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İLERİ BESLEMELİ YAPAY SİNİR AĞLARINDA KULLANILAN GİZLİ KATMAN SAYILARININ HARMONİK TANIMADA ETKİSİ

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ÖZET

Bu çalışmada Aktif filter işlemlerinde harmonic belirleme için iki farklı gizli katman sayıları ile ileri beslemeli yapay sinir ağlı metodu tanımlanmıştır. Distorsiyonlu dalga içinden 5,7,11 ve 13. harmoniklerin simülasyonu yapılarak bu harmoniklerin yapay sinir ağının eğitimi için kullanılmıştır. Distorsiyonlu dalga 25. harmonige kadar yapay sinir ağında test için hazırlanmıştır. İleri beslemeli yapay sinir ağları harmoniklerin her birini tanımada kullanılmıştır. sonuçlar gösteriyor ki yapay sinir ağları harmonic tanımada etkili bir şekilde kullanılabilir. İki gizli katmanlı yapay sinir ağlarının sonuçları digerlerinden daha iyidir.

Anahtar kelimeler: *Yapaya Sinir Ağları, Harmonik Belirleme, Gizli Katman, Aktif Filtre*

EFFECTS OF THE HIDDEN LAYERS IN THE HARMONIC DETECTION USING FEED FORWARD NEURAL NETWORKS

ABSTRACT

In this study, the methods to apply the feed forward neural networks with two different numbers of hidden layers for harmonic detection process are described. We simulated the distorted wave including 5th, 7th, 11th, 13th harmonics and used them for training of the neural networks. The distorted wave including up to 25th harmonics were prepared for testing of the neural networks. Feed forward neural networks were used to recognize each harmonic. The results show that these neural networks are applicable to detect each harmonic effectively. The results of the neural network with two hidden layers are better than that of the other.

Key Words: *Artificial Neural Networks, Harmonic Detection, Hidden Layer, Active Filter*

1. INTRODUCTION

Power quality has received increased attention in recent years with the widespread application of nonlinear loads employing advanced solid-state power switching devices in a multitude of industrial and commercial applications. The operation of solid-state power switching devices in power electronic converters deteriorates the power quality by injecting harmonics into the power system causing increased distortions, equipment and load malfunctions and losses [1-3].

AC power systems have a substantial number of large harmonic generating devices, e.g. adjustable speed drives for motor control and switch-mode power supplies used in a variety of electronic devices such as computers, copiers, fax machines, etc. These devices draw non-sinusoidal load currents consisting primarily of lower-order 5^{th}, 7^{th}, 11^{th}, and 13^{th} harmonics that distort the system power quality. [3]. With the widespread use of harmonic-generating devices, the control of harmonic currents to maintain a high level of power quality is becoming increasingly important. Harmonic standards (e.g. IEEE 519 and IEC 555) have been developed to address limits in allowable harmonics [4].

A common remedial measure for reducing the effects of harmonics is passive filtering [5]. The addition of passive "LC" filters alters, or interferes, with the system impedance, and is known to cause resonance with other network impedances and can result in an excessive amplification of harmonics rather than harmonic reduction. In addition, passive filters

An effective way for harmonic elimination is the harmonic compensation by using active power filter. Active power filter detect harmonic current from distorted wave in power line, then generates negative phase current as same as detected harmonic to cancel out the harmonic in power system. Using of the feed forward neural networks is one of the methods for harmonic detection. [6-8].

In this study, the methods to apply the feed forward neural networks with two different numbers of hidden layers for harmonic detection process in active filter are described. The feed forward neural networks were also used for comparison. The distorted wave including 5^{th}, 7^{th}, 11^{th}, and 13^{th} harmonics are used to be input signals for these neural networks at the training state. The output layer of network is consisted of 4 units in according to each order of harmonic. By effect of learning representative data, each component of harmonic is detected to each according unit. That means neural network structures can decompose each order of harmonic and detect only harmonic without fundamental wave in the same time.

2. THE METHOD TO DETECT HARMONIC BY USING NEURAL NETWORK

Figure 1.a depicts the concept of active power filter. Figure 1.b shows the process of the harmonic detection in the active power filter using feed forward neural networks (FFNN).

