HARMONIC EXTRACTION USING NEURAL NETWORK IN DYNAMIC VOLTAGE RESTORER

Mehmet TÜMAY M. Emin MERAL K. Çağatay BAYINDIR
email: mtumay@cu.edu.tr, email: emeral@cu.edu.tr , email: cbayindir@isdemir.com.tr
Çukurova University, Department of Electrical and Electronics Engineering,01130, Balcai, ,Adana/TURKEY
Tel: 90 322 3386868, Fax: 90 322 338632

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ABSTRACT

This paper presents a neural network based harmonic extraction for Dynamic Voltage Restorers. The algorithm employs a Multi Layer Perceptron (MLP) Neural Network with back propagation learning to effectively extract the 3rd and 5th voltage harmonics. The proposed MLP Neural Network algorithm is trained and tested in MATLAB.

I. INTRODUCTION

The wide usage of nonlinear loads, such as personal computers, variable speed drives, UPS systems, and the other electronic equipments produce harmonics which is a major problem in industrial and commercial power systems. The current harmonics are widely spread in industrial systems. These harmonics interact with system impedances and lead to voltage harmonics which badly affect voltage sensitive loads.

Dynamic Voltage Restorers (DVRs) are now becoming more established in industry to reduce the impact of voltage sags to sensitive loads. However, DVRs spend most of their time in standby mode, since voltage sags occur very infrequently, and hence their utilization is low. In principle, it would be advantageous if the series-connected inverter of a DVR could also be used to compensate for any steady-state load voltage harmonics, since this would increase the power quality "value-added" benefits to the grid system [1].

There are many methods for harmonic extraction such as Discrete Fourier Transform and Fast Fourier Transform [2-3], synchronous reference frame (dq) theory [4] and instantaneous power (pq) theory [5].

Harmonic extraction using Fourier Transform is a useful method for specific harmonic component compensation. However, Fourier Transform requires one more cycle of the voltage waveform data and corresponding time such that the delayed harmonic canceling can be occurred [6].

There are some potential problems for pq method in harmonic extraction [7]. The pq theory can determine the harmonic components under load conditions only.

The dq technique which is widely used for voltage sag extraction does not respond fast or does not give accurate results to the voltage harmonics because the inaccuracy which is associated with the PLL and passive filters used in this technique [8].

Artificial Neural Networks (ANN) is a method with learning ability and high speed recognition in the field of electric power. Some ANN applications in this field are as follows: load forecasting [9], harmonic source detection and identification [10], mitigation of voltage disturbances with adaptive perceptron based control [8].

In this paper, two different ANN structures such as fully and partial Multi Layer Perceptron (MLP) are used for extracting harmonics from distorted waves. The distorted waves including 3rd and 5th harmonics are used to be input signals for neural network and network trained with back propagation algorithm. Then, the network is tested with testing waves. The effect of various learning rate and hidden layers are also presented.

II. STRUCTURE OF DVR

DVR is a power electronics inverter-based series compensator that can protect critical loads from supply side voltage disturbances such as sags, unbalances and voltage harmonics. It injects three-phase or single phase ac output voltages in series with the distribution feeder voltages.

The structure of proposed DVR is shown in Figure 1. This device basically works by extracting the voltage harmonics and inject equal but opposite harmonic components into the power line.

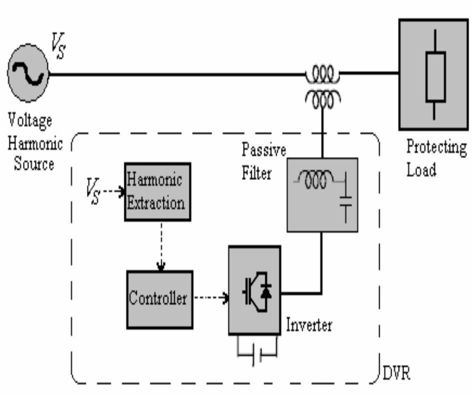


Figure 1. Structure of proposed DVR mitigating harmonics

At the neural network type harmonic extraction, when distorted voltage is detected, the amplitudes of half period voltage wave at regular interval of time axis are used as the input of neural network. This source voltage which has 3rd and 5th harmonics can be expressed as below equation:

$$Vs = V_1 \cos(2wt) - V_3 \cos(3wt) + V_5 \cos(5wt) \qquad (1)$$

where; w is angular frequency of signal, t is the time, V_1 is the fundamental component and V_3 and V_5 are 3rd and 5th harmonic components, respectively.

