WIDESPREAD ARTIFICIAL NEURAL NETWORK (ANN) STRUCTURES FOR CURRENT HARMONICS EXTRACTION

[1]Mehmet BÜYÜK, [2]Mustafa İNCİ, [3]Turgay İBRİKÇİ,
[1,2,3]Çukurova University, Electrical and Electronics Engineering, Adana, Turkey
[1]mbuyuk@cu.edu.tr, [2]mustafainci@ieee.org, [3]ibrikci@cu.edu.tr

[4]Mehmet TÜMAY
[4]Adana Science and Technology University, Electrical and Electronics Engineering, Adana, Turkey
[4]mtumay@cu.edu.tr

Abstract: *The extraction of current harmonics produced by nonlinear loads in the power system is significant issue for compensating them fast and accurately. In this paper, the main contribution is that widespread artificial neural network (ANN) structures are used to acquire harmonic components generated by a six-pulse uncontrolled rectifier. For this purpose, ANN including computational algorithms operate according to the functionality and structural scheme of biologic neurons. Among ANN network structures, radial basis function (RBF) and multilayer feedforward (MLF) networks are two widespread used architectures for harmonic extraction in literature. Thus, this paper examines harmonic extraction performances of these common used ANN structures by using MATLAB/Simulink environment. In this way, the networks are firstly trained by using sample input data and output data with respect of training algorithms. In order to train the networks, some training algorithms are applied, and the optimal network and algorithm are emphasized.*

Key words: *Radial basis function (RBF), multilayer feedforward (MLF), harmonic extraction, back-propagation.*

1. Introduction

Power quality is a significant issue in the power system. The voltage of the system is desired to be a pure sine wave. However, many nonlinear loads destroy the system voltage through drawing non-sinusoidal current waveform. The non-sinusoidal current components are compensated via active power filters (APF). In order to compensate the harmonic currents, APFs initially detect these currents as a reference signal and then perform the switching operation according to the reference signal.

Fast and accurate extraction of harmonic current is important for effectively compensation. In literature, many extraction methods are proposed such as synchronous d-q reference frame theory, FFT (Fast Fourier Transform) and instantaneous p-q theory [1,2]. Each of extraction methods has its benefits and drawbacks. Recently, ANN based extraction methods have progression and applications in power systems. Several papers in literature use ANNs to generate reference harmonic signal [3-12]. ANN based extraction methods have fast and improved extraction of harmonic current [6]. Some ANN structures are applied in literature such as adaline network [6], multilayer feed-forward (MLF) network [3, 4, 7] and radial basis function (RBF) network [9-12]. Besides, there are many training algorithm so as to teach the networks.

This paper introduces RBF and MLF networks based harmonic current extraction of six-pulse uncontrolled rectifier. In literature, these two networks are the most common applied architectures for harmonic extraction. In MLF network, tangent sigmoid and pure linear activation functions are usually used to generate the non-linear mapping properties which yield the suitability for harmonic component extraction. In RBF network, gaussian function is used as input layer activation function instead of tangent sigmoid function. In order to train the networks, some training algorithms are examined, and the optimal algorithm is emphasized. The data for training the network is obtained from Simulink/Matlab. The nonlinear load is built, and the inputs and targets are formed through d-q reference frame extraction methods. Then, the networks are trained by using Matlab Neural Network Toolbox [13].

2. Harmonic Current Extraction with d-q frame

In d-q frame extraction method, the load current is detected and transformed to d-q domain, then passed through low pass filter (LPF) to obtain only fundamental frequency component, as shown in Fig. 1. Then the filtered d-q components are transformed into a-b-c frame in order to get fundamental frequency current. The harmonic current are then generated by extracting the fundamental components from the load currents [14,15].

