Design of ANFIS Controller for DC-DC Step-Down Converter

Ömer Deperlioğlu[a], Uçman Ergün[b] ve Gür Emre Güraksın[c]
[a]*Afyon Kocatepe University, Engineering Faculty, Biomedical Engineering Department, Afyonkarahisar, Turkey*
e-posta: deperlioglu@aku.edu.tr
[b]*Afyon Kocatepe University, Engineering Faculty, Electronic & Communication Engineering Department, Afyonkarahisar, Turkey*
e-posta: uergun@aku.edu.tr
[c]*Afyon Kocatepe University, Engineering Faculty, Computer Engineering Department, Afyonkarahisar, Turkey*
e-posta: emreguraksin@aku.edu.tr

Geliş Tarihi: 18 Nisan 2011; Kabul Tarihi: 12 Mayıs 2011

Abstract

In this paper, a general purpose Adaptive Neuro Fuzzy Inference System (ANFIS) controller for dc-dc switching converters is researched. It has been proved that ANFIS controllers are capable of approximating any real continuous control function a compact set to arbitrary accuracy. In particular, any given linear control can be achieved with a ANFIS controller for given accuracy. For ANFIS, the presented approach is general and can be applied to any dc-dc converter topologies. Simulation of buck converter results demonstrated that the converter can be regulated with a good performance even thought subjected to input disturbance and load variation.
Key Words: ANFIS, Fuzzy logic control, dc-dc converters, switch-mode converters.

DA-DA Gerilim Azaltan Konvertörler için ANFIS Denetleyici Tasarımı

Özet

Bu makalede, DA-DA Buck Konvertörler (gerilim azaltan) için, genel amaçlı Uyarlamalı Sinirsel Bulanık Mantık Çıkarım Sistemli denetleyiciler araştırılmıştır. ANFIS denetleyicilerin, herhangi bir sürekli gerçek kontrol fonksiyonun çözümünde yetenekli olduğu ispatlanmıştır. Özellikle ANFIS denetleyici ile verilen herhangi bir doğrusal denetimde arzu edilen kesinlikte gerçekleştirilebilir. ANFIS için bahsi geçen yaklaşım geneldir ve herhangi bir DA-DA konvertör topolojisine uygulanabilr.Yapılan Simülasyon sonuçları konvertörün girişteki bozulmalara ve yük değişimlerine rağmen çıkış gerilimini düzenlediğini göstermektedir.
Anahtar Kelimeler: ANFIS, Bulanık mantık kontrol, DA-DA konvertör, Anahtarlamalı tip konvertörler.

1. Introduction

DC-DC converters are the power electronic circuits that convert the DC voltage to different DC voltage level and mostly produce regulated output. In general, these circuits are classified as switched-mode DC-DC converters. (Hart, 1997; Mohan et. al., 1995; Lander, 1993). In some resources, they are called as switching-mode regulators (Rashid, 1988) or DC-DC chopper (Gürdal, 1997, Bradley, 1987).

Many probabilistic methods have been developed over the past several decades, and are now being used more widely in power system operations and planning to deal with a variety of uncertainties involved. Examples of these uncertainties are equipment outages, load forecast uncertainties, weather conditions, uncertainties in the availability of basic energy and operating considerations (Singh and Wang, 2008). The DC-DC converters have been controlled successfully for years by using the analog integrated circuit technology and linear system design techniques. With beginning of operation of semi-conductive materials as a switch, the converter process could be defined with series of linear connections. The applied techniques can be used to obtain linear average models with a good approach to sectional behaviors of the system. Recently, researches make studies about application of the fuzzy logic principles on control of DC-DC converters. Controlling of the DC- DC converters with fuzzy logic controller has been tried to be developed through the world-wide researches. (Bay et. al., 2003; Elmas et. al., 2009; So and Tse, 1996; Lin, 1995; Mattavelli et. al., 1997; Lin, 1997; Leyva et. al., 1997).

The control action in the fuzzy logic controller is determined by means of evaluation of the group of simple language rules. Development of rules requires the system that is being controlled to be fully comprehensible. However, it does not require the mathematical model of the system. Consequently, technique is general and for this reason, a control schema developed for any type of DC-DC converters can also be easily applied on other types (Bay et. al., 2003).

The ANFIS can simulate and analysis the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given fuzzy inference system (FIS). It combines the benefits of artificial neural networks (ANNs) and FISs in a single model. Fast and accurate learning, excellent explanation facilities in the form of semantically meaningful fuzzy rules, the ability to accommodate both data and existing expert knowledge about the problem, and good generalization capability features have made neuro-fuzzy systems popular in the last few years (Daldaban and Ustkoyuncu, 2009). Because of these fascinating features.

In this paper, controlling of a buck converter by means of an ANFIS controller is considered. The fuzzy logic control rules and membership functions of the system have been established. A simulation study of the system control with the ANFIS controller in C programming language has been made.

2. Adaptive Neuro Fuzzy Inference System

The fuzzy inference systems and multi-layer perceptrons are special samples in very general calculation studies of adaptive networks. ANFIS is a class of adaptive networks that is functionally equal to fuzzy inference system. The ANFIS system that means a adaptive network-based fuzzy inference system or an adaptive neural fuzzy inference system consists of initials of its original name; Adaptive Network-based Fuzzy Inference System or Adaptive Neuro Fuzzy Inference System (Gupta et. al., 1997). Meanwhile, in some resources, ANFIS is defined as the TSK fuzzy rules and neuro-fuzzy controller. TSK means Sugeno fuzzy model or Takagi, Sugeno, Kant fuzzy logic model (Lin and Lee, 1996). It is also called as hybrid neural networks (Jang et. al., 1997). It is a method that depends on the principle of adjustment of fuzzy control parameters with neural networks from methods of combination of fuzzy logic and artificial neural networks.

