DESIGN OF INTELLIGENT CONTROLLERS FOR DC-DC CONVERTERS IN UNDERGRADUATE ENGINEERING LABORATORY

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Abstract

The primary goal of this paper is to develop a vehicle through which undergraduate students may design smart controllers that employ artificial intelligence control tools. This goal can be achieved through the design and construction of intelligent (fuzzy-neural-network) controllers for dc-dc converter topologies, the design of an interface with particular emphasis on laboratory environment, and the design and testing of the different control topologies. The control structure integrates the ideas of fuzzy control system and neural network architecture into an intelligent process. The fuzzy control design is equipped with a learning algorithm to adjust the control angle (or duty ratio) so that the steady state error is minimized and a zero-voltage regulation is achieved. The student has the opportunity to assume the role of a control system designer, who is given the task of designing a cost effective yet flexible controller. The fundamentals governing the design, control and performance of the DC-DC converters are also illustrated. The entire system is built and tested in the laboratory by using off-the-shelf components and software. A comprehensive analysis of the principle of operation, design consideration and experimental implementation of the converter topologies with built-in intelligent controller is developed. A rapid response is expected when the proposed controller is actually implemented in a real-time mode.

1.0 Introduction

Choppers themselves are generally divided into two groups: step-down or buck converter and step-up or boost converter [1]. For buck converters with constant output voltage, it is always desirable that the output voltage remains unchanged in both steady state and transient operations whenever the supply voltage and/or load current are disturbed. This condition is known as zero-voltage regulation and it means that the output voltage is independent of the supply voltage and the load current. To achieve zero-voltage regulation, the choice of the control method plays a very critical role in the performance of converters. The most commonly used control method in converters is the direct duty ratio control [2-5]. In this control method the output voltage is constantly monitored, fed-back, and compared with a reference voltage and their difference (the error) is amplified and used to control the duty ratio of the converter in such a way that the output voltage remains constant. This approach, however, cannot eliminate the supply voltage and load current disturbances until they are detected at the output. Another popular method is the current mode control, where the inductor current is also monitored and fed-back together with the output voltage. By a proper design, current mode control can eliminate the input voltage disturbances but it cannot eliminate the load current disturbance [6]. Feed-forward types of controllers have also been designed by sensing the input voltage to improve line regulation in applications with a wide range of input voltages and load currents. However, direct sensing of the input voltage through a feed-forward loop may induce large-signal disturbances that could upset the normal duty-cycle of the converter. A method to achieve zero-voltage regulation in buck converters has been introduced in [4]. Using circuit analysis, a direct relationship between the average output voltage and the reference voltage is determined. Based on this relationship, a proper control law (Function Control) is developed. Employing an averaged low frequency linear topology of buck converters, the control law shows that the output voltage is independent of both the input voltage and the load current and, thus, a zero-voltage regulation can be achieved. Using function control, however, the exact relationship between the input and output voltages becomes too complex to be practically executed. By means of human linguistic terms and common sense, several fuzzy logic-based controllers have been developed in [7-14]. These fuzzy controllers have shown promise in dealing with nonlinear systems and achieving voltage-regulation in buck converters [9-14]. Fuzzy logic control uses human like linguistic terms in the form of IF-THEN rules to capture the nonlinear system dynamics. Once in place, the fuzzy rules will not be able to adapt themselves to adequately capture the dynamics of the system. To become adaptive, fuzzy logic control must be able to learn to adjust its parameters in order to capture the dynamics of the system. Artificial neural networks (ANNs) have also found use in control systems [15-19]. One of the major features of ANNs is their learning capability. A drawback in using an ANN for control is that there is so much freedom in structural implementation choice that it is often difficult to decide how complex a structure is actually necessary for the desired control. Besides, the implementation is not at all intuitive and the inner workings of the network are very much invisible to the designer. The integration of neural network architectures with fuzzy control has resulted in a very powerful strategy known as adaptive-neural-network fuzzy system. Some researchers suggest that neural networks and fuzzy control are in fact special instances of adaptive networks [20-21].

2.0 Proposed Converter Topology with built-in Intelligent Controller

A fuzzy-neural-network control system is proposed in this paper. Both fuzzy logic principles and learning functions of neural networks are employed together to design a novel adaptive-fuzzy-based neural network (AFNN) controller-based dc-dc converter. The combination of both paradigms allows the merging of intelligent learning algorithm, which is developed in the realm of ANNs, together with the representation of qualitative and cognitive rules in fuzzy systems. A fuzzy controller is first designed which is the starting point of the AFNN. Then, ANN architecture is developed based on the pre-designed fuzzy controller. The network architecture is built, such that the designer knows the internal workings as they relate to fuzzy controller components. The basic structure of a converter topology with built-in intelligent controller is shown in Fig. 1. The converter is represented by a "block box" from which we only extract the terminals corresponding to input voltage, V_i, output voltage, V_o, one inductor current, i_L, and controlled switch, S. The controller output variable is the switch duty cycle, δ.