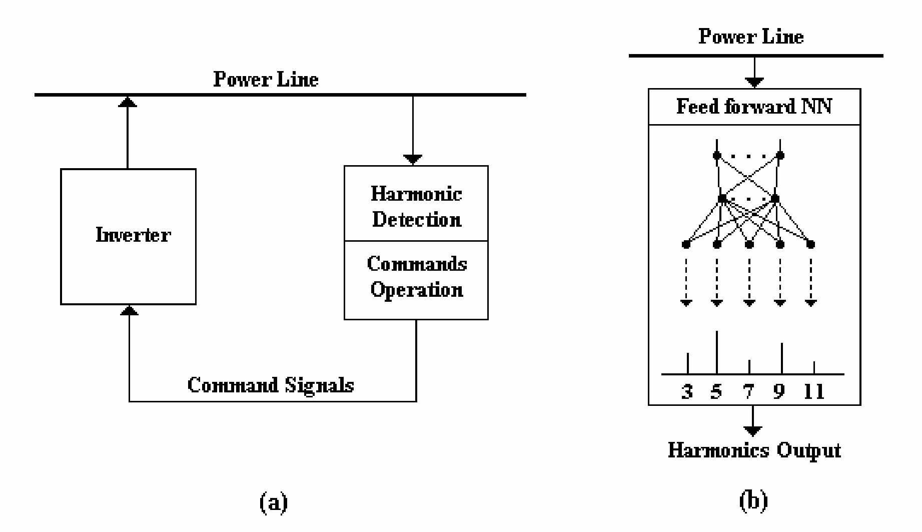

Figure 1. Concept of Active Power Filter (a), Process of Harmonic Detection in Active Power Filter Using Feed Forward Neural Networks (b)

The distorted current from power line is analyzed using FFNN. After recognizing of each harmonic using FFNN, these harmonics are output to be used for compensating current generation [6-8]. In this study, we use the feed forward neural networks with two different numbers of hidden layers to detect each component of harmonic. When distorted current is detected from power line, the amplitude from one cycle distorted wave is input to each unit of the neural networks in term of serial signals. By means of using the feed forward neural networks with two different numbers of hidden layers, each harmonic is decomposed separately.

3.FEED FORWARD NEURAL NETWORK FOR HARMONIC DETECTION

Because of non-sinusoidal load currents consisting primarily of lower-order 5th, 7th, 11th, and 13th harmonics that distort the system power quality, we consider about 5th, 7th, 11th, and 13th harmonics detection. We used the feed forward neural network as seen in Figure 2. This network is a multilayer network (input layer, hidden layers, and output layer). The hidden layer neurons and the output layer neurons use nonlinear sigmoid activation functions. Equations which used in the neural network model are shown in (1), (2), and (3).

Outputs of the first hidden layer neurons are,

$$X_j(n) = 1 \bigg/ \left(1 + \exp\left(b_j^{ih}(n) + \sum_{i=1}^{N} W_{ij}^{ih}(n) U_i(n)\right)\right) \qquad (1)$$

Outputs of the second hidden layer neurons are,

$$V_j(n) = 1 \Bigg/ \left(1 + \exp\left(b_j^{hh}(n) + \sum_{i=1}^{N1} W_{ij}^{hh}(n) X_i(n)\right)\right) \tag{2}$$

Outputs of the network are,

$$Y_l(n) = 1 \Bigg/ \left(1 + \exp\left(b_l^{o}(n) + \sum_{j=1}^{N2} W_{jl}^{ho}(n) V_j(n)\right)\right) \tag{3}$$

where $b_j^{ih}(n)$ are the biases of the first hidden layer neurons, $b_j^{hh}(n)$ are the biases of the second hidden layer neurons, $b_l^{o}(n)$ are the biases of the output layer neurons, $W_{ij}^{ih}(n)$ are the weights from the input to the first hidden layer, $W_{ij}^{hh}(n)$ are the weights from the first hidden layer to the second hidden layer, $W_{jl}^{ho}(n)$ are the weights from the second hidden layer to the output layer, *Uj(n)*, *i* = 1 to *N* are the sensor inputs, and *Yl(n)*, *l* = 1 to *N3* are outputs for concentrations. In this study, 128 is used as N, 4 is used as N3, and five different values which are 10, 20, 30, 60, and 90 are used as N1 and N2. The network with one hidden layer was also used for comparison.