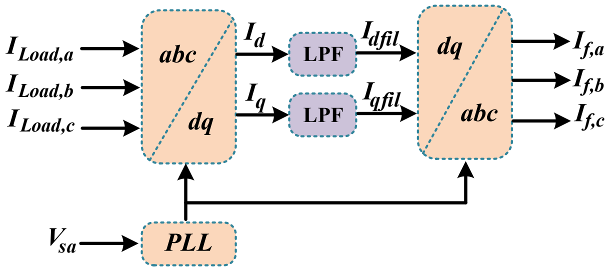

Fig. 1. The principle of dq frame-based harmonic extraction method

The d-axis and q-axis are acquired by the transformation illustrated below.

$$\begin{bmatrix} I_d \\ I_q \\ I_0 \end{bmatrix} = \mathbf{T} \begin{bmatrix} I_{Load,a} \\ I_{Load,b} \\ I_{Load,c} \end{bmatrix} \quad (1)$$

where:

$$T = \frac{2}{3}\begin{bmatrix} cos(\phi) & cos(\phi - 2\pi/3) & cos(\phi + 2\pi/3) \\ -sin(\phi) & -sin(\phi - 2\pi/3) & -sin(\phi + 2\pi/3) \\ 1/2 & 1/2 & 1/2 \end{bmatrix}$$

Then by applying inverse transformation for Idfil and Iqfil, the fundamental current components are obtained as

$$\begin{bmatrix} I_{f,a} \\ I_{f,b} \\ I_{f,c} \end{bmatrix} = \mathbf{T}^{-1} \begin{bmatrix} I_{dfil} \\ I_{qfil} \\ I_0 \end{bmatrix} \quad (2)$$

3. Harmonic Extraction with ANN

In this study, RBF and MLF networks are analyzed for harmonic extraction of six-pulse uncontrolled rectifier. Fig. 2 shows the block scheme of ANN for harmonic extraction. Four inputs and three outputs are used for training data in order to generate harmonic current components of three phases. The applied inputs shown in Fig. 2 are three load currents and the phase angle. The generated outputs are three fundamental current components of the load currents. The harmonic currents are then obtained by extracting fundamental currents from load currents.

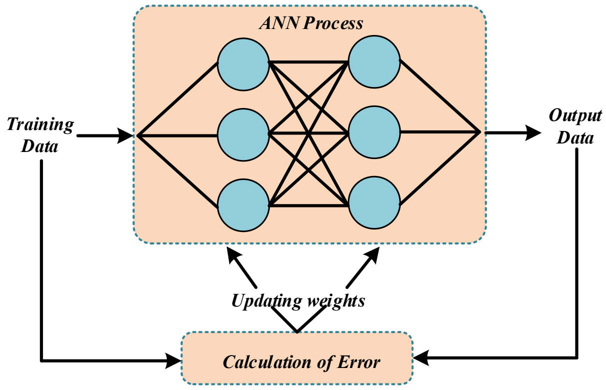

Fig. 2. Block scheme of ANN

3.1 Multi-layer Feedforward ANN

MLF network orders the neurons in layers and makes each neuron in one layer take as input only the outputs of neurons in the previous layer or the external inputs [16,17]. The multilayer perceptron network constitutes one input layer, one output layer and one/more hidden layers, as demonstrated in Fig. 3. In this study, one or two hidden layer is used in order to keep calculation time less. In this study, MLF network is trained by back-propagation algorithm.

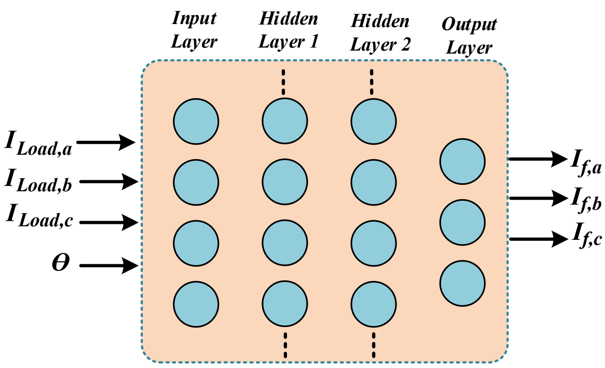

Fig. 3. The structure of MLF network

Back propagation, an abbreviation for "backward propagation of errors", is a training (or learning) algorithm rather than a network, which is used in conjunction with an optimization method such as gradient descent. The back propagation algorithm requires target, namely learns with samples. Thus, this algorithm is considered as supervised learning method. Back propagation algorithm consists of forward propagation and backward weight update [4].