2.1 Fuzzy Controller Design

Primarily, students will decide on the state variables of each converter topology that can be taken as the input signals to the controller. The controller-input variables include, output voltage error, inductor current error, and inductor current, which will be used for current limiting only. Consequently, the input to the converter unit would be a signal proportional to the converter duty cycle that is actually the output of the controller. After choosing proper fuzzy variables as input and output of the FLC, students must decide on the fuzzy sets. These sets transform the numerical values of the input of the FLC, to fuzzy quantities. Choosing the fuzzy sets to formulate the fuzzy control rules are, also, significant factors in the performance of the FLC. Empirical knowledge and engineering intuition play an important role in choosing fuzzy sets and their corresponding membership functions. The number of these fuzzy sets specifies the quality of the control, which can be achieved using the FLC. Also, students will recognize that as the number of the fuzzy sets increases, the management of the rules is more involved and the tuning of the FLC is less straightforward. Accordingly, a trade-off between the quality of control and computational time is required to choose the number of fuzzy sets. At this point, students will decide on the fuzzy sets for each of the input and output variables. They include, PL (positive large), PM (positive medium), PS (positive small), ZERO, NS (negative small), NM (negative medium), and NL (negative large). After specifying the fuzzy sets, students will determine their membership functions. The triangular membership functions are used in this paper. Finally, students will formulate the FLC by using a set of fuzzy decision rules. Following evaluation of the rules, students will use fuzzy centroid method to determine the fuzzy control output.

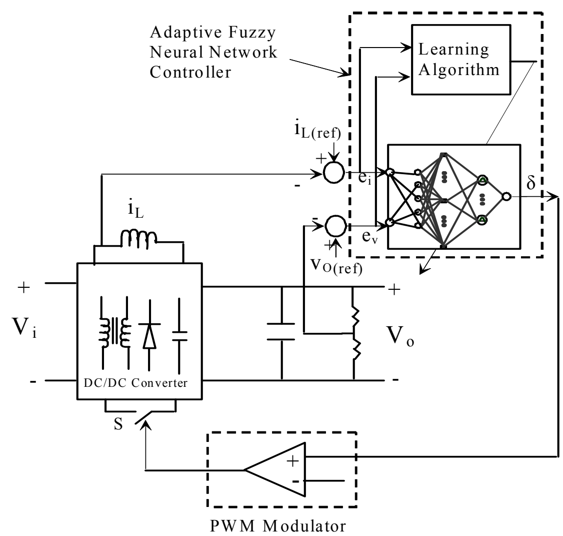


Fig. 1 Converter topology with built-in intelligent controller

2.1 Fuzzy Logic Controller Using Topology I

The block diagram of the fuzzy logic control scheme of topology I for the DC-DC converter is shown in Fig.2. The output is the duty cycle, δ_k. For this topology, there are two inputs, the voltage error $e = U_o - U_{ref}$ and the change of the voltage error $c_e = e_k - e_{k-1}$. The term U_o is the present output voltage, and U_{ref} is the reference output voltage.

2.1.1 Fuzzy Rules-Based Topology I

Students derived the heuristic fuzzy control rules based on the following criteria: 1) **IF** the output of the converter is far from the set point, the change of the duty cycle must be large to bring the output to the set point quickly, 2) **IF** the output of the converter is approaching the set point, a small change of duty cycle is necessary, 3) **IF** the output of the converter is near the set point **AND** is approaching it rapidly, the duty cycle must be kept constant to prevent overshoot, 4) **IF** the set point is reached **AND** the output still changing, the duty cycle must be changed a little bit to prevent the output from moving away, 5) **IF** the set point is reached **AND** the output is steady, the duty cycle remains unchanged, and 6) IF the output is above the set point, the sign of the change of the duty cycle must be negative, and vice versa.

