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An Adaptive Real-Time Technique for Harmonics Estimation Using Adaptive Radial Basis Function Neural Network

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Abstract— In this paper, a neural networks algorithm based on adaptive radial basis function (ARBF) is used to decompose the grid current drawn by nonlinear load, and the fundamental and harmonic components are estimated. The learning rate – considered as one of the most important parameters that govern the performance of the ARBF network - is investigated as well to reduce the system total error. Two methodologies are proposed to improve the estimation of the fundamental component of highly nonlinear current signal. One is based on fast Fourier transform (FFT) and the other is based on least mean square error (LMSE). The error between the reference signal and the reproduced signal (the sum of estimated fundamental and harmonic signals) is chosen as performance index. The obtained results unveil that both methodologies can be effective in enhancing the system accuracy, and that the proposed algorithm can provide better performance compared to the conventional RBF network.

Keywords— Power quality; Radial basis function; Neural networks; Adaptive technique; Harmonic estimation.

1. INTRODUCTION

Most of the modern loads in the power system are nonlinear loads. These loads can inject both voltage and current harmonics in electric power grid. The unacceptable level of harmonics can cause several problems to the reliability of the grids and to the loads connected to the grid, such as overheating of motors and transformers, malfunctioning of protection equipment, insulation deterioration, and can interfere communication frequencies [1-3].

Several means were used to mitigate harmonics content in the electric grid such as passive power filters (PPFs) and active power filters (APFs). APFs have emerged as more effective technique to solve harmonics and other power quality problems [4–6]. The APF principle depends on sensing the voltage and/or current. Then, the voltage and/or current signal is decomposed into fundamental components and harmonic contents. Then, the APF utilizes and inverter circuit to compensate the harmonic contents and other power quality problems such as reactive power and unbalanced waveforms. The harmonics detection phase is a crucial phase for the success of the APFs compensation process. The literature has several harmonics detection methodologies. They can be classified into three main methodologies: frequency domain methodologies, time domain methodologies, and artificial intelligence (AI) methodologies [7–9]. In time domain methodologies as the attenuation of the filter is increased, the phase delay will increases and vice versa. Also, a fast transition time can lead to unacceptable oscillations [10, 11]. The frequency domain methodologies suffer from different problems, they are not considered real-time filters [10].

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Several AI techniques have been proposed to cope with the drawbacks of frequency domain and time domain techniques. The AI techniques can be categorized into three main approaches: adaptive linear neuron (ALN), back propagation (BP), and radial basis function (RBF) neural networks [12, 13]. The ALN technique is employed in online harmonics detection. The performance of ALN relies on the number of harmonics included in its topology. As the included number increases, the convergence of the ALN slows down and becomes prone to stuck in local minima [12, 13]. On the other hand, The BP networks handle the harmonics detection as a pattern recognition issue. It uses a supervised learning scheme. This scheme detects the harmonics content offline. It suffers from long training and the optimal solution is not guaranteed [14]. The radial basis function network (RBFN) has many advantages over ALN and BP networks, such as its capability to handle highly nonlinear systems, the training phase is much easier than other schemes and the nature of the activation functions can lead to better generalization [14]. Even though adaptive radial basis function (ARBF) has been used for harmonic detection, the number of hidden neurons is still large and still uses algorithms resemble to that in BP networks. This makes RBF networks exposed to the same back propagation network (BPN) drawbacks.

An adaptive topology of the conventional RBF network was proposed in [15]. This adaptive RBF network adopts a weight change methodology based on least mean square error (LMSE). It shows improvement in estimation accuracy compared to the conventional RBF network. In [16], the authors study the stability constraints in the ARBF networks. Also, they proposed formula for optimal learning rates values, which ensure a minimum total error.

In this paper, two methodologies to update the value of each ARBF network learning rates are explored. The goal of these methodologies is to improve the individual estimation of the fundamental component of highly nonlinear current signal. One is based on fast Fourier transform (FFT) and the other is based on LMSE. The proposed algorithms are used to estimate the fundamental component in highly nonlinear current signal. Section 2 illustrates adaptive RBF network. Section 3 illustrates how ARBF networks are used for harmonics estimation. Section 4 demonstrates the effects of updating the learning rates. Sections 5 and 6 include updating the weight vectors based on FFT and LMSE methods, respectively.

2. ADAPTIVE RBF NETWORK

Conventional BP and RBF networks have a main weakness; after the training phase is finished, the learned system parameters are fixed and cannot be changed. In the case of noisy signals, these locked parameters can lessen the effectiveness of the neural networks. The ARBF network algorithm was introduced to boost the performance of the conventional RBF networks after finishing the training phase and inserting the RBF network in the system. This adaptive algorithm allows the RBF networks to modify the parameters of the network after the training phase is finished. The centers and the weights are the RBF network tunable parameters that can influence the output.

Fig. 1 shows the general structure of the ARBF network. It has three main layers, as conventional feedforward neural networks: input layer, hidden layer and output layer. The network has two additional parts: i) Summation part that is positioned after the output layer, where the error signal is calculated at this part by summing the estimated (y) and the actual (R) signals and ii) weights updating part that aims to modify the weights between the hidden and the output layers to minimize the error signal.

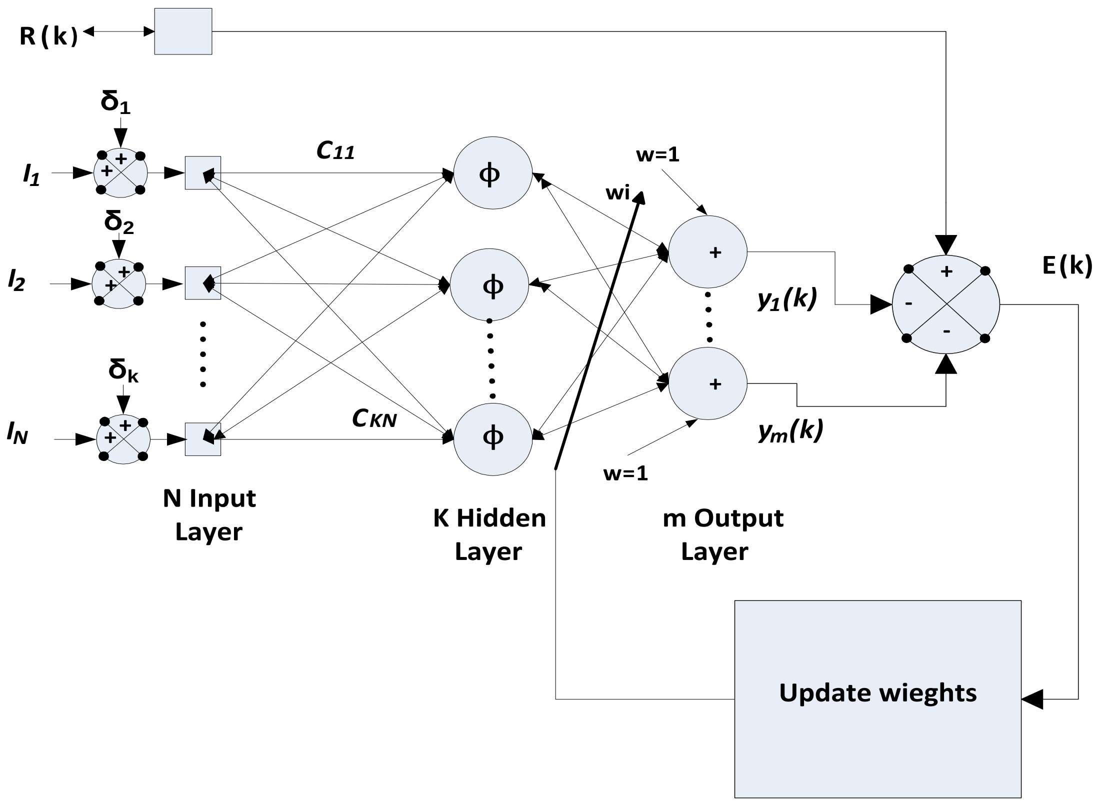

Fig. 1. Structure of the ARBF network.