In forward propagation, for each node j, the output of that node F is calculated as

$$F(net_j) = F(\sum_{k=1}^{n} w_{kj} x_k) \quad (3)$$

F(netj) is the jth node total-activation value from the hidden to the output layers, wkj are the weights between the hidden and the output layers and j is the number of samples used for the training.

The activation function F is usually chosen to be non-linear and differentiable [11]. Some activation functions like tanh, hardlim, sigmoid, log and linear are the most widespread used functions in ANNs. Linear and tanh activation functions can be applied in harmonic extraction, which form differential function. In backward update, the error between the desired output and network output is initially obtained through squared error function for jth node as

$$e_j = (t_j - y_j)^2 \tag{4}$$

where: t is the desired output and y is network output Then, the total error is calculated so as to decrease the error value for next training step.

$$e_k = \frac{1}{2} \sum_{j=1}^{n} e_j \tag{5}$$

After that the partial derivative of the error with respect to wkj is performed $\partial e_k / \partial w_{kj}$. The weight change is obtained for jth node as

$$\Delta w_{kj} = -\sigma \frac{\partial e_k}{\partial w_{kj}} \tag{6}$$

The minis sign is required so as to update in the direction of a minimum, not a maximum, of the error function [11].

The weights are then updated as below

$$w_{kj}(t+1) = w_{kj}(t) + \Delta w_{kj} \tag{7}$$

3.2 Radial Basis Function ANN

Radial basis function network is a feed-forward network that has simpler architecture than back-propagation [9]. Its structure includes one input layer, one hidden layer and one output layer as shown in Fig. 4. The connection is named as centers if it is between input layer and hidden layer, and named as weights if between hidden layer and output layer [10,18,19]. Radial basis functions are used as activation function of hidden layer. The most common used function is Gaussian function as given in (8).

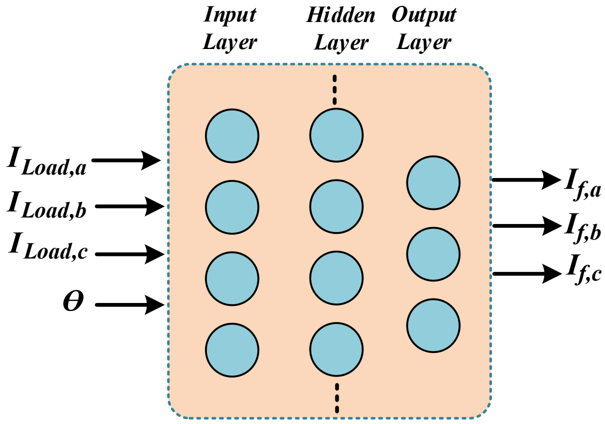

Fig. 4. The structure of RBF network

$$F_k = \exp\left(-\frac{\|x_k - c_k\|^2}{2\sigma^2}\right) \tag{8}$$

where: x, c and σ are input data, centers of Gaussian function and spread of the function, respectively. F is the hidden layer output. K-means clustering method is usually used in order to determine suitable centers. Then, the output of network is obtained as,

$$I_{fk,x} = \mathbf{w}_{\mathbf{k}}^{\mathbf{T}} \mathbf{F}_{\mathbf{k}}, \; x \in \{a, b, c\}, \tag{9}$$

w is the weight vector of output layer, which is updated according to gradient descent method. The updated weight values are obtained as in (10)

$$w_{k+1} = w_k + \eta e_k (x_k - c_k) \tag{10}$$

where: η is learning rate of the weights, and $e_k = (t_{k,x} - I_{fk,x})^2$. t is the desired outputs for a, b and c phases.

4. Performance Results

In this study, a six-pulse nonlinear load is constructed in Simulink/Matlab in order to create the data for neural network. The simulation is performed for 1 s and solution time step is selected as 1 us. Four inputs and three outputs with 500 samples for each are applied to train the network. The system parameters are given in Table 1. The voltage magnitude and frequency of grid are 400 V and 50 Hz, respectively. The range of adjustable resistor is between 1 ohm and 5 ohm. The created simulation for data generation is illustrated in Fig. 5. Besides, the waveforms of targets and inputs to train the network are demonstrated in Fig. 6.