2.2 Fuzzy Logic Controller Using Topology II

In this topology, students use three input variables: 1) Output voltage error, e_u, 2) Inductor current error, e_i and 3) Inductor current, i_L. A block diagram of the fuzzy controller structure is shown in Fig. 3. While the output voltage reference is usually available as an external signal, the inductor current reference depends on the operating point. For this reason, students computed the reference signal of the inductor current by means of a low-pass filter in the assumption that the dc value of the current is automatically adjusted by the converter according to the power balance condition. The controller output variable is the switch duty cycle controller, which is obtained by adding the outputs of two fuzzy controllers. One fuzzy (P) gives the proportional part δ_p of the duty cycle as a function of $e_i = I_{ref} - i_L, e_u = U_{oref} - U_o$ and i_L. The other fuzzy (I) gives as increment of δ_I, which is then integrated to provide an integral term δ_I of the duty cycle $\delta = \delta_p + \delta_I$.

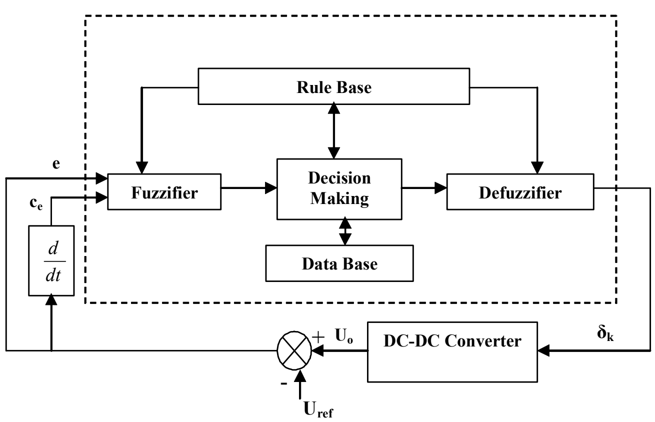


Fig. 2 Fuzzy Controller-based Topology I

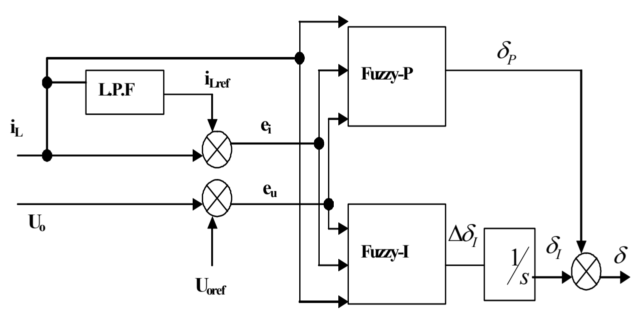


Fig. 3 Fuzzy Controller-based Topology II

2.2.1 Fuzzy Rules-Based Topology II

Far from the set point: students recognized that when the output voltage is far from the set point (e_u is PB or NB), the corrective action must be strong, meaning δ_p should be NB or PB, while δ_I should be zero. The basic control rules are:
IF e_u is PB AND i_L is NORM, THEN δ_p is PB AND δ_I is ZE.
IF e_u is NB AND i_L is NORM THEN δ_p is NB AND δ_I is ZE.
This shows that far from the set point, the control action is denoted by the output voltage error, provided the existence of the current limit.
Close to the Set Point: In dealing with this issue, students took properly into account the error of the current in order to ensure stability and rapidity of response. The goal in this region is centered in achieving a satisfactory dynamic performance with small sensitivity to parameter variations. The control rules are according to energy balance and inductor current is far from the limit.

- IF e_u AND e_i are both Zero, δ_p AND nd δ_I must be zero too (steady state condition).
- IF the output voltage error e_u is Negative AND inductor current is greater than the reference value ($e_i < 0$), δ_p and δ_I should be negative.
- IF output voltage error is Positive AND the inductor current is greater its reference value, THEN δ_p and δ_I must be kept to zero to prevent undershoot and overshoot.
- IF the output voltage is Positive AND the current is lower than its reference value ($e_i >$ 0), δ_p and δ_I must be positive, the system energy increases in this condition.

3.0 Adaptive Network Architecture-Based Topology I

Five-layer neural network architecture is proposed in this research. Fig. 4 shows the module of the neural network architecture. The two input nodes in layer 1 only transmit input signals to the next layer. Each node corresponds to one input variable. The input variables are the output voltage error and the inductor current error. For every node *i* in this layer, the input and the output of the network are represented, respectively, as:

$$net_i^1 = X_i^1, \qquad Y_i^1 = f_i^1(net_i^1) = net_i^1$$

where X_i^1 represents the *i-th* input to the node of layer 1.
The nodes in layer 2 are term nodes that act as membership functions to express the input/output fuzzy linguistic variables. In this proposal, the Gaussian activation function will be used to represent the membership function. Therefore, for the *j-th* node

$$net_j^2 = -\frac{\left(X_i^2 - \mu_{ij}\right)^2}{2\left(\sigma_{ij}\right)^2}, \qquad Y_j^2 = f_j^2(net_j^2) = \exp(net_j^2)$$

where μ_{ij} and σ_{ij} are, respectively, the mean and the standard deviation of the Gaussian function in the *j-th* term of the *i-th* input linguistic variable X_{i2} to the node of layer 2. The weights between the input and membership layer are assumed to be unity.

