evolutionarily optimized features in functional link neural network for classification" Expert Systems with Applications, Vol.37 (2010) ,pp-4379–4391.

[5] S. Dehuria,∗, R. Roy, Sung-Bae Choc, A. Ghosh "An improved swarm optimized functional link artificial neural network(ISO-FLANN) for classification" The Journal of Systems and Software ,Vol.85 (2012) pp-1333– 1345

[6] S. Chakravarty, P.K. Dash, "A PSO based integrated functional link net and interval type-2 fuzzy logic system for predicting stock market indices" Applied Soft Computing 12 (2012) 931–941

[7] C.R.Hema.M.P.Paulraj.S.Yaacob,A.H.Adom.R.Nagarajan,"particl swarm optimization neural network based classification of mental task" biomed 2008,Proceedings 21;pp. 883-888,2008, (c) Springer-Verlag Berlin Heidelberg 2008

[8] James Kennedy and Russell Eberhart (1995) Particle Swarm Optimization, Proc. IEEE International Conf. on Neural Networks, Perth , Vol. 4, pp 1942-1948

[9] C. Xudong, Q. Jingen,N. Guangzheng,Y. Shiyou,Z. Mingliu, "An Improved Genetic Algorithm For Global Optimization Of Electromagnetic Problems", *IEEE Transactions on magnetic*, Vol.37, pp.3579–3583, Sept.2001.

[10] F. Zhao and R. Yang, "Power-Quality Disturbance Recognition Using S-Transform", *IEEE Transactions on Power Delivery* Vol.22, No.2, pp.944–950, 2007.

[11] C. R. Pinnegar, L. Mansinha, "The *S*-Transform With Window Of Arbitrary And Varying Shape," *GEOPHYSICS*, Vol.68, No.1, pp. 381-385, 2003.

[12] C. R. Pinnegar, L. Mansinha, "Time-Local Fourier Analysis With A Scalable, Phase-Modulated Analyzing Function: The *S*-Transform With A Complex Window," *Signal Processing*, Vol.84, pp. 1167-1176, July 2004.

[13] S. Assous, A. Humeau, M. Tartas, P. Abraham, and J. L. Huillier, "S–Transform Applied To Laser Doppler Flowmetry Reactive Hyperemia Signals", *IEEE Trans. Biomed. Eng.* Vol.53, pp.1032-1037,2006.

[14] P.K. Dash, B.K. Panigrahi and G. Panda, Power Quality Analsis using S-Transform, *IEEE Trans on Power Delivery* Vol.8, No.2, pp.406–412, April 2003.

[15] T. Wang et al., "A Wavelet Neural Network For The Approximation Of Nonlinear Multivariable Function", *The Trans. of the Institute of Electrical Engineering C*, 102-C, pp.185-193, 2000.

[16] D.F. Specht and H. Romsdahl, "Experience With Adaptive Probabilistic And General Regression Neural Networks", Proceedings *of the IEEE World Congress Computational Intelligence*, F.L. Orlando, ed., Vol.2, pp. 1203–1208, 1994.

[17] S. Albrecht and J. Busch et al., "Generalized Radial Basis Function Networks for Classification And Novelty Detection: Self Organization Of Optimal Bayesian Decision", *Neural Networks* Vol.13, pp. 1075–1093, 2000.

[18] M. Plutowski, H. White, "Selecting Concise Training Sets From Clean Data", *IEEE Trans. Neural Networks*, Vol.4, pp.305–318, 1993.

[19] R. Reed, S. Oh, R.J. Marks, II, "Similarities Of Error Regularization, Sigmoid Gain Scaling, Target Smoothing, And Training With Jitter", *IEEE Trans. Neural Networks* ,Vol.6, pp.529–538.

[20] M.D. Richard, R.P. Lippmann, "Neural Network classifier estimates Bayesian a posteriori probabilities", *Neural Computing*, Vol.3, pp.461–483, 1991