A Brief Review on Advances of Harmonic State Estimation Techniques in Power Systems

U. Arumugam, N. M. Nor, and M. F. Abdullah

Abstract—**As the demand for power increases, the need for harmonic state estimation (HSE) has been increasing as well. Harmonics, injected by the non-linear equipments along the distribution networks, causes several power quality issues. Therefore, HSE plays an important role in harmonics monitoring and control. Various HSE techniques and algorithms have been developed since 1989, which would be reviewed and discussed in this paper. The author outlines the role of artificial intelligence (AI) in the field and the process overview of neural network and also a hybrid algorithm which combines particle swarm optimization (PSO) and gradient descent (GD) to train the weights of neural network (NN).**

Index Terms—**Artificial intelligence, gradient descent, harmonics state estimation, neural network, power quality.**

I. Introduction

Power quality is defined as a set of electrical boundaries that allows an equipment to function in its intended manner without significant loss of performance or life expectancy. An ideal power system is defined such when a perfect sinusoidal voltage signal is seen at load-ends. In reality, however, such idealism is hard to maintain. Any deviation from the perfect sinusoidal waveform is considered as distortion, often referred to as *harmonic distortion* [1]. Harmonics are currents or voltages with frequencies that are integer multiples of the fundamental power frequency. Harmonics current are fed by the non-linear equipment, which disrupts the desired ideal linear system [2]. These distorted current pulses, due to Ohm's law, will also begin to distort the voltage waveforms, where these distortions would be carried back to the distribution network [3]. Common risks of harmonics includes potential fire hazard, excessive heat, false tripping of branch circuit breakers and subsequently increases maintenance cost [1].

As part of the EPRI (Electric Power Research Institute) Reliability Benchmarking Methodology project, investigators explored the idea of estimating the voltages at locations, given the data [1]. This led to the development of the harmonics state estimator (HSE), which uses feeder models and recorded data to estimate the system output. There are two parts to state estimation (SE); modeling and algorithms. The overall approach is to use a model to foretell the behaviour of the system in a particular state, and then compare it with the actual telemetry from the system. This is to conclude which state is most likely to produce the observed system behaviour [2]. Harmonics state estimation (HSE) techniques have been used since 1989 for harmonics analysis in power systems. Many mathematical methods have been developed over the years. It is proven that by using only partial or selected measurement data, the entire harmonic distribution of the actual power system can be obtained effectively [4]. However, these assumptions have simplified the implementation but generate several practical problems.

Artificial intelligence (AI) began with "an ancient wish to forge the gods". Modern AI was developed by classical philosophers, back in 1940s, who attempted to describe the process of human thinking as a mechanical manipulation of symbols [5]. Since the early to mid 1980s much of the effort in power system analysis has turned away from formal mathematical modeling to the less rigorous techniques of AI [6]. AI techniques have been introduced to overcome the disadvantages of non-parametric techniques, such as the fast fourier transform (FFT) and wavelet transform (WT) [7]. Among the various techniques of AI, few most suitable and popular techniques for harmonics estimation in power systems have been highlighted and discussed in this paper. This paper also attempts to provide a review on harmonics state estimation (HSE) studies over time and weighs the advantages and disadvantages of each method. The theories behind HSE and AI have also been presented here.

II. State of Art

Various studies have been conducted on harmonics and distortion since 1960s. One of the earliest methods used to calculate the steady-state solution was to integrate the accompanying system of non-linear differential equations for as many cycles as required, until the transient response disappears, leaving only the periodic, steady-state response. This is the case in any of the highly developed electromagnetic transient programs; EMTP [8] and PSCAD/EMTDC [9]. This approach, however, does not always yield satisfying results because some power networks are lightly damped and because of difficulties in establishing suitable steady-state initial conditions [10]. This solution approach is also time-consuming and sometimes inconclusive [11].