Students defined the fuzzy sets for the input/output variables as PL, PS, ZE, NL, and NS. Hence, 10 and 25 nodes are included in layers 2 and 3, respectively, to indicate the input/output linguistic variables. Each node in layer 3 is denoted by Π which multiplies the incoming signal and outputs the result of the product. Consequently, each node of this layer is a rule node that represents one fuzzy control rule. In total, there are 25 nodes in layer 3 to form a fuzzy rule base for two linguistic input variables. The links of layer 3 define the preconditions and the outcome of the rule nodes, respectively. For each rule node, there are two fixed links from the input term nodes. For the *k-th* rule node

$$net_k^3 = \Pi_j w_{jk}^3 X_j^3 , \qquad Y_k^3 = f_k^3(net_k^3) = net_k^3$$

where X*j* represents the *j-th* input to the node of layer 3, and w_{jk} is the link that connects the output of the *j-th* node in layer 2 with the input to the k-th node in layer 3. The weights between the input and membership layer are, also, assumed to be unity. The links of layer 4, which are surrounded by a dotted line, will be adjusted in response to varying control circumstances. The link weights, w_{kl}, represent the output action of the *k-th* rule. Each node in layer 4 consists of nonlinear mappings, which are sigmoidal functions. The sigmoidal activation function imposes bounds on the signal, and enhances stability. For the *l-th* node in this layer, the input and output of the network are represented as:

$$net_l^4 = Y_k^3 w_{kl} , \qquad Y_l^4 = f_l^4(net_l^4) = \frac{2}{1+\exp(-\gamma \cdot net_l^4)} - 1$$

The output of layer 5 is the output layer and acts as a defuzzifier. The single node Y_o in this layer is labeled Σ, and it sums all incoming signals to obtain the final inferred results:

$$net_o^5 = \sum_l Y_l^4 , \qquad Y_o = f_o^5(net_o^5) = net_o^5$$

The defuzzification aims at producing a non-fuzzy control action that best represents the possibility of distribution of an inferred fuzzy control action. The weighted average (centroid) method, in which the fuzzy centroid constitutes the controller output signal, is utilized.

3.1 Adaptive Network Architecture-Based Topology II

Six-layer neural network architecture is proposed in this section. Fig. 5 illustrates the module of the network architecture. The two input nodes in layer 1 only transmit input signals to the next layer. Each node corresponds to one input variable. The input variables are the output voltage error, e_v, and the inductor current error, e_i. The first four layers are parallel to the ones in topology I. Thus, layer 5 acts as a defuzzifier. The nodes δ_p and $\Delta\delta_I$ in this layer are labeled Σ and they sum all incoming signal to each branch to obtain the final inferred results for δ_p and $\Delta\delta_I$.

$$net_m^5 = \sum w_{lm}^4 Y_l^4 , \qquad Y_m^5 = f_m^5(net_m^5) = net_m^5$$

The fifth layer is the one we training or updating its weights, w_{lm} which represents the weight connecting layer k and layer m, to satisfy the desired value. The output of Layer 6 is the summation of δ_p and the integration of $\Delta\delta_I$ that generates the change in the converter duty cycle.

