“Adaptive Wavelet Neural Network a Efficient Technique for Estimating Low Order Dominant Harmonic”

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ABSTRACT

Harmonic is becoming more and more important day by day in the emerging power system. It is one of the most critical power quality parameters. An accurate assessment of harmonics is the most fundamental requirement in the field of harmonic analysis. It’s because it forms the basis for other harmonic-related issues, such as harmonic monitoring, harmonic source identification, design and operation of harmonic mitigation circuits, harmonic metering, and tariff realization.

In recent years, harmonic pollution has worried the power engineers considerably due to the increased penetration of power-electronics-based devices in the utility grid. Monitoring of certain low-order harmonics in the power supply is more important than monitoring of the entire spectrum because, these are usually, the most significant ones. In this paper, dominant low-order harmonic estimated using a technique based on an adaptive wavelet neural network is presented. The proposed method works with only half-cycle data point inputs, compared to the requirement of at least one-complete-cycle data for other estimation techniques. A simple, fast converging, and reliable learning algorithm based on back propagation is used for training of the network parameters. The proposed method is examined with a number of simulated and experimental signals.

Keywords— Adaptive wavelet neural network (WNN) (AWNN), artificial intelligence, fast Fourier transforms (FFT), harmonic estimation, power quality.

1. INTRODUCTION

A key technology power electronics is for the efficient conversion, control, and conditioning of electric energy from the source to the load. In the area of power engineering there is opened up new vistas, because of continuous developments in power electronic devices and converter technologies, such as flexible ac transmission systems, inverters, cycloconverters, and variable-frequency drives[1]. These new technologies enable easier control of the industrial processes, better utilization of the distributed and renewable energy resources and more efficient and reliable operation of the power system, and result in compact and robust home appliances. However, it has given rise to an important problem of power supply waveform distortion, which is harmonics and interharmonics which is represented as a set of higher order frequency components.

The Advancement of high-power semiconductor devices and their excellent control capabilities have resulted in extensive use of power-electronics-based nonlinear equipment in domestic, commercial, and industrial sectors for various applications. These devices inject harmonics and interharmonics into the system, because of these cause many severe problems to the system and equipment[2]. The problems such as increased losses, resonance, control malfunction, and interference. To define allowable harmonics limits we developed total harmonics distortion (THD), harmonics group, and subgroups, and also framed some guidelines in various standards. For monitoring and to properly design and plan suitable solutions for its mitigation and control, an accurate estimation and measurement of harmonics or interharmonics is essential.

For harmonic monitoring, harmonic source identification, design and operation of harmonic mitigation circuits, harmonic metering, and tariff realization etc An accurate assessment of harmonics is the most fundamental requirement in the field of harmonic analysis. In recent years, on harmonic estimation, and a number of signals processing intensive research has been done. Artificial intelligence techniques have been applied in a quest to achieve high accuracy and low computation burden. But in practice, these two attributes are contradictory to each other, i.e., when one is improved, the other one deteriorates. A better option is to estimate selective dominant harmonics accurately with minimal computational burden is adopted in many control applications.[3].

This paper proposes a simple and robust approach based on an adaptive wavelet neural network (WNN) (AWNN) for estimation of dominant low-order harmonics. The key features of the proposed method include the following:

1) With total five free parameters, namely, input-to-output layer weights, hidden-to-output layer weights, bias, translation, and dilation, the AWNN offers better adaptivity;

2) The AWNN uses wavelet coefficients as compared to the radial distances used in the RBFNN, therefore providing better harmonic estimates;
3) Since wavelets are localized functions, a fast heuristic initialization approach is employed in the proposed work to initialize the wavelet parameters that not only reduces the training time but also improves the accuracy;

4) A linear relationship between input and output is mapped directly; and

5) A simple and reliable back propagation (BP) algorithm with adaptive learning rate is used for network parameter training.

2. ADAPTIVE WAVELET NEURAL NETWORK (AWNN)

Zhang et al was first proposed a wavelet neural network (WNN), as an alternative to the classical FFNN for approximating arbitrary nonlinear functions. WNNs are having better generalization property because of the local properties of wavelets and the concept of adapting the wavelet shape according to training data set rather than adapting the parameters of the fixed shape basis function [5]. The WNN having an objective of an explicit link between the network coefficients and wavelet decomposition to achieve good approximation quality with reduced network size. Wavelet decomposition follows a regular grid structure for its parameters, but the WNN parameters are adapted from data. Thus, it is more commonly referred to as the AWNN. Some diverse applications of AWNN are identification and control of dynamic plants, energy price forecasting, available transfer capability determination, modelling the development of fluid dispensing, power transformer diagnosis, and wind speed forecasting, show its efficacy and potential. But the features of the AWNN are not yet utilized for harmonic estimation. A heuristic initialization approach is adopted in this paper, which is not used in any of the aforementioned applications

