ISSN 1392 – 1215 ELECTRONICS AND ELECTRICAL ENGINEERING 2007. No. 1(73)
ELEKTRONIKA IR ELEKTROTECHNIKA

T 180 TELECOMMUNICATIONS ENGINEERING
TELEKOMUNIKACIJŲ INŽINERIJA

Dynamic Back Propagation based MRAC with Fuzzy Emulator for DC-DC Converter

S. G. Kadwane, A. Kumar, B. M. Karan
Birla Institute of Technology, Mesra, India, e-mail: sgkadwane@bitmesra.ac.in

Introduction

With the advent of digital signal processors, advanced control methodologies through artificial intelligence can be applied in most of the industrial applications. The power supplies have emerged as an independent industry which is inevitable in all the manufacturing process. The practical challenge in most of the SMPS is to design the advanced control strategies to tackle the nonlinearity and uncertainty of plant model. The stability is also and important issue. The main strength of the neural network structures lies in their learning and adaptive abilities. Neural networks finds potential solution in the field of plant identification and pattern recognition problems in its parallel form i.e. neural network controller is parallel connected with the plant. But the requirement of a plant emulator can not be avoided when ANN controller is in between the plant and the control input.

Many researches suggest direct type of neuro-control systems [10],[6],[5]in order to overcome the difficulties of conventional PID in non-linear system theory. The major difficulty of this control strategy is the requirement of a plant emulator which serves as a teacher for the Neural Network controller (supervised learning).

In [13], Narendra and Parthastry suggest a sensitivity model for the plant which requires some information regarding the jacobians of the plant. This is difficult for the online implementation. This paper is concerned with a procedure suggested by that of Narendra and Parthastry's , but avoids the development of the sensitivity model for the plant just by replacing the sensitivity model with a simple Fuzzy based emulator.

In [12] Suwat, Robert and Rees proposed a Neural Network based plant emulator, but it requires an off-line training before use. Moreover off-line training requires exact model of the plant for the simulation, introduces model uncertainty in case of a nonlinear plant.

In [8] Park, choi and Lee, proposed a neuro identifier concept which computes the derivatives associated with the plant. But this requires the knowledge of the plant and is also complex for the on line implementation. Recently back propagation based dynamic neural for buck converter is implemented which replaces the tuning of PID parameters [1]. Newly introduced dynamic backpropagation learning framework for the training of feedforward neural networks with a simple fuzzy emulator is proposed (which eliminates the need of PID controller for training [1]).

The new control makes use of the MRAC system design principle, common in traditional adaptive control system design. This design work can be extended for the class of nonlinear system with structural uncertainty. This simple new method incorporates the online training algorithm. Simulation studies are carried out for the DC-to-DC converter system and the same is implemented using DSP processor (TMS320LF2407 DSK)[22], to obtain the real time response. The overall simple control methodology requires less memory in DSP. The practical and simulation results shows that the proposed method gives far better response as compared to conventional PID controller.

The Elements of Model Reference Adaptive Controller

The nature of the dynamical system usually shows slow changes of system parameters and changes of the parameters due to the different operating conditions or operating point. In this case an adaptive controller should be designed to follow the changes of operating conditions and adapt in certain prescribed way. Robustness of the adaptive systems to unmodeled dynamics and bounded disturbances is treated in[19].

The basic idea of MRAC is to introduce a global stability criterion into the design procedure and to choose the adaptive control law in such a way that the requirement of the stability criterion is fulfilled. In other words, it is desired to design a controller that computes a control action signal, such that the overall control system respond dynamically as the specified reference model. Limitations of the classical PID design is, the controller parameters must be tuned by some appropriate algorithm to obtain the desired response and also re-tuning is required for the different values of load changes. The system is affected by the environmental conditions, hence, not a robust system.

On the other hand a MRAC can completely replace the conventional PID and also can produce reasonable output for inputs that not encountered during training, making it a robust controller.