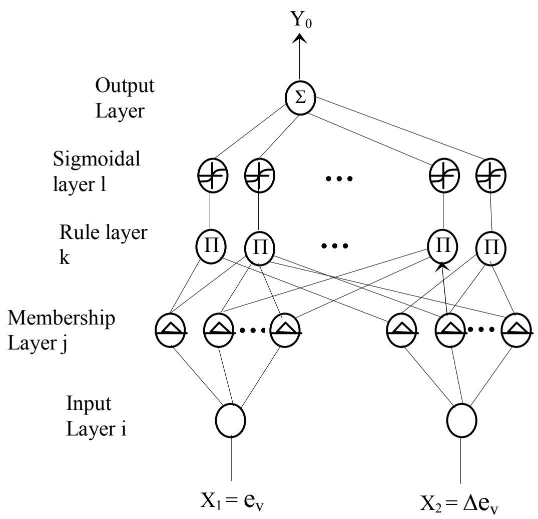


Fig. 4 Network architecture of topology I

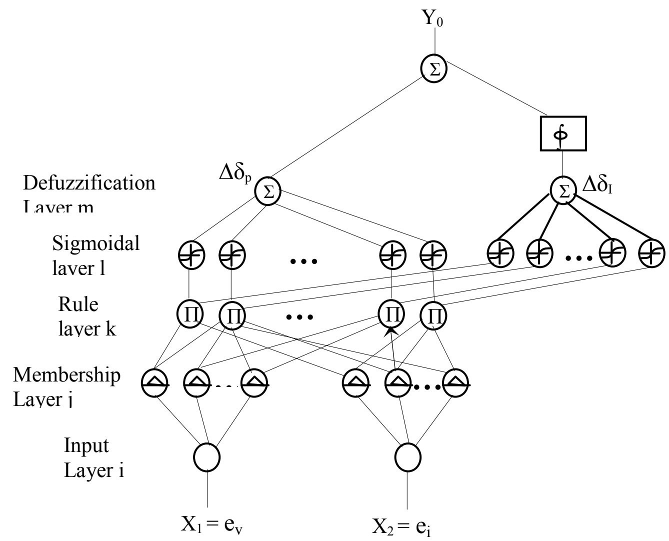


Fig. 5 Network architecture of topology II

4. Laboratory Setup

The overall system is composed of four major elements: 1) a DC-to-DC switch mode power stage converter 2) a 14-bit PCI Data Acquisition Processor (DAP 840/103) [14], 3) a termination board (MSTB 010-06-C1Z) [14], 4) a Pentium III 550-MHz personal computer (PC) with Windows NT 4.0, and a microcontroller (PIC16F877). Fig. 6a displays the experimental setup. The power stage concept is based on that of a “dual-output forward" configuration operating in a continuous mode of energy storage. When the power MOSFET switch Q1 is turned ON energy is transferred from the input power source (VIN) to the two secondary sides of the transformer. The voltage potential across the terminals of C11 will be that of the reflected line voltage, namely $N_{S1}*V_{IN}/N_P$. When Q1 turns OFF, the 5V and 15V load power is sustained by the energies of the two ‘inductors’(L1 & L2) and the energy stored in C11 as a result of the potential $N_{S1}*V_{IN}/N_P$, will then flow back into the 5V secondary winding in a resonant manner with the magnetization inductance of the transformer. This causes the voltage across the 5V secondary to reverse polarity in a sinusoidal manner, until the energy in C11 is completely dissipated.

The PCI Data Acquisition Processor (DAP 840/103) occupies one expansion slot in the Personal computer and has onboard processor, (TI486SXLC2-50 CPU), 14-bit A/D converter, 50ns TIME resolution, 800K samples per second, memory, and a dedicated multitasking real-time operating system. The MSTB (010-06-C1Z) termination board allows secure connection of discrete wires to the DAP 840/103 and it combines analog and digital termination on the same board. The feedback network provides as input to the adaptive fuzzy controller the error value at the output, for the appropriate control signal to be issued. It is built around an optocoupler that provides ground isolation between the input and the output with a potentiometer for the adjustment of the two output voltages to desired levels. The termination board, DAP 840/103, reads the reads the error value from the feedback network using an input channel pipe to the PC in binary format. The source program (written in Matlab and Dapview language) running on the PC is configured to read the data and correctly processed. The processed data is finally sent as an input to the adaptive fuzzy controller code running on the PC to issue the appropriate command signal for the microcontroller through pin 3 of the RS232 to generate the control signal, which is the duty cycle. Using a microcontroller the duty cycle is generated by a peripheral Interface Controller (PIC16F877), which uses the Harvard Architecture and mostly used in RISC (Reduced Instruction Set Computer) Computers. It has a separate program bus and data bus, which can be of different widths. A single instruction cycle time of the PIC 16F877 is 0.2 μs. A code was written using MPLAB and loaded into the PIC16F877 to generate pulses at 100 kHz with variable duty cycle depending on the input data received through pin 3 of the RS232 sent by the fuzzy logic controller running on the PC. The output pulses are sent through pin 2 of the RS232 to the gate of transistor Q1 which in turn produces the necessary drive pulse to the power stage of the converter to keep the output voltage constant. Fig. 6b displays a snap shot of the hardware of the laboratory setup