In fact, the fuzzy inference system is stronger than the multi-layer perceptron. For instance, some unique features of ANFIS controllers can be defined;

1. Learning ability,
2. Parallel processing,
3. Structured information representation,
4. Better integration with other control design methods.

The multi-layer perceptron also has the features given in 1st and 2nd but not the features given in the 3rd and 4th.

2.1. The ANFIS Architecture

To easily understand the architecture of fuzzy inference system in structure of ANFIS, if it is considered that it has two inputs as x and y and one output as z, the two fuzzy If-then rules for the first degree Sugeno fuzzy model will be as in equation 1.

$$\left.\begin{array}{l}\text{Rule 1: IF } x = A_1 \text{ and } y = B_1 \text{ Then } f_1 = p_1x+q_1y+r_1 \\ \text{Rule 2: IF } x = A_2 \text{ and } y = B_2 \text{ Then } f_2 = p_2x+q_2y+r_2\end{array}\right\} \quad (1)$$

In the equation, i=1,2 and j=1,2 ; and x_i represents the input variable , y output variable, A_i, μA_i the linguistic terms of sub modes together with the membership function, $p_i, q_i, r_i \ \varepsilon \ R$; $f_j(x_1, x_2)$ represents the coefficients of linear equations. The output of i. node in L layer is given as O_{li} ,besides ,all nodes in the same layer have the same node function.

In figure 1, the Sugeno type fuzzy inference method with two inputs and two rules is given. f=f(x,y) corresponds to the newest function in result and w_i to firing strength in A and B fuzzy sets, and all the outputs are obtained with weighted average.

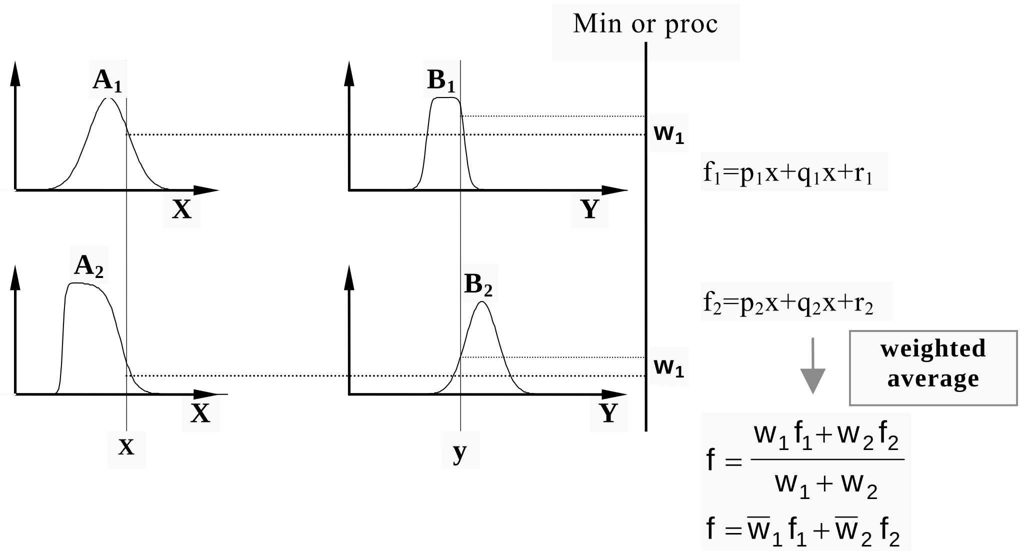

Figure 1. Sugeno type fuzzy inference with two inputs and two rules

In Figure 2, the ANFIS architecture that is equal to the Sugeno type fuzzy inference with two inputs and two rules is seen. The node functions that belong to each layer in the ANFIS architecture and so, functions of layers are given below respectively.

Layer 1: Each node in this layer is an input node where external signals are transferred to other layers. Layer 2: Each node in this layer behaves like the membership function of $\mu_{A_i}(x)$ and the degree of its output characteristics conforms to x that characterizes A_i. So, it is an adaptive node with its node function and the node outputs are as in equation 2.

$$\begin{array}{l} i = 1,2 \text{ for } o_{2,i} = \mu_{A_i}(x) \\ i = 3,4 \text{ for } o_{2,i} = \mu_{B_{i-2}}(y) \end{array} \qquad (2)$$

Here, x and y are inputs to i. node and A_i or B_{i-2} are linguistic labels like "less-more" that combine with this node. In other words, $o_{2,i}$ is the membership degree of fuzzy set A like $A=A_1$, A_2, B_1 and the given input determines the membership degree that corresponds to the quantity determinant A for x or y. Here, any desired membership degree can be used. In general, bell-shaped membership functions (maximum = 1 and minimum = 0) is used and the result function is given in equation 4.

