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Online Learning Neural Network Control of Buck-Boost Converter

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***Abstract*—This paper proposes a neural network control scheme of a DC-DC buck-boost converter using online learning method. In this technique, a back propagation algorithm is derived. The controller is designed to stabilize the output voltage of the DC-DC converter and to improve performance of the Buck-Boost converter during transient operations. Furthermore, to investigate the effectiveness of the proposed controller, some operations such as starting-up and reference voltage variations are verified. The numerical simulation results show that the proposed controller has a better performance compare to the conventional PI-Controller method.**

Keywords - Buck-Boost converter; neural network; online learning algorithm.

I. Introduction

Recently, DC power supplies are often utilized to provide electric power supply not only for portable electronic devices such as notebook computers, but also for electric vehicle and aerospace applications. To provide the DC voltage source level requirements of the load to the DC power supply, the DC-DC converter is widely used. Moreover, the DC-DC converter is also important in applications such as power conditioning of the alternative electrical energy in photovoltaic, wind generator and fuel cell system. For these reasons, DC-DC converter applications will become more potential market in the future.

Basically, the DC-DC converter consists of power semiconductor devices which are operated as electronic switches. Operation of the switching devices causes the inherently nonlinear characteristic of the dc-dc converters including one known as the Buck-Boost converter. Consequently, this converter requires a controller with a high degree of dynamic response. Proportional-Integral-Differential (PID) controllers have been usually applied to the converters because of their simplicity. However, implementations of this control method to the nonlinear plants such as the power converters will suffer from dynamic response of the converter output voltage regulation. In general, PID controller produces long rise time when the overshoot in output voltage decreases.

In order to improve dynamic response of DC-DC converters, several intelligence controllers such as fuzzy logic control, neural network control and hybrid neuro-fuzzy control methods for DC-DC converter have been reported in [1]-[8]. Simulation of the fuzzy logic control to the Buck-Boost and Sepic converter has been developed in [1]. Implementations of the fuzzy logic controller to buck converter and power stage DC-DC converter using micro controller have been verified in [2] and [3] respectively. Basically, in the development of the fuzzy logic controller, the fuzzy logic method utilizes linguistic variable and common rule without requiring exact model. Hence, this method has shown promise in dealing with nonlinear system achieving voltage regulation in DC-DC converter [4].

Although the fuzzy logic controllers have achieved many practical successes, it has not yet been viewed as a rigorous science due to lack of formal analysis and synthesis technique [4]. Due to this reason, a lot of research has been carried out to develop adaptive fuzzy logic controllers. Several adaptive fuzzy logic controls using neural method as a hybrid neuro-fuzzy controller for DC-DC converter application have been reported in [4] and [5].

As another option of intelligence controls, based on their ability to update the internal controller parameters, the neural network controls [NNC] are suitable for nonlinear system. Implementation of the NNC for DC-DC converter in computer simulation model has been proposed in [6]. Experimental verification of the NNC for the DC-DC converter has been developed successfully in [7]. In addition, the NNCs also have been applied for several others power electronic and drive applications [8]-[9]. In order to improve performance of the NNC some research has been done to develop online learning scheme of the NNC.

In this paper, an online learning neural network control (OLNNC) method for Buck-Boost converter is proposed. The developed OLNNC has the ability to learn instantaneously and adapt its own controller parameters based on external disturbance and internal variation of the converter with minimum steady state error, overshoot and rise time of the output voltage.

The organization of this paper is as follows: Section II discusses basis concept of a Buck Boost converter as a step-up and step-down of a DC-DC Buck-Boost converter. In section III, the design of online learning neural network control is described. Simulation results are carried out in section IV. Finally, conclusions are summarized in Section V.

II. Buck Boost Converter

A Buck-Boost converter is a type of step-down and step-up DC-DC converter. Output of the Buck-Boost converter is regulated according to the duty cycle of the Pulse Width Modulation (PWM) input at fixed frequency. When the duty cycle (d) is less than 0.5, the output voltage of converter is

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lower than the input voltage. However, when the duty cycle is more than 0.5 the output voltage of converter is higher than the input voltage. The basic power stage of a Buck-Boost converter is depicted in Fig. 1 where V_1 is input voltage source, V_o is output voltage, S_w is switching component, D is diode, C is capacitance, L is inductance and R is load resistance.