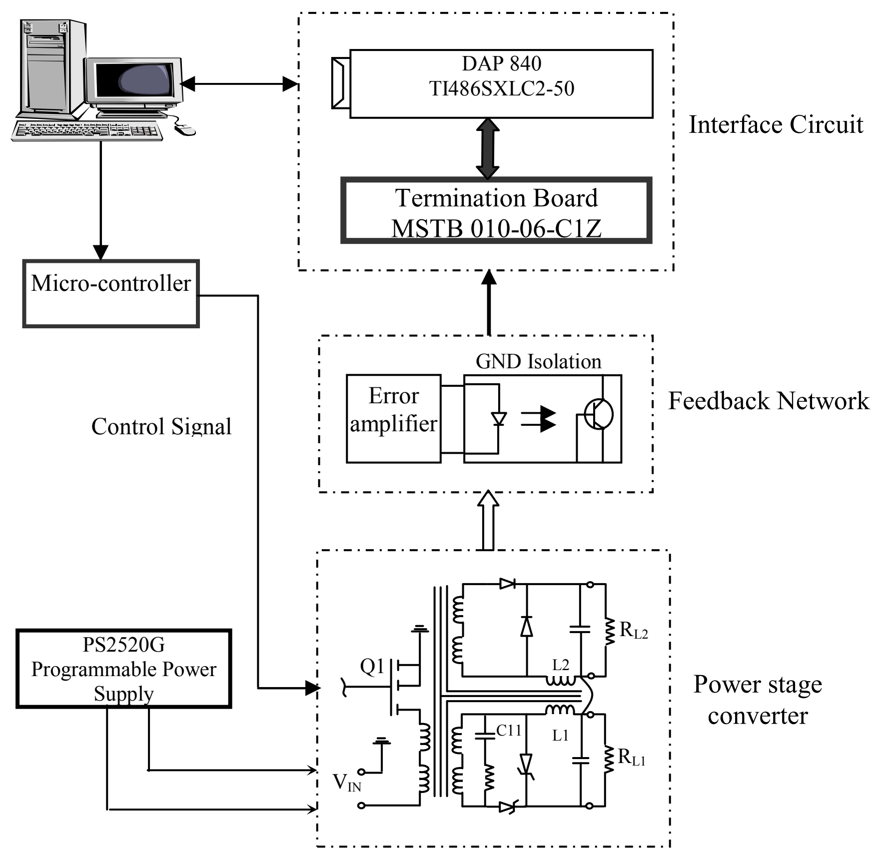


Fig. 6a Experimental setup

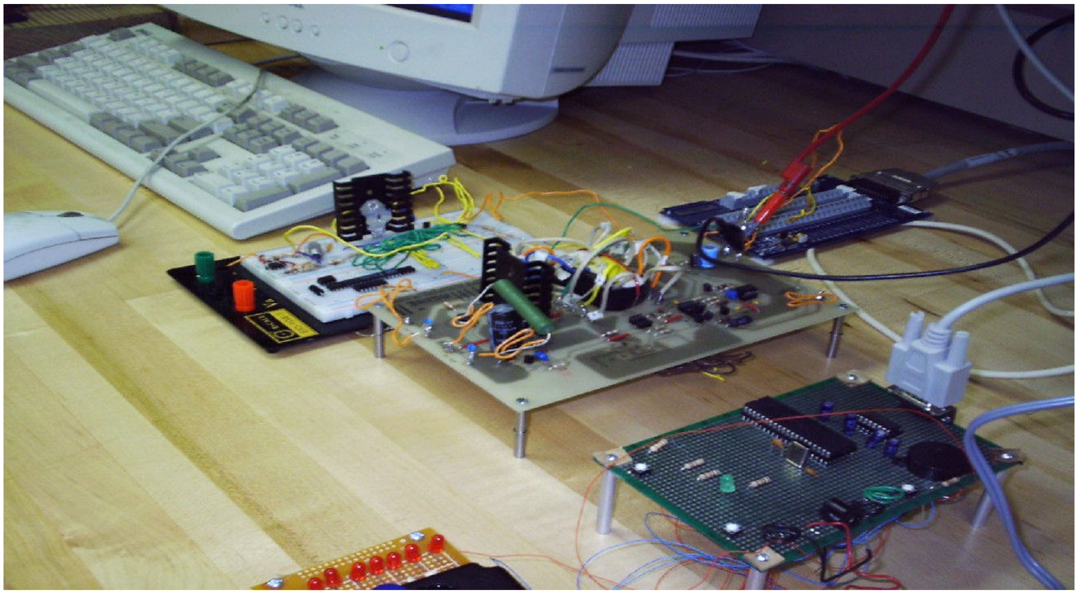


Fig. 6b Snap shot of the laboratory setup

4.0 Simulation Results

Several cases are examined but only salient cases are presented. In case I, the adaptive fuzzy controller of topology I is examined for the buck-boost converter where the load resistance is varied from 10 Ω to 5 Ω and back to 10Ω. Fig. 7 shows the performance of fuzzy and adaptive fuzzy controllers, while Fig. 8 shows the corresponding duty cycle. It can be seen from Fig. 7 that the adaptive fuzzy controller reduces the ripple in the output voltage as it almost brings the output voltage to its reference value most of the time. In case II, the input voltage is varied from 15 V to 20 V and back to 15 V. Figs. 9 and 10 show the controlled output voltage and the corresponding