III. ESTABLISHMENT OF NEURAL NETWORK

TWO DIFFERENT NEURAL NETWORK STRUCTURES

The pattern recognition ability of neural Networks is used for harmonic extraction. For this purpose, 2-types MLP neural network is applied with back propagation learning algorithm. The amplitudes of half period distorted waves taken 80 points at regular interval of time axis are used as input signals of neural network. The fully connection network is shown in Figure 2 (a). It is consisted of 80 input nodes, 20 hidden nodes and 2 output nodes. Each output-node is the normalized value of 3rd and 5th harmonic components. In this structure, each nodes of hidden layer fully connects to all nodes in output layer. Another type neural network is partial connection network which is shown in Figure 2(b). The structure is same as previous structure. However, hidden nodes are divided to two groups in this structure. The nodes in each group connect with only one output node. As each output node never connects with the same hidden nodes, each output node is independent each other.

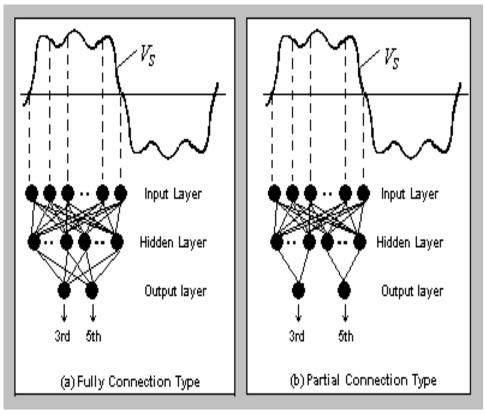


Figure 2. Network types of proposed method

DISTORTED WAVES

Table 1. The contents of each component in supervisor waves

Sample number supervisor waves	3rd Harmonic component (V_3) (%)	5th Harmonic component (V_5) (%)
1	0	0
2	10	0
3	20	0
4	30	0
5	0	10
6	10	10
7	20	10
8	30	10
9	0	20
10	10	20
11	20	20
12	30	20
13	0	30
14	10	30
15	20	30
16	30	30

For the purpose of extraction harmonic from distorted waves, it is necessary to use some sample distorted (supervisor) waves for training. Supervisor waves have four normalized values of harmonic components as 0.0, 0.1, 0.2 and 0.3 and these values are used target output at training. The variation of each component in the 16 learning waves is shown in Table 1 as percentage of fundamental component's amplitude.

IV. THE EFFECTS OF VARIOUS PARAMETERS IN NEURAL NETWORK

NETWORK STRUCTURE

Figure 3 shows the changing of learning error of fully connection network and partial connection network by learning waves (Table 1). The learning error of fully connection network completes around $7x10^{-4}$ while the learning error of partial connection network completes around $2x10^{-4}$ at total 2000 epochs. It is seen that, the learning error of partial connection network is much less than fully connection network.

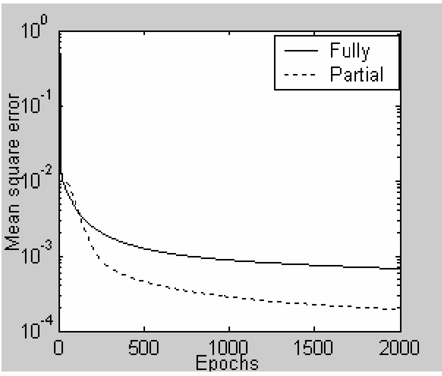


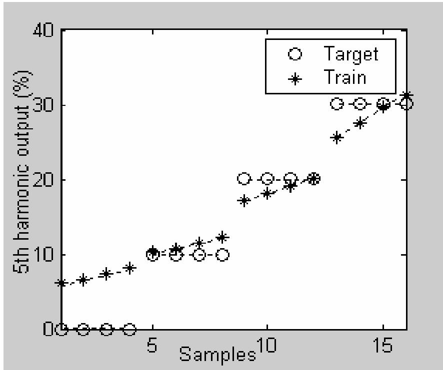
Figure 3. The variation of mean square error

While the total epoch number is 400, the training output of harmonic extraction for fully connection and partial connection are shown in Figure 4 (a) and (b), respectively. From Figure 4 (a), it is seen that the content of 3rd harmonic which neural network extracted is not approximate to target value. Moreover, the output of 3rd harmonic is affected by the variation of 5th harmonic. However, from Figure 4 (b) it is seen that the extraction results approximate to ideal value and each output is not influenced by 5th harmonic.