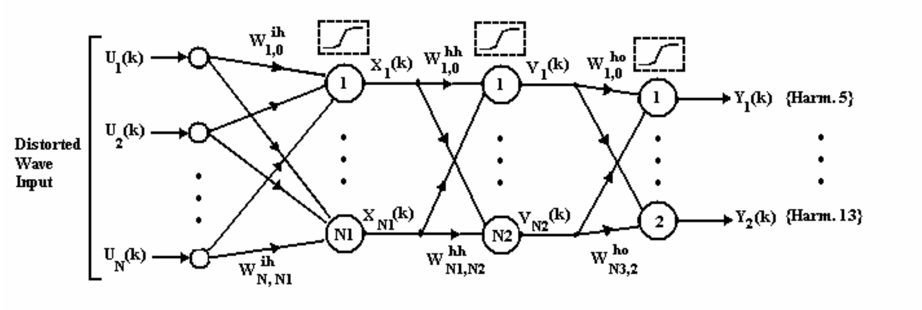

Figure 2. Feed Forward Neural Network Structures With Two Hidden Layer For Harmonics Detection

4. TRAINING OF THE NETWORKS

A back propagation (BP) method is widely used as a teaching method for an NN. The main advantage of the BP method is that the teaching performance is highly improved by the introduction of a hidden layer [9]. In this paper, BP learning rules with momentum and adaptive learning rate are used to adjust the weights and biases of networks to minimize the sum-squared error of the network. This is done by continually changing the value of the network weights and biases in the direction of steepest descent with respect to the error.

The BP with momentum method decreases BP's sensitivity to small details in the error surface. This helps the training process to avoid being stuck in shallow minima.

Training time can also be decreased by the use of an adaptive learning rate, which attempts to keep the learning rate step size as large as possible while keeping learning stable [10]. These two techniques can be used with BP to make it a faster, more powerful, and more useful learning paradigm [10].

In order to make neural network enable to detect harmonics from distorted wave, it is necessary to use some representative distorted waves for learning. These distorted waves are made by mixing the component of the 5^{th}, 7^{th}, 11^{th}, and 13^{th} harmonics in fundamental wave. For this purpose, 5^{th} harmonic up to 70%, 7^{th} harmonic up to 40%, 11^{th} harmonic up to 10% and 13^{th} harmonic up to 5% were used and approximately 2500 representative distorted waves were generated for training process.

During the training process, the distorted waves were used for recognition. As the result of recognition, output signal from each output unit means the coefficient of each harmonic which is including in the input distorted wave and these harmonics are eliminated from the distorted wave. Equations which used in the elimination process are shown in (7), and (8).

$$V_f(t) = V_d(t) - \sum_h V_h(t) \tag{7}$$

$$V_h(t) = A_h Sin(2\pi ft + \theta) \tag{8}$$

where, $V_f(t)$ is active filtered wave, $V_d(t)$ is distorted wave, h = 5,7,11,13, A_h are coefficients of lower-order 5^{th}, 7^{th}, 11^{th}, and 13^{th} harmonics, f = 50 Hz, θ is phase angle and equal to zero in this study.

5. THE QUALITY OF POWER SYSTEM WAVES

The common index used to determine the quality of power system currents and voltages are total harmonic distortion (*THD*) [1,2], which is defined as

$$THD = \sqrt{\frac{\sum_2^{\infty} V_h^2}{V_1^2}} \tag{9}$$

where V_h represents the individual harmonics and V_1 is the fundamental component of load wave.

6. RESULTS AND CONCLUSIONS

The non sinusoidal load currents consist the higher order harmonics such as 17th, 19th, etc., but they do not carry any significant current [1]. So, for the performance evaluation of the neural network structures, 5th harmonic up to 70%, 7th harmonic up to 40%, 11th harmonic up to 10% and 13th harmonic up to 5%, 17th harmonic up to 5%, 19th harmonic up to 2.5%, 23rd harmonic up to 2.5%, 25th harmonic up to 2% were used [11] and approximately 250 representative distorted waves were generated as a test set.