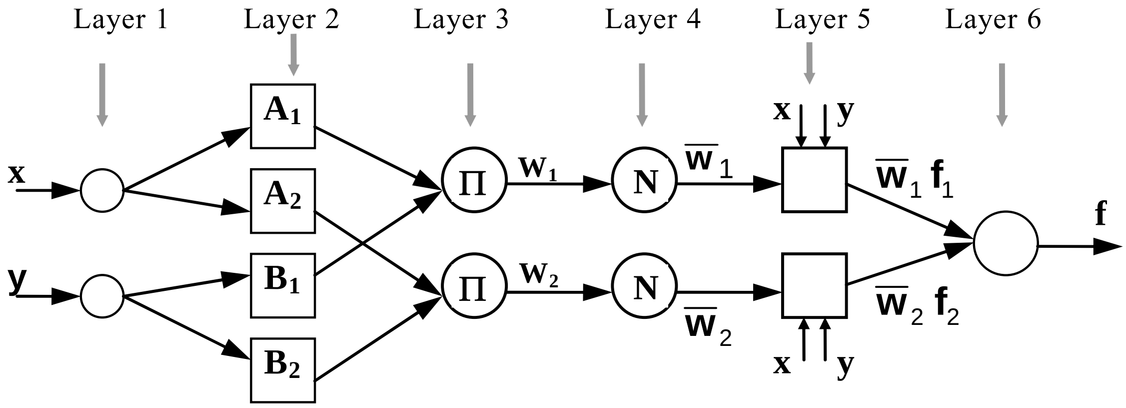

Figure 2. The ANFIS architecture that is equal to the Sugeno type fuzzy inference with two inputs and two rules

$$\mu_{A_i}(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{3}$$

$$\mu_{A_i} = \exp\left[-\frac{x-c_i}{a_i}\right]^{2b_i} \tag{4}$$

where, $\{a_i, b_i, c_i\}$ is the parameter set having the adjustment parameters. With changing of values of these parameters, the value of bell-shaped curve function also changes. So, various structures of membership functions for the fuzzy set A are exhibited. The parameters in that layer are called as antecedent parameters.

Layer 3: Each node in this layer is labeled with Π and it points out the multiplier of all inputting signals. In other words, the output of this node is a product of all signals and it sends the obtained product to outside. The output of node can be expressed as in equation 5.

$$o_{3,i} = w_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \quad i = 1, 2. \tag{5}$$

The output of each node represents the firing strength of one rule. Any of T-norm operators that realize the generalized fuzzy AND can be used as a node function for nodes in that layer.

Layer 4: Each node in this layer is labeled with N and a normalized firing strength of one rule is calculated. As it is seen in equation 6, the firing strength of i. rule for i. node is equal to total of firing strength of all rules.

$$o_{4,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{6}$$

Layer 5: Each i node in that layer is an adaptive node with the node function. Each i node calculates the values of weighted results. The output function of node is given in equation 7.

$$o_{5,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{7}$$

Here, $\overline{w}_i$ is the output of layer 4 and a normalized firing strength. The adjustment parameter set is required to adjust the $\{p_i, q_i, r_i\}$. Parameters in that layer correspond to consequent parameters.

Layer 6: In that layer, there is only one node and is labeled with ∑. This means the total of all consequent signals for the whole system. With total of all signals, the result given in equation 8 is obtained.

$$overall\ output = o_{6,1} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (8)$$

So, a model ANFIS structure that is functionally equal to Sugeno fuzzy inference model is defined. The structure of the network is not fully constant. Establishment of the network and separation of the node functions according to their duties can be elected arbitrarily depending on what is ensured by each node in every layer and their modular functionality.

It can be easily passed from the Sugeno type ANFIS to the Tsukamoto type ANFIS. Generally, these two types are used. For the ANFIS corresponding to the Mamdani type fuzzy inference, the Max-Min composition and result can be obtained by means of the Center of Gravity Defuzzification Method for output. However, this is very difficult and complex for the Sugeno or Tsukamoto type ANFIS. Besides, it does not make a significant contribution to the learning ability and approaching power. Adjustment and updating of the adjustment parameters in the ANFIS architecture is only possible with backpropagation method. Besides, the Kalman filter method can also be used to find the result parameters of ANFIS (Fullér, 1995; Nauck and Kruse, 1997). For this process, all the result parameters are arranged as a vector in form of $(p_1, q_1, r_1, p_2, q_2, r_2)^T$ and with Kalman filter method, it can be obtained as below in equation 9.

$$\begin{bmatrix} \overline{w}_1^{(1)} & \overline{w}_1^{(1)}x^{(1)} & \overline{w}_1^{(1)}y^{(1)} & \overline{w}_2^{(1)} & \overline{w}_2^{(1)}x^{(1)} & \overline{w}_2^{(1)}y^{(1)} \\ \overline{w}_1^{(2)} & \overline{w}_1^{(2)}x^{(2)} & \overline{w}_1^{(2)}y^{(2)} & \overline{w}_2^{(2)} & \overline{w}_2^{(2)}x^{(2)} & \overline{w}_2^{(2)}y^{(2)} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ \overline{w}_1^{(n)} & \overline{w}_1^{(n)} & \overline{w}_1^{(n)}y^{(n)} & \overline{w}_2^{(n)} & \overline{w}_2^{(n)}x^{(n)} & \overline{w}_2^{(n)}y^{(n)} \end{bmatrix} \begin{bmatrix} p_1 \\ q_1 \\ r_1 \\ p_2 \\ q_2 \\ r_2 \end{bmatrix} = \begin{bmatrix} d^{(1)} \\ d^{(2)} \\ \vdots \\ d^{(n)} \end{bmatrix} \quad (9)$$

[(x(k), y(k)), d(k)] k=1, 2,…, n used in the equation is the k. education part and besides, $\overline{w}_1^{(k)}$ *and* $\overline{w}_2^{(k)}$ is the output of layer 4 that is combined with $\left(x^{(k)}, y^{(k)}\right)$ inputs.