2.1 ARCHITECTURE OF AWNN

An AWNN is a multilayer feedforward neural network having a hidden layer with wavelet function wavelets, also known as neurons. Fig. 1 shows the typical architecture of a multiple-input multiple-output Adaptive Wavelet Neural Network, where \( \mathbf{x} = (x_1, x_2, \ldots, x_n) \) is the input vector, and \( \mathbf{W} = (\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_n) \) is the weight matrix of connections between input layer and output layer neurons. \( \mathbf{V} = (\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_n) \) is the weight matrix which is connections between hidden layer wavelets and output layer neurons. \( \mathbf{b} = (b_1, b_2, \ldots, b_k) \) is the bias vector of the output layer neurons. \( \mathbf{y} = (y_1, y_2, \ldots, y_k) \) is the output vector. The \( n \)-dimensional input at the input layer is directly transmitted to the hidden layer wavelets with the fixed unity weight. The output of AWNN can be obtained as

\[
\mathbf{y} = \mathbf{W} \cdot \mathbf{x}^T + \mathbf{v}^T + \mathbf{b}
\]

where \( \mathbf{z} = (z_1, z_2, \ldots, z_m) \) is the output vector of the hidden layer and \( (.)^T \) represents the transpose of the vector/matrix. Wavelets of many types are possible with different shapes and sizes, e.g., Daubechies, Haar, B-spline, Morlet, Gaussian, and Mexican hat. The accuracy and efficiency of the AWNN depends on selection of a suitable wavelet function. Among the variety of wavelets. The Mexican hat wavelet function is is computationally efficient and differentiable so it commonly used in nonlinear system modeling. A multidimensional Mexican hat wavelet function is realized by a tensor product of single-dimension wavelet Functions is

\[
Z_j = \sum_{i=1}^{m} \left( (1 - \frac{z_i - a_i}{\sigma_i}) \right) \left( \frac{z_i - a_i}{\sigma_i} \right)^{-2} \left( \frac{z_i - a_i}{\sigma_i} \right) \]

\[\forall j=1:m \] 

(2)

2.2 PARAMETER LEARNING

Parameter learning is the most important process of any Adaptive Neural Network. In ANN the free model parameters are iteratively adjusted to the most appropriate values, using a set of priory input–output data. It is used to best represent the system under consideration. The gradient-descent BP algorithm is simple and have ability to update each parameter simultaneously, so it has been used in this study. To counter its slow convergence rate, and to ensures faster learning adaptive learning rate and momentum terms are used.

Minimization of cost function is the objective of parameter learning, which is derived from the instantaneous total meansquare error and expressed as

\[
E = \frac{1}{2} \sum_{k} (y_k - y_k)^2
\]

(3)
where $x_a$ and $y_a$ are the desired and actual responses of the $k$th output neuron, respectively. $K$ is the number of output neurons. Two other stopping criteria are also used in the learning algorithm to optimize the total training time. These two algorithms are the limit on the maximum number of training iterations and no significant improvement in the cost function for, generally, three to four iterations.

The free parameters are updated in each iteration using the following generalized expression:

$$\beta(k+1) = \beta(k) + \eta \beta \Delta \beta(k) + \Delta \beta(k-1)$$ .........................(4)

where $k$ is the iteration count, $\eta$ is the learning rate, and $\Delta \beta$ is the momentum coefficient. Here, $\beta$ designates either of the free parameters, viz., $w$, $v$, $b$, $\lambda$, or $d$. The negative of the gradient of the cost function $E$ in that iteration will be equal to the change in any parameter $\Delta \beta$ in the $k$th iteration. The learning process requires some initial values of the free parameters to begin with, which play a important role in the optimal learning of the parameters.

2.3 NETWORK INITIALIZATION

Initialization is the selection of appropriate initial values of different free parameters, through, weight, bias, translation, and dilation of a wavelet network. For the initialization purpose some of the applications use random initialization of the network parameters. But in some other application use a clustering technique to determine the initial guess for the translation parameter. The heuristic initialization proposed by Oussar and Dreyfus is adopted in this work. Heuristic initialization utilizes the input data and ensures that wavelets extend initially over the whole input domain. Selection of the number of wavelons is also important because it affects both the computation burden and the estimation accuracy. While increasing the number of wavelons increases the computation burden.

