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POWER SYSTEM HARMONICS ANALYSIS DUE TO SINGLE PHASE WELDING MACHINE USING RADIAL BASIS FUNCTION NEURAL NETWORK

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ABSTRACT

Welding machines are widely used in each and every construction works, in various industries, automobiles, and in many more applications. They are large sources for harmonics, interharmonics and subharmonics. This means, harmonics of different magnitude originate with fundamental frequency. Due to the origination of harmonics of different magnitude, the quality of power system becomes poor which means power system gets polluted. When the load gets polluted power system, there occurs various kinds of losses and also lays an adverse effect on the working of equipment and also hampers generation, transmission, distribution and utilization. In order to maintain the quality of power distribution, it is important to find out the components of harmonics in the power system. An efficient measurement instrument should be used to find out the harmonic component in every power system. Different methods are used from time to time for this. In recent years, neural network has got special attention by the researchers because of its simplicity, learning and generalization ability and it has been applied in the field of engineering. The theory of neural network is becoming more and more mature and is also making certain breakthrough progress in various fields. It has the advantages of parallel information processing, learning, distribution patterns and memory which can be used in the measurement of the harmonic to construct an appropriate network. In this paper we used radial basis function neural network to find out the components of harmonics in power system generated by welding machine.

Keyword: Power System, ANN, RBFNN, Harmonics, Welding Machine.

1. INTRODUCTION

Welding machines are widely used in each and every construction works, in various industries, automobiles, and in many more applications. They are large sources for harmonics, interharmonics and subharmonics. This is caused by the non-linear behavior of the welding process and also due to the individual welding action varying between a second and several seconds. Due to the origination of harmonics of different magnitude, the quality of power system becomes poor which means power system gets polluted. When the load gets polluted power system, there occurs various kinds of losses and also lays an adverse effect on the working of equipment and also hampers generation, transmission, distribution and utilization. In order to maintain the quality of power distribution, it is important to find out the components of harmonics in the power system. For which an efficient measurement instrument should be used. Scientists and researchers are also exploring different methods in order to bring improvement in the quality of power system The problem for measuring power system harmonics is that they are of harmonics generating load dynamics nature. Fast method is very necessary to measure harmonics component. Various types of digital signal analysis technique are used to measure power system harmonics. In recent years, neural network has got special attention by the researchers because of its simplicity, learning and generalization ability and it has been applied in the field of engineering. The theory of neural network is becoming more and more mature and is also making certain breakthrough progress in various fields. It has the advantages of parallel information processing, learning, distribution patterns and memory which can be used in the measurement of the harmonic to construct an appropriate network. In this paper we used radial basis function neural network to find out the components of harmonics in power system generated by welding machine. Radial basis function networks (RBFN) provide an attractive alternative to back-propagation [1], [2]. Radial basis function (RBF) networks are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function hidden units [3] [4] [5].

2. WELDING MACHINE

Welding machines are widely used in each and every construction works, in various industries, automobiles, and in many more applications. It is a fabrication process that joins materials by causing coalescence. They are large sources for harmonics, interharmonics and subharmonics. This is caused by the non-linear behaviour of the welding process and also due to the individual welding action varying between a second and several seconds. This voltage fluctuation cause changes in luminance of lamps. Welding usually requires high current (over 80 amperes) and it can need above 12,000 ampere in spot welding. Welding machine are classified as constant current machine & constant voltage machine. Shield metal arc welding & gas tungsten arc welding will use a constant current source gas metal arc welding will use a constant voltage source. In pulsed gas metal arc welding mixed process in which current control & voltage control process are performed. The current can be controlled in SMAW with a frequency between 10 Hz and 300 Hz.

3. RADIAL BASIS FUNCTION NEURAL NETWORKS

The multi-forward neural network (MLFFNN) with back-propagation learning algorithm as described in section (5.8.1) and (5.8.2), has been widely used to solve a number of applications [6], [7]. Due to its universal functions approximation capability the MLFFNN is widely used in system identification, prediction, regression, classifications, control, feature extraction and associative memory. However despite the practical success the back-propagation algorithm has serious training problems and suffers from slow convergence [3]. While optimization of learning rate and momentum coefficient, parameters yields overall improvements on the network, it is still inefficient and time consuming for real time applications [8], [2].

Radial basis function networks (RBFN) provide an attractive alternative to back-propagation [1] [2]. Radial basis function (RBF) networks are feed-forward networks trained using a supervised training algorithm. They are typically configured with a single hidden layer of units whose activation function is selected from a class of functions called basis functions. While similar to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function hidden units [3], [4] [5].

