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An Intelligent Controller for a non Linear Power Electronic Boost Converter

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Abstract: This study describes the design and development of a novel controller for a non-linear power electronic converter. The Neuro-Fuzzy controller is proposed to improve the performance of the boost converter. The duty cycle of the boost converter is controlled by Neuro-Fuzzy controller. The conventional PI controllers for such converters designed under the worst case condition of maximum load and minimum line condition present a lower loop band width and the system response also sluggish. The common bottleneck in fuzzy logic is the derivation of fuzzy rules and the parameter tuning for the controller. The Neural Networks have powerful learning abilities, optimization abilities and adaptation. The Fuzzy logic and Neural Networks can be integrated to form a connectionist adaptive network based Fuzzy logic controller. This integrated adaptive system modifies the characteristics of rules and the structure of the control system. This study aims to establish the superior performance of Neuro-Fuzzy controller over the conventional P I controllers and Fuzzy controllers at various operating points of the boost converter.

Key words: ANFIS, DC-DC converter, FLC, ANN, AI, linear power boost converter, neuro fuzzy controller

INTRODUCTION

Traditional frequency domain methods for design of controllers for power converters are based on small signal model of the converter. The small signal model of the converter has restricted validity and changes due to changes in operating point. Also the models are not sufficient to represent systems with strong non-linearity. Moreover, the performance of the controllers designed by frequency domain methods is dependent on the operating point, the parasitic elements of the system and the load and line conditions. Good large signal stability can be achieved only by decreasing the bandwidth, resulting in slow dynamics. A state space averaged model of the classical boost DC/DC converters suffers from the well known problem of Right-Half-Plane zero in its control to output transfer function under continuous conduction mode. The movement of the zero on the complex S-plane as the operating point changes further compounds the problem. Designers are generally forced to limit the overall closed loop bandwidth to be much less than the corner frequency due to the worst case right half plane zero location. As a result of this, the system has a sluggish small signal response and a poor large signal response. There are two possible routes to achieve fast dynamic response. One way is to develop a more accurate non-linear model of the converter based on which the controller is designed. The other way is the artificial intelligence way of using human experience in decision-making. Among the various techniques of artificial intelligence, the most popular and widely used technique in control systems is the fuzzy logic. Such an intelligent controller designed may even work well with a system with an approximate model.

Several researchers have contributed in evolving such Artificial Intelligent (AI) controllers for boost converters (So *et al*., 1996; Lin and Hua, 1993). Among the various techniques of artificial intelligence, the most popular and widely used technique in control systems is the Neuro-fuzzy logic. In recent years Fuzzy Logic Control (FLC) has emerged as one of the practical solution when the process is too complex and non-linear for analysis by conventional quantitative techniques (Mattavelli *et al*., 1993; Gupta *et al*., 1997). However, the development of a fuzzy controller has to rely on the experience of the experts for deriving effective fuzzy control rules. Recently there has been an increasing use of Artificial Neural Networks (ANNs) for various

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applications particularly because of their capability for learning from examples and adaptation (Huh and Park, 1999). This study aims to establish the superior performance of Neuro-fuzzy controllers at various operating points of the boost converter. The basic concept of Neuro-Fuzzy control method (Lin, 1991) is first to use structure-learning algorithm to find appropriate Fuzzy logic rules and then use parameter-learning algorithm to fine-tune the membership function and other parameters. Simulation results are shown and settling time and peak overshoot have been used to measure the performance.

Linearized model: Rigorous determination of the stability and the control characteristics of power electronic converters require solving the non-linear model. Linearization of the non-linear model greatly simplifies analysis. Linearized model approximately describe small deviations or perturbations from nominal operation of the system.

Deriving the small signal model of the converter: The boost converter in Fig. 1, when operating in continuous conduction mode, switches between these two linear states, depending on the state of the switch 'S'. The first step in the design of controller for such a bi-linear system is to obtain its control-to-output transfer function. Using the state space averaging technique, the control-to-output transfer function of the classical boost converter operating in continuous conduction mode can be obtained as in (Albert *et al*., 2005). The transfer function shows a right-half-plane zero, which moves with the operating point in the s-plane.

$$\frac{Vo(s)}{D(s)} = \frac{Vs}{(1-D)^2}\frac{\left(1 - s\frac{L}{R(1-D)^2}\right)}{1 + s\frac{L}{R(1-D)^2} + s^2\frac{LC}{(1-D)^2}} \tag{1}$$

Where,
D = Duty ratio at the operating point
Vs = Supply voltage, L = filter inductor
C = Filter (output) capacitor
Vo = Output voltage
R = Load resistor.

It can be seen from (1) that the control-to-output transfer function is dependent on the operating point and its validity is limited to in and around the operating point. As the operating region of the converter is wide, the conventional way of designing the controllers involves selecting the worst case operating point i.e. under the minimum line and maximum load conditions. The transfer function of the converter under the worse case conditions is taken as the base in the design of the controller.