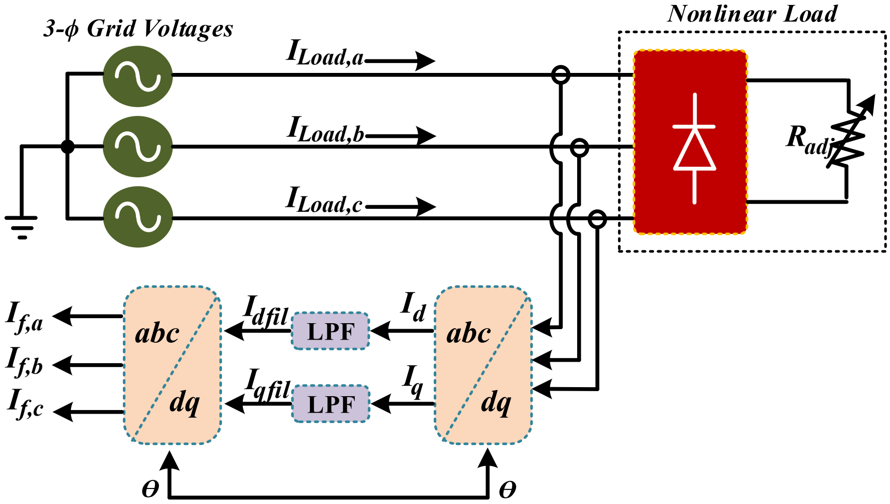

Fig. 5. Nonlinear load construction in Simulink for data generation

Table 1
System Parameters

	Parameter	Value
Source	Voltage	400 V (rms)
	Frequency	50 Hz
Nonlinear Load	Rating	32-160 kVA
	Adjustable Resistor	1 Ω ≤ Radj ≤ 5 Ω
	THD	26.7 %

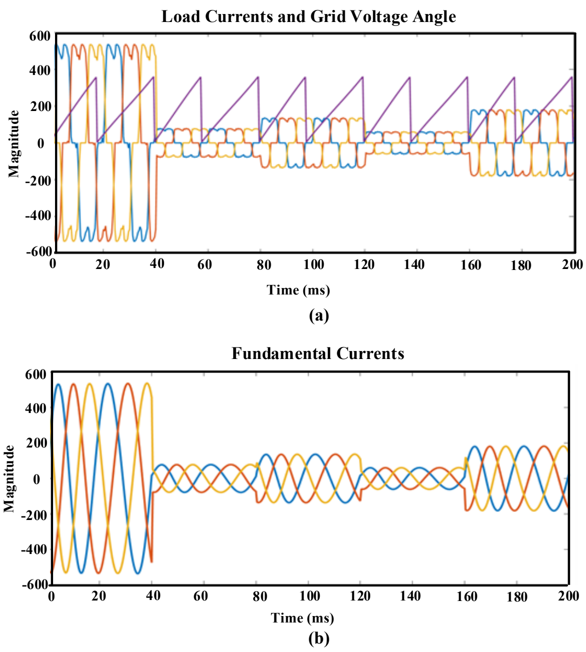

Fig. 6. The waveforms of inputs (a) and targets (b) to train the network for harmonic generation

In order to update the weights and biases of MLF network, four different training algorithms are examined and compared. The examined algorithms are Levenberg-Marquardt (LM), BFGS Quasi-Newton, Resilient Back-propagation (RB) and Scaled Conjugate Gradient (SCG) algorithms. Four training algorithms with one or two hidden layers and various neuron numbers are applied to compare and find the best one. The activation functions of hidden layers and output layer are tansig and pureline, respectively. The examined hidden layer and neuron numbers for training algorithms are “20” and “40” neurons for one hidden layer, and “20x30” neurons for two hidden layers.

The best performance result for MLF network is obtained once LM algorithm is used for one and two hidden layers with different neuron numbers. LM algorithm shows better performance when one hidden layer with 40 neurons is applied. Fig. 7 shows the waveform results obtained by LM algorithm. The upper figure is the waveform obtained by ANN outputs, and the lower figure is obtained by extracting the ANN outputs from nonlinear load currents. The results show that it is better to apply LM algorithm with single hidden layer for harmonic extraction of nonlinear load. The other methods have less accuracy and more epoch numbers, which results in more calculation time.