Popularized by Moody and Darken (1989), RBF networks have proven to be useful neural network architecture. The major difference between RBF networks and back propagation networks (that is, multi layer perceptron trained by Back Propagation algorithm) is the behavior of the single hidden layer. Rather than using the sigmoidal or S-shaped activation function as in back propagation, the hidden units in RBF networks use a Gaussian or some other basis kernel function. Each hidden unit acts as a locally tuned processor that computes a score for the match between the input vector and its connection weights or centers. In effect, the basis units are highly specialized pattern detectors. The weights connecting the basis units to the outputs are used to take linear combinations of the hidden units to product the final classification or output [5], [9]

3.1 Network Architecture

The construction of a radial basis function (RBF) network (RBFN) in its most basic form involves three layers with entirely different roles. The input layer is made up of source nodes (sensory units) that connect the network to it invorment. The second layer; the only hidden layer in the network applies a nonlinear transformation from the input space to the hidden space in most applications the hidden space is of high dimensionality. The output layer is linear, supplying the response of the network to the activation pattern(signal) applied to the input layer [10]. The RBF network of three-layer [J1-J2-J3] feed forward neural network, as shown in Figure (1) by [5]

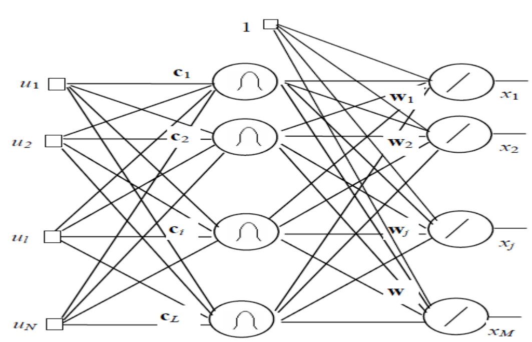

Figure 1: Architecture of the RBF network

3.2 Hidden layer

The second layer is the hidden layer which is composed of nonlinear units that are connected directly to all of the nodes in the input layer. Each hidden unit takes its input from all the nodes at the components at the input layer. As mentioned above the hidden unit contains a basis function, which has the parameters center and width. The center of the basis function for a node *i* at the hidden layer is a vector ci whose size is the as the input vector u and there is normally a different center for each unit in the network.

First, the radial distance *di*, between the input vector x and the center of the basis function ci is computed for each unit *i* in the hidden layer as

$$d_i = \|\mathbf{u} - \mathbf{c}_i\| \tag{9.1.1}$$

using the Euclidean distance.

The output *hi* of each hidden unit *i* is then computed by applying the basis function G to this distance

$$h_i = \mathrm{G}(d_i, \sigma_i) \tag{9.1.2}$$

As it is shown in Figure 9.2, the basis function is a curve (typically a Gaussian function, the width corresponding to the variance, σi) which has a peak at zero distance and it decreases as the distance from the center increases [5].

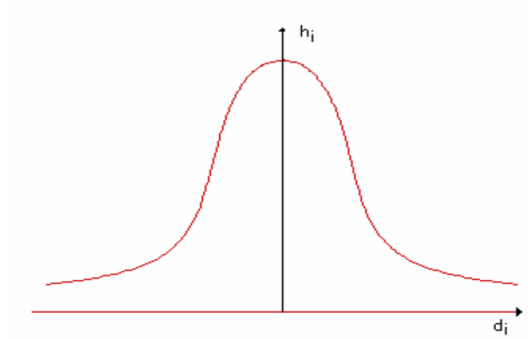

Figure 2: The response region of an RBF hidden node around its center as a function of the distance from this center

3.3 Output layer

The transformation from the input space to the hidden unit space is nonlinear, whereas the transformation to the hidden unit space to the output space is linear.

The jth output is computed as

$$x_j = \mathrm{f}_j(\mathbf{u}) = w_{0j} + \sum_{i=1}^{L} w_{ij} h_i \quad j = 1,2,..,M \tag{9.1.3}$$

3.4 Designing of Radial Basis Function Neural Network

In Matlab nn tool box the function newrb iteratively creates a radial basis network one neuron at a time. Neurons are added to the network until the sum-squared error falls beneath an error goal or a maximum number of neurons have been reached. The call for this function is:

net = newrb(P,T,GOAL,SPREAD)

The function newrb takes matrices of input and target vectors P and T, and design parameters GOAL and SPREAD, and returns the desired network. At each iteration the input vector that result in lowering the network error the most is used to create a radbas neuron. The error of the new network is checked, and if low enough newrb is finished. Otherwise the next neuron is added. This procedure is repeated until the error goal is met or the maximum number of neurons is reached. The Architecture RBFNN is shown in figure (3).