For the training and test processes, input signals of the neural networks are the amplitudes of one period of distorted wave. The amplitudes are taken 128 point at regular interval of time axis. The amplitudes are used to be input signals of the neural networks without any pre processing. At the training phase, the higher order harmonics such as 17th, 19th, etc., are ignored for *THD* calculations.

As a first step, five different numbers of hidden layer neurons were used to determine the effects of hidden layer neurons. Figure 3 shows the comparative training results of the feed forward neural networks with adaptive learning rate. Optimum number of hidden layer neurons for the feed forward neural networks is approximately 20 as seen in Figure 3. For all comparisons, the numbers of iterations taken for training are 50000 as seen in Figure 4.

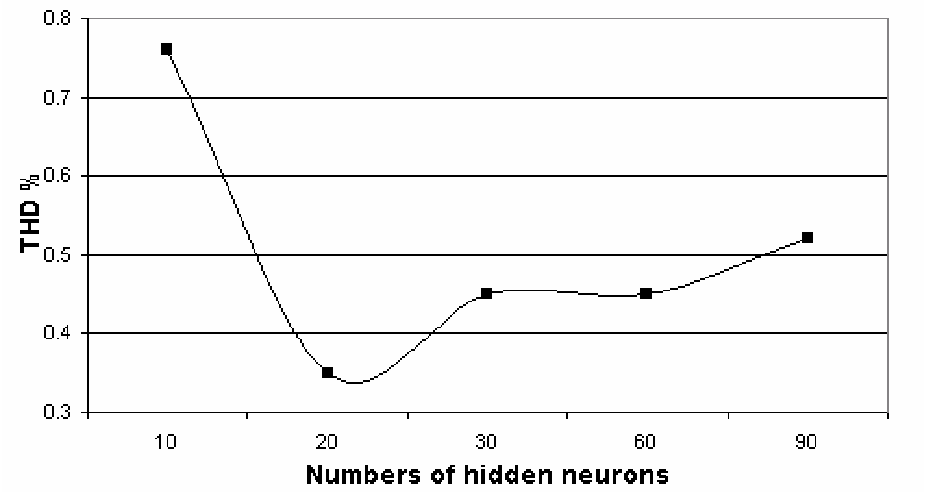

Figure 3. Training Results of Feed Forward Neural Networks With One Hidden Layer

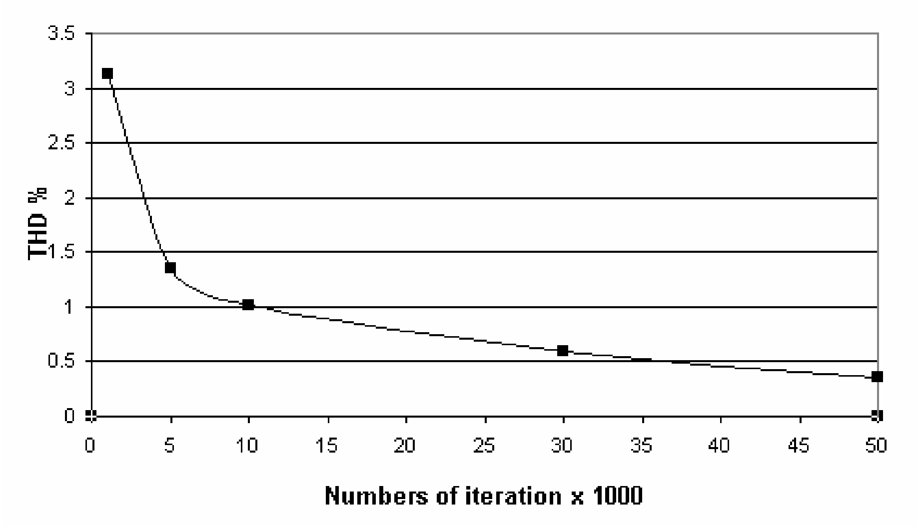

Figure 4. Training Results of Feed Forward Neural Network With 20 Hidden Neurons

Figure 5 shows the training results of feed forward neural networks with one hidden layer and two hidden layers. As seen in this figure, the results of FFNN with two hidden layers are the same that of FFNN with one hidden layer.

