Facilitating On-Line Harmonic Estimation Based on Robust Adaptive RBFNN

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Abstract— **In this paper, An adaptive Radial Basis Function Neural Networks (RBFNN) algorithm is used to estimate the fundamental and harmonic components of nonlinear load current. The learning rates for adaptive RBFNN are further investigated to minimize the total error and to minimize the error in each of the fundamental and harmonics components. The performance of the adaptive RBFNN is evaluated based on the difference between the original signal and the constructed signal (the summation between fundamental and harmonic components). The methodology used in this paper facilitates the development and design of signal processing and control systems. This is done by training the system and obtaining the initial parameters for the RBFNN based on simulation. After that, the adaptive RBFNN can be in the real system with these initial parameters.**

Keywords: **Energy efficiency, Power quality, Radial basis function, neural networks, adaptive, harmonic.**

I. INTRODUCTION

. With the proliferation of nonlinear loads in the power system, harmonic pollution becomes a serious problem that affects the power quality in both transmission and distribution systems. The problems caused by harmonics include malfunctioning of fuses or circuit breakers relays, heating of conductors and motors, insulation degradation, and communication interference [1] – [3].

Active Power Filters (APFs) have been introduced as an effective means to mitigate voltage and current harmonics. The APF measures the distorted signal and based on a harmonic detection algorithm, decomposes the distorted signal into fundamental component and other harmonic components. The APF then uses power electronics based circuit to compensate for the harmonic components, reactive power, and any other distortion (such as unbalanced waveforms). Harmonic detection techniques have been extensively studied. They can be categorized into three main techniques; (i) time domain filters, (ii) frequency domain filters, and (iii) artificial intelligent techniques [5-8]. With time domain filters there is a tradeoff between the attenuation and the phase delay (the high attenuation the higher phase delay and vice versa), and faster transition time can cause oscillations [7].The main problem with frequency domain filters is that these filters are not real-time filters [7]. The artificial intelligent filters have been introduced to overcome the disadvantages of the time and frequency domain filters. The three main techniques used in artificial intelligent filtering are (i) adaptive linear neuron (ADALINE), (ii) the popular back propagation neural networks (BPNN), and (iii) radial basis neural networks (RBFNN). The ADALINE is used as online harmonics identifier and its performance depends on the number of harmonics included in its structure. The convergence of the ADALINE slows as the number of harmonics included increases and also subjected to fall in local minima [9]-[10]. The BPNN on the other hand, deals with harmonic detection problem as a pattern recognition problem. It uses offline supervised training to identify selected harmonics. The long training time required in BPNN and the chance of falling into local minima is always present [11] – [12]. The RBFNN has several advantages over ADALINE and BPNN; capable of approximating highly nonlinear functions, its structural nature facilitate the training process because the training can be done in a sequential manner, and the use of local approximation can give better generalization capabilities [11] – [12]. Even though RBFNN has been used for harmonic detection, the number of hidden neurons is still large and still uses algorithm similar to that of BPNN. This makes RBFNN networks subjected to the same problem found in BPN [9]. An adaptive version of RBFNN was proposed in [13]. This adaptive RBFNN shows the possibility of improving the estimation accuracy by introducing weight change based on the error signal. In [14], the optimal values of learning rates that govern the weight updating were investigated. In this paper, the value of each of these learning rates are further investigated to minimize the total error and to minimize the error in each of the fundamental and harmonics components.

II. ADAPTING RBFNN

One of the major disadvantages of the feed forward neural networks (BPNN and conventional RBFNN) techniques is that; the obtained parameters do not changed once the training process is completed. In the presence of the noise, these fixed parameters can degrade the performance of the neural networks. The main objective of the adaptive RBFNN algorithm is to enhance the reliability of the conventional RBFNN after embedding the network in the system. This can be achieved by introducing an adaptive algorithm for RBFNN structure that allows the change of the weights of RBFNN after the training process is completed. As shown in II, the RBFNN adjustable parameters that will affect the output is the centers and the weights. This algorithm assumes that the noise present in the system can be mitigated only by adjusting the weights between the hidden and the output layers, without the need of adjusting the values of the centers between the input and hidden layers.