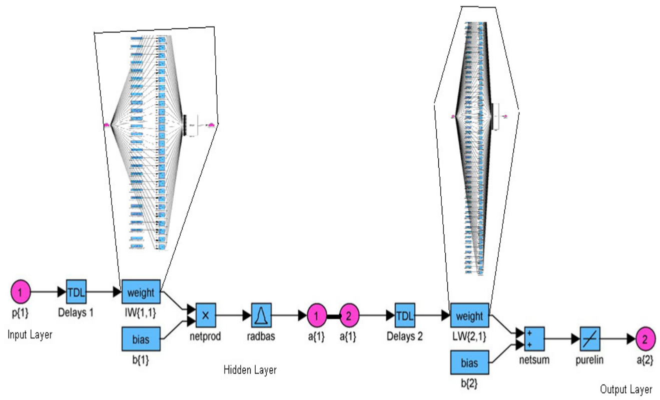

Figure 3: RBFNN Circuit

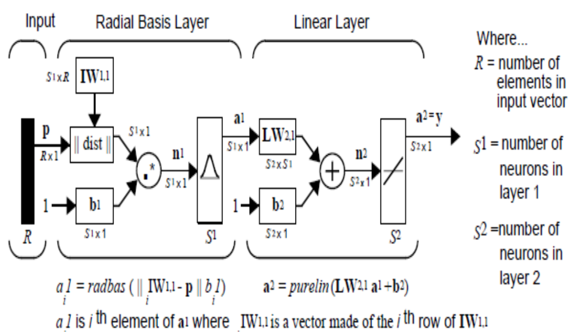

Figure 4: Architecture of Radial Basis Function Neural Network in Matlab (ANN Tool)

the net input of a radbas neuron is the vector distance between its weight vector w and the input vector p, multiplied by the bias *b*. (The || dist || box in this figure accepts the input vector p and the single row input weight matrix, and produces the dot product of the two) [9] .

3.5 Learning of RBFNN

RBF network learning requires the determination of the RBF centers and the weights. Selection of the RBF centers is most critical to RBF network implementation. The centers can be placed on a random subset or all of the training examples, or determined by clustering or via a learning procedure [11].

3.6 Learning RBF Centers

RBF network learning is usually performed using a two-phase strategy: the first phase specifies suitable centers _c_i and their respective standard deviations, also known as widths or radii, σ_i, and the second phase adjusts the network weights W [11].

3.7 Learning the Weights

After RBF centers and their widths or covariance matrices are determined, learning of the weights W is reduced to a linear optimization problem, which can be solved using the LS method or a gradient-descent method.

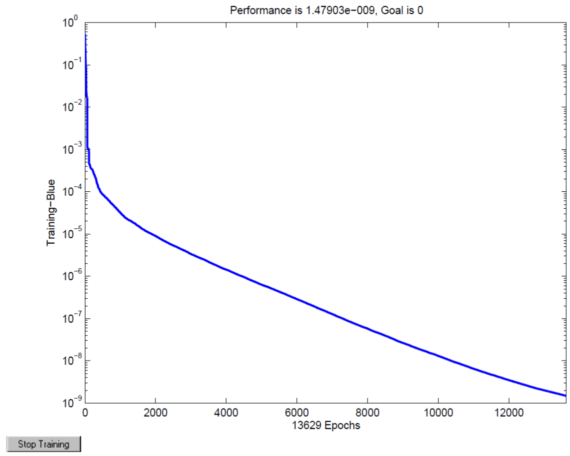

Figure 5: Training graph of RBFNN

4. TECHNICAL SPECIFICATION OF EXPERIMENTAL SET-UP

Table 1: Single Phase Welding Machine(Oil cooled)

particulars	specification
Input voltage	220 V
phase	1
Manufacture	Sharp Electric Works Rajkot (Serial no-19207 & Model-2007)
KVA	5
Input Current (max)	200 A
Cycle	50

4.1 Gathering Input Data

The configuration of the experimental system and experimental system block diagram is shown below in