If the input side (signal) has no noise δ(k), the algebraic sum of all outputs of the ARBF model will be the same as the reference signal R(k). In this condition, the error signal E(k) willbe zero and there is no change in the ARBF weights as seen in Eq. (1).

$$E(k) = R(k) - \{y_1(k) + y_2(k) + \cdots + y_m(k)\} \quad (1)$$

If the input side is contaminated by noise, the jth node in the output layer of the ARBF will be impacted by the presence of noise as:

$$y_j(k) = y_{oj}(k) + \delta_j(k) \quad (2)$$

where $y_{oj}(k)$ is the jth node in the output layer without noise and $\delta_j(k)$ is the additional error to the jth node because of the noise. The error E(k) in this condition has a value greater than zero.

The ARBF can reduce the error's impact on the performance. This is achieved by using the error E(k) to modify the weights vector between the hidden and output layer based on the LMSE algorithm [7] as:

$$w_{1new} = w_{1old} + \eta_1 \emptyset(k) E(k) \quad (3)$$

$$\vdots$$

$$w_{mnew} = w_{mold} + \eta_m \emptyset(k) E(k) \quad (4)$$

where η_j is a regulation parameter for the j^{th} node in the output layer. The weights parameter will be continuously updated till the error is minimized and reaches zero again.

3. ARBF NETWORKS FOR HARMONICS ESTIMATION

The ARBF network for harmonics estimation has two outputs: i) estimated fundamental component y_f and ii) the estimated harmonic content y_h. These outputs are calculated as follows:

$$y_h(k) = W_h \Phi(k) \tag{5}$$

$$y_f(k) = W_f \Phi(k) \tag{6}$$

The weights will be modified as follows:

$$W_h = W_h + \eta_h \Phi(k) E(k) \tag{7}$$

$$W_f = W_f + \eta_f \Phi(k) E(k) \tag{8}$$

The weight vectors for the fundamental component and harmonics contents will be updated based on μ_f and μ_h values. μ_f and μ_h are crucial parameters and they will control convergence speed and system stability. The acceptable limits of η_f and η_h values are determined by maximum eigenvalue λ_{max} of autocorrelation matrix, where

$$R = E[\Phi(k)\Phi^H(k)] \tag{9}$$

So, the range of any η should be as: $0 < \eta < \frac{2}{\lambda_{max}}$

The value of η can be written in terms of λ_{max} as: $\eta = \mu \frac{1}{\lambda_{max}}$

So, to maintain system stability, μ must be in the range 0 < μ < 2.

The stability margin and the optimal value to minimize the error were discussed in details in our former paper [16]. It defined the range of η_f and η_h that can ensure stable system. Also, it determined the optimal combination of η_f and η_h that produces the minimum error which is:

$$\eta_f + \eta_h = 1 \tag{10}$$

which means that there are infinite individual values of η_f and η_h that can give the minimum error, so the main aim in this paper is to set the value of each one of them to minimize the total error and to minimize the error in each of the fundamental and harmonicscomponents.

4. ANALYZING THE INDIVIDUAL VALUES OF WEIGHT VECTORS

The reference signal from the circuit shown in Fig. 2 (solid-blue line) and the estimated signal using conventional RBF filter (dashed-red line) are shown in Fig. 2. The difference between them is obvious (the MSE between them is 1.4459e+004). In order to reduce the MSE and getting better estimation, the weighting vectors must be modified.

The optimal value is $\eta_f + \eta_h = 1$ [16], and the MSE between the reference signal and estimated signal by ARBF network filter is now 3.2127e-015 and this is a significant reduction in the MSE value. The error between reference signal and estimated signal by conventional RBF (solid-blue line) and between reference signal and estimated signal by ARBF network (dashed-red line) are shown in Fig. 3.

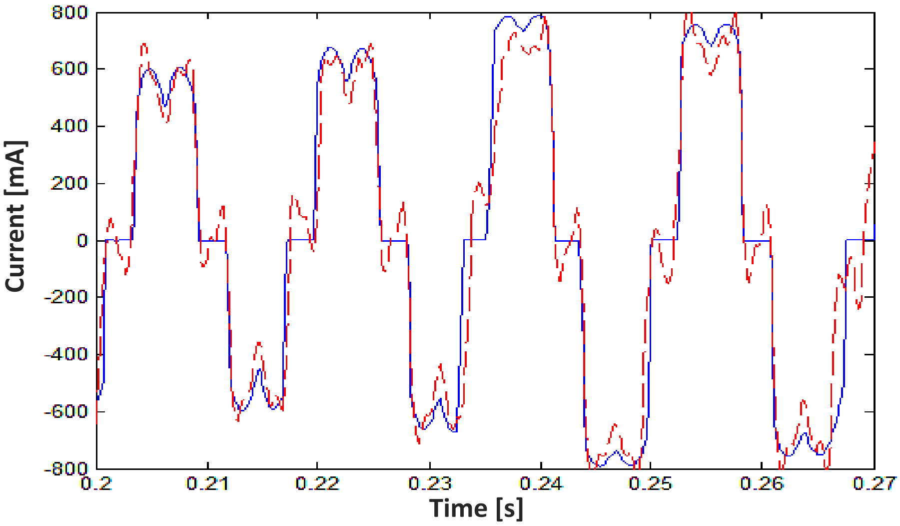

Fig. 2. Reference signal (solid-blue line) and the estimated signal (dashed-red line) using conventional RBF filter.