2.2. Application of the hybrid learning method to ANFIS

When values of antecedent parameters in the ANFIS architecture are constant, from end to end output can be expressed as linear combination of the result parameters. For the ANFIS architecture with two inputs and two rules given in Figure 2, the f output can be rewritten as in equation 10.

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \overline{w}_1 (p_1 x + q_1 y + r_1) + \overline{w}_2 (p_2 x + q_2 y + r_2) \\ &= (\overline{w}_1 x) p_1 + (\overline{w}_1 y) q_1 + \overline{w}_1 r_1 + (\overline{w}_2 x) p_2 + (\overline{w}_2 y) q_2 + \overline{w}_2 r_2 \end{aligned} \quad (10)$$

Here, the p_1, q_1, r_1, p_2, q_2, r_2 result parameters are linear. So, the hybrid learning method can be directly applied to ANFIS. Here, node outputs of the hybrid learning method are dispersed forward up to Layer 5 during their forward pass and the consequent parameters are defined with least squares method. In backward pass, the error rates propagate backward and the antecedent parameters are upgraded by the gradient descent. So, the defined consequent parameters are the most appropriate when the antecedent parameters are constant. For this reason, as the hybrid forecast decreases the research space dimensions of the original backpropagation method, the speed direction towards to a one point is speeder. These passes are briefly given in Table 1.

Table 1. Two passes in the hybrid learning method for ANFIS

	Forward pass	Backward pass
Antecedent parameters	Constant	Gradient descent
Consequent parameters	Least squares method	Constant
Signals	Node outputs	Error rates

The learning mechanism in Sugeno type ANFIS does not require addition for definition of membership functions. So, the linguistic and objective definitions of badly defined concepts are not moved. In that case, it may be thought that the decision is left to the user. In principle, if the input and output data set is very big, the membership functions must be adjusted fully. In contrary, if the data set is very small and does not cover sufficient information about the target system, it represents significant information that does not reflect on the membership functions data group defined by people. For this reason, the membership functions must be kept constantly during learning processes.

If the membership functions are constant and the result piece can be adjusted, Sugeno ANFIS can be considered as a functional connection network. Here, the raised representations of input variables can be obtained with membership functions. These raised representations are defined by views of experts who know the system very well by being produced with product models outside or functional expansion. The updating of formulas for the antecedent and consequent parameters completely depends on the hybrid learning rule.

3. The Sample ANFIS Application For DC-DC Converters

In this section, control of a buck converter with ANFIS controller is defined. The fuzzy logic control rules and membership of the system have been established. The simulation study of controlling of the system with ANFIS controller has been made in C programming language.

In figure 3, the schema of closed loop ANFIS controller system for DC- DC buck converter is given. The control input impulsing rate of converter in the system is “d”. The error is represented with “e” and defined in equation 11.

$$e=V_{ref}-V_o \tag{11}$$

Here, V_o is the output voltage of DC-DC converter and V_{ref} is the desired output voltage. The change or derivative of error is represented with “de” and for the k. step , it is as in equation 12.

$$du(k)= e(k)-e(k-1) \tag{12}$$

Output of the fuzzy control algorithm is the change or increase amount in duty ratio du(k). The duty ratio d(k) is obtained as in equation 13 where duty ratio in previous phase is added to the change calculated in k. sampling time.

$$d(k) = d(k-1) + du(k) \tag{13}$$

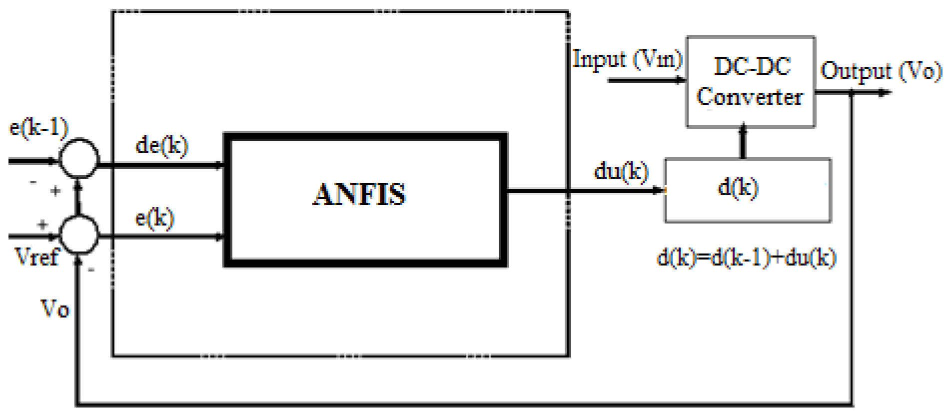

Figure 3. The schema of close circuit ANFIS controller system for DC- DC buck converter.