Experimental –setup

Figure 6: Single phase ARC welding machine setup

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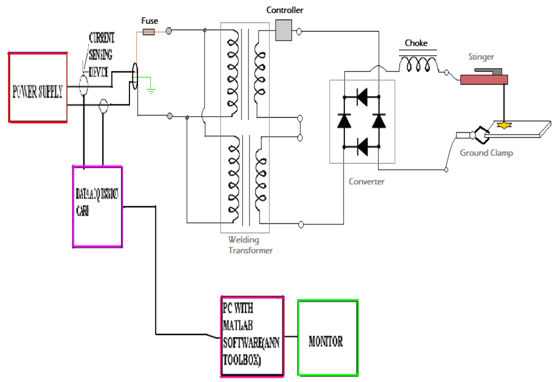

Figure 7: Block diagram of physical set-up for single phase ARC welding machine set-up

In the above block diagram set-up, a transformer is connected with power supply. A linear or non-linear load is connected with this transformer. Due to transformer and other loads are generated harmonics in power system. Due to this power supply waveform is distorted. A data acquisition card is connected at power common connection to collect the distorted current/voltage waveform or data. These collected waveform/data transmitted to PC through RS-485 for ANN input which is designed in MATLAB. Collected data is shown in waveform in fig (7).

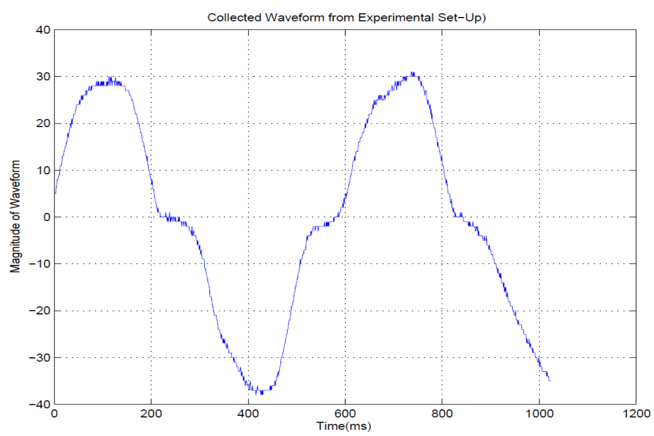

Figure 8: Collected current waveform for single phase ARC welding machine load

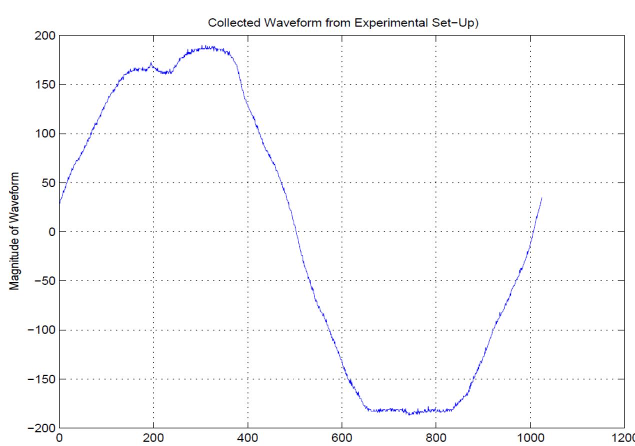

Figure 9: Collected Voltage waveform for single phase ARC welding machine load

4.2 Normalization of input

Normalization of data is a process of scaling the numbers in a data set to improve the accuracy of the subsequent numeric computation and is an important stage for training of the ANN. Normalization also helps in shaping the activation function. For this reason [-1, 1] normalization function has been used.

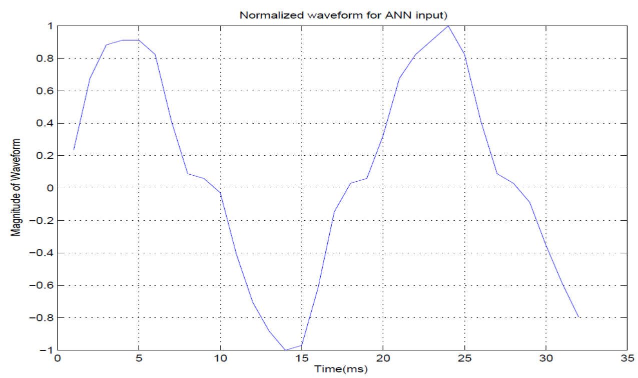

Figure 10: Normalized data of collected current waveform for single phase ARC welding machine load