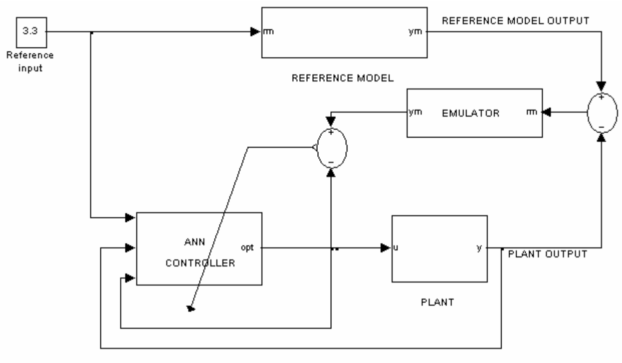

Fig. 1. Basic structure of MRAC

Fig. 1 shows the basic components of MRAC. The block labeled "REFERENCE MODEL" is the required trajectory of the plant to be followed. This may be explained in the mathematical term as follows. A plant with an input-output pair u(n), y(n), and a stable reference model specified by its input-output pair $r_m(n)$, $y_m(n)$ with the reference input signal of the system r_m Є $L_{œ}$. Then the objective is to determine a control action law, u(n), for all n>0, and an updating law of the controller parameters such that .

$$\lim_{n \longrightarrow \infty} \; | ym(n) - Y(n) | \le \varepsilon \, . \qquad (1)$$

For a specified constant ε > 0. each component of the MARC is discussed below.

The reference model. Here the reference model is considered as a second order stable system with 0.15 ms rise time and 0.3 ms of settling time. The discrete time version of the reference model is given as

$$y_m(n)=1.2913*y_m(n-1)-0.2917*+0.2083*r_m(n-1)+ + 0.1388*r_m(n-2). \qquad (2)$$

The plant. To prove this fact a highly nonlinear buck converter is considered as a plant in Fig. 1. A buck converter is a step down DC to DC converter. DC to DC converters are inherently nonlinear due to switching operation. The regulation is normally achieved by the Pulse Width Modulation technique (PWM) at fixed frequency. Buck converter gives a regulated DC supply to load according to the duty cycle of the PWM input. The basic structure of the Buck converter is shown in Fig. 2.

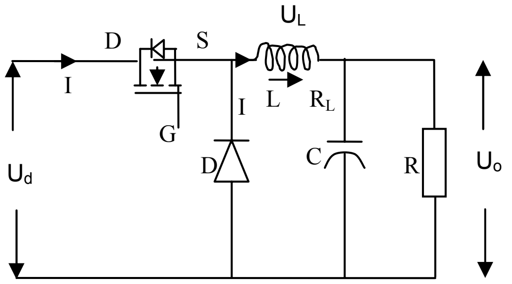

Fig. 2. Step down or Buck converter

The transfer function [3] of buck converter is written below.

$$G_2(s) = \left. \frac{\tilde{u}_o(s)}{\tilde{\delta}(s)} \right|_{\tilde{u}_d = 0} = \frac{u_d}{as^2 + bs + c} \quad , \qquad (3)$$

where $a = LC$, $c = 1 + \dfrac{R_L}{R}$, $b = \dfrac{L}{R} + R_L C$.

For the experimental purpose the buck converter was designed with R = 2Ω, L = 2.05mH, C = 47μF, R_l = 0.25 Ω and Ud = 15 V.

The transfer function of the buck converter

$$G_p(s) = \frac{1.557 \times 10^8}{s^2 + 1.076 \times 10^4 s + 1.168 \times 10^7} \qquad (4)$$

Modeling of the plant is not required for the real time implementation purpose. To obtain the simulation results, the discrete time model is developed by Tustin method with the sampling frequency 30 KHz. The obtained modeling equation is

$$y(n)=1.688*y(n-1)-0.6986*y(n-2)+0.0769*u(n-1)+ + 0.06828*u(n-2). \qquad (5)$$

The artificial Neural Network (ANN) controller. A neural network can be thought of as a black box that maps the inputs to the output. The mapping is done without explicit rules. The ANN adapts the desired mapping through a learning process, which requires presenting to the network a set of input-output pattern pairs.