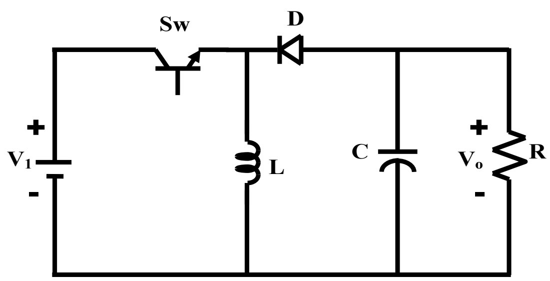

Figure 1. Circuit diagram of a buck boost converter

The equivalent equations for Buck-Boost converter during switching-on and switching-off of the power semiconductor device in continuous conduction mode (CCM) can be derived as follow:

$$\frac{di_L(on)}{dt} = \frac{1}{L}v_1 \tag{1}$$

$$\frac{dv_c(on)}{dt} = \frac{-v_o}{RL} \tag{2}$$

$$\frac{di_L(off)}{dt} = \frac{v_o}{L} \tag{3}$$

$$\frac{dv_c(off)}{dt} = -\left(\frac{i_L}{LC} + \frac{v_o}{RC}\right) \tag{4}$$

To develop dynamic model of the Buck-Boost converter, the state space averaging method is applied. By using this method, equations of the Buck-Boost converter in state space form, with ***d'=1-d*** are given as

$$\dot{X} = AX + BU \tag{5}$$

$$Y = CX \tag{6}$$

where

$$X = \begin{bmatrix} i_L \\ v_C \end{bmatrix} \tag{7}$$

$$U = v_1 \tag{8}$$

$$Y = v_o \tag{9}$$

$$A = \begin{bmatrix} 0 & \frac{d'}{L} \\ \frac{-d'}{C} & \frac{-1}{RC} \end{bmatrix} \tag{10}$$

$$B = \begin{bmatrix} \frac{1}{L} \\ 0 \end{bmatrix} \tag{11}$$

$$C = \begin{bmatrix} 0 & 1 \end{bmatrix} \tag{12}$$

The transfer function of the Buck-Boost converter in the continuous system is finally found as

$$G(s) = \frac{-d'R}{LRCs^2 + Ls + d'^2 R} \tag{13}$$

III. NEURAL STRUCTURES AND LEARNING SCHEME

A. *Structure of Neural Network Controller*

To design the neural network control, some information about the plant is required. Basically, the numbers of input and output neuron at each layer are equal to the number of input and output signals of the system respectively. The structure of the proposed neural network control of a buck-boost converter is as shown in Fig. 2.

Based on the number of neurons in each layer of the proposed OLNNC architecture, the network has a 2-3-1 structure. In the input layer consists of two input neurons. The first input neuron is error signal between desired signal and actual signal. The second input neuron is different between previous error signal and current error signal.

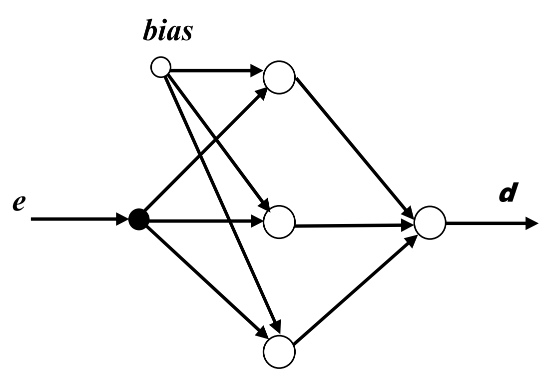

Figure 2. Architecture of the proposed neural network controller

The connections weight parameter between ***j_{th}*** and ***i_{th}*** neuron at ***m_{th}*** layer is given by ***w_{ij}***, while bias parameter of this layer at i_{th} neuron is given by b_{mi}. Transfer function of the network at t_{th} neuron in m_{th} layer is defined as