Initial growth in power quality was the replacement of conventional analysis of harmonics by state estimations. Early studies suggest the usage of Global Positioning System (GPS) receiver at every local system to synchronize harmonic phase measurements with accuracy of 1μs. However, the high expense of harmonic instruments and installation of communication channels limits the number of

Manuscript received September 18, 2011; revised October 22, 2011.This work was supported in part by the Unversiti Teknologi PETRONAS's GA scheme sponsor.
The authors are with the Department of Electrical and Electronics Engineering, Universiti Teknologi PETRONAS, 31750 Tronoh, Perak, Malaysia(e-mail:ugasciny@gmail.com),(e-mail:nursyarizal_mnor@petronas.com.my), (e-mail: mfaris_abdullah@petronas.com.my).

meters in the network. Research papers [4,12] suggested similar approach of integrating with the fast Fourier transform (FFT) and least-square methods respectively for state-estimation. FFT has been proved of its non-feasibility in later researches [13].

T. Lachman *et. al.*, 2010, revealed that with FFT, it is possible to have an estimation of the fundamental amplitude and its harmonics with a reasonable approximation but however, window dependency resolution is a disadvantage. FFT performs well for estimation of periodic signals in stationary state but fails to perform well for detection of sudden or fast changes in waveform [13]. The later paper, with state-estimation by least-squares, uses direct solution using rectangular coordinate system and implements sensitivity and observability analysis to increase precision of estimation. However, the confidence level computation showed the existence of constant instrument error. Huaiwei Liao later, pointed out that standard least-square based method have difficulty obtaining reliable estimates when measurements are less than state variables, which are identified as underdetermined system [14].

Generally, in traditional methods, the technical challenge in HSE is to solve the underdetermined systems of equations. This issue is often solved by assuming those busses with or without loads thought not likely to contribute harmonic emission, as zero harmonic injection. T. L.Tan *et. al.*, 2005, underlines that the problem with this technique that the voltage measurements at those buses known or assumed not to have harmonics producing devices cannot be used. Loads that are thought not likely to emit harmonics may not be true [15]. Huaiwei Liao, 2006, showed that underdetermined system can be observable by utilizing the spatial sparsity of harmonic sources under proper measurement arrangement. However, this approach is rather time-consuming and expensive in meter placements [14].

The most common and popular state estimation technique in industry is based on the weighted least squares (WLS) method [16]. It usually operates in a cycle of estimation-detection-elimination until an acceptable result is obtained. Despite its advantages in detecting and identifying single and multiple gross measurement errors, H. Salehfar *et. al.*, 1995, pointed out that WLS is rather time consuming to perform such bad-data detection and identification procedures online for large systems [17]. N. Mohd Nor *et. al.*, 2008, states that a basic Newton Raphson WLS method has a very long computational time due to the gain and Jacobian matrices associated with the basic algorithm which requires large storage and has to be evaluated every iteration. The author attempts to reduce the time taken to construct the Jacobian matrix by reconstructing or rearranging the H matrix and proves its effectiveness in reducing the computational-time. Though, the WLS based estimator cannot effectively detect and identify multiple interactive and conforming bad data [16]. According to Hervé Abdi, the most important drawback of least square method and alternatives is their high sensitivity to outliers. This is a due to the usage of *squares* as squaring exaggerates the magnitude of difference (*e.g.*, the difference between 20 and 10 is 10 but the difference between 20^2 and 10^2 is equal to 300) and therefore gives a much stronger importance to extreme observations [18].

For non-linear systems, several Fuzzy Kalman filtering algorithms have been developed to extend Kalman filtering for such system. Hazem N. Nounou, 2005, presented multi-scale fuzzy state estimation using stationary wavelet transforms or known as multi-scale Fuzzy Kalman (MSFK) filtering algorithm. A fuzzy system is an approximator which consists of a set of IF-THEN type rules, each of which has a premise and a consequent part. Fuzzy models have been found very useful for control purposes as for their ability to describe complex system in an efficient manner. However, to achieve a good fuzzy control, reliable state estimation is essential. In terms of harmonics state estimation where measured data usually contain multi-scale features, fuzzy filtering techniques are not effective. Fuzzy filtering techniques are single scan methods where it is assumed that the measured process data only contains features with fixed contribution over time and frequency. MSFK then uses scaling function coefficients of the data obtained using Stationary Wavelet Transform (SWT), and then selecting the optimum fuzzy Kalman filter, which minimizes a cross validation estimation error criterion [19]. Although Kalman Filter is fairly accurate, it has high mathematical burden which limits its use for on-line tracking [20]. Wavelet-based signal processing algorithm in general, introduces lag that is equal to the length of the used window and hence, impose limitation on on-line applications.

