International Conference on Control, Automation and Systems 2008
Oct. 14-17, 2008 in COEX, Seoul, Korea

# An Adaptive Neuro-Fuzzy Controller for DC-DC Converter

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**Abstract**: In this paper an Adaptive Fuzzy controller is designed for controlling a DC-DC Buck converter. In order to make the controller adaptive and overcome the variations of the input voltage, an Artificial Neural Network is applied to the Fuzzy controller and tuned its coefficients online with system input ripples and variations. Neural Network is trained by direct searching method through successive simulations to optimize fuzzy coefficients versus increasing input voltages. These coefficients and related input voltages constitute the set of training data for artificial neural network which is applied offline by Lauvenberg-Marcoardet method. The resulting Neuro-Fuzzy controller, shows a very good behavior in controlling the output voltage and the simulation results reflect improvement of the system response.

**Keywords:** Adaptive Neuro-Fuzzy Control, DC-DC Converter

## 1. INTRODUCTION

Switched mode power converters lie at the heart of DC power supplies, bringing the advantages of high efficiency and low mass. They can be modeled as variable structure systems because of the abrupt topological changes that the circuit, commanded by a discontinuous control action, undergoes [1].

One of the most exciting areas of power semiconductors and power electronics in general is the area of DC/DC converters [2].

Switched mode DC-to-DC power converters are used in a variety of electric power supply systems, including cars, ships, aircraft and computers. Application of sliding mode control in tracking a real-time voltage profile is very promising because a switching control strategy is traditionally employed in power converters, and because of the inherent robustness properties of the sliding mode [3].

Switched mode DC/DC power converters are used in a wide range of applications, including power supplies for personal computers, DC motor drives, active filters, etc. Pulse-width modulation (PWM) sets the basis for the regulation of switched mode converters [4].

In recent years, there has been increasing interest in the development of efficient control strategies to improve dynamic behavior of DC–DC converters by using fuzzy logic controller (FLC), neural networks (NN), and Neuro-Fuzzy Controller (NFC) [5].

## 2. BUCK CONVERTER

### 2.1 Constitution of the circuit

The Buck transfer circuit is a kind of DC single transistor converter and is not isolated, whose output voltage is nearly equal to the input voltage or a little lower than it. It is composed of the switch tube *Q*, the diode D, the output smoothing inductance *L* and the output smoothing capacitance *C* (the topological structure see Fig. l) [6],[8].

The first part starts when the switch is turned on at $t=0$. The input current which is rising passes through *L* filter inductor, *C* filter capacitor, and *R* charge resistance. The second part starts when the switch is turned off at $t=t_1$. Due to the presence of stored energy in the inductor, the inductor current continues passing from *L*, *C*, load and *D*. The inductor current declines until the second switch switching in the next cycle.

By adding a high-frequency transformer, the Buck transfer circuit becomes an isolation forward converter (Fig. l). There are two modes: the Continuous Conduction Mode-CCM and Discontinuous Conduction Mode-DCM. The CCM mode is that the current which flows through the output smoothing inductance ***L*** is greater than zero. The DCM is that when the switch tube Q is switched.

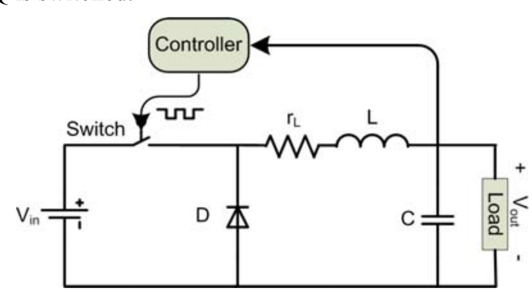


Fig.1 Buck converter.

On the basis of the above analysis and the state equations, the conversion function of the above converter is obtained as (1).

$$\frac{V_{out}(s)}{\delta(s)} = -\frac{V_{in}}{LCs^2 + s\left[\frac{L}{R} + r_L C\right] + \left[1 + \frac{r_L}{R}\right]} \tag{1}$$

## 3. NEURAL NETWORK BASICS

Fig. 2 shows a schematic diagram of the ANN required to proposed controller.

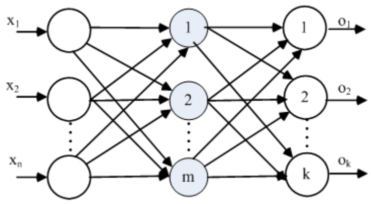


Fig. 2 ANN structure.