3.1. Values of the Simulated Converters

The elements of buck converter and its necessary values are elected as in Table 2. The state variables of the circuit according to these elected values are as in Equations 14, 15 and 16.

$$A_1 = A_2 = \begin{bmatrix} 0 & -1000 \\ 10000 & -2500 \end{bmatrix} \quad ; \qquad (14)$$

$$B_1 = \begin{bmatrix} 1000 \\ 0 \end{bmatrix} \; ; \; B2=0 \quad ; \qquad (15)$$

$$C1=C2=[\,0 \;\; 1\,] \qquad (16)$$

The calculation step in simulation is taken as ts= 0.000001. Besides, reference value for the above values is elected as V_{ref}=15 V. The values of buck converter input voltage Vin= 50 V, output voltage Vref=15 V, inductance L= 1 mH, capacitor C=100 μF, equivalent load resistance R= 4 Ω, switching frequency fs= 5 Kh.

The output voltage obtained as a result of the simulation and bobbin current are given in figure 4 and 5 respectively.

3.2. PI Controller wiht Current Control for Buck Converter

For purpose of comparison, the step-down (buck) converter was firstly operated with current controlled PI controller. After several trials, the most appropriate PI controller coefficients were found as follows.

- Gain for current control “β”: 0.2
- Integral time constant “T_i”: 400
- Switching frequency “F_s”: 5000 Hz

3.3. Buck Converter Control with ANFIS

The control model in figure 2 was applied same to the buck converter given in table 2. The initial membership function group that changes in [-100, 100] interval of the system is seen in figure 6.