In early years, neural network have been actively used for estimation of harmonic components in a power system [21, 22, 23, 24, 25, 26]. Various techniques were also used. An adaptive perceptron approach in neural networks has been tested and applied successfully for harmonic estimation in a power system. The neural estimator was based on the use of an adaptive neuron called ADALINE (Adaptive Linear Network). Adaptive tracking of harmonic components of a power system could easily be done using this algorithm [27]. However, ADALINE network is limited to only one output neuron. The convergence of ADALINE slows as the number of harmonics included increases and it is also subjected to fall in local minima [28, 29, 30].

The back propagation neural network uses offline supervised training to identify selected harmonics. This method treats harmonics detection problem as a pattern recognition problem [7]. However, a common drawback is seen in a basic back propagation approach where the time taken for convergence is fairly long and the solution often stuck at local minima [31, 32, 33]. A radial basis neural network has been tested and proved to impose several advantages over ADALINE and basic back propagation methods [7]. It is capable of approximating highly nonlinear functions, the training can be done in a sequential manner, and the use of local approximation gives better generalization capabilities [31, 32]. However, this method seems to show the same disadvantages found in a back propagation neural network approach [7].

M. Gupta *et. al.*, 2010, had introduced a faster training algorithm for estimation purposes. It utilizes particle swarm optimization (PSO) combined with gradient descent (GD) to train weights of neural network. This hybrid algorithm has also been proved to be more advantageous than genetic algorithm (GA), PSO or GD on stand-alone. The advantage of this hybrid algorithm is fast convergence with no possibility of getting stuck in local minima. The surety of not getting stuck in local minima is due to PSO and fast convergence is because of GD. The NNs are trained to uniquely identify various types of devices using their distinct harmonic "signatures" as their input [20].

To simplify, the discussion is summarized in table below:

TABLE I. SUMMARY: LITERATURE REVIEW

Author(s)	Year	Technique(s)/Research
A.P.Sakis Meliopoulos, *et. al.*	1994	Least-squares method
Norikazu Kanao, *et. al.*	2005	Fast Fourier Transform (FFT)
T.L.Tan, *et. al.*	2005	Weighted Least Squares (WLS)
Huaiwei Liao	2007	Sparsity Maximization
N.Mohd Nor, *et. al.*	2008	Systematically constructed Jacobian matrix (SECJ)
T.Lachman, *et. al.*	2010	Wavelet Transform technique
R.K. Hartana,*et. al.*	1990	Neural networks
S.Osowski	1992	Neural networks for harmonic component estimation
H.Salehfar, *et. al.*	1995	Neural networks preestimation filter
P.K. Dash, *et. al.*	1996	Adaptive Perceptrons
M.Negnevitsky, *et. al.*	2005	Neural network to monitor harmonic multiple sources
Hazem N.Nounou	2005	Multiscale Fuzzy Kalman (MSFK) filtering technique
Joy Mazumdar, *et. al.*	2006	Neural networks for load harmonics prediction
Bogusław Świątek, *et. al.*	2007	Neural network for power system harmonic estimation
Hsiung Cheng Lin	2007	Neural network for harmonic detection
H.Selcuk Nogay, *et. al.*	2007	Neural network for harmonic estimation (induction motor)
M.Gupta *et. al.*	2010	Hybrid algorithm (PSO & GD) to train the weights of neural networks

III. HARMONIC STATE ESTIMATION

The state estimation measurement model relates the measurements to the state variable. The vector of measurements;

$$z = Hx + e \tag{1}$$

where H is the observational matrix defined by the power system configuration and measurement terms, x is the vector of true values which are unknown, and e is the vector of random errors [15].