After the training process is completed, the general distorted waves (test set) were used for recognition. As the result of recognition, output signal from each output unit means the coefficient of each harmonic which is including in the input distorted wave and these harmonics are detected from the distorted wave.

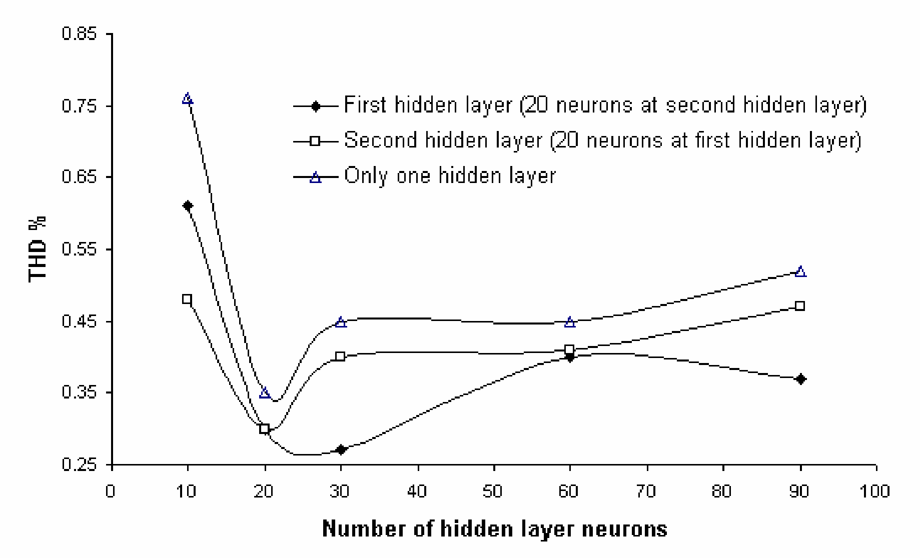

Figure 5. Training Results of Feed Forward Neural Networks With One and Two Hidden Layers

Table 1 shows the average *THD* values of restored waves obtained by using the feed forward neural networks for the test set.

Table 1. Average *THD* Values

Numbers of hidden layers	Numbers of hidden layers at first hidden layer	Numbers of hidden layers at second hidden layer	Average *THD* (%)
Before compensation			46.36
1	10	-	3.73
	20	-	3.66
	30	-	3.67
	60	-	3.67
	90	-	3.68
2	10	20	3.70
	20		3.66
	30		3.66
	60		3.67
	90		3.67
	20	10	3.68
		20	3.66
		30	3.68
		60	3.67
		90	3.67

The recommendation IEEE 519 allows a total harmonic distortion (*THD*) of 5% in low-voltage grids [12]. As seen in the table 1, average *THD* value is 46.36% before compensation. After compensation the average *THD* values are less then 4% for all networks. *THD* values 3.65% come from the higher order harmonics such as 17^{th}, 19^{th}, etc which are not used in the training. This means that there is a improvement potential. The *THD* values obtained by using FFNN with two hidden layers are almost the same as the *THD* values obtained by using FFNN with one hidden layer. The sample source wave and the restored waves are shown in Figure 6 and 7.

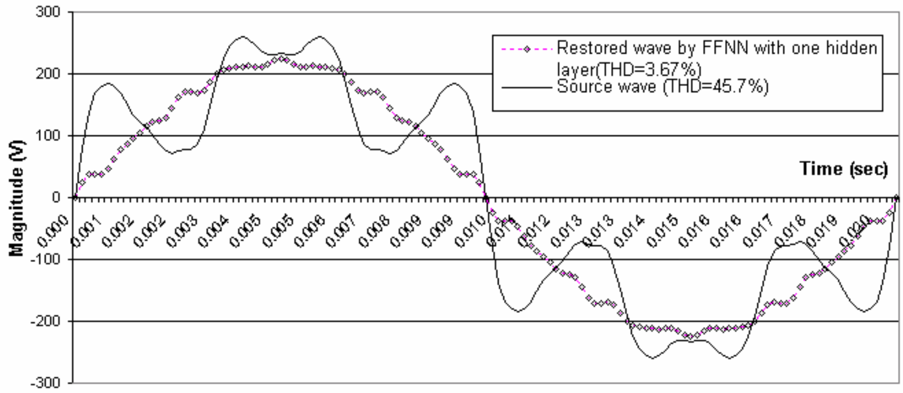

Figure 6. Sample Source and Restored Waves (by FFNN with one hidden layer)