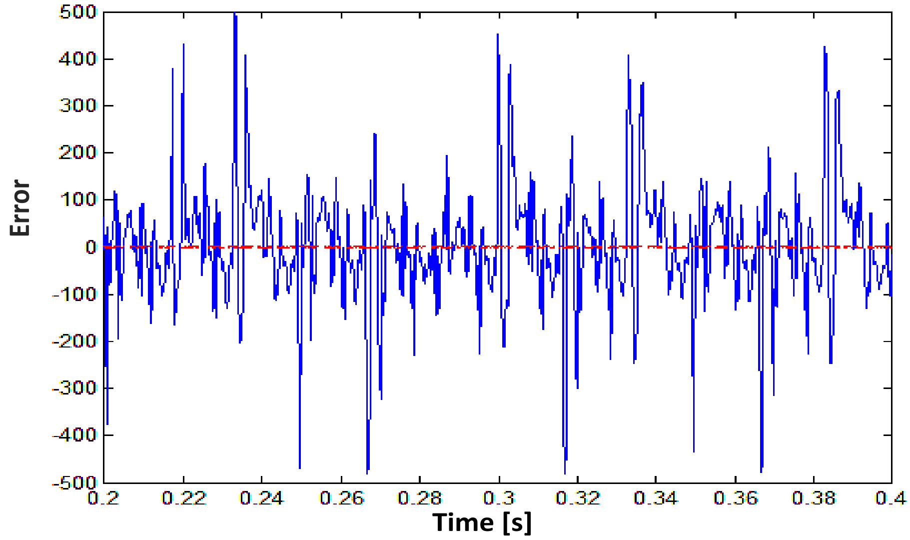

Fig. 3. Error signal between reference and estimated signals by conventional RBF filter (solid-blue line), and the error signal between reference and estimated signals by ARBF network filter (dashed-red line).

Any values of η_f and η_h satisfying the equation $\eta_f + \eta_h$=1 will give the same minimum error (i.e. 3.2127e-15); so to examine the effect of these values on each of the fundamental and harmonic signals, η_f is changed from 0 to 1, while η_h is selected in such a way to satisfy the optimal equation (i.e. $\eta_f + \eta_h$=1), for example, if η_f= 0.2 then η_h will be 0.8. After that, the FFT is used to calculate the fundamental and harmonics componentfor each value of η_f; the results are shown in Figs. 4 and 5. As the value of η_f is increased, the value of fundamental component in the estimated fundamental signal is increased and approaches the value of the fundamental component in the simulated signal while the fundamental component in the estimated harmonic signal is decreased and approaches zero. At the same time when η_f is increased, the amplitude of harmonic component in both of estimated fundamental and estimated harmonic signals is increased. The harmonic component in the estimated signal for all the values of η_f and η_h satisfies the equation that gives minimum error (i.e. $\eta_f + \eta_h$=1) is constant, this means that the harmonic components in the estimated fundamental and estimated harmonic signals are out of phase in order for their summation to be constant and approaches the harmonic component in the simulated signal. The important remarks which can be concluded from Figs. 4 and 5 are that adapting the weight of the estimated fundamental signal, will lead to having a harmonic component in this signal, and the same can be concluded for the estimated harmonic signal; additionally the value of the η_h has increased, causing a fundamental component in the estimated harmonic signal. Fig. 6 shows the estimated fundamental components by conventional RBF (red line) and ARBF network (blue line), when η_f=0.8 and η_h=0.2. It is clear that the estimated fundamental component by ARBF network has harmonics components.

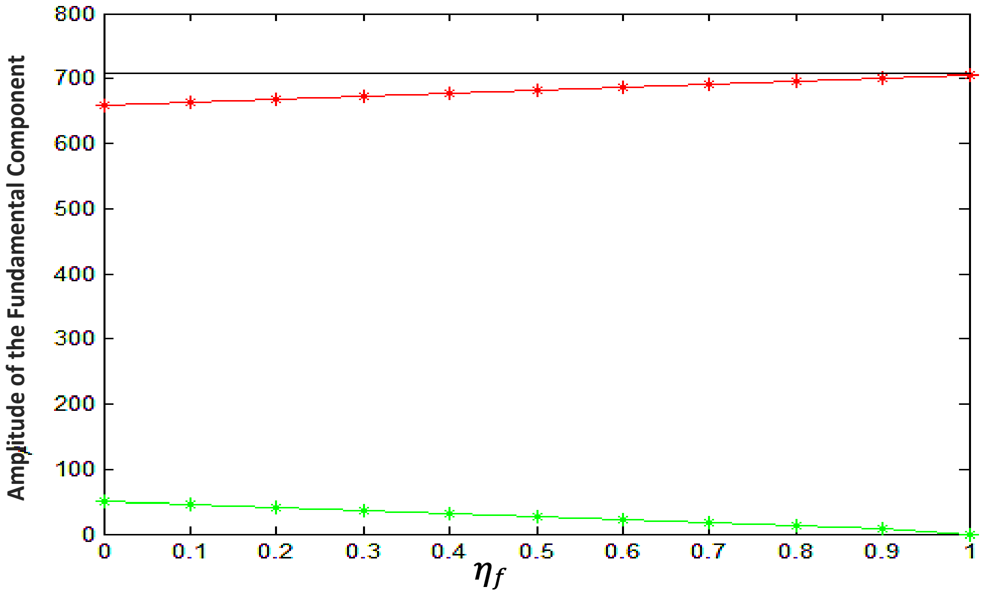

Fig. 4. Fundamental component in the estimated fundamental signal (red line) and in the harmonic estimated signal (green line) versus η_f; η_h is selected to satisfy η_f + η_h=1.

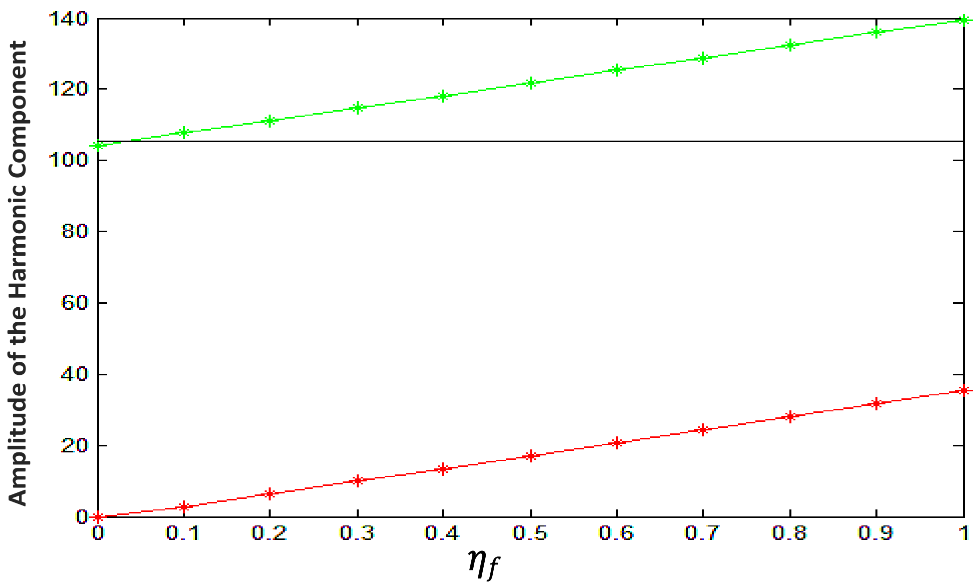

Fig. 5. Harmonic component in the estimated fundamental signal (red line) and in the estimated harmonic signal (green line) versus η_f; η_h is selected to satisfy η_f + η_h =1.