Objective function is a function which indicates how much each variable contributes to the value that needs to be optimized in the problem. Optimization can be either maximization or minimization. In this case, for an estimation value of $\hat{x}$;

$$\min f(\hat{x}) = (z - H\hat{x})^t W (z - H\hat{x}) \tag{2}$$

where W is the weighting factor, and σ_i^2 is covariance of measurement data z_i. In order to obtain the estimated value z^* of measurement data, the best-estimate value x^* with minimizing objective function is given as follow [4]:

$$W = \begin{bmatrix} \frac{1}{\sigma_1^2} & . & . & . \\ . & \frac{1}{\sigma_2^2} & . & . \\ . & . & . & . \\ . & . & . & \frac{1}{\sigma_{m+k}^2} \end{bmatrix} \tag{3}$$

$$z^* = Hx^* \tag{4}$$

$$x^* = (H^t W H)^{-1} H^t W z \tag{5}$$

The best-estimate function (5) above was derived from differentiation of objective function. Once the state estimates are known, standard techniques can be used to calculate estimates of measured quantities and residual estimates [15].

IV. ARTIFICIAL INTELLIGENCE

Many intelligent systems have been developed over the last decade. The ultimate goal of AI, despite the various approaches, is to produce intelligent machines which simulate or emulate human beings' intelligence.

Three most popular AI techniques include artificial neural network (ANN), fuzzy systems and evolutionary computing. ANN and fuzzy systems are similar in several ways: their ability to store knowledge, self-organization, fault tolerance ability, and real-time operation. However, ANN acquires knowledge through training whereas fuzzy systems rely on a set of rules. This nature of ANN has a major advantage in HSE where its training set composed of actual observation, rather than being formed of the human opinions as used for fuzzy systems. Evolutionary computing, on the other hand, is based on principles of genetics and natural selection. i.e.: genetic algorithm (GA). Fuchs *et. al.* concludes that the more advanced methods such as fuzzy set theory, genetic algorithms, artificial neural networks, and particle swarm methods are able to identify the global optimum better than the straightforward search methods where the gradient is employed guiding the optimization process [34].

In the complex real world problems, two or more techniques need to be integrated in order to overcome each other's weaknesses to generate hybrid solutions. This is indeed an important way forward in the next generation of intelligent systems [6].

V. ANN FOR HARMONICS ESTIMATION

Hence, the latest generation of harmonic estimation employs artificial intelligence (AI). ANN model has very high estimate accuracy. It has a recursive nature that makes possible to use it for real-time measurements. It also performs well in a noisy environment. ANN has been tested for on-line harmonic estimation study and was able to estimate the harmonic component of voltage and current at various levels [23, 24]. Harmonic prediction using neural networks has been focused in measuring the actual harmonics current injected into a power system network by three phase nonlinear loads [25]. Harmonic source monitoring has also been successful using neural networks [26].

Harmonics analysis of a three-phase system can be carried out based on per-phase although the power in each phase is pulsating because the total instantaneous power is constant and equal to three times the real power in each phase [35].

A. Neural Network

NN is an information processing paradigm. A trained NN can be thought of as an "expert" in the category of information it was provided to analyze. The trained NN then can be used to provide projections given new situation of interest and solve the "what if" questions. The most common and simplest type of neural network is the feed forward neural network. Fig. 2 illustrates a simple neuron topology. Each input is 'weighted'; w_{k1}, w_{k2}, … ,w_{kp} for p number of inputs. Therefore, the effect that each input has at decision making is dependent on the weight of the particular input.

The teaching input of the NN would be based on the hybrid algorithm discussed in [20].

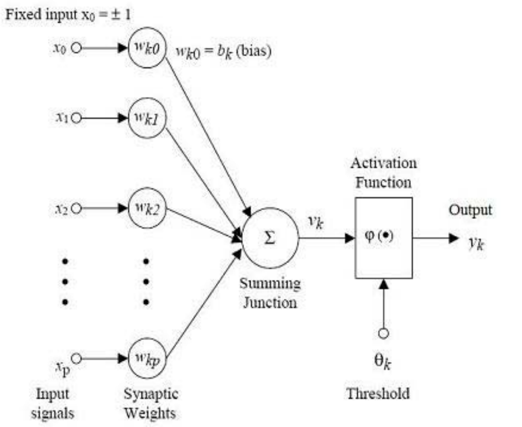

Fig. 1. A single neuron model [36]

Figure 1 illustrates a basic perceptron neuron model with p number of elements in input vectors and k outputs. The weighted sum of inputs, v_k, is sent to an activation function which gives a perceptron the ability to classify its input vectors based function limits. The threshold value determines whether or not a neuron fires. Therefore, a neuron output can be written mathematically as;

$$y_k = \varphi(Wx_p + b_k) \tag{6}$$

where b_k is the bias value, often 1, and φ is the activation function [37].