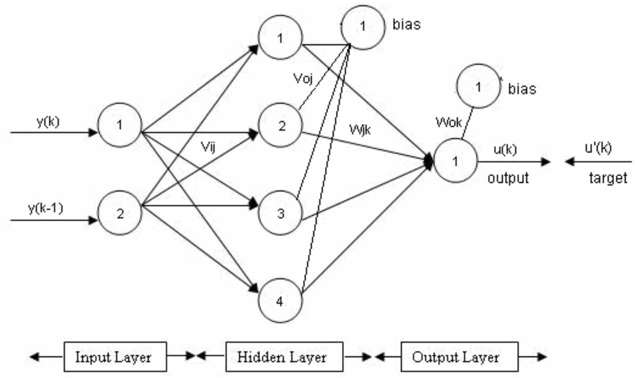

Fig. 3. Basic structure of Neural Network

Fig. 3 shows the basic Neural Network with one input layer, one hidden layer and one output layer with biases. It is proven fact that ANN architecture with one hidden layer and with sigmoid activation function can approximate any linear or non linear function with desired accuracy. Neural Network designer mainly faces problems with the architecture selection; how many hidden layers to use and how many neurons to choose in each hidden layer? The common practice is to choose a large number of computing neurons, which often results a bulky network with large memory requirement. One new method suggested in [2] describes, if the basic geometric shape of the target function is known in advance then the number of hidden neurons is equal to the minimal number of line segments (or hyper planes in large–dimensional cases) that can construct the basic geometrical shape of the target function. Using Dynamic Back Propagation training if the training phase is stopped at a local minima then a single hidden unit must be added to ensure the global minimum solution.

The second factor, which directly affects the stability of the network, is the choice of the learning rate (μ). The learning rate determines the stability and convergence rate. For input patterns dependent on time, convergence of the mean and the variance of the weight vector is ensured for the most practical purpose if

$$0 < \mu < \frac{1}{trace[R]},$$

where trace[R] = $\sum$(diagonal elements of R), is the average signal of the weight vectors $E(X^T X)$ with μ set within this range, the algorithm converges in the mean weight. Proof can be found in [21].

From the above discussion the 4-6-1 architecture of ANN is found to be optimal for the given problem. The four inputs of the ANN are the two delayed plant outputs(y(n)), one delayed duty cycle(u(n)) and the reference input(r_m(n)). The Back propagation algorithm is a generalized windrow-Hoff rule to multiple-layer networks and non-linear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities. Dynamic back propagation (see Appendix 1) is also a gradient descent algorithm, in which the network weights are moved along the negative of the gradient of the performance function. The training algorithm of the dynamic back propagation is well established in [13] for the reference it is attached in Appendix 1. The weight updating rule is given as

$$w_{jk}(new) = w_{jk}(old) + \Delta w_{jk},$$
$$v_{ij}(new) = v_{ij}(old) + \Delta v_{ij}, \qquad (6)$$

where $\Delta w_{jk} = -\alpha \frac{\partial e'}{\partial w_{jk}} = -\alpha \delta_k z_j$, $\Delta v_{ij} = -\alpha \frac{\partial e'}{\partial v_{ij}} = -\alpha \delta_j x_i$, α is the learning rate parameter.

The Emulator. The emulator is the main heart of the MRAC as it provides the training signal to the ANN controller. Plant emulator can not be avoided when ANN controller is in between the plant and the control input. Several methodologies for constructing the plant emulator have been proposed but they require either off-line training of the plant emulator or an exact mathematical model of the plant. This limits the capability of a neural system in generalization and control problem of a nonlinear plant. Another alternate is to use a heuristic approach like Fuzzy logic to build a plant emulator. To approximate the plant we need not design a precise emulator hence a simple fuzzy controller can serve as a plant emulator by just knowing some plant input-output data. It is shown in a result section that the real time results are much matched with its simulation counterpart.

The structure of proposed fuzzy logic emulator consists of three modules fuzzification, rule base and defuzzification. Structure of emulator is designed to produce the value of the duty cycle u'(n) based upon the difference in the reference model(y_m(n)) and plant output(y(n)). The rule base is of Mamdani-style fuzzy inference system. The term set for input variable e(n) and output variable has a 7 linguistic values as shown if Fig. 4 & 5. All these Fuzzy Sets are selected as overlapping isosceles triangles Both the input and output variables are defined on the normalized domain of [-1 1]. The rule base is developed with some prior knowledge of the plant data. The rule surface formed by inference is shown in Fig. 6, which indicates the nature of rules fired.