$$n_i^m = \sum_{j=1}^{S^{m-1}} w_{ij}^m a_j^{m-1} + b_i^m \tag{14}$$

The output function of neuron at m^{th} layer is given by

$$a_i^m = f^m(n_i^m) \tag{15}$$

where f is the activation function of the neuron. In this design, the activation function for the output layer and the hidden layer are unity and a tangent hyperbolic function respectively. The activation function of the hidden layer is given as

$$f^m(n_i^m) = \frac{2}{1+e^{-2n_i^m}} - 1 \tag{16}$$

Updating of the connection weight and bias parameters are given by

$$w_{ij}^m(k+1) = w_{ij}^m(k) - \alpha \frac{\partial F(k)}{\partial w_{ij}^m} \tag{17}$$

$$b_i^m(k+1) = b_i^m(k) - \alpha \frac{\partial F(k)}{\partial b_i^m} \tag{18}$$

where k is sampling time, α is learning rate, and F is performance index function of the network.

B. Online Learning Algorithm of BPEOC

After the neural network architecture is modelled, the next stage defines the learning model to update network parameters. By this learning capability, it makes the ANN suitable to be implemented for the system with motor parameters which are difficult to define and vary against with environment. The training process minimizes the error output of the network through an optimization method. Generally, in learning mode of the neural network controller a sufficient training data input-output mapping data of a plant is required. Since the motor parameters of the induction motor drive vary with temperature and magnetic saturation, the online learning Back propagation algorithm is developed.

Based on the first order optimization scheme, updating of the network parameters is covered. The performance index sum of square error is given by

$$F(k) = \frac{1}{2}\sum_i e_i^2(k) \tag{19}$$

$$e_i(k) = t_i(k) - a_i(k) \tag{20}$$

where t_i is target signal and a_i output signal on last layer.

The gradient descent of the performance index against to the connection weight is given by:

$$\frac{\partial F}{\partial w_{ij}^m} = \frac{\partial F}{\partial n_i^m}\frac{\partial n_i^m}{\partial w_{ij}^m} \tag{21}$$

The sensitivity parameter of the network is defined as

$$s_i^m = \frac{\partial F}{\partial n_i^m} \tag{22}$$

$$s_i^m = \frac{\partial F}{\partial a_i^m}\frac{\partial a_i^m}{\partial n_i^m} \tag{23}$$

Gradient of the transfer function again to the connection weight parameter is given by

$$\frac{\partial n_i^m}{\partial w_{ij}^m} = a_i^{m-1} \tag{24}$$

From substitution equation (22) and (24) into (17) the updating connection parameter is given by:

$$w_{ij}^{m-1}(k+1) = w_i^{m-i}(k) - \alpha s_i^m(k) a_i^{m-1}(k) \tag{25}$$

With the same technique the updating bias parameter is given by:

$$b_i^{m-1}(k+1) = b_i^{m-i}(k) - \alpha s_i^m(k) \tag{26}$$

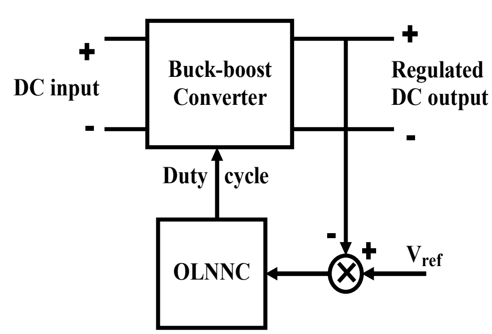

Figure 3. Block diagram of the proposed OLNNC control of Buck-Boost converter

IV. Simulation Results

To investigate the effectiveness of the proposed controller, a computer simulation using Simulink-MATLAB has been conducted. Block diagram of the proposed OLNNC for the buck-boost converter is show in Fig. 3. The Buck-Boost converter parameters are shown in Table 1.

TABLE I. PARAMETERS OF BUCK-BOOST CONVERTER

Symbol	Parameter	Value
L	Inductance	1 (mH)
C	Capacitance	100 (μF)
F	Switching frequency	25 (KHz)
V_I	Input voltage	12 (volt)

In this simulation, the conventional PI controller was compared to the proposed OLNNC. It is found that the output voltage startup transient response of the buck-boost converter with reference voltage is lower than the input voltage source as in the case of the buck converter and higher than the input voltage source as in the case of the boost converter as shown in Fig. 4 and Fig. 5 respectively.