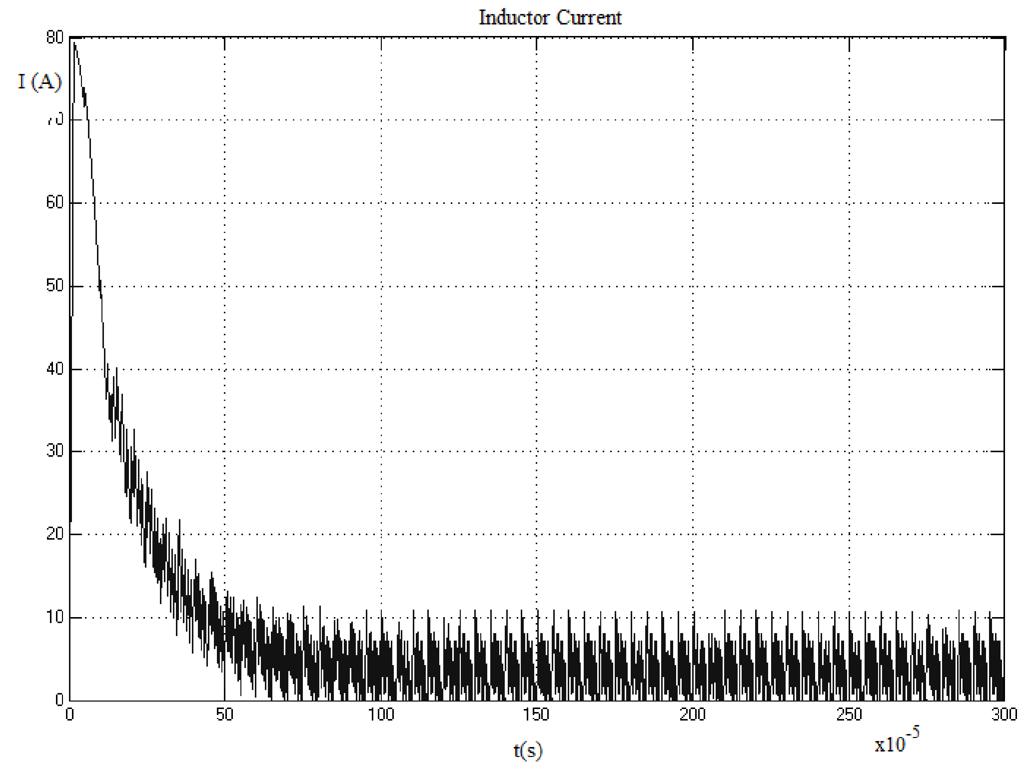

Figure 4. Inductor current for PI controller

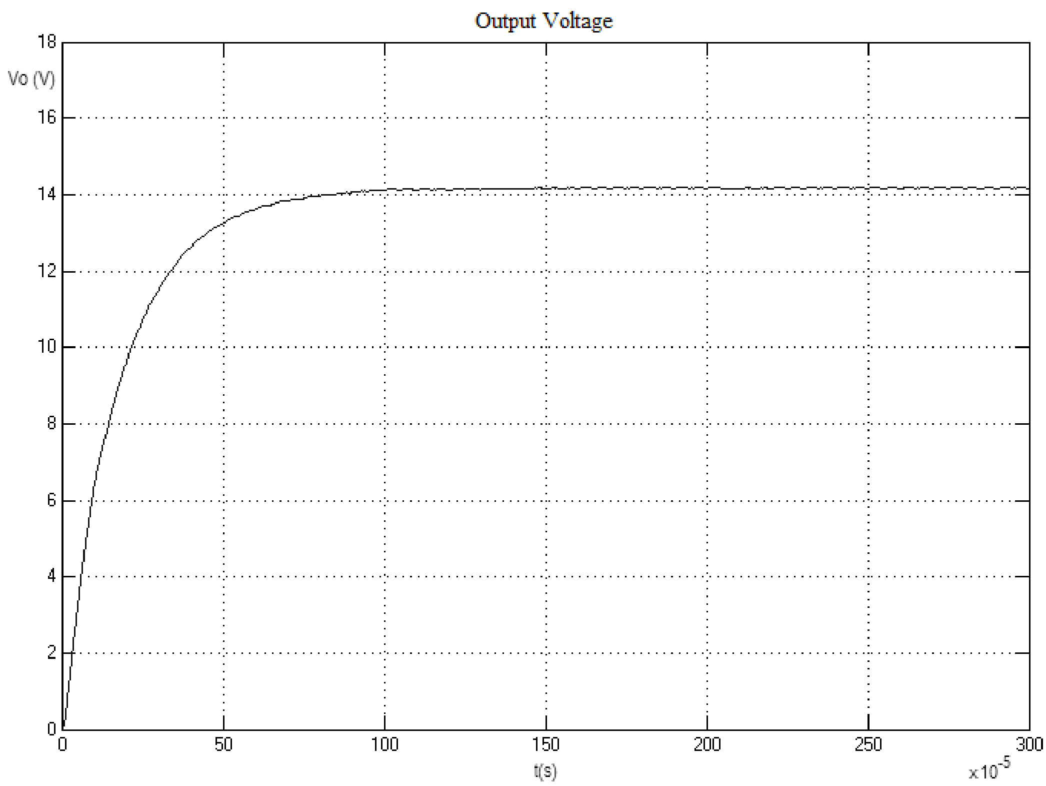

Figure 5. Output voltage for PI controller

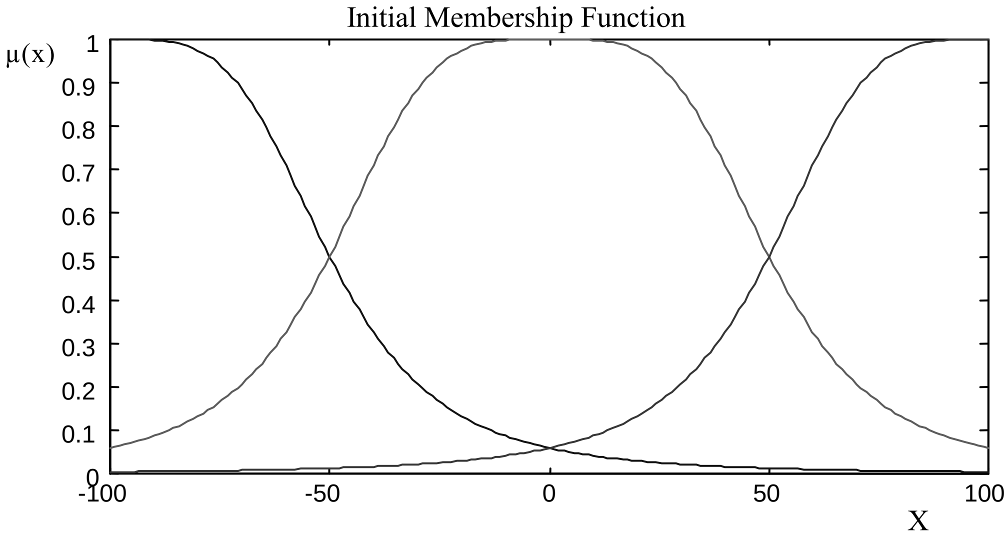

Figure 6. The initial membership functions

Once the controller is operated and the consequent parameters are used as antecedent parameters, after total 20 learning epochs, it may find necessary parameters for the membership functions and rules. The step sizes curve during the learning epochs is given in figure 7. As far as the learning epoch's advances, the step size decreases like a stairs step. For this reason, the decreasing –increasing rates of parameters during learning decrease with step size.

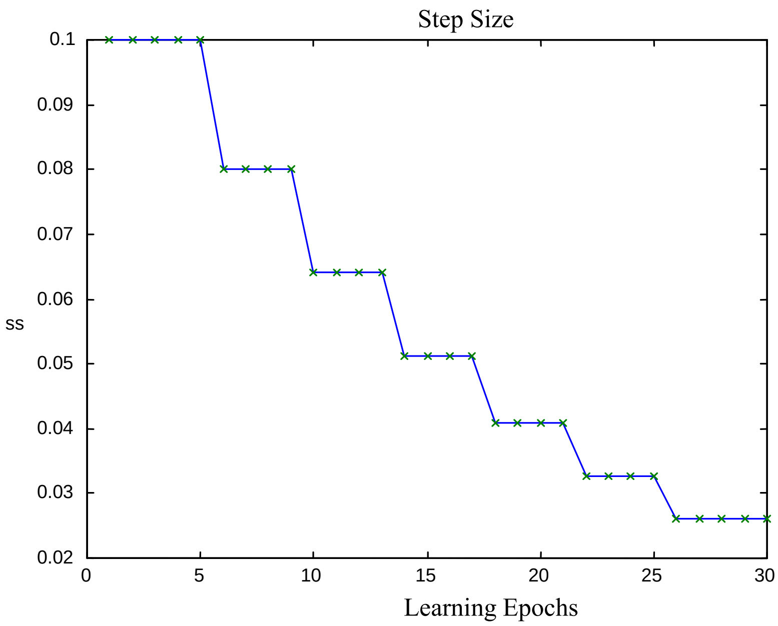

Figure 7. Pitch measure according to learning cycles

The Gaussian Bell or bell curve membership function given in equation 4 has total three parameters as a_i, b_i and c_i. As the determinant of three membership functions for A and B sets is i=1, 2, 3, the total parameter number in both sets is 6. The number of p_i, q_i and r_i parameters of rules sampled in equation 7 is 32 = 9 for two inputs and three membership functions.

This system established by calculating the parameters was used to find the duty ratio of buck converter of which characteristics given above.