Fig.1 shows the general structure of the adaptive RBFNN algorithm. It has the same conventional RBFNN structure regarding input layer, hidden layer, and output layer. But it has two extra components; (i) Summation component, which is located after the outputs of the RBFNN. The goal of this component is to calculate the error signal between the estimated outputs y and the reference (actual) signal (R). (ii) Weights updating component. The goal of this component is to

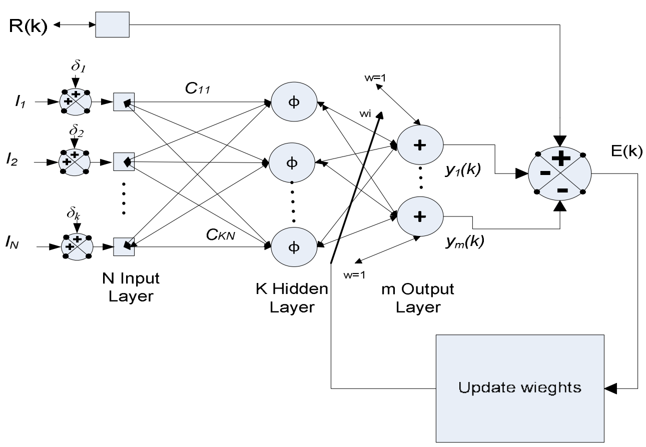

Fig. 1 General Structure of Adaptive RBFNN

adjust the weights in order to reduce the error signal. In the absence of the noise δ(k) in the input side, the summation of the outputs of the RBFNN model is equal to the reference signal R(k). In this case the error E(k) equal to zero and no change in the RBFNN weights.

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

In the presence of noise in the input side, the jth output node of the RBFNN will be affected by this noise as

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

where $y_{oj}(k)$ is the jth output node without noise and $\delta_j(k)$ is the added noise error to the jth output node.

In this case the error E(k) is not equal to zero.

In order to mitigate the effect of the noise in the performance of the RBFNN, the error E(k) is used to update the weights vectors based on the least-mean- square-error 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 the regulation factor for the j^{th} output node.

The weights updating will continue until the error E(k) become zero again.

The above algorithm has several advantages including the following:

- It has a fast convergence time because it adjusts only the weights between the hidden and output layers, which is a linear relationship. Therefore, fast convergence can be achieved.
- The updating process could be initiated based on threshold value for E(k) (different from zero), which gives the flexibility to the algorithm and saves excessive computations.

This algorithm has greater capabilities compare to the popular neural linear adaptive algorithm (ADALINE) because, the RBFNN structure can be used to realize linear and nonlinear functions.

III. METHOLDGY

RBFNN in this paper have two outputs; one of them to estimate the fundamental component y_f and the other is for the harmonic component y_h, these outputs are calculated as follows:

$$y_h(k) = W_h \Phi(k) \quad (5)$$

$$y_f(k) = W_f \Phi(k) \quad (6)$$

were Φ is the most common radial basis function used in RBFNN and is given by

$$\phi_i(x) = \exp\left[-\frac{(x-c_i)^T(x-c_i)}{2\sigma_i^2}\right], \quad i=1,2,\ldots,K \quad (7)$$

The values of the weights will be updated as follows:

$$W_h = W_h + \mu_h \Phi(k)E(k) \quad (8)$$

$$W_f = W_f + \mu_f \Phi(k)E(k) \quad (9)$$

Updating the weight vectors of fundamental and harmonic components depend on the values of μ_f and μ_h. These values should be selected carefully to ensure fast convergence and system stability. The range of μ_f and μ_h depends on the greatest eigenvalue $\lambda_{\max}$ of autocorrelation matrix R, where

$$R = E[\Phi(k)\Phi^H(k)] \quad (10)$$

And $0 < \mu < \frac{2}{\lambda_{\max}}$,

The value of μ can be express in terms of $\lambda_{\max}$ as follows:

$$\mu = \eta \frac{1}{\lambda_{\max}}$$

So to achieve the system stability

$$0 < \eta < 2$$

Adapting W_h and W_f can improve RBFNN performance, if the values of η_f and η_h are selected carefully, where some values of them can cause the system to diverge. Our previous work in [14] defined the stable margin of η_f, η_h and defined the optimal values of η_f and η_h. The combinations of η_f and η_h that give the minimum Mean squared Error (MSE) can be given by:

$$\eta_f + \eta_h = 0.9778 \qquad (11)$$

which means that any combination of η_f and η_h satisfies this equation will produce an estimated signal with minimum MSE. 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 harmonics components.

IV. Adapting Fundamental Signal Using FFT

The main feature of the conventional RFBN filter, that the estimated fundamental signal has only fundamental component, with amplitude differ than the amplitude of the measured fundamental signal. While the adapting process is necessary since the error between the simulated and the estimated signal is high. So the main modification is needed here is to scale the weight vector of the fundamental component to have the same magnitude, where the scaling process will guarantee that the estimated fundamental signal will not having a harmonic component.