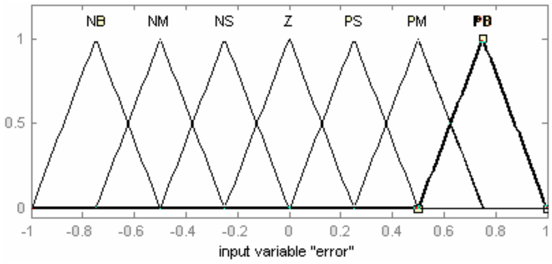

Fig. 4. Input variable "error"

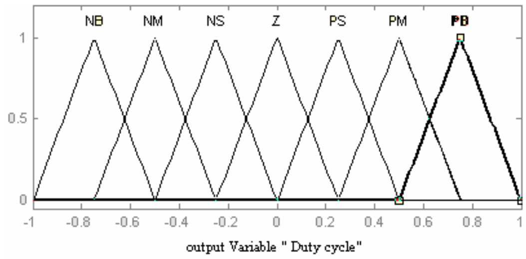

Fig. 5. Output variable "Duty cycle"

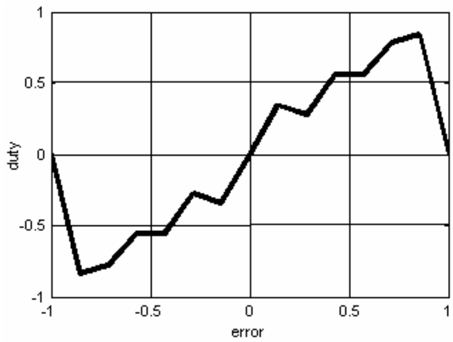

Fig. 6. Rule surface

The real time implementation scheme of MRAC

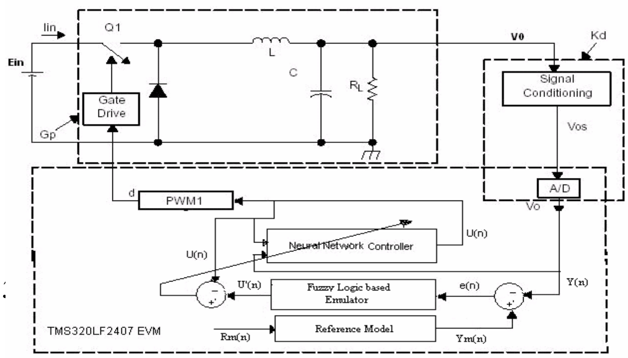

Fig. 7. Implementation scheme for MRAC with DSP processor

Fig. 7 shows a simplified block diagram of a digitally controlled dc-dc converter interfaced to TMS320LF2407A DSP controller. As indicated in the Fig. 7, a single signal measurement is needed to implement the voltage mode control of the dc-dc converter. The instantaneous output voltage V_{out} is sensed and conditioned by the voltage sense circuit and then input to the DSP via the ADC channel. The digitized sensed output voltage y(n) is compared with the reference model output $y_m(n)$.

A software routine is implemented through code composer studio (CCS) tool provided by Texas Instruments in C language programming. Once the error e(n) is calculated the fuzzy emulator provides the target duty cycle command to ANN controller. By the dynamic back propagation learning algorithm, ANN is trained to produce next duty cycle command u(n) to the converter regulator switch Q1. This command output is used to calculate the appropriate values for the timer compare registers in the on-chip PWM module. The PWM module uses this value to generate the PWM output, PWM1 in this case, that finally drives the buck converter switch Q1.

CCS is used to load and run the controller to achieve real time control. Furthermore, the parameters of the controller like learning rate can be adjusted while the converter is running, so that the online adjustment is achieved. This avoids the shutting down the system re-assembling and re-compiling the source code each time the parameters are adjusted. The software code which implements the neural network controller is written in timer interrupt service routine is given in appendix 2.

The test setup

For the simulation purpose the model of the plant is considered as given in equation (5) and the Reference model as (2). The MRAC code is written in "C" language.

The real time results were obtained by implementing the controlled digitally on TMS320LF2407A DSK for the proposed converter. The transient response is obtained with the initial load of 2Ω and then the load was changed to 0.66Ω by connecting a 1Ω resistor in parallel to obtain the transient response. The frequency of the PWM is chosen 30 KHz. And the output voltage was kept constant at 3.3V. The sampling time in all the above calculation is chosen 1/30000 sec with the thumb rule that sampling time is chosen as the inverse of the PWM frequency.

