A NEURAL CONTROLLER FOR QUASI–RESONANT CONVERTERS

[redacted]

Abstract. A neural controller implementing an energy feedback control law is proposed to improve the stability and dynamic characteristics of the series resonant converter (SRC). The energy feedback control is introduced and analysed in discrete time domain. A novel formulation of the control law is suggested. The adaptive control law is learnt by an analog neural network (ANN). An easy implementation of this controller is proposed and applied to a SRC circuit. Simulation results show a good improvement in the SRC response and confirm the validity of the controller.

Keywords. Resonant converters, optimal control, adaptive control, neural networks.

I. INTRODUCTION

Multi–Loop control schemes have been used to improve the stability and dynamic characteristics of many different SRC topologies (Ridley, 1991; Kim, 1991). These schemes imply two feed–back loops : a fast inner one around the power stage and an outer voltage feed–back loop via the error amplifier (see figure 1).

As a result, some quite remarkable improvements in the dynamic behaviour of the resonant converters have been achieved. All these approaches analyse the response of the SRC when its behavioural equations are linearized about its equilibrium state. That is the reason why they fail to provide a good response when changing its stable state. Stable adaptive laws for the adjustement of parameters assure the global stability of the relevant overall systems.

Multilayer networks have proved extremely successful in identification and control of dynamical systems (Narendra, 1990; Quero 1990). They adaptively change their connections by means of a learning algorithm. In this paper we show how a multilayer perceptron (Rumelhart, 1986) is able to recognize the state of the SRC and to provide the switching schedule that ensures optimal response.

This paper is organized as follows: section II deals with modeling of SRC's and energy feed–back control. In section III, the multilayer perceptron and its dynamic learning algorithm are introduced. Section IV is devoted to describing the proposed control scheme. Section V shows the simulation results using Hspice (Hspice, 1987). Finally, in section VI some ideas are given for future work.

II. DISCRETE TIME DOMAIN MODELING OF ENERGY FEEDBACK CONTROLLED SRC

Development of this neural controller is illustrated in this section by its application to the SRC circuit shown in figure 1.

Basic operation of a SRC

Many authors (Kim, 1991; Elbuluk, 1988) have analysed the steady state operation of the SRC. In this subsection a brief description of the behaviour of this converter is included. Figure 1 shows a SRC with the control switch implemented by transistors Q_1 Q_2 Q_3 Q_4 and their antiparallel diodes D_1 D_2 D_3 D_4 respectively. The transistors are triggered in a time sequence as illustrated in figure 2.

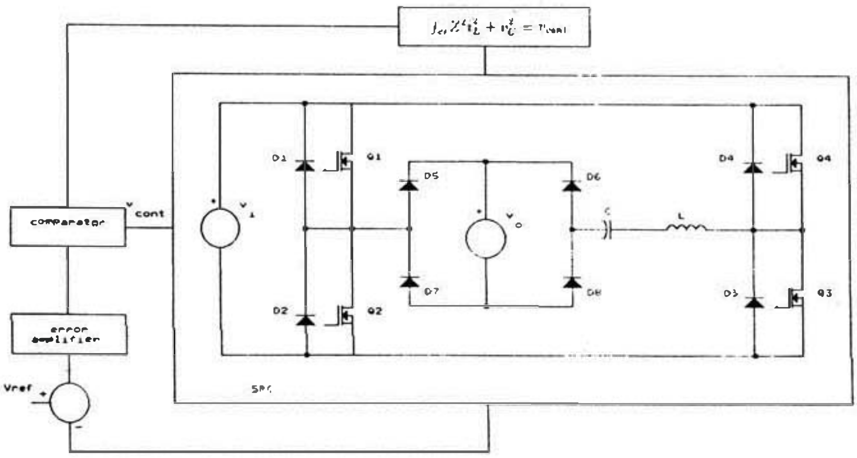

Figure 1: Schematic diagram of SRC with proposed multi loop control.

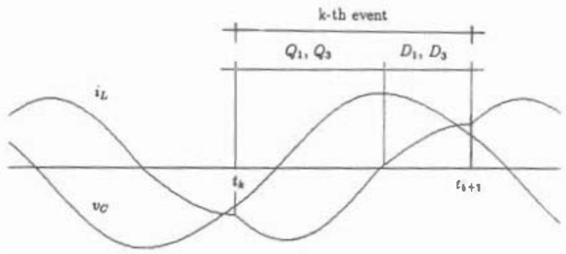

Figure 2: Waveforms of a SRC for different conduction intervals.

All the transistors are driven with 50% of duty cycle gating signals. Transistors Q_1, Q_3 are triggered according to a clock signal whose frequency determines the operating frequency of the converter. Transistors Q_2 Q_4 are triggered with a controllable time delay with respect to the triggering of Q_1, Q_3.

A typical circuit operation of a SRC is illustrated in figure 2. At t=0 transistors Q_1 and Q_3 turn on, while all diodes are off. At $t = T1$, i_L decreases to zero, due to resonance, and diodes $D1$, $D3$ begin to conduct. The first half switching cycle finishes at $t = T_s/2$. At the beginning of the second half of the switching cycle, the transistors Q_2 and Q_4 are triggered and a similar process occurs with the roles of Q_1, Q_3, D_1, Q_3 and Q_2, Q_4, D_2, Q_4 interchanged, respectively.