The general Structure of Adaptive RBFNN using FFT for Adapting Fundamental Signal is shown in Fig.2. The weight vector of the fundamental component is scaled based on FFT, where the amplitude of the fundamental component in the simulated signal can be determined using FFT, and the harmonic component can be adapted by using equ.(8), where η_h is chosen to be 1, since η_f will now be zero to achieve minimum total error between the estimated and the simulated signals.

The weight vector of the fundamental component will be modify as follows:

$$W_f = JW_f \qquad (12)$$

Where: J is the ratio between the amplitude of the fundamental component in the measured signal and the fundamental amplitude of the estimated signal, both of amplitudes can be calculated using FFT.

The amplitude of the fundamental component in the estimated fundamental signal and in the simulated signal is calculated over a one cycle period, where at each sampled data the FFT is calculated over a one cycle length ending with the most recent sampled data, and this will be done at each sampled data, where all the time the FFT is calculated for one cycle length.

At the beginning, let $\eta_h = 0$, to discuss the effect of scaling the estimated fundamental signal, where Fig.3 shows the amplitude of the fundamental component in the simulated signal (blue line), estimated fundamental signal by conventional RFBNN filter (red line) and estimated fundamental signal by scaling adaptive RFBNN filter using FFT (green line), where it is clear that scaling adapting RFBNN filter has better estimation of the fundamental component compared with the conventional RFBNN, while the error between the estimated signal by scaling adapting RFBN filter and the simulated signal is high as it shown in Fig.4, where this error due to the differences between the estimated and simulated harmonic component.

Now let $\eta_h = 1$, and scaling the fundamental component using FFT, the result shown in Fig.5 and Fig.6. the fundamental component estimation is not effected by changing η_h where Fig.3 and Fig.4 show the same result for η_h=0 and, η_h=1 while the error between the estimated signal and the simulated signal is significantly reduce by choosing η_h=1.

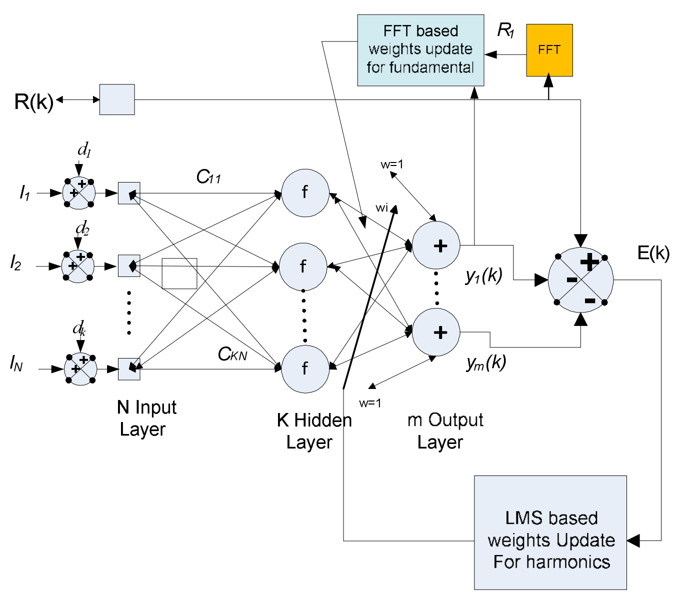

Fig. 2 General Structure of Adaptive RBFNN using FFT for Adapting Fundamental Signal

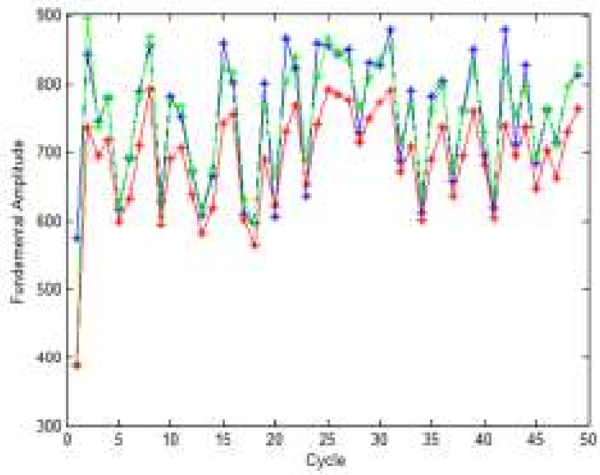

Fig.3 Fundamental amplitude of the simulated signal (blue line), estimated fundamental signal by conventional RFBNN (red line), estimated fundamental signal by scaled adaptive RFBNN based on FFT (green line) for $\eta_h = 0$