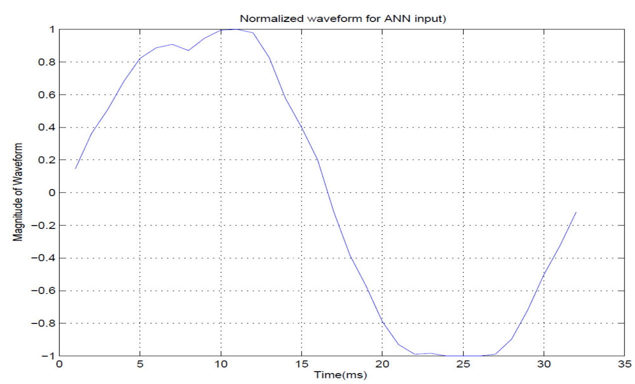

Figure 11: Normalized data of Collected Voltage waveform for single phase ARC welding machine load

4.3 ANN OUTPUT

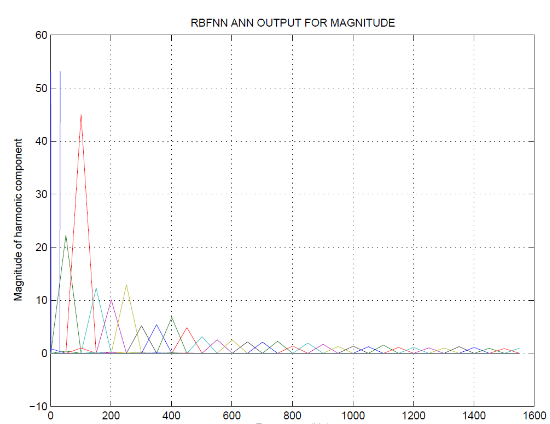

Figure 12: RBFNN Output for Collected Current waveform for single phase ARC welding machine load

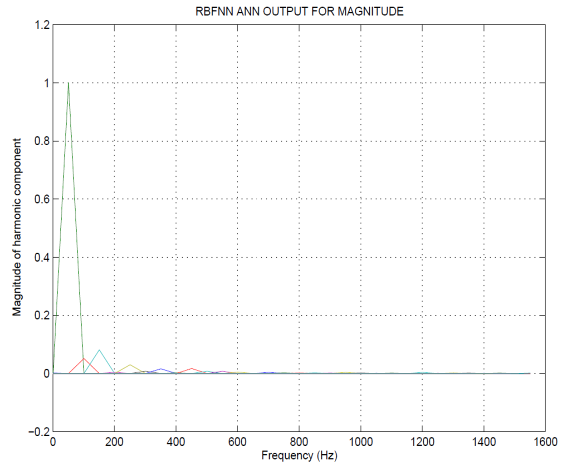

Figure 13: RBFNN Output for Collected voltage waveform for single phase ARC welding machine load

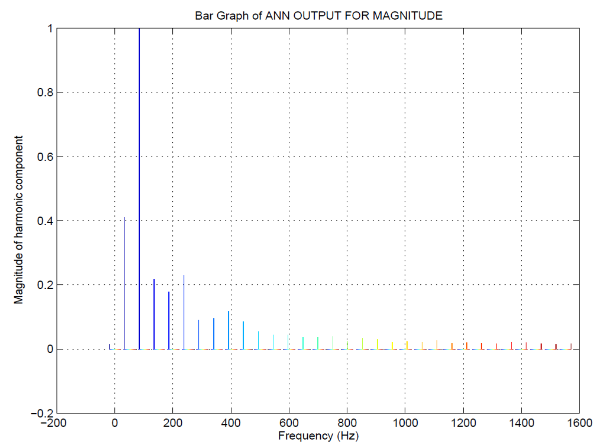

Figure 14: Bar Graph of RBFNN Output for Collected Current waveform for single phase ARC welding machine load

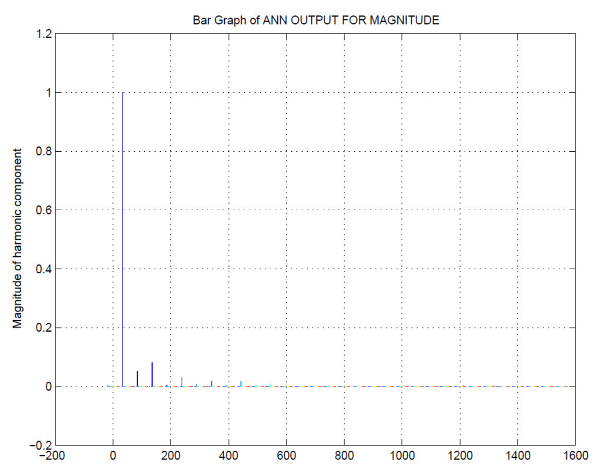

Figure 15: Bar Graph of RBFNN Output for Collected Voltage waveform for single phase ARC welding machine load