Single hidden layer is only applied in RBF network, which has radial basis activation function. Gaussian or inverse multiquadratic function are analyzed as activation function. The performance results of harmonic current generation are better when Gaussian function is used. Fig. 8 shows the waveforms of ANN outputs and harmonic currents of nonlinear loads obtained by RBF network with Gaussian function.

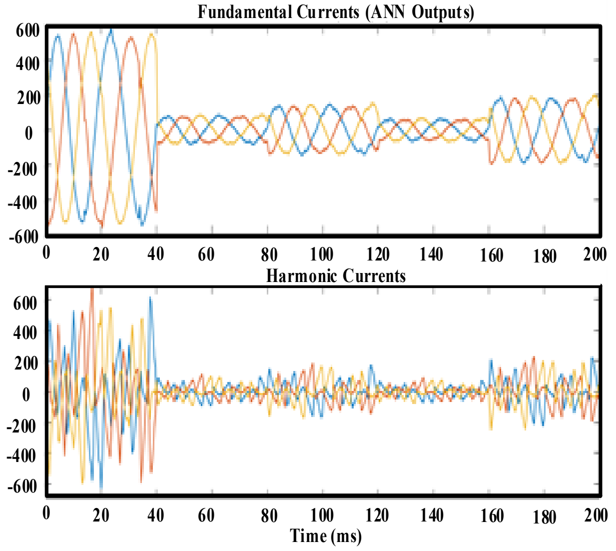

Fig. 7. Waveforms of MLF network outputs (upper) and harmonic currents (lower)

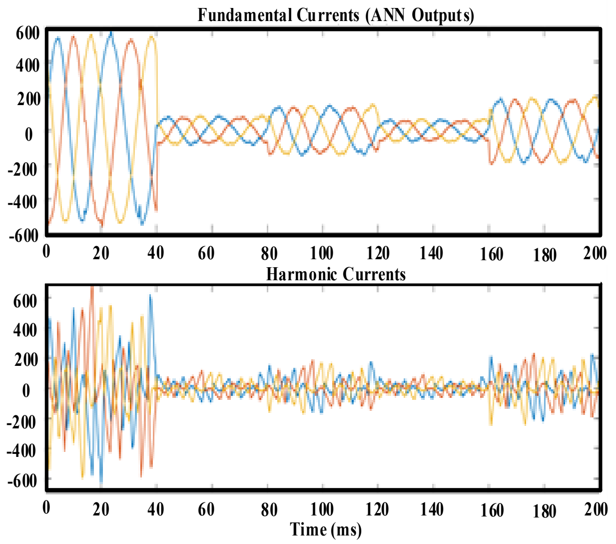

Fig. 8. Waveforms of RBF network outputs (upper) and harmonic currents (lower)

It can be seen from Fig. 7 and Fig. 8 that harmonic extraction of RBF network with Gaussian function is superior to MLF network with LM backpropagation algorithm. The reason of superiority is clustering by which RBF cluster the input data via hidden layer activation function and then approximate the output value to desired value. Besides, RBF network is faster than MLF due to clustering.

5. Conclusions

In this paper, RBF and MLF artificial neural networks are used in order to extract the harmonic current components of six-pulse uncontrolled rectifier. One of the most common ANN structure multilayer feed-forward network with back-propagation algorithm is used. Four different training algorithms are applied and the results are compared. Among these algorithms, LM algorithm is found as the best one for harmonic extraction. This algorithm with one hidden layer shows optimum result in spite of less epoch number. The other widespread ANN architecture for harmonic extraction is RBF network with Gaussian function. RBF network has better harmonic extraction performance compared with MLF network. And owing to clustering of input data, RBF shows faster response.