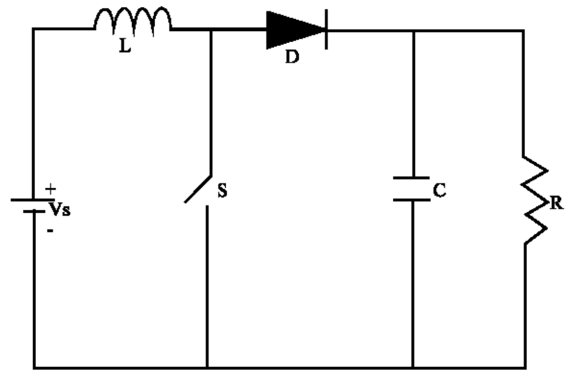

Fig. 1: Circuit diagram of boost converter, L-Inductance, S-Switch, D-Diode, R-Load Resistance, C-Capacitance

Control requirements: The control specifications of the converter are:

- Steady state error
- Settling time and allowable transient overshoot

In frequency domain terms, the steady state error is related to the DC loop gain. Thus the higher the open loop DC gain, the lower will be the steady state error.

Design procedure: Neuro-Fuzzy controller is designed based on an average state space model of the classical boost DC-DC converter. The design of Neuro Fuzzy controller needs a good knowledge of the system operation. The various steps involved in the design of Neuro Fuzzy controller for power converter are stated below. A universal Sugeno type Neuro Fuzzy controller has been simulated for the boost converter.

Identification of inputs and outputs: This step in the design identifies the key inputs that affect the system performance. The goal of the designer is to ensure that the output voltage matches the reference voltage. The inputs to the Neuro Fuzzy controller are:

- The voltage error.
- The change of voltage error.

Some controllers even may use more information in the form of inductor current. The voltage error input is sampled once in every cycle.

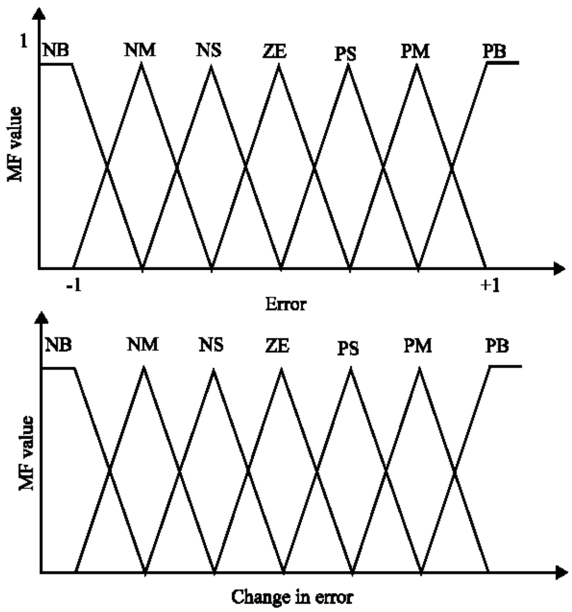

Fig. 2: Membership function for inputs

The output of the controller is the incremental control action i.e., the incremental duty ratio.

Fuzzifying the inputs and outputs: The universe of discourse of the inputs is divided into seven fuzzy sets of triangular shapes. Outputs are also mapped into several fuzzy regions of several singletons.

Development of rule base: The rules connecting the inputs and the output singletons are based on the understanding of the system. Normally the fuzzy rules have if…then… structure. The inputs are combined by AND operator. The rule-base contains the fuzzy IF-THEN rules of sugeno's first order type.

Defuzzification: The output space with the 'fired 'singletons is 'defuzzified' to get a final crisp value of the incremental control, in which the output of each rule is a linear combination of input variables plus a constant term.

Layer 1: Each node in this layer performs a Triangular membership function (Fig. 2).

$$O_1, I = \max(\min(x\text{-}a/b\text{-}a,\ c\text{-}x/c\text{-}b), 0),\ i=1\ldots7 \quad (2)$$

Where the parameters a and c locate the "feet" of the triangle and the parameter b locates the peak of the fuzzy set, x_i is the input to the node i.

Layer 2: Every node in this layer (Fig. 3) represents the firing strength of the rule.

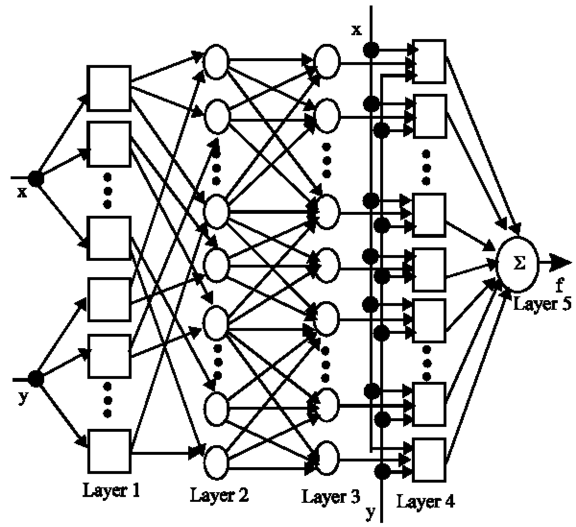

Fig. 3: Structure of Adaptive Network Based Fuzzy Inference Systems (ANFIS)

$$O_2, i = w_i = \min(\mu_{Ai}(x), \mu_{Bi}(y))\ i=1\ldots7 \quad (3)$$

Eventually the nodes of this layer perform fuzzy AND operation.