The prototype model was constructed at the laboratory of Control Systems in Birla Institute of Technology India as shown in Fig. 8 and Fig. 9 with following parameters:

Input Voltage	:	15v DC
Output Voltage	:	3.3v DC
Rated Load	:	2 Ω
Switching frequency	:	30 KHz
Inductor	:	2.05 mH, 0.11 Ω
Mosfet	:	IRF 840
Mosfet driver	:	TLP 250
Diode	:	UF5407
Capacitor	:	47µF, 35V
DSP	:	TMS320LF2407A DSK

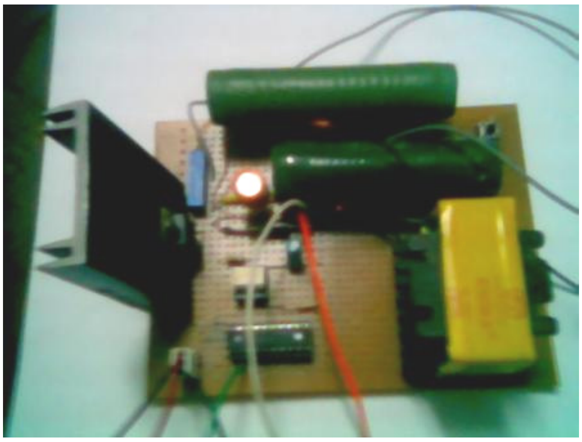

Fig. 8. Buck converter Prototype

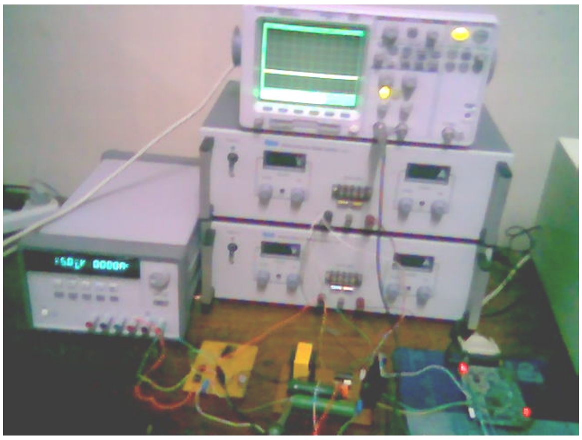

Fig. 9. Buck converter interfaced to TMS320LF2407A

Results

Fig. 10 shows the simulation result for the startup and reference change for the conventional PID controller. As the buck converter being highly non-linear device, we can expect that the PID parameters designed for the simulation purpose will not give the comparable result in real time, which is shown in Fig. 12. In comparison to the Fig. 10 the overshoot of the system remains at 15%. But the settling time is increased in case of the real time 0.05 sec. the results anticipate for the design of adaptive controllers like MRAC.

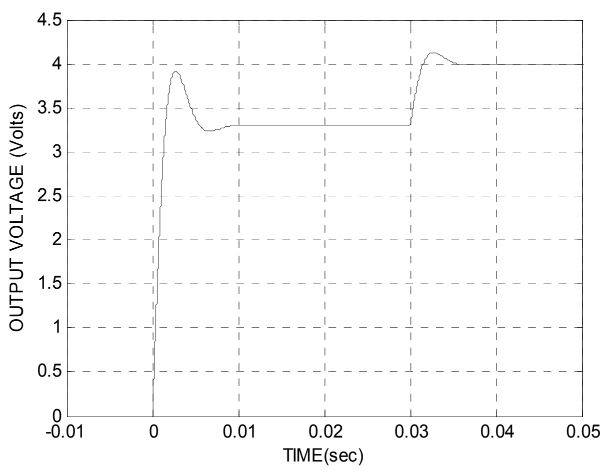

Fig. 10. Simulation result for startup

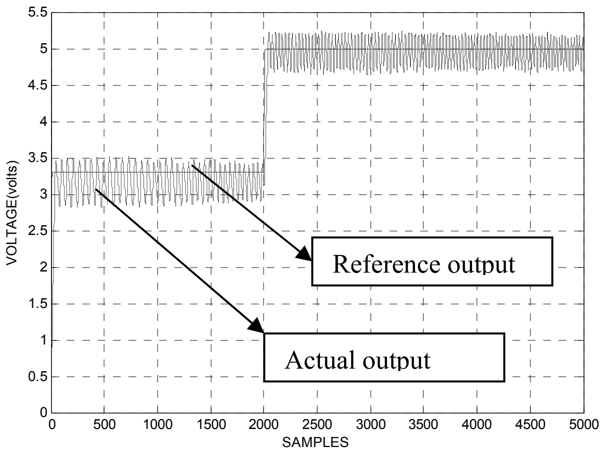

Fig. 11. Simulation result for startup and reference change of PID and reference change of MRAC