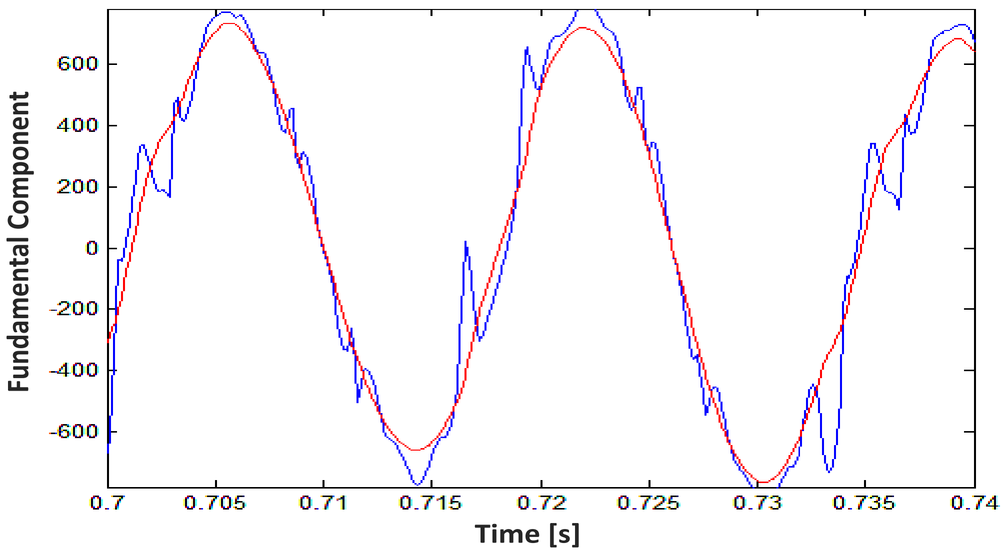

Fig. 6. Estimated fundamental component by conventional RBF (red line) and the estimated fundamental signal using ARBF network (blue line) η_f=0.8 and η_h =0.2.

Hence, the weight vectors are adapted to minimize the error between the estimated and the reference signals. This goal was achieved by using LMSE method, and there is no restriction inside the adapting process to guarantee that the fundamental signal will have only the fundamental component and the harmonic signal will have only the harmonic component.

For that reason, the adapted method should be modified to minimize the error between the estimated signal and the reference signal in one hand and to minimize the difference between the estimated fundamental and the estimated harmonic components with the reference fundamental and harmonic components in the other hand.

5. UPDATING FUNDAMENTAL COMPONENT USING FFT

While the conventional RBF network filter has an advantage (the estimated fundamental signal is pure and no other components (harmonics) are included in it), it still hasa huge error between the estimated and reference signals. On the other hand, the ARBF reduces the total error, but the estimated fundamental signal is contaminated with harmonics contents. So, to get a pure fundamental component, a modified ARBF network is proposed as illustrated in Fig. 7. The updating process is changed in the proposed network. This change is done by multiplying the weight vector, related fundamental component, by a factor to have the exact fundamental magnitude of the reference signal. At the same time, this change will ensure that the estimated fundamental component will be pure and will not have any harmonics contents.

The multiplying factor (J) - which will be used to update the weight vector (W_f) - can becalculated based on FFT algorithm. The FFT algorithm will be used to determine the amplitude of the fundamental component in the reference signal. On the other hand, the harmonics weight vector (W_h) can be updated using Eq. (7), where η_h and η_f are chosen to be *1* and zero, respectively. These values are chosen to obtain minimum total error between the reference and estimated signals.

The weight vector (W_f), will be updated as:

$W_{f(new)} = J * W_{f(old)}$

where J is a multiplication factor that equals the ratio between the magnitude of the fundamental components in the reference and estimated signals, where both magnitudes can be found using FFT. The sampled data - representing one cycle length - is used to calculate the fundamental magnitudes. The FFT is continuously founded with the latest sampled data.

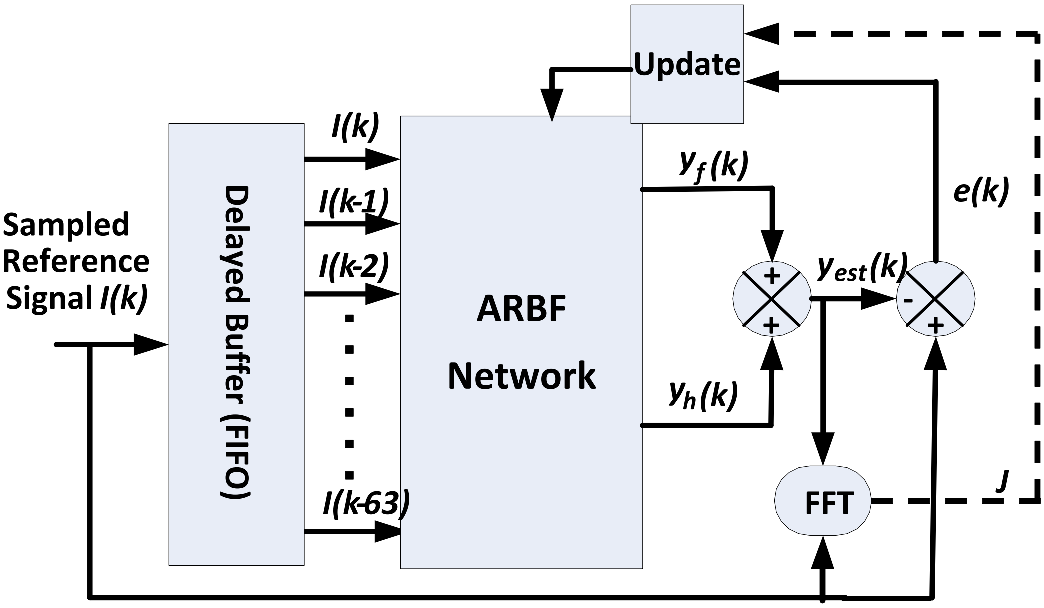

Fig. 7. The proposed ARBF network using FFT.

To validate the proposed algorithm, the performance of the proposed ARBF filter is compared with conventional RBF filter. First, η_h is chosen as 0. Fig. 8 shows the performance of the two algorithms to track the fundamental amplitude of the reference signal. It is clear that the proposed ARBF filter, based on the scaling technique, has better performance. It can estimate the amplitude of the fundamental component with a small margin of error, compared with the conventional RBF filter. On the other hand, Fig. 9 shows the total error, for the proposed algorithm, between the estimated signal and the reference signal. The error between the two signals is high. This is because of the effect of not updating the weight vector of the harmonics when choosing η_h equal to zero. This proves that the proposed algorithm can estimate only the fundamental component, without the need to have a good estimation of the harmonics content in the signal. Now, to prove that this algorithm can have good estimation for both components (fundamental and harmonics), let η_h = 1 and update the fundamental component based on FFT scaling. Figs. 8 and 10 show that the performance of proposed ARBF filter is not affected by changing η_h. The fundamental component in both cases is the same. However, when looking at Figs. 9 and 11 that depict the total error for the proposed algorithm when η_h =0 and η_h =1, we see that the total error between the estimated and reference signals is reduced impressively by choosing η_h =1.