Each neuron has a bias and is connected via summing weights to the preceding neuron layers [9]. The activation ($x_j$) of the neuron is calculated by a weighted sum of the outputs of the neurons in the previous layers as determined by the connecting weights ($W_{i,j}$) and the bias ($b_j$) for the j the layer as shown in Eqn. 2 (first line). The summation is carried out over all the neurons connected to neuron j. The output (O) of a given neuron is usually calculated as a non-linear function of the activation. In our case, the best results were obtained with a sigmoid function for the hidden layer neurons (2), and a linear function for the output layer.

$$x_j(k) = \sum_{i=0}^{N_{i-1}} w_{i,j} O_i + b_j$$
$$O(h) = \frac{1}{1+e^{\beta x}} \tag{2}$$

## 4. Adaptive Neuro-Fuzzy Controller

In this article, for controlling connected buck to unbalanced operation, fuzzy controller is used, but because of non-linear nature of an unbalanced operation a constant controller cannot have an optimized function. One important note in fuzzy controllers is parameter tuning. We can refer to membership functions, scaling factors, Reasoning Algorithm, fuzzification and difuzzification. It is proved that for adjusting fuzzy controllers we can consider membership functions linear and constant and instead all non-linear properties will be transferred to scaling factors [10]. In this article, for tuning parameters, scaling parameters are used in input and output of controller. In fact, real time optimizing is done with scaling factors' arrangements. For this purpose, by using of an artificial neural network in any active and reactive power, we multiply some coefficients in controller's inputs and output. For training neural network, we require data that we find them by using direct search algorithm for several powers.

### 4.1 Fuzzy controller

The inputs of fuzzy controller are voltage of output in buck error and its changes that are computed like below;

$$e(k) = V_{ref}(k) - V_O(k)$$
$$se(k) = se(k-1) + e(k) \tag{3}$$

In Fig. 3, the block diagram of system with fuzzy method is shown.

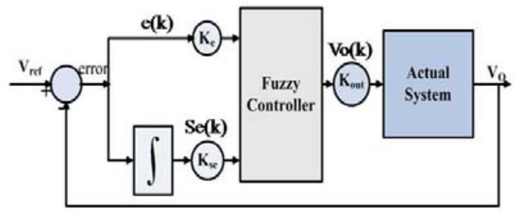


Fig. 3 Buck with Fuzzy Controller.

Considered membership for voltage error and its changes are brought in Fig 4.

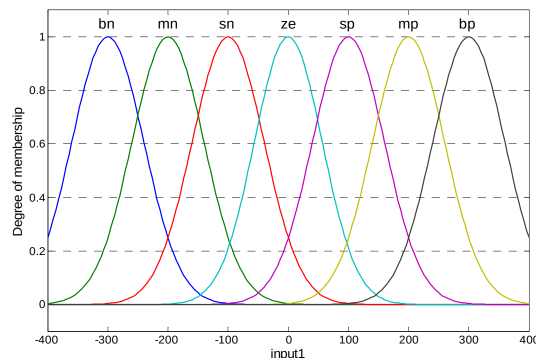


Fig. 4 Input-output membership function.

Rules for fuzzy controller are also brought in Table 1. Reasoning Algorithm is done by Mamdani method. Below equations state the calculation way of fuzzy controller. Where M is number of rules, P is number of inputs, $\Theta_L$ is gravity center of membership functions, $\mu F_i(x_i)$ is membership grade of $x_i$ in $F_i$, and v is crisp output of fuzzy controller.

Table 1 Fuzzy controller's rules

| Se(k) \ e(k) | bn | mn | sn | ze | sp | mp | bp |
|---|---|---|---|---|---|---|---|
| bn | bn | bn | bn | mn | sn | Sn | Ze |
| mn | bn | mn | mn | mn | sn | ze | sp |
| sn | bn | mn | sn | sn | ze | sp | mp |
| ze | bn | mn | sn | ze | sp | mp | Bp |
| sp | mn | sn | ze | sp | sp | mp | bp |
| mp | sn | ze | sp | mp | mp | mp | bp |
| bp | ze | sp | sp | mp | bp | bp | bp |

$$V = \frac{\sum_{L=1}^{M} \theta_L \prod_{i=1}^{P} \mu F_i(x_i)}{\sum_{L=1}^{M} \prod_{i=1}^{P} \mu F_i(x_i)} \tag{4}$$

### 4.2 Artificial neural network

Neural network used for this controller has one neuron in input layer and three in output layer. The input of neural network is reference voltage and $V_{in}$ and outputs are three coefficients multiplied in fuzzy controller's inputs and output respectively. In Fig. 5, the structure of neural network is drawn.