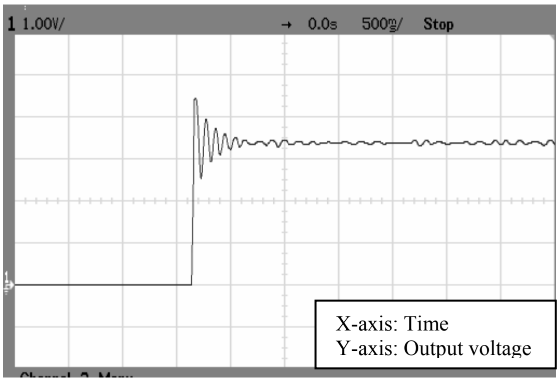

Fig. 12. Practical result for startup of PID

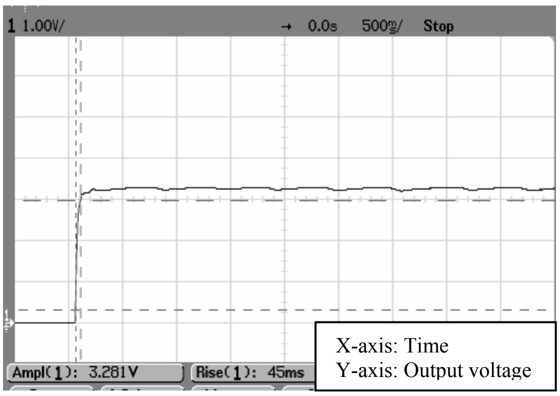

Fig. 13. Practical result for startup of MRAC

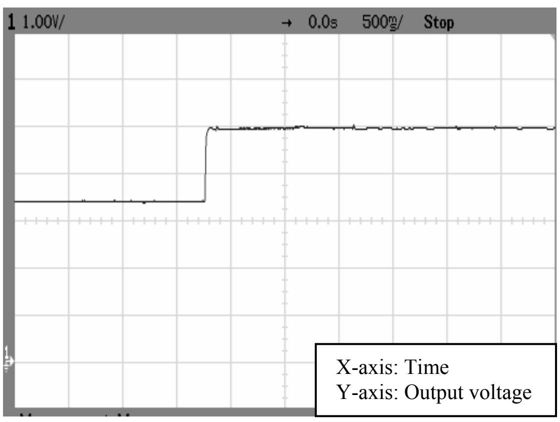

Fig. 14. Real time response for reference change form 3.3V to 5V

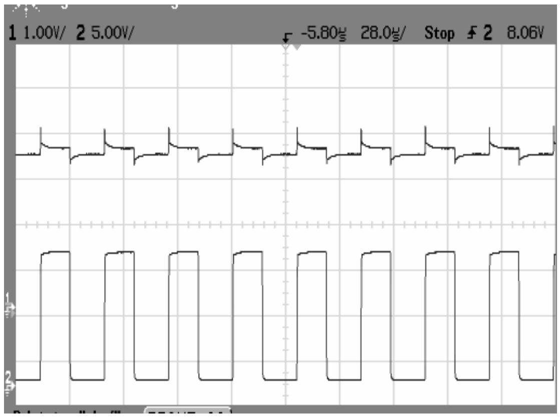

Fig. 15. Real time result for load Voltage and PWM signal for MRAC

Fig. 11 shows simulation result for the startup and reference change of MRAC. We see the overshoot has been reduced to 3%. If look at the real time response of the MRAC in Fig. 13, we can conclude the results are comparable. The real time response is much better than the simulation. It has nearly 0% overshoot. The rise time of the MRAC system when compared to PID is more, but if we compare the practical responses it is around 0.04sec. Fig. 14 shows the real time reference change form 3.3V to 5V. Fig. 15 shows the variation of the output Load voltage with reference to its PWM signal.

Conclusions

A Novel simple emulator for MRAC with dynamic back propagation algorithm applied to industrial power supplies is proposed. This design work can be extended for the class of nonlinear system with structural uncertainty. This simple new method incorporates the online training algorithm. The suggested overall simple control methodology requires less memory requirement in DSP. The improvements in practical and simulation results are stated by comparing with conventional PID controller. The proposed method can be widely used in most of the industrial nonlinear and complex applications.