Back propagation is a common method of teaching a neural network to perform its task. It was first invented in 1969 by Bryson and Ho, but was largely ignored until mid-1980s [38]. It is a supervised learning method which implies delta rule. Delta rule is a gradient descent learning rule for updating the weights of the artificial neuron. For a neuron k with p^{th} weight w_{kp} is given by;

$$\Delta w_{kp} = \alpha(t_k - y_k)\varphi'(Wx_p + b_k)x_p \tag{7}$$

where α is the learning rate, t_k is the target output, and φ' is the derivation of the activation function. Figure 2 shows a feed forward neural network with back propagation training and weight updating technique.

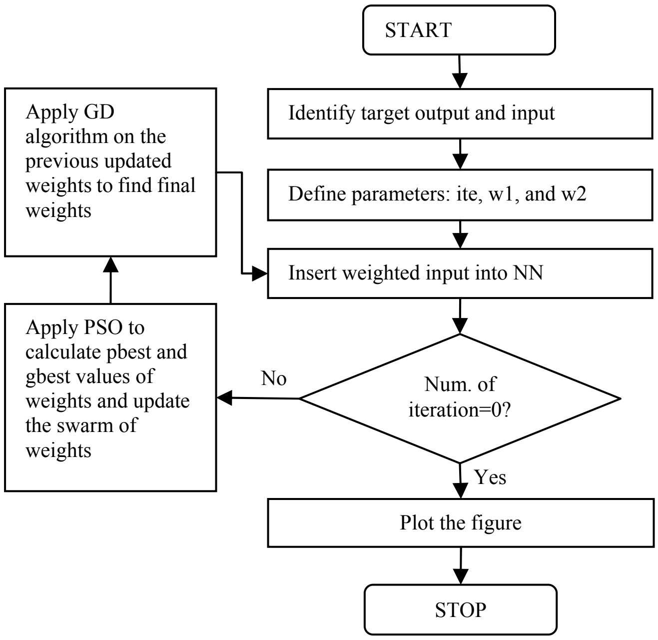

Fig. 1. Hybrid algorithm flow chart.

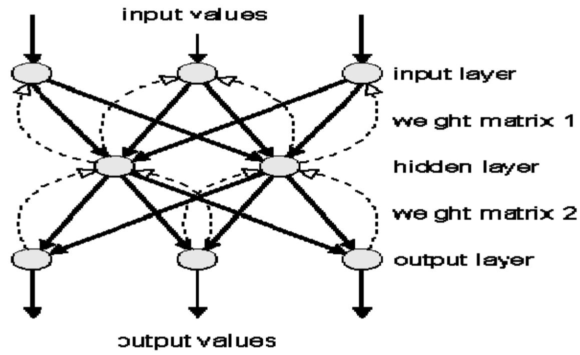

Fig. 2. A feed forward neural network with back-propagation training technique [39].

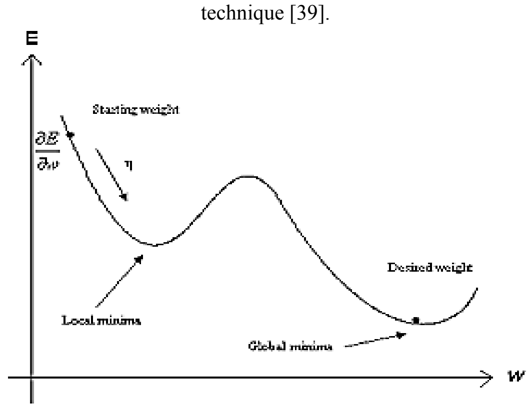

Fig. 3. Local and global minima

B. Hybrid Algorithm

An attractive hybrid technique, employing PSO and GD to train the weights of NN, have been proposed and tested in [20] and proven effective for HSE. On each iteration/epoch, the objective function would be optimized to obtain the best estimation of harmonics voltage magnitudes and their corresponding phase angles. This is the case in any NN algorithm. The hybrid technique improves the algorithm speed and efficiency. Hence, the harmonics vectors can be obtained at the NN output at a much faster rate.