duty cycle, respectively. Fig. 9 shows that the adaptive fuzzy controller reduces the ripple in the output voltage. In addition, it almost brings the output voltage to its reference value most of the time. The maximum tolerance that the adaptive fuzzy generates occurs at "0.016 second" with a value of "1.304 %" while at the same point the fuzzy logic has a tolerance of "6.6006 %". It is also shown that when the input voltage is increased suddenly from 15 V to 20 V, the duty cycle has to compensate by a reduction from 0.25 to 0.2 to keep the output voltage constant.

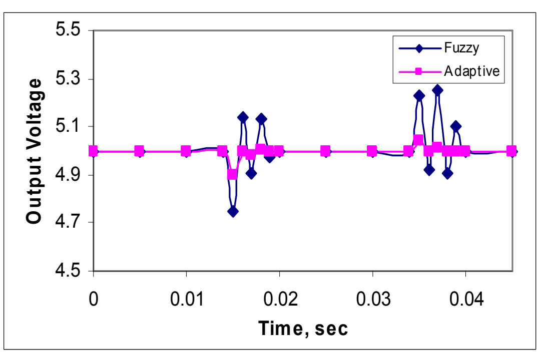


Fig. 7 Fuzzy/adaptive fuzzy trajectories

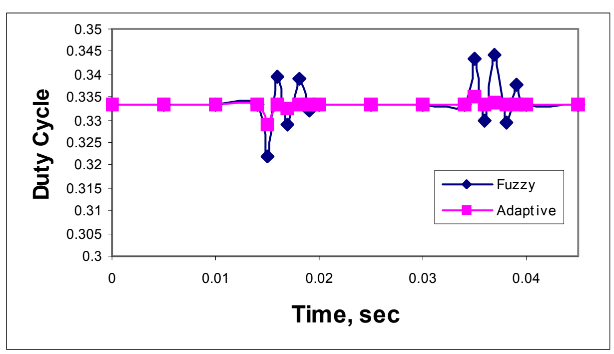
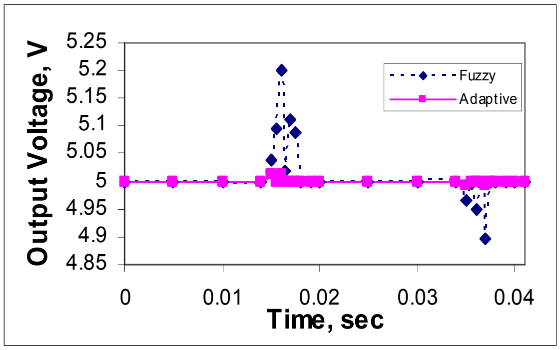


Fig. 8 Duty cycle trajectory



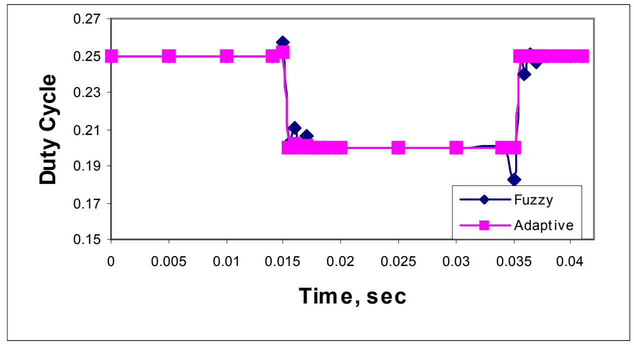
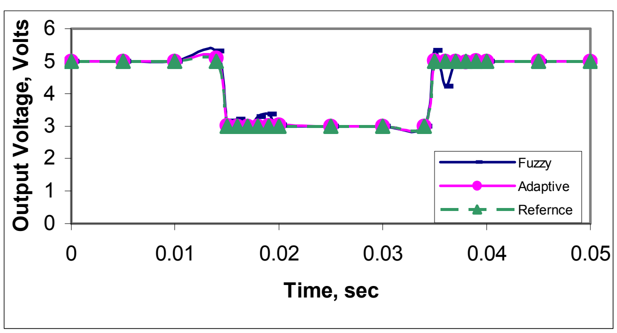