2.4 PROBLEM FORMULATION

A Fourier series represents a distorted periodic signal as the sum of sinusoids as

$$x(t)=\sum_{k=1}^{\infty} A_k \sin(2\pi f_k t + \phi_k)$$ ......................(5)

where $t$ is the time, $H$ is the set of frequency components present in the distorted signal, and $f_k$, $A_k$, and $\phi_k$ are the frequency, amplitude, and phase angle of the $k$th component, respectively. This signal when sampled at regular intervals of $T_s$ and is represented in discrete form for the $i$th sample as

$$y_i = \sum_{k=1}^{\infty} A_k \sin(2\pi f_k i T_s + \phi_k)$$ ......................(6)

Amplitudes and phase angles estimation is considered as a nonlinear input–output mapping problem with $n$ measurements at equal time interval as the input. It can be represented as

$$A(n) = F_A(x) \quad \forall x \in H$$ .............................(7)

$$\phi(n) = F_\phi(x) \quad \forall x \in H$$ .............................(8)

where $x$ is an $n$-dimensional measurement vector at time instant $t$, which consists of $n$ samples taken from half the fundamental cycle of the distorted signal. $FA$ and $F\phi$ are the mapping functions for the amplitude and phase angle, respectively. For the estimation of $f$ amplitudes and phase angles the AWNN is used to implement these nonlinear functions after successful training of the network parameters.

The important steps of the proposed AWNN-based harmonic estimation method is as follows.

1) Initialize the network parameters.

1.1) The translation of the $j$th wavelon is initialized at the center of the parallelepiped defined by the $n$ intervals $[a_j, b_j]^n$, where $[a_j, b_j]$ is the domain of the $j$th input.

1.2) The dilation of the $j$th wavelon for the $i$th input is initialized as

$$\gamma_{ij} = \alpha \cdot (a \cdot \delta_{ij})$$ ......................(9)

where $\delta$ is an arbitrary value, chosen according to the degree of localization required. Typically, values in the range of $0.2$–$0.5$ can be used.

1.3) Initialize the input-to-output layer weights $w$ and bias $b$ as zero and the hidden-to-output layer weight to small random values.

2) the parameters are updated using the learning procedure.

3) Apply the trained AWNN to compute the selected harmonic components of the measured distorted signal.

3. DISCUSSION

In harmonic estimation the effectiveness of any harmonic estimation technique is determined by two main features, accuracy and computational complexity. Unfortunately, it is difficult to achieve both of them together from the available techniques. The FFT is very fast but requires at least one-complete-cycle data for analysis. It suffers from low frequency resolution and poor accuracy problems in the practical scenarios of fundamental frequency deviation and presence of
interharmonics. The parametric techniques, have high frequency resolution and provide accurate estimates, but these technique have very high computational burden.

The proposed AWNN method have fast convergence and simple architecture. It also capable of handling nonlinearities. In the method proposed in the paper, linear mapping between input and output is achieved through direct weighted links between input and output layers. Thus resulting in better performance. The proposed technique is quite robust against noise and fundamental frequency deviations, which are unavoidable in practical applications and are the common causes of inaccuracies in different techniques. FPGAs and Digital signal processors are two possible options for hardware implementation of most of the signal processing algorithms. For the proposed method, FPGA is suggested because of easy parallel processing of neurons, flexibility for adaptive AWNN architecture, etc.

the system stores them in the Item Bank, accesses the MIMIC-II database, and generates new rules. The efficiency of rule generation depends on the computation power of the running PC and can be increase by parallel computing. The current system can produce from 52 rules per minute on a single-core processor to 434 rules per minute on a 12-core processor [1]. The system stores created new rules in the Rule Bank. Afterwards, users can retrieve the rules in the Rule Bank via the Rule Mining window without waiting for duplicated rule generation. A real-time rule mining system can gradually be achieved, as the number of stored rules keeps growing.

4. CONCLUSION

This paper has described to estimate low-order dominant harmonic by an AWNN-based technique. AWNN utilizes the universal approximation property of wavelet decomposition and adaptively tunes the translation and dilation parameters to optimal values so that local variations in the signal due to interharmonics, noise, and frequency deviation do not affect the estimation accuracy. The proposed method in this paper has been tested on experimental and synthetic measured signals. Against the presence of interharmonics, noise, and fundamental frequency deviation the results confirm high estimation accuracy and robustness of the proposed technique. The AWNN works satisfactorily with just half-cycle data samples as the input. The low computation time makes it suitable for online applications in power quality conditioners, metering equipment, etc. The proposed method is suitable for monitoring and control of selected low-order harmonic components in the utility grid. It also isolated distributed generation systems

REFERENCES


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