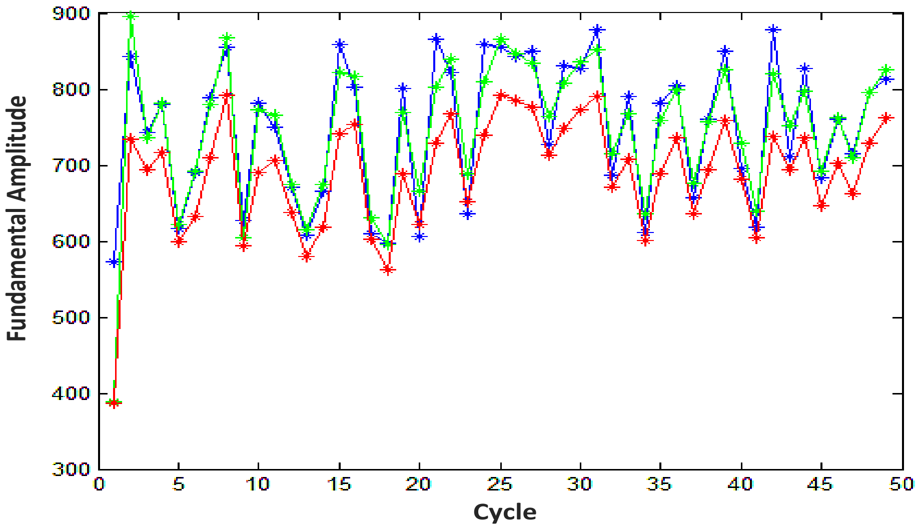

Fig. 8. Fundamental amplitude of the simulated signal (blue line), estimated fundamental signal by conventional RBF (red line) and estimated fundamental signal by scaled ARBF network based on FFT (green line) for η_h= 0.

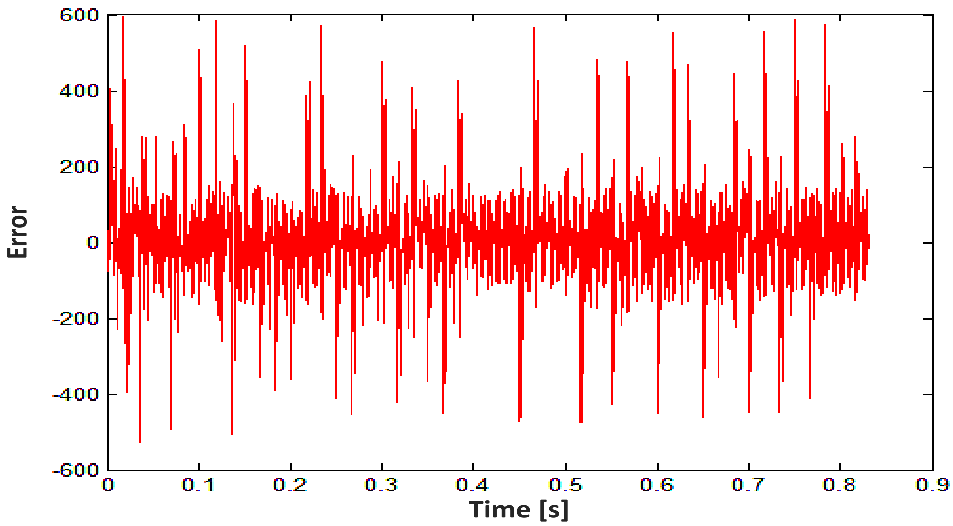

Fig. 9. Total error between the simulated signal and the estimated signal by scaling ARBF network using FFT for η_h=0.

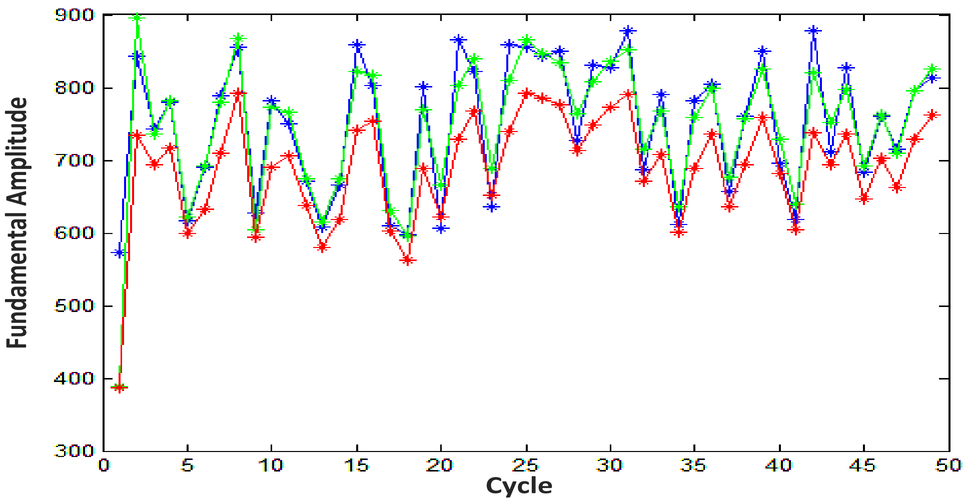

Fig. 10. Fundamental amplitude of the simulated signal (blue line), estimated fundamental signal by conventional RBF (red line) and estimated fundamental signal by scaled ARBF network based on FFT (green line) for η_h = 1.

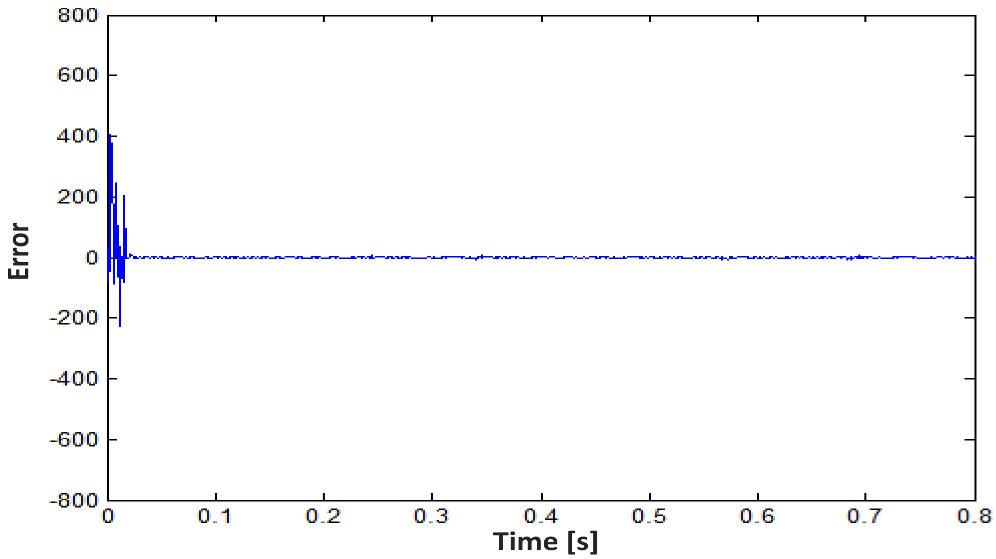

Fig. 11. Total error between the simulated and the estimated signals by scaling ARBF network using FFT for η_h = 1.

6. SCALING FUNDAMENTAL WEIGHT VECTOR BASED ON LMSE METHOD

In the conventional RBF filter, the estimated fundamental signal (Y_{Fest}) always has a signal with the same frequency of the fundamental signal ($Y_{Fsignal}$), but differs in magnitude; so the weight vector in this case must be scaled to modify the magnitude of Y_{Fest} as it is suggested in the previous section.

$$W_f = J * W_f$$

where J is a scaling coefficient.