References

1. Bhattacharya A., Chakraborty C., Bhattacharya S.: Shunt *Compensation - Reviewing Traditional Methods of Reference Current Generation.* IEEE Industrial Electronics Magazine, Vol. 3, No 3, 2009, p. 38–49.
2. İnci M., Demirdelen T., Tümay M.: *Fuzzy Logic Controlled DC-DC Converter Based Dynamic Voltage Restorer.* Journal of Electrical Systems, Vol .11, No. 4, 2015, p. 367-375.
3. Mangaiyarkarasi B., Balasubramaniam P.M.: *Implementation of Artificial Neural Network Controlled Shunt Active Power Filter for Current Harmonics Compensation.* International Journal of Advanced Research in Computer and Communication Engineering, Vol. 4, No. 5, 2015, p.450-457.
4. Saribulut L., Teke A., Tümay M.: *Artificial neural network-based discrete-fuzzy logic controlled active power filter.* IET Power Electronics, Vol. 7, No. 6, 2014, p. 1536–1546.
5. Rukonuzzaman M., Nakaoka M.: *An Advanced Active Power Filter with Adaptive Neural Network Based Harmonic Extraction Scheme.* IEEE 32nd Annual Power Electronics Specialists Conference, 2001, Vancouver, BC, p. 1602-1607.
6. Dehini R., Bassou A., Ferdi B.: *The harmonics extraction method based on neural network applied to harmonics compensation.* International Journal of Engineering, Science and Technology, Vol. 2, No. 5, 2010, p. 258-267.
7. Wei R., Li Z.: *Approach of dynamic extracting harmonics and fundamental reactive current.* in Proceedings of the International Conference of Electrical Engineering (ICEE), 1999, Hong Kong, C l-01, p. 1-4.
8. Elango M.K., Kumar A.N.: Duraiswamy K., *Identification of Power Quality Disturbances using Artificial Neural Networks*. International Conference on Power and Energy Systems (ICPS), 2011, p. 1-6.
9. Chang G.W.: Chen C., Teng Y.F., *Radial-Basis-Function-Based Neural Network for Harmonic Extraction.* Industrial Electronics, IEEE Transactions on, Vol. 57, No 6, 2010, p. 2171 – 2179.
10. Almaita E., Asumadu J.A.: *Harmonic Content Extraction in Converter Waveforms Using Radial Basis Function Neural Networks (RBFNN) and p-q Power Theory.* IEEE Power and Energy Conference at Illinois (PECI), 2011, p. 1-7.
11. Singh B., Arya S.R., Dube S.K.: Chandra A., Al-Haddad K., *Implementation of DSTATCOM using Neural Network Based Radial Basis Function.* IEEE Industry Applications Society Annual Meeting, 2013, p. 1-8.
12. Guangjie F., Hailong Z.: *The study of the electric power harmonics detecting method based on the immune RBF neural network.* Second International Conference on Intelligent Computation Technology and Automation,

2009, p. 121-124.
13. Neural Network Toolbox/MATLAB R2010B
14. Büyük M, Tan A., Bayindir K. Ç., Tümay M.: *Analysis and Comparison of Passive Damping Methods for Shunt Active Power Filter with Output LCL Filter.* ACEMP-OPTIM International Conference on, 2015, p. 434-440.
15. Desouky S.S, Sayed K.F., Abdalla Y.S., Hafez W.A.: *Shunt Active Filter For Harmonic Mitigation Of A Resistance Spot Welding Machine.* Journal of Electrical Engineering, Vol. 16, No. 4, 2016, p. 1-8.
16. Parma G.G., Menezes B.R., Braga A.P.: *Sliding mode algorithm for training multilayer artificial neural networks.* IEEE Electronic Letters, Vol. 34, No. 1, 1998, p.97-98.
17. Raji C.G., Chandra S.S.V.: *Long-Term Forecasting the Survival in Liver Transplantation Using Multilayer Perceptron Networks.* IEEE Transactions on Systems, Man, and Cybernetics: Systems, Vol. 47, No. 8, 2017, p. 2318-2329.
18. Barisal A.K., Hota P.K.: *An evolutionary programming based neuro-fuzzy technique for multiobjective generation dispatch*. Energy, Automation, and Signal (ICEAS), 2011 International Conference on, Odisha, India, 28-30 Dec. 2011, p.1-6.
19. Ertuğrul Ö.F., Tekin R., Kaya Y.:*Randomized feed-forward artificial neural networks in estimating short-term power load of a small house: A case study,* Artificial Intelligence and Data Processing Symposium (IDAP), 2017 International, Malatya, Turkey, 16-17 Sept. 2017, p. 1-5.