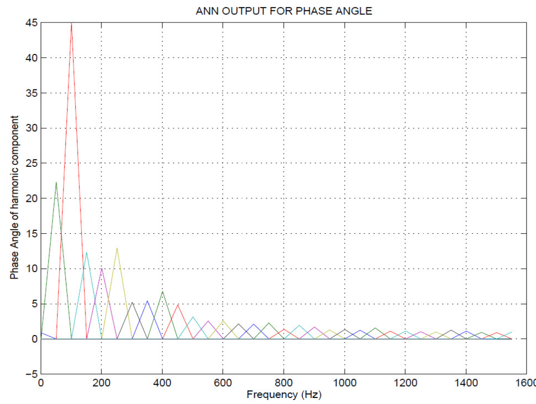

Figure 16: Phase angle of RBFNN output for collected current waveform for single phase ARC welding machine load

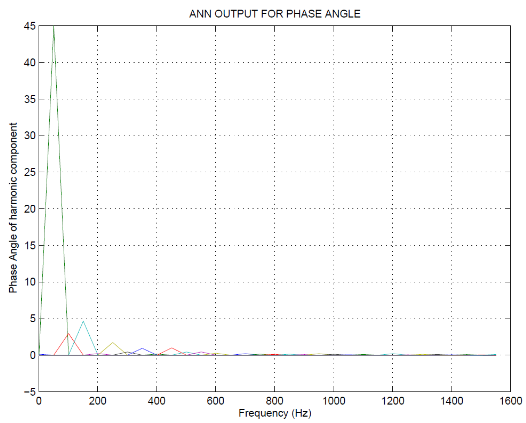

Figure 17: Phase angle of RBFNN output for Collected Voltage waveform for single phase ARC welding machine load

5. RESULT AND DISCUSSION

The output of the RBFNN is shown in fig (12) for current, fig (13) for voltage. The bargraph of the RBFNN is shown in fig (14) and phase angle of the RBFNN output is shown in fig (15). From fig (12) and Fig (14) it is found that due to the welding machine odd and even harmonics generate in power system.

6. CONCLUSION

A Radial basis function neural network (RBFNN) model is developed and implemented for measuring harmonics component in power system. This model is tested offline under different condition. the result outcome from offline test indicate that the RBFNN model has providing very high accuracy in harmonic component measurement, the proposed RBFNN model is implemented on pc with MATLAB software using a data acquisition card. It was tested off-line under different conditions. The result of the off-line test indicates that the RBFNN model has very high power system harmonics component measurement accuracy. The developed RBFNN model was implemented on a PC with MATLAB Software (with RBFNN Toolbox) using a data acquisition card. The RBFNN model was able to measure the harmonic components of voltage and current at various levels. The data is collected at Machine lab in Dr.C.V.Raman University where the system is available. The output of the RBFNN is shown in fig (12) for current, fig (13) for voltage. The bargraph of the RBFNN is shown in fig (14) and phase angle of the RBFNN output is shown in fig (15). From fig (12) and Fig (14) it is found that due to the welding machine odd and even harmonics generate in power system.

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BIOGRAPHIES

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Dr. A. S. Zadgaonkar has obtained B. E. degree in Electrical Engineering from Pt. Ravishankar Shukla University, studying at Govt. Engineering College, Raipur in 1965. He obtained M. E. in 1978 from Nagpur University. His research paper for M. E. was awarded "best paper" by the Institution of Engineers (India) in the year 1976 & 1977 respectively. The testing technique for quality of wood developed by him was included in ISI in 1979. He was awarded Ph. D. in 1985 by Indira Gandhi Kala & Sangeet University, Khairagah for his work on "Acoustical and Mechanical Properties of Wood for Contemporary Indian Musical Instrument Making." He obtained another Ph. D. in 1986 by Pt. Ravishankar Shukla University on "Investigation of Dynamic Properties of Non-Conducting Materials Using Electrical Analogy." He has 47 years of teaching experience. He is currently adding glory to the post of Vice Chancellor of Dr. C. V. Raman University. He has published more than 500 technical papers for journals, national and international conferences. He was the Joint Director, Technical Education, Govt. of Chhattisgarh in 2004 & the Principal of NIT, Raipur in 2005. He is life member of Acoustical Society of India, Biomedical Society of India, Linguistic Society of India, Indian Society for Technical Education and many social bodies.