J must be selected in such a way that, the error between of Y_{Fest} and $Y_{Fsignal}$ is minimum

$$y_h(k) = W_h \Phi(k) \tag{11}$$

$$y_f(k) = jW_f \Phi(k) \tag{12}$$

and the estimated output of ARBF is

$$y_{est}(k) = W_h \Phi(k) + jW_f \Phi(k) \tag{13}$$

The value of J can be modified based on LMSE method, the difference now, that the weight vector of the fundamental signal is not updated as it was done in Eq. (8). The fundamental component is now scaled, as shown in Fig. 12 and Eq. (12) to ensure that all the time the weight vector is only having the fundamental component,

$$J = J + \mu_J \Phi(k) W_f E(k) \tag{14}$$

$$W_h = W_h + \mu_h \Phi(k) E(k) \tag{15}$$

where

$$E(k) = Y_{sig} - Y_{est} \tag{16}$$

$$\mu_J = \eta_J \frac{1}{\lambda_{1max}}$$

λ_{1max} is the greatest eigenvalue of autocorrelation matrix R_1 where:

$$R_1 = E[\Phi(k) W_f (\Phi(K) W_f)^H] \tag{17}$$

Let us first apply this method for a signal with known fundamental and harmonic components. For example, let the signal equals: $y(t) = 700\, cos(120\pi t) + 100\, sin(600\pi t)$, the fundamental component of this signal is 700 cos($120\pi t$) and the harmonic component is

100 sin($600\pi t$). The reason for selecting such system is that it has first and fifth order harmonics as the simulated signal, but the simulated signal has a variable magnitude.

The fundamental component is scaled every sample as described in this section. Fig. 13 shows $Y_{Fsignal}$ (blue line), Y_{Fest} of the conventional RBFN filter (red line)and the Y_{Fest} of the scaled adapting RBFN, η_J is chosen to be 1. The result shows that the scaled Y_{Fest} is closer to $Y_{Fsignal}$, the difference between $Y_{Fsignal}$ and Y_{Fest} of the conventional filter (redline), and the difference between $Y_{Fsignal}$ and Y_{Fest} of the scaled adapted filter (green line) is shown in Fig. 14. It is clear in this figure, that the difference between the estimated fundamental using scaled adaptive RBFN and the reference signal is reduced significantly. The total signals, including fundamental and the harmonic components, i.e., the conventional RBFN signal (red line) and the scaled adapting RBFN signal (green line) are shown in Fig. 15.

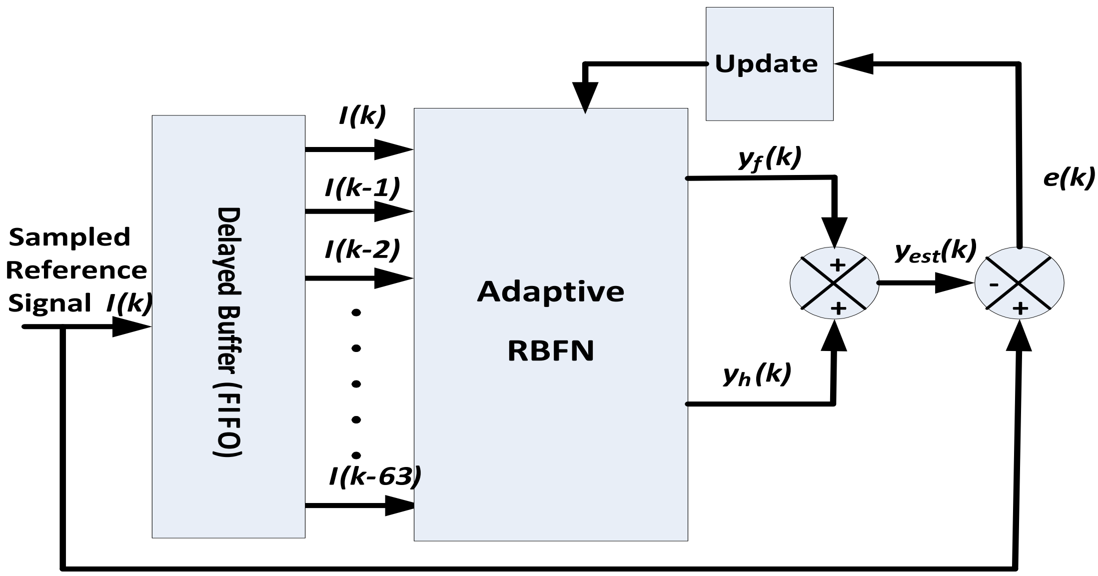

Fig. 12. The proposed ARBF network using LMSE.

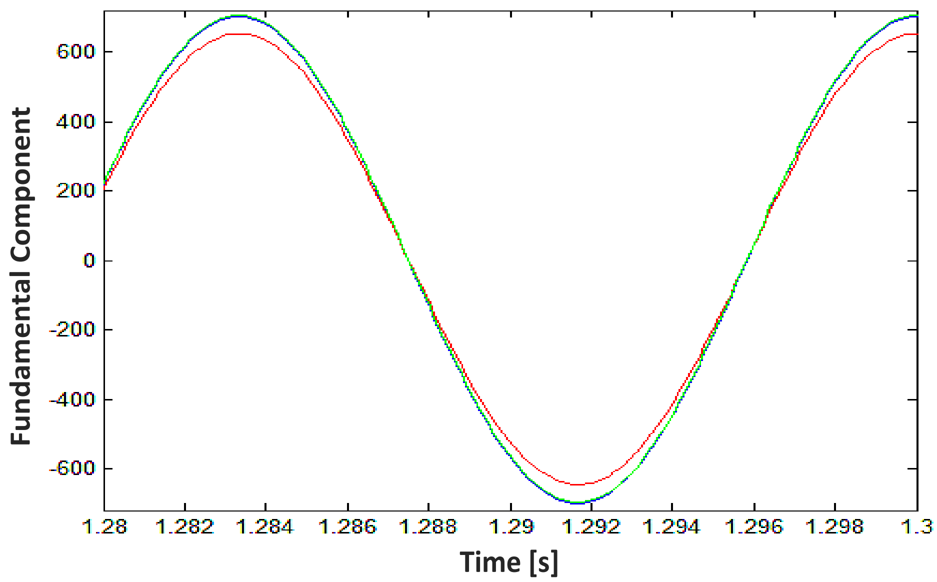

Fig. 13. Fundamental components of the signal (blue line), of the conventional RBFN filter (red line) and of the scaled ARBF network filter (green line).