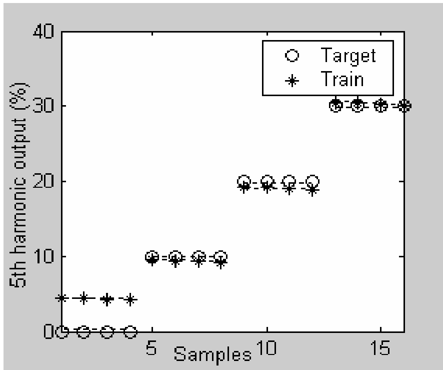
As learning error of partial connection network has decreased more (Figure 3), it means that the precision of learning could be improved. Thus, the testing waves may be used for recognition in order to confirm the recognition precision. The distorted waves for testing are made as following case in which there are 15 distorted waves:

i) 3rd harmonic content varies as “1%, 3%, 5%, …, 29%” while 5th harmonic content is fixed at “15%”.

ii) 5th harmonic content varies as “1%, 3%, 5%, …, 29%” while 3rd harmonic content is fixed at “15%”.



(a) Fully Connection



(b) Partial Connection

Figure 4. 5th harmonic outputs

The results of recognition by using distorted waves (i) in which 3rd harmonic content varies while 5th harmonic content is fixed at 15%, are shown in Figure 5 and also the results by using distorted waves (ii) in which 5th harmonic content varies while 3rd harmonic content is fixed at 15%, are shown in Figure 6. It is seen that 5th harmonic is not influenced by 3rd harmonic changing. However, the test outputs approximate to target value (actual values of harmonic components).

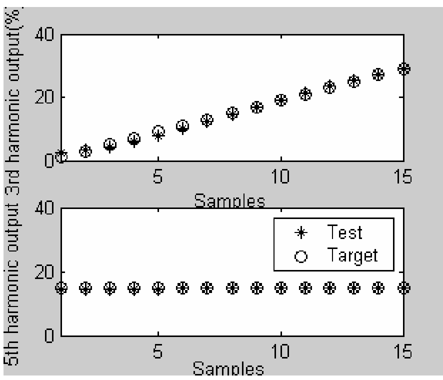


Figure 5. The test results of recognition by using distorted waves (i)

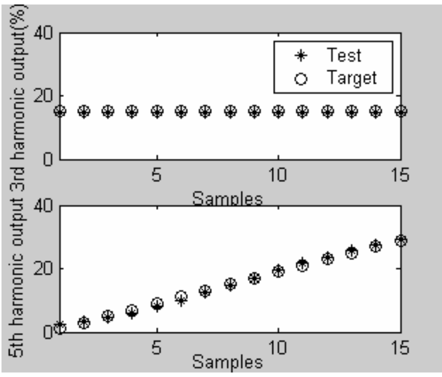


Figure 6. The test results of recognition by using distorted waves (ii)

HIDDEN LAYER'S STRUCTURE

It is necessary to use hidden layer for non-linear solving. For example XOR problem can not solve without hidden layer. Figure 7 shows at various states, such as "$h = 4{,}10{,}20$" the MSEs of the partial connection-type network trained with supervisors.

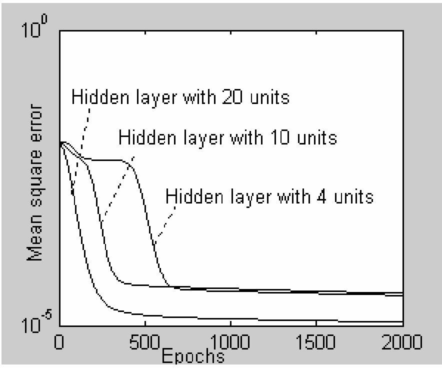


Figure 7. The changing of MSE for various hidden layer structures

Train MSE, test MSE and average percentage success (PS) are shown in Table 2 for each state.

$$PS = \frac{T - O}{T} * 100 \qquad (2)$$

where; T is desired value of test output, O is calculated value.