Layer 3: The nodes of this layer calculate the normalized firing strength of each rule.

$$O_{3,i} = w_i = w_i / \Sigma w_i,\ i=1\ldots7 \quad (4)$$

w_i –firing strength of a rule.

Layer 4: The nodes in this layer output the weighted consequent part of the rule table.

$$O_{4,i} = w_i f_i = w_i(p_i x + q_i y + r_i),\quad i=1,\ldots7 \quad (5)$$

where $\{p_i, q_i, r_i\}$ is the parameter set of this node.

Layer 5: The single node in this layer computes the overall output
as the summation of all the incoming signals.

$$O_{5,i} = \Sigma w_i f_i / \Sigma w_i,\quad i=1\ldots7. \quad (6)$$

Where $O_{5,i}$ denote the output of the 'i'th node in layer 5.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) training is done assuming that no expert available and the initial values of the membership functions parameters are equally distributed along the universe of discourse and all consequent parts of the rule table set to zero. The ANFIS starts from zero output and during training it gradually learns the rules and functions as close to the desired controller. Thus during training the network structure update membership functions and rule base parameters according to the gradient descent update procedure.

RESULTS

The Neuro-fuzzy control algorithm is now verified by simulation (Simulink, 1992). The simulation is performed in time domain for load regulation and line regulation of boost converter. The specification for

Table 1: Converter specifications

Input voltage	L	C	R	Output
10-20V	275μH	540μF	12.5-100Ω	25V 50W

L-Inductance, C-Capacitance, R-Load Resistance

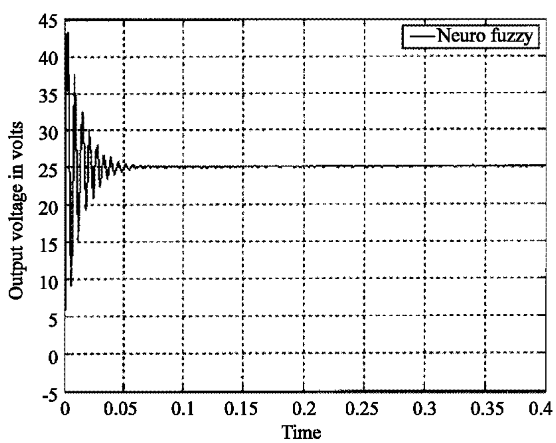

Fig. 4: Output voltage for a minimum line and maximum load condition Vs = 10V

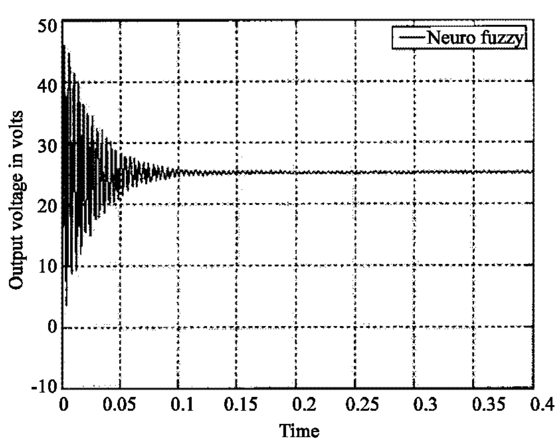

Fig. 5: Output voltage for a midrang line and load condition Vs = 15V, Io = 1A

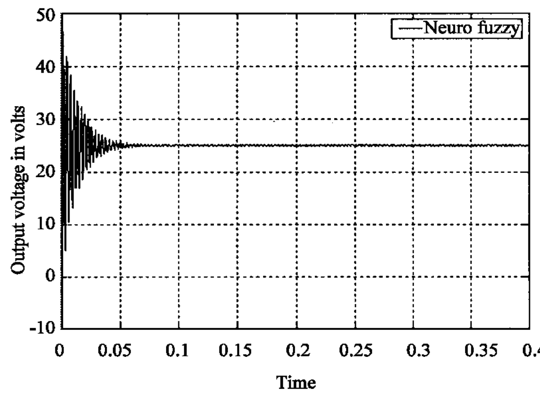

Fig. 6: Output voltage for a maximum line and load condition Vs = 140V, R = 11Ω

the 25V, 50 W bench mark converter used is given in Table 1. The switching frequency of the converter is taken as 50 kHz.

The Fig. 4-6 demonstrate the effectiveness of the proposed Neuro-fuzzy controller for output voltage regulation in the closed loop control of boost converter.

CONCLUSION

The boost converter subjected to various disturbances of input voltage and load changes is performed to demonstrate the effectiveness of the proposed controller.

The conclusions drawn from the results are:

- The proposed novel controller gives small overshoots and has much superior performance compared to the local PI controllers.
- The intelligent controller behaves effectively like an adaptive local tuned controller designed for each operating point and gives an improved performance compared to the conventional PI controller.

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