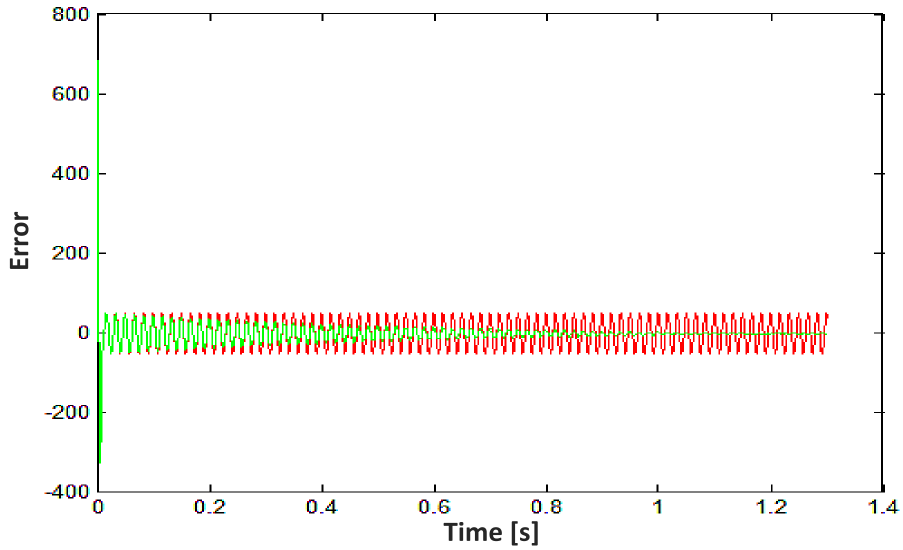

Fig. 14. Error on the fundamental signal using conventional RBFN filter (red line) and using scaled ARBF network (green line).

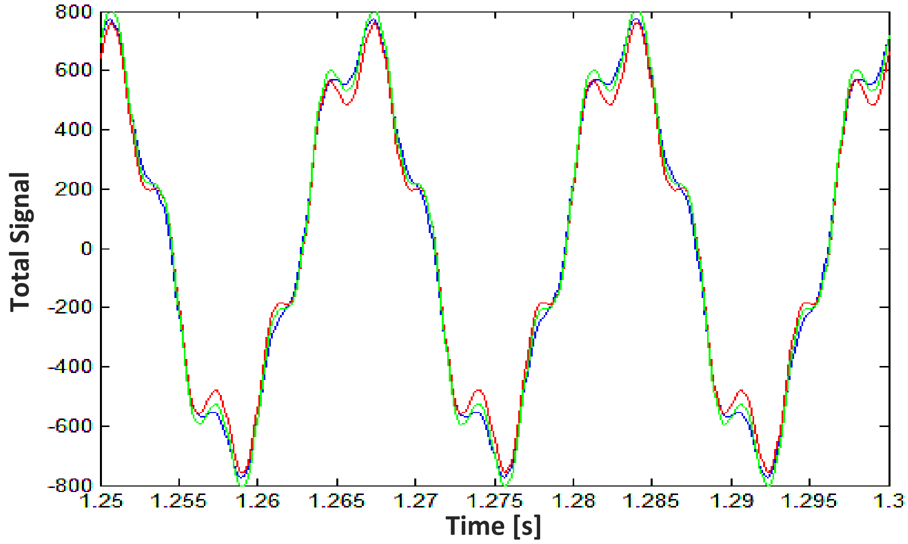

Fig. 15. Total signal (including fundamental and harmonic components) of the synthesis signal (blue line), conventional RBFN (red line) and scaled adapting RBFN (green line).

Now, let us return to the simulated and scaled signals, with focus only on the fundamental component. Since the fundamental component of this signal is unknown, we will use the FFT to analyze the result. Fig. 16 shows the fundamental component using FFT every cycle, the simulated fundamental component (blue line), the conventional RBFN (red line) and scaled adapting RBFN (green line). The scaled adapting RBFN filter has fundamental component closer to the simulated signal compared to the conventional RBFN filter. The total signal includes both fundamental and harmonic components as shown in Fig. 17. The difference between the estimated signal using scaled adapting RBFN and the simulated signal is still obvious since the fundamental component is the only component being adapted, which means that there is a need to adapt the harmonic component to reduce the total error between the estimated signal and the input signal.

The harmonic component will be adapted in the same way as described in Eq. (7). The results of adapting both the fundamental and harmonic components are shown in Figs. 18 and 19, respectively. Both of the fundamental signal and the harmonic component of the scaled adapting RBFN filter (green line) are closer to the simulated signal (blue line) compared to the conventional RBFN (red line).

The difference between the simulated signal and the scaled adapting RBFN filter (green line) and the difference between the simulated signal and the conventional RBFN (red line) are shown in Fig. 20. It is clear that the estimated signal using scaled adapting RBFN filter - compared to the conventional RBFN filter - has better estimation of the fundamental component, harmonic component and total estimating signal.

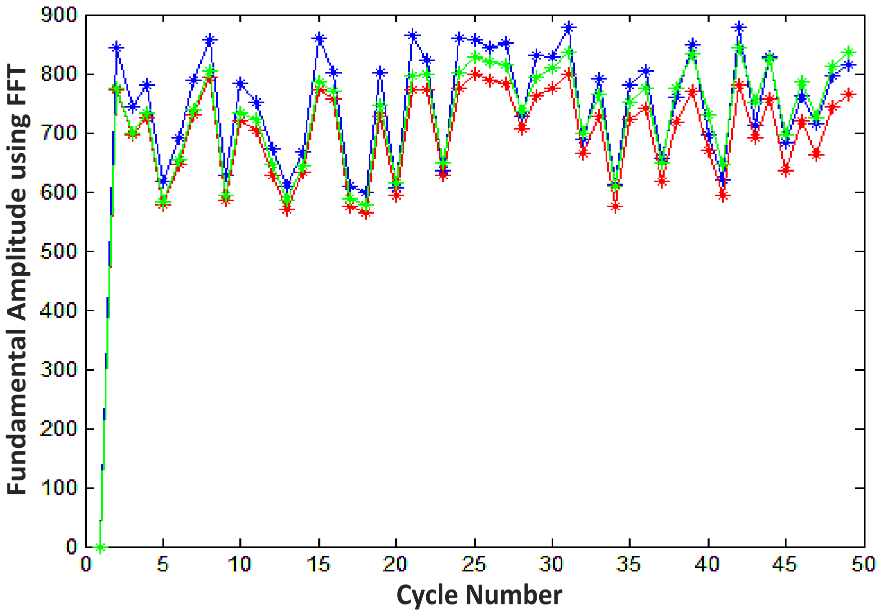

Fig. 16. Magnitude of the fundamental component using FFT of the simulated signal (blue line), conventional RBFN (red line) and scaled adapting RBFN (green line).