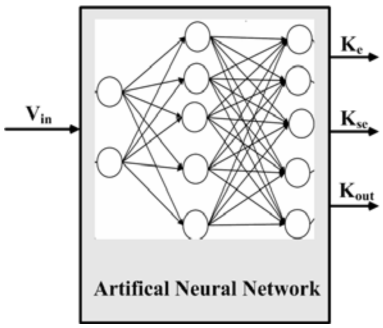


Fig. 5 Neural Network Structure.

The specifications of neural network are also given in Table 2.

Table 2 Neural network specifications

| Layer | One | Two |
|---|---|---|
| Neurons | 1 | 3 |
| Type | Input | Output |
| Member ship function | Sigmoid | Linear |

In Fig 6, the block diagram of buck with adaptive neuro-fuzzy controller is drawn. The input of each neuron is realized with below relation;

$$I_i = \sum_{j=k}^{N} w_{ji} y_j \tag{5}$$

Where in above relation $W_{ji}$ is weight coefficient between neuron j and neuron $_i$ and $Y_j$ is the output of neuron j. the output of each neuron can be stated with below relation;

$$y_i = f(I_i) \tag{6}$$

Sigmoid and linear functions used in artificial neural network are defined as below;

$$f(x) = x \quad \text{Linear function} \tag{7}$$

$$f(x) = \frac{1}{1+e^{-x}} \quad \text{Sigmoid function} \tag{8}$$

Levonberg-Marcoardt [10] algorithm is used for training artificial neural network.

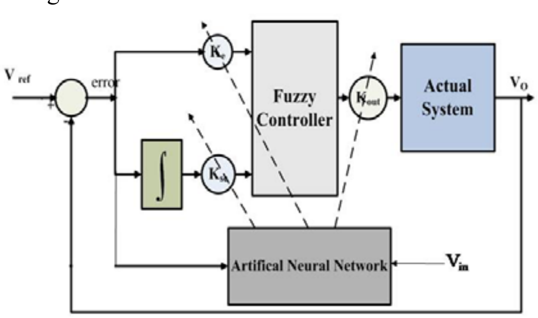


Fig.6 Buck block diagram
with adaptive neuro-fuzzy controller.

As referred, for training neural network, we require training data. In this part, it is explained that how these data are obtained. At first, we select some different input voltages $V_{in}$. Information required for training data are optimized input and output coefficients for fuzzy controller. We name variable x as below;

$$x = \left[K_{error} \quad K_{serror} \quad K_{output}\right]^T \tag{9}$$

Then we define below function as performance function;

$$J = \int_{t=10\text{sec}}^{t=30\text{sec}} |error(t)|dt \tag{10}$$

In next level, by selecting different quantities for reference speed we will find optimized quantity of vector *x*. We mean that optimized quantity of vector x is a quantity that makes performance function minimum. In Table 3, optimized quantities for fuzzy controller are brought.

Table 3 Optimize input-output coefficients
for fuzzy controller

| | $K_e$ | $K_{se}$ | $K_{out}$ |
|---|---|---|---|
| Fuzzy 1 | 10 | 40.2 | 0.25 |
| Fuzzy 2 | 8.5 | 12.9 | 0.56 |
| Fuzzy 3 | 7.7 | 10.4 | 0.7 |
| Test System | With Neuro-Fuzzy | | |

The information of Table 3, is used for training of neural network.

## 5. THE RESULT OF SIMULATION

The Buck converter open loop response will be in the form of Fig. 7 [7], [8].

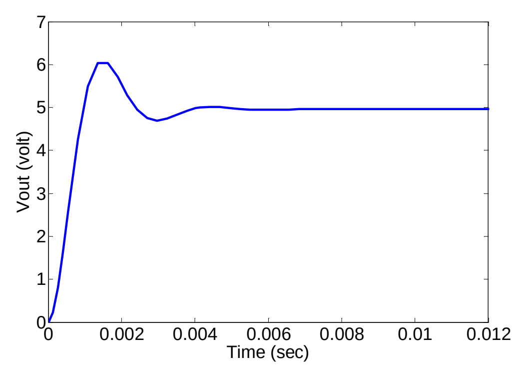


Fig. 7 Open Loop response of Buck converter.

As it is evident from the study of outputs, the open loop system can't hold the output in constant and ideal conditions. Of course, the outputs will eventually approximate the ideal rate with regard to the stability of the system.

### 5.1 Fuzzy controller

The results of fuzzy control method with the rules in Table. 1, are shown in Fig. 8. In this simulation the gains in Table. 3 are used.