Gradient based supervised-learning algorithms are computationally simple to implement. GD is a local algorithm where it makes use of information which is immediately available at current weight vector. The training system using GD does not recognize the global minima and it simply proceeds downhill until it finds a place where the error gradient is zero. However, the local minima is not the desired solution. Fig. 3 illustrates the error-weight relation schematically on local and global minimums.

One way to avoid getting stuck at local minima is to combine PSO and GD techniques to train the weights of neural network. However, PSO algorithm on stand-alone is also inefficient as it is seen that square of error fluctuates randomly and it may take many iterations to converge. PSO is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality, while GD is a first-order optimization algorithm. In each iteration, the hybrid algorithm first applies PSO on a population of weights beforecalculating weights of NN using GD [40]. In each generation in PSO, the velocity of each particle is updated to its personal best position (pbest) and global best position (gbest) using:

$$v_i(t+1) = wv_i(t) + c_1 r_1(t)(pbest_i - w_i(t)) + c_2 r_2(t)(gbest_i - w_i(t)) \tag{8}$$

where c_1 and c_2 are acceleration coefficients; $r_1(t)$ and $r_2(t)$ are random values between zero and one; w is the inertia weight. The position of each particle is updated every generation by:

$$w_i(t+1) = w_i(t) + v_i(t+1) \tag{9}$$

The algorithm output is the gbest particle, which contains final trained weights.

ACKNOWLEDGMENT

The authors gratefully acknowledge Universiti Teknologi PETRONAS, Malaysia for providing the facilities and financial support to carry out the studies. This work was partially supported by the Minister of Higher Education of Malaysia under Exploratory Research Grant Scheme.

REFERENCES

[1] C.Sankaran, *Power Quality*, CSC Press: 2002.

[2] Victor A.Ramos Jr, *Treating Harmonics in Electrical Distribution Systems*, Computer Power & Consulting Corporation: 1999.

[3] Francisco C. De La Rosa, "*Harmonics and Power Systems"*, Missouri,: Taylor & Francis Group, LLC, 2006..

[4] Norikazu Kanao, Mitsunori Yamashita, Hikoni Yanagida, Munehisa Mizukami, Yasuhiro Hayashi, and Junya Matsuki, "Power System Harmonic Analysis Using State-Estimation for Japanese Field Data", *IEEE Trans. Power Del.*, vol.20, no.2, pp. 970 - 977, April 2005.

[5] Pamela McCorduck, *Machine who thinks: a personal inquiry into* history *and prospects of artificial intelligence*, Natick, Mass.:A.K.Peters, 2004.

[6] Kevin Warwick, Arthur Ekwue, and Raj Aggarwal, *Artificial* Intelligence *Techniques in Power Systems*, London: IEE, 1997.

[7] Eyad Almaita and Johnson A. Asumadu, *On-line harmonic estimation in power system based on sequential training radial basis function neural network*, IEEE Int. Conf. on Industrial Tech. (ICIT): 2011, pp. 139-144.

[8] Juan A.Martinez,"Power Quality Analysis using Electromagnetic Transient Programs", *Harmonics & Quality of Power Proceedings. 8th Int. Conf.,* vol.1, pp.590 – 597, 1998.

[9] C.L.Zhang, S.Chen and S.S.Choi, "Directional Methods for Locating Sources of Voltage Sag/Swells", *14th PSCC*, Sevilla; Section 16, Paper 5, pp.1, June 2002.

[10] Enrique Acha & Manuel Madrigal, *Power System Harmonics;* Computer *Modelling & Analysis*; John Wiley & Sons, Ltd, pp. 6-7, 2001.