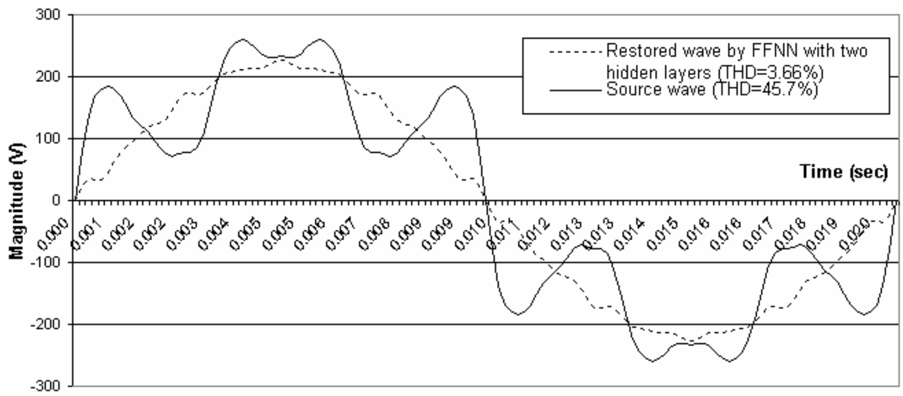

Figure 7. Sample Source and Restored Waves (by FFNN with two hidden layers)

As the result, the possibility of the feed forward neural networks to detect harmonics is confirmed by compensating the distorted waves and it can be said that the feed forward neural networks are effective to use as an harmonic detection.

REFERENCES

[1] W.R.A. Ryckaert, J.A.L. Ghijselen, J.A.A. Melkebeek, Harmonic mitigation potential of shunt harmonic impedances, Electric Power Systems Research 65 (2003) 63-69

[2] S.M.R. Rastegar, W.T. Jewell, A new approach for suppressing harmonic disturbances in distribution system based on regression analysis, Electric Power Systems Research 59 (2001) 165-184

[3] A. Unsal, A.R. von Jouanne, V.L. Stonic, A DSP controlled resonant active filter for power conditioning in three phase industrial power system, Signal Processing, Vol. 82 (2001)1743-1752

[4] IEEE Standarts 519-1992, IEEE Recommended Practice and Requirements for Harmonics Control in Electric Power Systems, Piscataway, NJ, (1992)

[5] IEEE Recommended Practices for Power System Analysis, IEEE Inc., New York, NY (1992)

[6] N. Pecharanin, M. Sone, H. Mitsui, An application of neural network for harmonic detection in active filter, ICNN (1994) 3756-3760

[7] M. Rukonuzzaman, M. Nakaoka, Adaptive neural network based harmonic detection for active power filter, IEICE Transactions On Communications, E86B (5) (2003) 1721-1725

[8] R. Gunturkun, N. Yumusak, F. Temurtas, Detection of Harmonics by using Artificial Neural Network, TAINN 03 Conference, July (2003)

[9] M.M. Abdelhameed, F.F. Tolbah, A recurrent neural network based sequential controller for manufacturing automated systems, Vol. 12, (2002) 617-633

[10] S. Haykin, Neural Networks, A Comprehensive Foundation, Macmillan Publishing Company, Englewood Cliffs, N.J. (1994)

[11] W.E. Reid, Power quality issues – standards and guidelines, IEEE Trans. on Ind. App., Vol. 32(3) (1996) 625- 632

[12] T.E., Nunez-Zuniga, J.A. Pomilio, Shunt active power filter synthesizing resistive loads, Vol. 17(2) (2002) 273-278