Fig. 9 Output voltage trajectory

Fig. 10 Duty cycle trajectory

In case 3, test results are given for the output voltage of a buck converter with the reference voltage changing from one level to another (square-wave reference track with amplitude of 20 V). Figs 11 and 12 show the controlled output voltage and the corresponding duty cycle. Fig 11 shows the voltage trajectory, when the desired voltage changes from one value to another, using fuzzy and adaptive fuzzy control. The converter operates at voltage of 5 V and drops to 3 V and then proceeds to desired voltage of 5 V. The actual voltage is superimposed on the specified reference voltage in order to compare tracking accuracy. It is observed that the fuzzy controller exhibits errors especially near the corners at t= 0.014 S, t= 0.02 S, t = 0.035 S, and t= 0.04 S. However, the adaptive fuzzy controller almost manage to follow the reference voltage every where, especially in the corners when the fuzzy logic almost fails to do so.



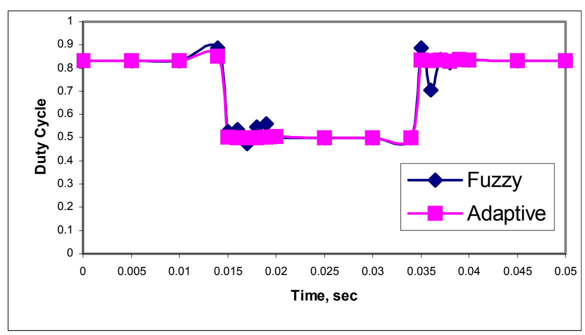


Fig. 11 Output voltage trajectory

Fig. 12 Duty cycle trajectory

The second control architecture whose performance is to be studied is the control topology II. First, topology II is tested on the buck-boost converter where the load regulation is varied from 20 Ω to 150 Ω and back to 20Ω. Fig. 13 shows the output voltage using PI, fuzzy logic, and the adaptive fuzzy controllers. It is shown from Figure 13 that the adaptive fuzzy controller almost matches the output voltage to its reference value of 20 volts. Fig. 14 shows the controlled output voltage of a Sepic converter using PI, fuzzy, and adaptive fuzzy controllers with load regulation varying from 20 Ω to 200 Ω and back to 20Ω.

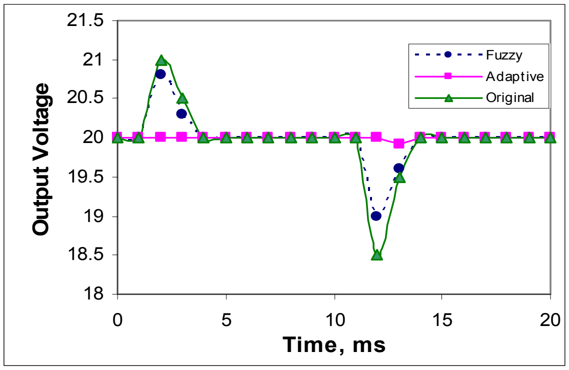


Fig. 13 Output voltage trajectories

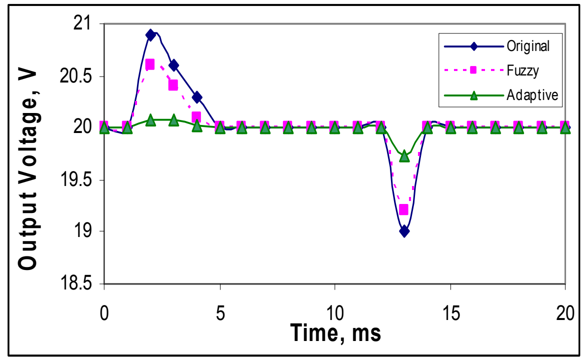


Fig. 14 Voltage trajectories of Sepic converter

Conclusions

The proposed adaptive fuzzy system is designed in such that only one layer is to be trained. The weights of this layer are trained to capture the system dynamics and therefore minimize the ripples around the operating point. Two adaptive fuzzy neural network topologies are designed and tested; the differences between them are basically in the input variables and in the fuzzy logic structure. That is, the number of the neuron needed in the learning layer. Many cases are tested concluding that the adaptive fuzzy topologies are efficiently reducing the effect of external disturbances such as load changes and input voltage changes, on different types of DC/DC converters.

A commensurate number of components is designed and built. The components are tested individually and in various combinations of hardware and software segments. The entire system will be fully tested. The other work to be completed includes the integration of the full system and the start of the implementation stage of the project. Two categories of tests, namely, load regulation, and line regulation will be carried out to evaluate the performance of the proposed control system.

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