[11] Neville R.Watson,"Power Quality State Estimation",*Euro.Trans.Electr.Power,*pp.19-33,2010.

[12] A.P.Sakis Meliopoulos, Fan Zhang and Shalom Zelingher, *"Power* Systems Harmonic State Estimation*", IEEE Trans. Power Del.*, vol. 9, no. 3, pp. 1701 – 1709, July 1994.

[13] T.Lachman, A.P.Memon, T.R.Mohamad, and Z.A.Memon, "Detection of Power Quality Disturbance Using Wavelet Transform Techinque*"*, *Int. Journal for the Advancement of Science & Arts*, vol. 1, no.1, pp. 1-13, 2010.

[14] Huaiwei Liao, "Power System Harmonic State Estimation via Sparsity Maximization", *IEEE Trans. Power System*, vol. 22, no.1, pp. 15 – 23, February 2007.

[15] T.L.Tan, S.Chen, and S.S.Choi, *"*An Overview of Power Quality State Estimation*"*, *Power Engineering Conference, IPEC, The 7th International*, pp. 1-276, 2005

[16] Nursyarizal Mohd Nor, Prof. Dr. Ramiah Jegatheesan and Ir.Perumal Nallagowden, *"*Newton-Raphson State Estimation Solution Employing Systematically Constructed Jacobian Matrix*"*, *World Academy of Science, Engineering and Technology,* pp.42, 2008.

[17] H.Salehfar, and R.Zhao, "A neural network preestimation filter for bad-data detection and identification in power system state estimation", *Elec.* Power *Systems Research,* vol.34, pp. 127-134, August 1995.

[18] Hervé Abdi, "Least Squares", In Neil Salkind (Ed.), Encyclopedia of Research Design; Thousand Oaks, CA: Sage. 2010.

[19] Hazem N.Nounou, *"*Multiscale Fuzzy State Estimation using Stationary Wavelet Transforms*"*, *Proceedings of the 44th IEEE Conference on Decision and Control, and the European Control Conference*; Seville, December 12-15, 2005.

[20] M.Gupta, S.Srivastava, J.R.P.Gupta, and M.S.Singh, *"*A Faster Estimation Algorithm Applied To Power Quality Problems*"*, *International Journal of Engineering Science and Technology*, vol.2(9), pp. 4448-4461, 2010.

[21] S.Osowski, *Neural network for estimation of harmonic components in a* power *system,* IEE Proceedings-C, Vol.139, No.2: 1992.

[22] P.K.Dash, D.P.Swain, A.Routray, and A.C.Liew, *Harmonic estimation in a power system using adaptive perceptrons*, IEE Proc.-Gener. Transm, Distrib., Vol.143, No.6: 1996.

[23] Hsiung Cheng Lin, *Intelligent Neural Network-Based Fast Power* Systems *Hamonic Detection*, IEEE Trans. On Industrial Electronics, Vol.54, No.1: 2007.

[24] H.Selcuk Nogay and Yasar Birbir, *Application of Artificial Neural* Network *for Harmonic Estimation in Different Produced Induction Motor,* Int. Journal of Circuits, Systems and Signal Processing, Issue 4, Vol.1: 2007, pp.334-339.

[25] Joy Mazumdar, R.G. Harley, F.Lambert and Ganesh K.Venayagamoorthy, *Predicting Load Harmonics in Three Phase Systems using Neural Networks*, Applied Power Electronics Conf. & Exposition, 2006. APEC '06. Twenty-First Annual IEEE: 2006, pp.1738-1744.

[26] M.Negnevitsky, and M.Ringrose, *Monitoring Multiple Harmonic Sources in Power Systems using Neural Networks,* Power Tech 2005 IEEE Rusia: 2005, pp.1-6.

[27] Bogusław Świątek, Marek Rogóż, and Zbigniew Hanzelka, *Power System* Harmonic *Estimation Using Neural Networks,* 9th Int Conf. Electrical Power Quality & Utilisation: 2007.