References

1. **Kadwane S.G., Kumar Amit, Karan B.M., Ghose T.** Online Trained Simulation and DSP Implementation of Dynamic Back Propagation Neural Network for Buck Converter // International Journal of Automatic Control and Systems Engineering, ICGST. – Issue (1), 2006. – Vol. (VI). – P. 27–34.
2. **Xiang Cheng, Ding Shenqiang Q., Lee Tong Heng.** Geometrical interpretation and architecture selection of MLP. // IEEE Transaction on Neural Networks. – January, 2005. – Vol. 16, No. 1.
3. **Gleich Dusan, Milanovic Mira, Uran Suzana, Mihalic Franic.** Digitally controlled buck converter // IEEE power electronics society. – ISCAS, 2004. – V944–V947.
4. **Mohan, Underland, Robbins.** Power Electronics converters applications and design. - John Wiley & sons, inc. 2003.
5. **Goire Maria M., Flores Jose M., Bonilla Moises, Baruch Lerohan S.** Model Reference Neural control for a variable structure system by output feedback. 0-7803-7044-9/01/$10.00 ©2001 IEEE.

6. **Patino H. D., Liu Derong.** Neural Network-Based Model Reference Adaptive control system // IEEE transaction on systems. Man and Cybernetics-Part B: Cybernetics. – February 2000. – Vol. 30, No. 1.
7. **Dillon T., Arabshahi P., Marks II R J.** Special issue on everyday applications of neural networks // IEEE trans. Neural netwoks, 8,4, July 1997.
8. **Park Young-Moon, Choi Myeon-Song Lee Kwang Y.** An optimal Tracking Neuro-Controller for Nonlinear Dynamic Systems // IEEE Transaction on Neural Networks. – September, 1996. – Vol. 7, No. 5.
9. **Gori Marco, Maggini Marco.** Optimal Convergence of On-Line Backpropagation // IEEE transactions on neural networks. – January 1996. – Vol. 7, No. 1. – P. 251–254.
10. **Yuan M., Poo A. N., Hong G. S.** Direct neural control system: Nonlinear extention of adaptive control // IEE Proc,- Control Theory Appl. – November, 1995. – Vol. 142, No. 6.
11. **Bezdek J.** Special Issue on Fuzzy Logic and Neural Networks // IEEE Trans. on Neural Networks. Sept. 1992. – Vol. 3, No. 5.
12. **Kuntanapreeda Suwat, Gundersen Robert W., Fullmer R. Rees.** Neural Network Model Reference Control of Nonlinear Systems. – IEEE, 1992. – 0-7803-0559-0/92.
13. **Narepndra Kumpati S., Parthasarathy Kannan.** Gradient Methods for the optimization of Dynamical systems containing Neural Networks // IEEE Transaction on Neural Networks. – March 1991. – Vol. 2, No. 2.
14. Weymare, N. and Martens, J.P. Fast Robust Learning Algorithm for Feedforward Neural Networks // Neural Networks, 1991. – Vol.4. – 361–369.
15. **Kerlirzin P., Vallet F.** Robustness in Multilayer perceptron. // Neural computation, 1991. – Vol. 5. – P. 473-482.
16. **Silva F. M., Almeida L. B.** Speeding up Backpropagation. Advances of Neural Computers. Eckmiller, R.(ed), Elsevier Science Publications B.V., North Holland. –1990. – P. 151–158.
17. **Chen Fu-Chuang**. Back-propagation Neural Neworks for Nonlinear self Tuning Adaptive Control // IEEE control system magazine, 1990. – P. 44–48.
18. **Narendra Kumpati S., Parthsarathy Kannan.** Identification and control of dynamical systems using neural networks // IEEE transaction on Neural Networks. – March 1990. – Vol. 1, No. 1. – P. 4–26.
19. **Oxtega R., Tang Yu**. Robustness of Adaptive controllers // A survey. Automatica, 1989. – Vol. 25, No. 5. – P. 651–667.
20. **Hornik K, Stinchcombe M and White H.** Multilayer feedforward networks are universal approximators // Neural Networks, 1989. – Vol. 2. – P. 359–366.
21. **Widrow B., Stearns S.D.** Adaptive signal processing // Prentice-Hall, Englewood Cliffs, NJ, 1985.
22. **TMS320LF/LC240XA** DSP Controllers system and peripherals user's guide. – Literature number SPRU357B.

Submitted for publication 2006 10 25

S. G. Kadwane, A. Kumar, B. M. Karan. Dynamic Back Propagation based MRAC with Fuzzy Emulator for DC-DC Converter // Electronics and Electrical Engineering. – Kaunas: Technologija, 2007. – No. 1(73). – P. 49–54.