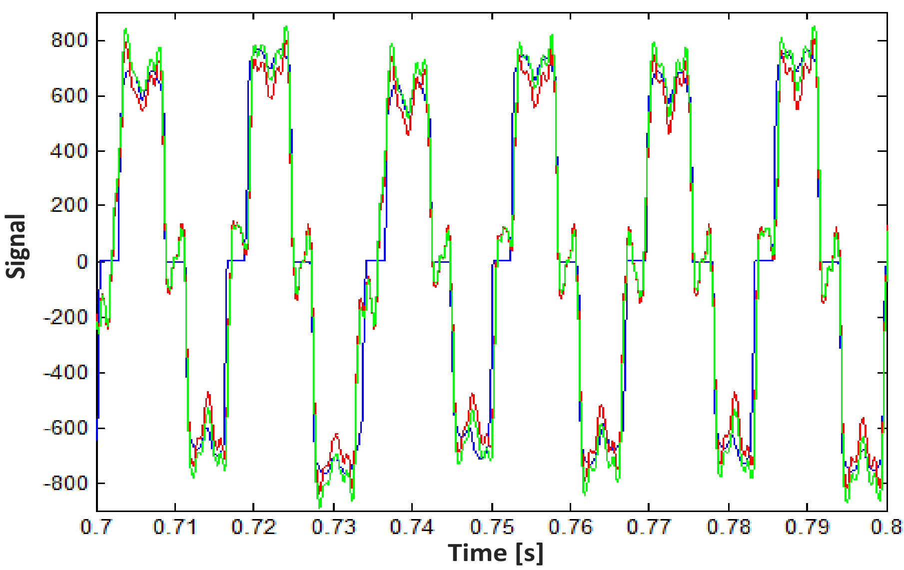

Fig. 17. Total signal (including fundamental and harmonic components) of the simulated signal (blue line), conventional RBFN (red line) and scaled adapting RBFN (green line).

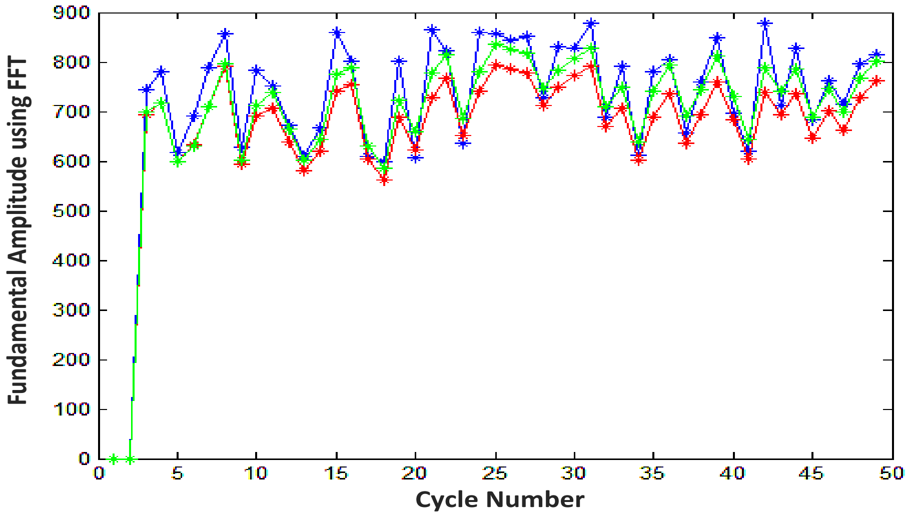

Fig. 18. Magnitude of the fundamental component using FFT of the simulated signal (blue line), conventional RBFN (red line) and scaled adapting RBFN (green line), when adapting both of the fundamental and harmonics components.

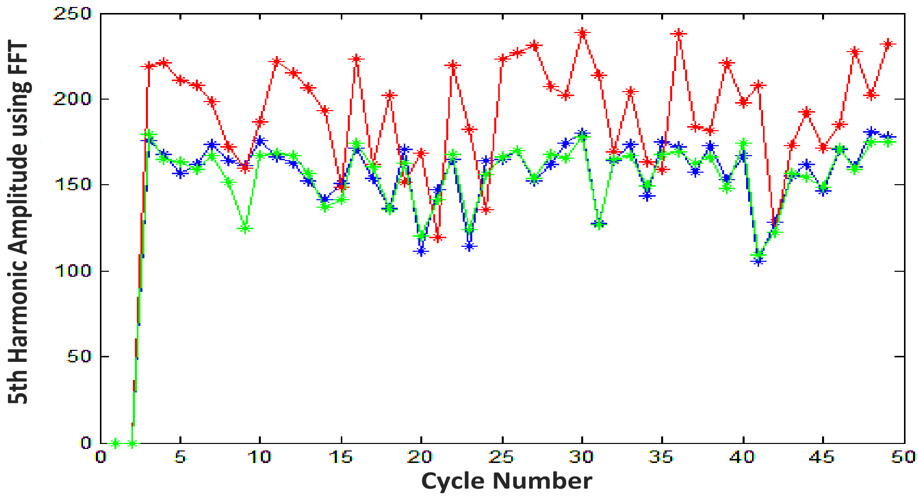

Fig. 19. Magnitude of the 5th harmonic component using FFT of the simulated signal (blue line), conventional RBFN (red line) and scaled adapting RBFN (green line),when both of the fundamental and harmonics components are adapted.

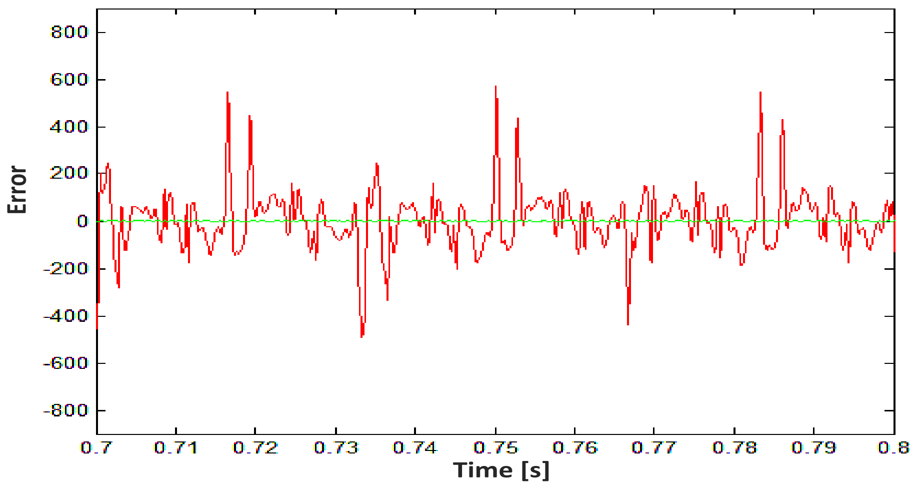

Fig. 20. Error between the simulated signal and the signal using conventional RBFN filter (red line) and the signal using scaled ARBF network (green line), when both of the harmonic and fundamental components are adapted.

7. CONCLUSIONS

Conventional RBF network and ARBF network were used to infer the fundamental and harmonics content for grid current drawn by nonlinear load. One of the most important parameters that govern the performance of the ARBF network is the learning rate. The learning rates for the ARBF network were further investigated to reduce the system total error. A detailed analysis showed a minimum total error between the estimated signal and the input signal; but this did not imply that the individual ARBF network outputs have also minimum error. This is because updating the learning rate for the fundamental component might affect the estimated signals and the fundamental component will have harmonics contents.

Updating of the fundamental component - for the ARBF network weights - was achieved in two different techniques; one is based on the FFT and the other is based on the LMSE. The learning rate of the harmonics content was updated using LMSE. The results showed that both methodologies can be effective in enhancing the system accuracy. Also, the results showed that the proposed algorithm can provide better performance compared to the conventionalRBF network. WE hope that the proposed - in this work techniques - can be of help in the design and implementation of signal processing and control systems.

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