[28] G. W. Chang, Cheng-I Chen and Yu-Feng Teng, "Radial-Basis-FunctionBased Neural Network for Harmonic Detection," Industrial Electronics, IEEE Transactions on, vol. 57, pp. 2171-2179, 2010.

[29] A. Zouidi, F. Fnaiech, K. Al-Haddad and S. Rahmani, "Adaptive linear combiners a robust neural network technique for on-line harmonic tracking," in Industrial Electronics, 2008. IECON 2008. 34th Annual Conference of IEEE, 2008, pp. 530-534.

[30] A. Bhattacharya and C. Chakraborty, "Predictive and adaptive ANN (adaline) based harmonic compensation for shunt active power filter," in Industrial and Information Systems, 2008. ICIIS 2008. IEEE Region 10 and the Third International Conference on, 2008, pp. 1-6.

[31] S. S. Haykin 1931-, Neural Networks : A Comprehensive Foundation /. Upper Saddle River, N.J. : Prentice Hall, c1999.

[32] N. K. Kasabov, Foundations of Neural Networks, Fuzzy Systems, and Knowledge Engineering /. Cambridge, Mass. : MIT Press, c1996.

[33] J. Duan, D. Czarkowski and Z. Zabar, "Neural network approach for estimation of load composition," in Circuits and Systems, 2004. ISCAS '04. Proceedings of the 2004 International Symposium on, 2004, pp. V-988-V-991 Vol.5.
[34] Fuchs, Ewald F, Masoum, Mohammad A.S., *Power Quality in Power Systems and Electrical Machines*, Elsevier: pp. 438, 2008.
[35] Hadi Saadat, *Power System Analysis; Second Edition*, McGraw Hill International Edition, pp.38, 2004.
[36] *Neuro AI – Intelligent systems and Neural Networks*, Retrieved from website: http://www.learnartificialneuralnetworks.com/
[37] Howard Demuth and Mark Beale, *Neural Network Toolbox; For Use with* MATLAB*,* The MathWork Inc.:1998, pp.5-5.
[38] Stuart Russell and Peter Norvig, *Artificial Intelligence A Modern Approach*: 1995, pp.578.
[39] Jens Langner, *Leaves Recognition v1.0: Neuronal network based recognition system of leaf images*, LightSpeed Comminucations: 2006. Available at http://www.jens-langner.de/lrecog/
[40] Kevin Gurney, *An Introduction to neural networks*, London: UCL Press, 1997.

Ugasciny Arumugam (M'1888, F'17) was born in Pulau Pinang, Malaysia, on December 4, 1987. She received B.Eng. (Hons) in Electrical & Electronics Engineering from Uniersiti Teknologi PETRONAS (UTP), Perak, Malaysia, in 2010. She is currently pursuing her M.Sc. degree at UTP. Her research interests include power systems state estimation and artificial neural network applications in power quality. She is a member of Board of Engineering, Malaysia.

Nursyarizal Mohd Nor was born in Perak, Malaysia, on July 20, 1974. He has obtained MSc in Electrical Power Engineering from The University of Manchester Institute of Science and Technology (UMIST), UK in 2001. In year 2009, he obtained his Ph.D. from Universiti Teknologi PETRONAS (UTP), Malaysia. His research interests are in Power Economics Operation and Control, Power Quality, Power System Analysis and Electrical Machines.

He has several publications at his credit. Presently he is working as Senior Lecturer in the Department of Electrical and Electronics Engineering at Universiti Teknologi PETRONAS. He is a member of Board of Engineering, Malaysia.

Mohd Faris Abdullah completed his Master of Electrical Engineering from Universiti Tenaga Nasional (UNITEN) in 2006 and now pursuing PhD at Universiti Teknologi PETRONAS, Malaysia. He is currently a senior lecturer at UTP since 2009. Prior to that, he was working with TNB since 1989 and serving distribution division for 12 years and transmission division for 8 years. His experience in distribution division includes planning, construction, maintenance, metering and protection. In transmission division, he was working in maintenance department that responsible for substation, lines, cables, protection, telecontrol and technical support. He is a Professional Engineer (Board of Engineers Malaysia), Competent Engineer (Energy Commission) and a member of The Institute of Engineers, Malaysia (IEM).