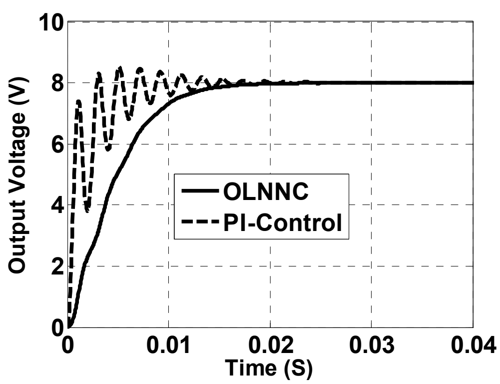

Figure 4. The output voltage transient response of the converter during starting-up

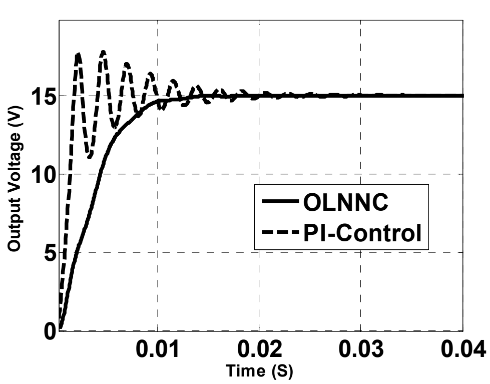

Figure 5. Transient response to load variation

Figs. 4 and 5 show that during starting-up the output voltage startup transient of the proposed OLNNC produce a better performance than PI-Controller such as removing overshoot and oscillation to achieve desired output voltage. In addition, the settling time of the OLNNC is also faster than PI-Controller.

The output voltage transient responses of the buck-boost converter to the reference voltage change are shown in Figs. 6 and 7 respectively. In Fig. 6, the reference voltage is stepping-up from 8 to 14 volts. In Fig. 7, the reference voltage is stepping-down from 14 to 7 volts.

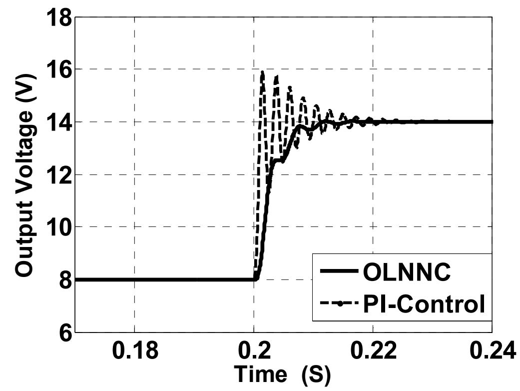

Figure 6. The output voltage transient response to reference change from 8 to 14 volt

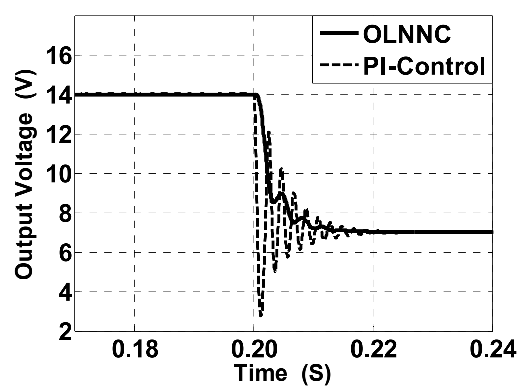

Figure 7. The output voltage transient response to reference change from 14 to 7 volt

It is evident from Figs. 6 and 7 that under the reference voltage-step variations, the proposed OLNNC has a better transient response rather than those obtained from the PI-Controller.

V. Conclusion

A neural network control for Buck-Boost DC-DC converter has been discussed in this paper. To improve performance of the neural network controller, an online learning algorithm based on back propagation scheme was employed. Simulation results show that implementation of the online learning technique is feasible for the Buck-Boost converter. The results prove that the OLNNC has a fast response to track desired output voltage and is also effective in decreasing overshoot, oscillation and settling time.

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