The simulation study of fuzzy logic controller obtained with adaptive neural fuzzy inference method and the buck converter was made and the obtained curves are given in figures below. While the load at output during operation is 4 Ω, it is decreased half after 2ms and made 2 Ω. The output voltage against the said load change is affected less than other method. In figure 8, a curve of circuit operation current and in figure 9, a curve of converter output voltage is given. The curves obtained as a result of the application indicate that the ANFIS controller reaches to the reference value faster than the PI controller and is affected from load changes lesser than it.

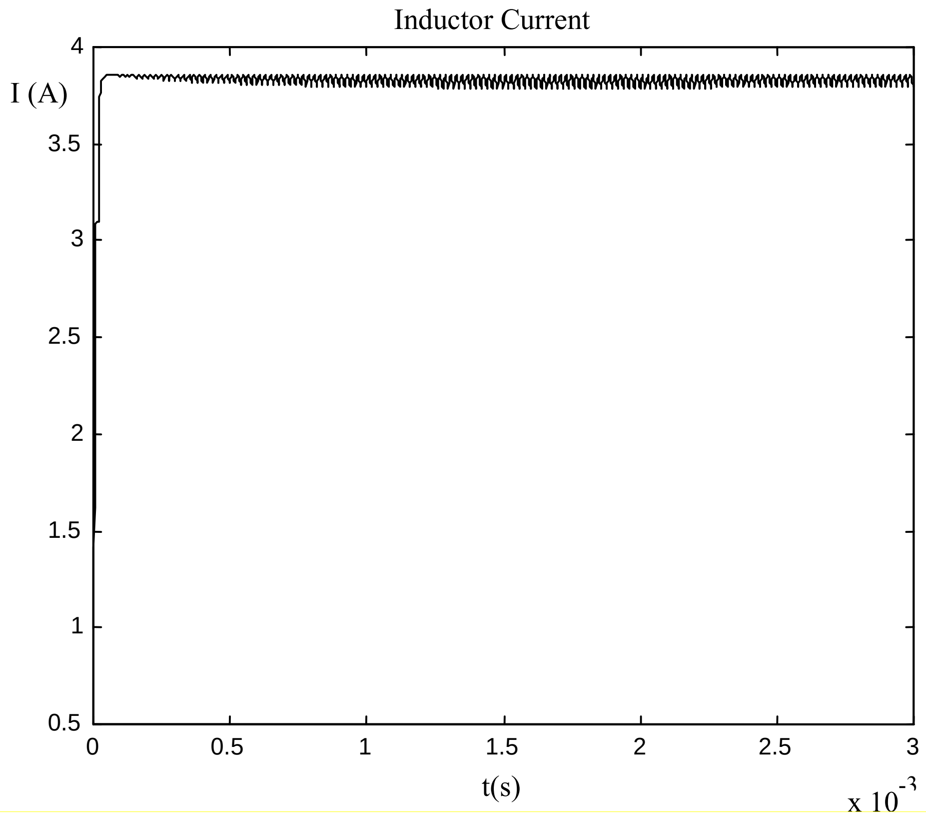

Figure 8. Inductor current for ANFIS controller

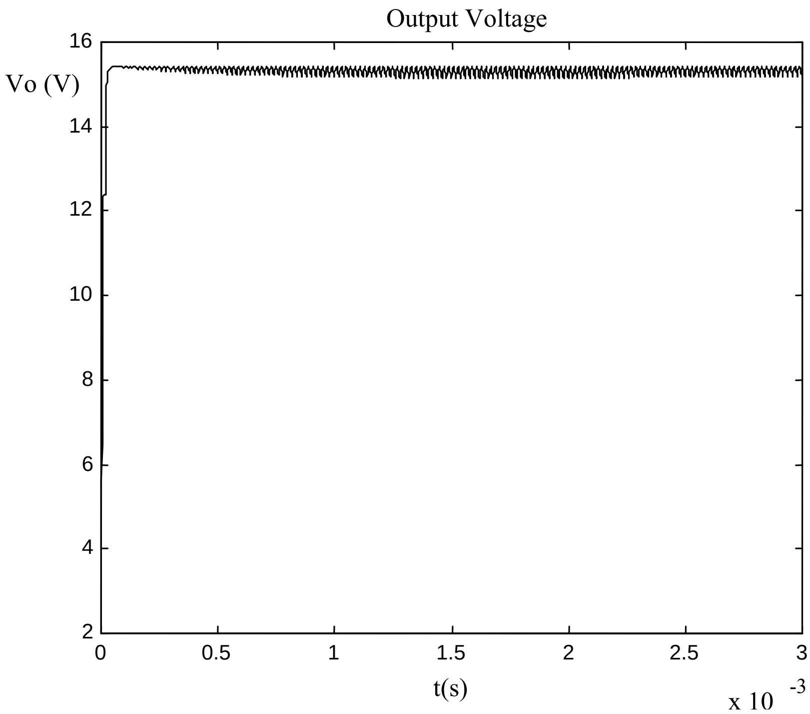

Figure 9. Output voltage for ANFIS controller

4. Simulation Results and Discussion

In the controller design realized in this study, the adaptive fuzzy control or neural-fuzzy control was used. In short, with this method that may be defined as combination of learning ability of artificial neural networks with inference mechanism of fuzzy logic, it was aimed to increase adaptiveness of the system. Consequently, by using the neuro–fuzzy inference system with 3 membership functions and 9 rules called as ANFIS, an Adaptive controller was designed and applied to a buck converter. From the experiments made for purpose of comparison, it was determined that the ANFIS controller is more effective and faster than the PI controller. The ANFIS controller reaches to the reference value faster than the PI controller and is affected from load changes lesser than it.