Model Reference Adaptive Control (MRAC) is commonly used in traditional neural network based adaptive controller design. Neural network based MRAC often requires plant emulator when neural controller is connected in between the plant and the control input. Several methodologies for constructing the plant emulator have been proposed but they require either off-line training of the plant emulator or an exact mathematical model of the plant. This limits the capability of a neural system to generalize the controller for a nonlinear plant. Authors suggest a simple combination of Nero-Fuzzy technique to address this problem. Newly introduced dynamic back propagation learning framework for the training of feed forward neural networks with a simple fuzzy emulator is proposed. This design work can be extended for the class of nonlinear system with structural uncertainty. This simple new method incorporates the online training algorithm. Simulation studies are carried out in Matlab for the DC-to-DC converter and the prototype of buck converter is implemented using DSP processor, to obtain real time response. The overall simple control methodology requires less memory in DSP. The practical and simulation results are compared and contrasted with PID controller. The proposed method can be used in most of the industrial applications. Ill. 15, bibl. 22 (in English; summaries in English, Russian and Lithuanian).

С. Г. Кадване, А. Кумар, Б. М. Каран. MRAC с нечетким змулятором на основе динамического обратного распространения для конвертера постоянного тока // Электроника и электротехника. – Каунас: Технология, 2007. – № 1(73). – С. 49–54.

Модель адаптивного контроля (MRAC) обычно используется в проектировании адаптивных контроллеров на базе традиционных нейронных сетей. MRAC на базе нейронной сети часто требует эмулятора устройства, когда нейронная сеть помещяется между устройством и входом сигнала контроля. Было предложено несколько методологий для создания эмулятора устройства, но они требуют или автономного обучения эмулятора, или точной математической модели устройства. Это ограничивает способность нейронных сетей обобщять нелинейные устройства. Авторы предлагают простую комбинацию нечеткой техники, чтобы решить эту проблему. Представлена техника обучения применяя динамическое обратное распространение, которую можно использовать для обучения нейронных сетей применяя простой эмулятор. Эта работа может быть расширена до класса нелинейной системы со структурной неопределённостъю. Метод включает алгоритм прямого обучения. С помощью Matlab выполнено моделирование конвертера постоянного тока; опытный образец конвертера осуществлен используя процессор цифровой обработки сигналов с целью получить реакцию в реальном времени. Практические результаты и результаты моделирования сравнены с PID контроллером. Ил. 15, библ. 22 (на английском языке; рефераты на , английском, русском и литовском яз.).

S. G. Kadwane, A. Kumar, B. M. Karan. Nuolatinės srovės keitiklio MRAC su neraiškiuoju emuliatoriumi, pagrįstas dinaminiu atgaliniu sklidimu // Elektronika ir elektrotechnika. – Kaunas: Technologija, 2007. – Nr. 1(73). – P. 49–54.

Modeliu paremtas adaptyvusis valdymas (MRAC) dažnai naudojamas kuriant tradicinių neuroninių tinklų pagrindu veikiančius adaptyviuosius valdiklius. Tokiam MRAC dažnai reikalingas įrenginio emuliatorius, kai neuroninis valdiklis įjungiamas tarp įrenginio ir valdiklio įėjimo. Pateiktos kelios įrenginio emuliatoriaus sudarymo metodikos, tačiau joms įgyvendinti reikalingas arba autonominis įrenginio emuliatoriaus mokymas, arba tikslus įrenginio matematinis modelis. Tai riboja neuroninės sistemos gebą valdyti netiesinį įrenginį. Problemai spręsti pasiūlytas paprastas neraiškusis neuroninis metodas. Pasiūlyta nauja dinaminio atgalinio sklidimo mokymo sistema, skirta neuroniniams tinklams mokyti naudojant paprastą neraiškųjį emuliatorių. Šis darbas gali būti pritaikytas netiesinių sistemų su struktūrine neapibrėžtimi klasei. Numatytas tiesioginio mokymo algoritmas. Atliktas DC-DC keitiklio modeliavimas Matlab terpėje, o impulsinio reguliatoriaus prototipas sudarytas naudojant DSP procesorių, siekiant gauti realaus laiko reakciją. Praktiniai ir modeliavimo rezultatai lyginami su PID valdikliu. Il. 15, bibl. 22 (anglų kalba; santraukos anglų, rusų ir lietuvių, k.).