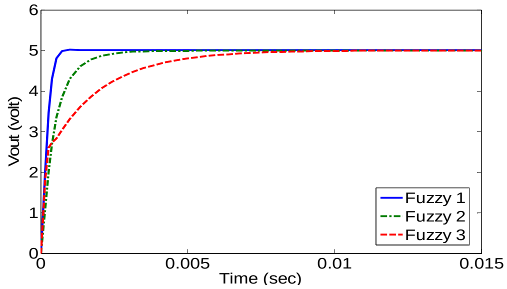


Fig. 8 The response of system with fuzzy control.

For the optimum adjustment of the parameters of fuzzy controller in this article the neural network is employed and a novel control method as Fig. 6 is used, and the training of this neural network is shown in Fig. 9.

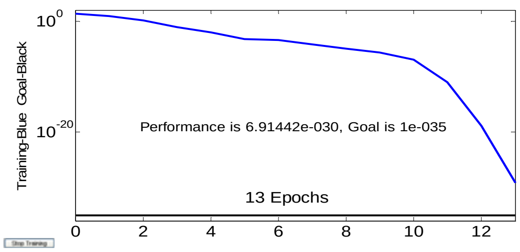


Fig. 9 Training of proposed fuzzy neural network.

Simulations are carried out to show how the system recovers after a major disturbance. In this study, the system operating is tested in the input voltage deviation as Fig. 10.

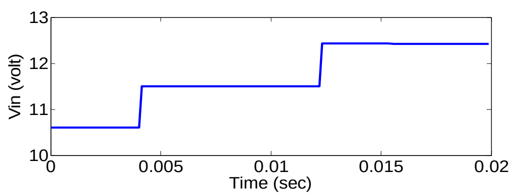


Fig. 10 The input voltage signal to test the work of the system.

With the above deviations in the input voltage, the output voltage is shown in open loop manner as Fig. 11, and the results of fuzzy control method in several gains are shown in Fig. 12.

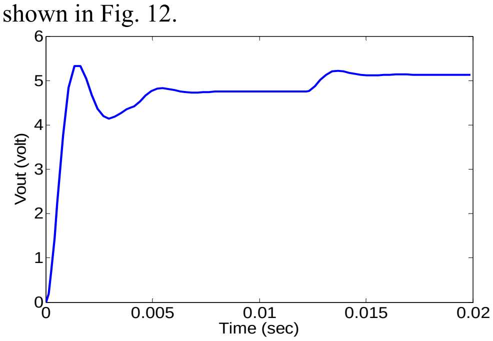


Fig. 11 Open Loop response of Buck converter to the signal test.

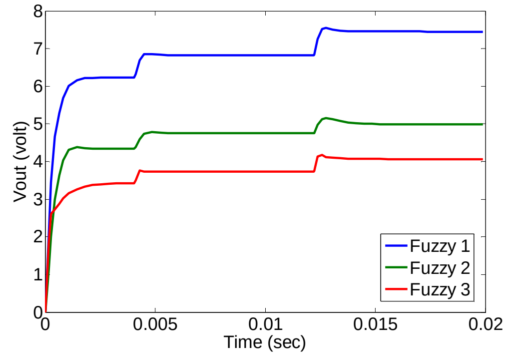


Fig. 12 Time response of system with fuzzy control to the signal test.

The membership functions employed for the inlet and outlet signals are of Gaussian-shaped type. For the adjustment of the fuzzy controllers in this article, the parameters related to the inlet and outlet signal membership functions are in the form of genetic function chromosome. By using neuro-fuzzy control method for test conditions the response of system is as Fig. 13.

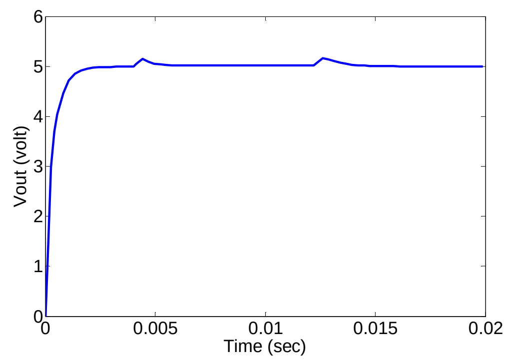


Fig. 13 Response of DC-DC converter with neuro-fuzzy control to the signal test.

## 6. CONCLUSIONS

In this paper the operation of buck converter is improved by a novel neuro fuzzy control method. This method can control the fuzzy controller to have a good response of this converter. Also the result of this method is compare with manual fuzzy controller which are used to instruction the neural network Therefore the proposed method has robust response and the simulation prove the improvement of the functioning of this controlled converter.

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