Besides, an Adaptive fuzzy logic controller that is at least two times faster and more sensitive than the controllers made with only fuzzy logic control or artificial neural networks in references (So and Tse, 1996; Lin, 1995; Daldaban and Ustkoyuncu, 2009) was realized. As seen from the Figures the output voltage V_o is kept almost constant under large input voltage or load changes.

5. Conclusions

This paper has focused on an ANFIS controller for DC-DC converters. The design of ANFIS controller for DC-DC converters has described and computer simulation is made.

As it is stated previously, in fact there is a combined difficulties series in the design of fuzzy logic controller. The common bottleneck in derivation of fuzzy control rules is that it often takes much time; it is difficult and requires expert knowledge and experience related to the system. For this reason, experts have to remove difficulties and decrease the adaptiveness ability and learning ability of fuzzy systems. In that case, the first thing that must be done is to benefit from the learning ability of artificial neural networks. Election of learning method, duty knowledge field and naturality of available information are determined. Recent studies attempt to combine fuzzy logic, artificial neural networks and genetic algorithm to understand learning in diversification of applications. The common approach is to use Genetic Algorithms (GA) in derivation of parameters of fuzzy or adaptive networks. Though the structures and algorithms of Artificial Neural Networks are complex, it is known that they conform to dynamic behaviors of physical systems. On the other hand, it is said that GA is especially convenient in complex information areas. So, it can be used for structuralism in fuzzy or neural networks systems and parameter adaptation. However, to find convenient solutions may take very long time. This is a very powerful learning approach that possesses the advantages of values peculiar to these three methodologies. In following studies on controlling of converters, this method may be considered for its more powerful learning and more effective response ability.

References

Hart, D. W.,1997, Introduction to Power Electronics, Prentice Hall International Inc, U.S.A..

Mohan, N., Undeland, T. M., Robbins, W.P.,1995, Power Electronics: Converters, Application and Design, Second edition, John Wiley & Sons, Newyork.

Lander, W. C.,1993, Power Electronics, Mc Graw-Hıll, London.

Rashid, M. H., 1988, Power Electronics Circuits, Devices and Application, Prentice- Hall Int. Inc, New Jersey, USA.

Gürdal, O., 1997, Güç Elektroniği, GÜTEF, Ankara.

Bradley, D. A., 1987, Power Electronics, VNR (international) Co. Ltd., London.

Singh, C., Wang L., Role of Artificial Intelligence in the Reliability Evaluation of Electric Power Systems, Turk J Elec Engin, Vol.16, No.3, 2008, 189-200, ,

Bay, O., Deperlioglu, O., Elmas, C., 2003,Fuzzy control of dc-dc converters based on user friendly design, International Journal of Electronics, vol.90, no.7, pp.445-458.

Elmas, C., Deperlioglu, O. and Sayan, H. H., 2009, Adaptive fuzzy logic controller for DC–DC converters, Expert Systems with Applications, Mar 2009, Vol.: 36 Issue: 2 p-p: 1540-1548.

So, W-C., Tse, C. K., 1996, Development of a fuzzy logic controller for DC/DC converters: Design, computer simulation, and experimental evaluation, IEEE Transactions on Power Electronics, Vol. 11, No:1, 24-31.

Lin, B-R., 1995, Power converter control based on neural and fuzzy methods, Electric Power Systems Research, 35, 193-206.

Mattavelli, P., Rossetta, L., Spiazzi, G. and Tenti, P., 1997, General-purpose fuzzy controller for DC-DC converters, IEEE Transactions on Power Electronics, Vol. 12, No:1, 79-85.

Lin, B-R., 1997, Analysis of neural and fuzzy-power electronic control, IEE Proc. -Sci. Meas. Technol., Vol. 144, No:1, 25-33.

Leyva, R., Martinez-Salamero, L., Jammes, B., Marpinard, J. C., and Guinjoan, F., 1997, Identification and control of power converters by means of neural networks, IEEE Transactions on Circuits and Systems-1: Fundamental Theory and Applications, Vol. 44, No:8, 735-742.

Daldaban, F., Ustkoyuncu, N., 2009, Inductance Estimating of Linear Switched Reluctance Motors with the Use of Adaptive Neuro-Fuzzy Inference Systems, G.U. Journal of Science, 22(2): 89-96.

Gupta, T., Boudreaux, R.R., Nelms, R. M. Ve Hung, J. Y., 1997, Implementation of a fuzzy controller for DC-DC converters using an inexpensive 8-b microcontroller, IEEE transaction on industrial electronics, Vol. 44,No. 5, October, 661-668.

Lin, C.-T., George Lee, C. S., 1996, Neural Fuzzy Systems, Prentice Hall PTR, New Jersey, USA.

Jang, J.-S. R., Sun, C.-T., Mizutani, E., 1997, Neuro-Fuzzy And Soft Computing, Prentice-Hall Inc., New Jersey, USA.

Fullér, R., 1995, Neural Fuzzy Systems, Ábo Akademi, Ábo.

Nauck, D., Kruse, R., 1997, Neuro-fuzzy systems for function approximation, Otto-von-Guericke-University of Magdeburg, Magdeburg, Germany.