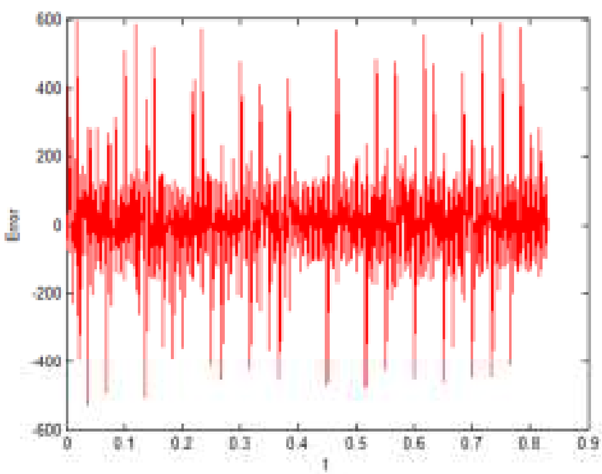

Fig.4. Difference between the simulated signal and the estimated signal by scaling adapting RFBNN using FFT for $\eta_h = 0$,

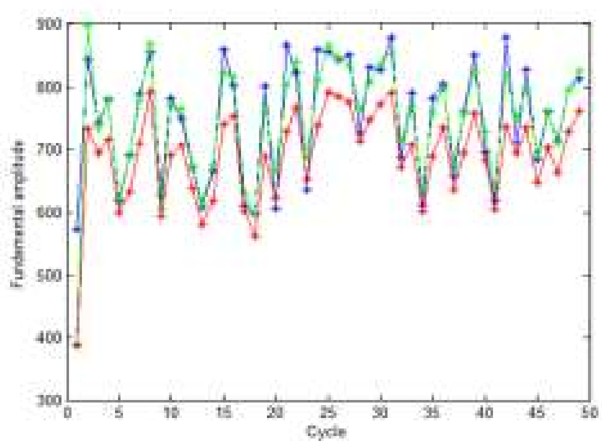

Fig.5 Fundamental amplitude of the simulated signal (blue line), estimated fundamental signal by conventional RFBNN (red line), estimated fundamental signal by scaled adaptive RFBNN based on FFT (green line) for $\eta_h = 1$

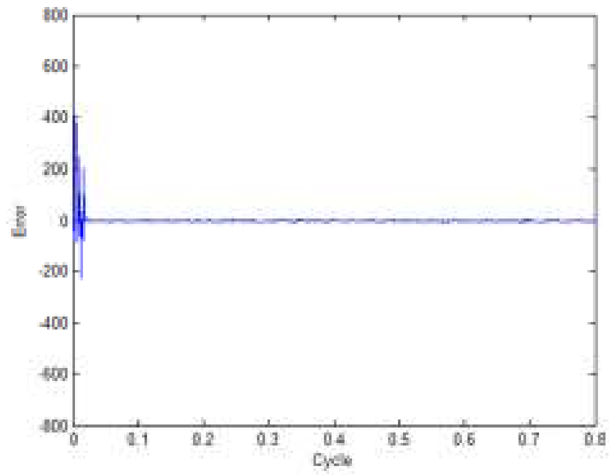

Fig.6. Difference between the simulated signal and the estimated signal by scaling adapting RFBNN using FFT for $\eta_h = 1$,

V. CONCLUSIONS

Adaptive RFBNN were used to estimate the fundamental and harmonic signal of a simulated signal obtained from power electronics circuit, the results show that adapting the weight vectors of the fundamental and harmonic components based on the total error between the estimated signal and the input signal using LMS is very effective to get estimated signal similar to the input signal with minimum error, and there are infinite individual values of η_f and η_h can give this result, where the summation of them is restricted to be equal to 1. But the results also show that when the error between the estimated signal and the input signal is minimum, this doesn't imply that the estimated fundamental component or the estimated harmonic component getting closer to the fundamental and harmonic components in the input signal, where adapting fundamental component may distort the estimated fundamental component and it will have harmonics.

The adapting method is modified here in such way that the weight of the fundamental component is scaled using FFT, while the harmonic component is adapted using LMS, the results show that using scaling process of adapting the fundamental weight vector improve the performance of RFBNN filter to estimate the fundamental, harmonics and the total signal.

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