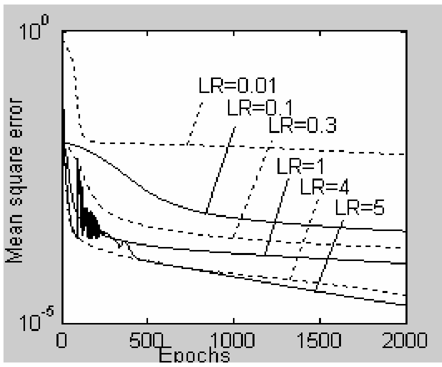
As it is seen from Table 2, the structure which has 10 nodes in hidden layer is better than 4-nodes structure at the low epoch numbers. But at the high epoch numbers, they are almost same. 20-nodes structure has the most success for all cases. But, if the simulation time and a little success difference are taken into account, it would might be said that hidden layer with 4-nodes is more suitable.

Table 2. MSE and PS values with different number of hidden layer nodes

The number of hidden layer nodes	Epoch number of train for $MSE = 5x10^{-5}$	Test MSE after 1000 epochs training	Average Percentage Success of test after 1000 epoch training
4	635	1.297 x10-5	99.180
10	403	1.929 x10-5	98.944
20	201	0.644x 10^{-5}	99.377

LEARNING RATE VALUE

As the constant called learning rate (η) gets larger, the changing rate of weight get larger. In practice, the aim is to select the biggest learning rate without oscillation, because the magnitude of this constant provides a fast learning. The train errors according to changing of learning rate (LR) are shown Figure 8.

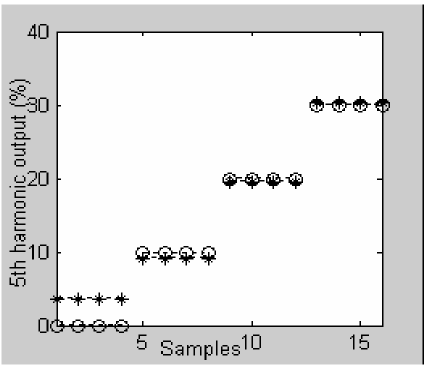


(a) $\eta = 0.01$ to $\eta = 5$

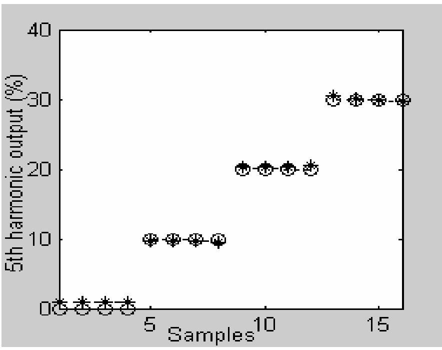
Figure 8. The MSEs of train according to various η values

It is seen that, when the learning rate increases, more rapid learning is obtained. Oscillations starts after $\eta = 5$, but MSE has continued to decrease. Also, it would might be said that, learning rate around 5 more suitable. For, $\eta = 0.1$ and $\eta = 5$, the 5th harmonic outputs of train are shown in Figure 9.

As mentioned in Reference [10]; for logistic function which is used in each unit, it may be difficult to get 0.0 ~ 0.3 output (Figure 4). This may be the cause which make learning error does not decrease lower. In this paper, the accuracy of training is improved by changing learning rate. It is seen that from Figure 9, the learning of harmonics near zero, is better when η has bigger values.



(a) $\eta = 0.1$



(b) $\eta = 5$

Figure 9. Train outputs

V. CONCLUSION

In this paper, an application of MLP neural network for harmonic extraction is explained. The possibility of proposed neural network to extract harmonics is confirmed by using distorted waves which include 3rd and 5th harmonic components. It is seen that the process is simplified with neural network and using neural network is an effective method to extract harmonics in Dynamic Voltage Restorer by means of high speed recognition and practicability. The partial MLP neural network structure is more effectively extracted 3rd and 5th harmonic components of testing waves. It is also shown that the train of harmonic extraction in which harmonic values are close to zero, are most accurate when η has bigger values.

VI. ACKNOWLEDGEMENTS

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