Dynamic modeling

Very little work has been done in the area of dynamic modeling of a resonant converter. A general sample data representation of power electronic circuit dynamics has been used (Elburuk,1988) to model the discrete time domain behaviour of the SRC. The discrete time domain modeling is carried out under the following asumptions:

- All components are ideal.
- The input voltage v_i, the output voltage v_o and the control input v_{cont} are constant.
- The turns ratio transformer is 1:1.

The series converter goes through four switch configurations every cycle. Each configuration has a linear time invariant (LTI) state-space description of the form

$$\frac{dx(t)}{dt} = A_i x(t) + B_i u(t), \quad i = 1, 2, 3, 4$$

$$and \quad t_k + T_{k,i-1} < t < t_k + T_{k,i} \tag{1}$$

where

$$x(t) = \begin{bmatrix} v_C(t) \\ i_L(t) \end{bmatrix} \tag{2}$$

$$u(t) = \begin{bmatrix} v_i(t) \\ v_o(t) \end{bmatrix} \tag{3}$$

and where

A_i,B_i coefficient matrices, and the subscript i is the number of the switching configuration,

t_k end of the kth cycle and the beginning of the $(k+1)$th cycle,

$T_{k,i}$ time from the end of the kth cycle till the end of the ith switching configuration,

$t_{k,4}$ is the switching period T_s.

The state vector x is continuous across each change in the switch configuration: the final state in one configuration is the initial state in next. Therefore, by combining the solution of 1 for the switch configuration over a cycle, a large signal model that describes the state $x(t_{k+1})$ at the end of the $(k+1)$th cycle in terms of the state $x(t_k)$ is given by the following:

$$x(t_{k+1}) = f(x(t_k), P_k, T_k) \tag{4}$$

where

$$P_k = \begin{bmatrix} v_i(t) \\ v_o(t) \\ L \\ C \\ T_{k,2} \\ T_{k,4} \end{bmatrix} \tag{5}$$

$$T_k = \begin{bmatrix} T_{k,1} \\ T_{k,3} \end{bmatrix} \tag{6}$$

T_k is a vector composed of indirectely controlled transition times ($T_{k,1}$ and $T_{k,3}$). These are times that depends on the state trajectories of the system, specifically, when the inductor current goes to zero and turns off the diode that is on, as given by the following threshold equations:

$$\begin{aligned} i_L(t_k + T_{k,1}) &= c_1(x(t_k, P_k, T_k)) = 0 \\ i_L(t_k + T_{k,3}) &= c_2(x(t_k, P_k, T_k)) = 0 \end{aligned} \tag{7}$$

P_k is a vector of controlling parameters. These include the circuit parameter and the directly controlled transition times ($T_{k,2}$ and $T_{k,4}$).

All the computations involved in deriving this model can be carried out using symbolic manipulation programs like Macsyma, as Verghese (1986) suggests.

Energy Feedback Control Law

The proposed energy feedback control law is of the form:

$$f_{er} Z^2 i_L^2 + v_C^2 = v_{cont} \tag{8}$$

where f_{er} is the energy feedback gain ratio.

Expressions 4 and 8 can be linearized and combined to provide the small signal sampled data modeling. Analysing the eigenvalues of the characteristic equation of the resulting dynamic transfer function, a critical f_{cr} can be found. When f_{cr} is less than the critical value, the response of the controlled system after a disturbance is underdamped, and overdumped when f_{cr} is greater than the critical f_{cr} (Kim, 1991). The critical f_{cr} is given by :

$$f_{cr}|_{crit} = \frac{v_C}{v_C + v_i + v_o} \tag{9}$$

The above critical f_{cr} can also be derived from the optimal trajectory control law (OTCL) (Oruganti, 1987)

From 4 and 9 an adaptive version of the optimal trajectory control law is obtained:

$$\frac{v_C}{v_C + v_i + v_o} Z^2 i_L^2 + v_C^2 = v_{cont} \tag{10}$$

III. MULTILAYER NETWORKS

A typical multilayer network with a hidden layer is shown in figure 3, where γ is the sigmoidal transfer function [i.e., $\gamma(x) = 1 - e^{-x}/1 + e^{-x}$] and W^i are weight matrices. Each unit that composes the network can be regarded as a filter that sums up its input signals linearly, according to

$$o_j = \sum_i w_{ji} o_i \tag{11}$$

It has been shown (Hornic,1988), using the Stone–Weierstrass theorem, that a two layer network with an arbitrarily large number of nodes in the hidden layer can approximate any continuous function $f \epsilon C(\mathcal{R}^n, \mathcal{R}^m)$ over a compact subset of $\mathcal{R}^n$. In order to obtain a desired set of connections that approximates a given function, the *backpropagation learning algorithm* (Rumelhart,1986) can be used. The weight on each line should be changed by an amount proportional to the product of an error signal δ available to the unit receiving input along that line and the output of the unit sending activation along that line.

$$\Delta_p w_{ij} = \eta \delta_{pj} o_{pi} \tag{12}$$

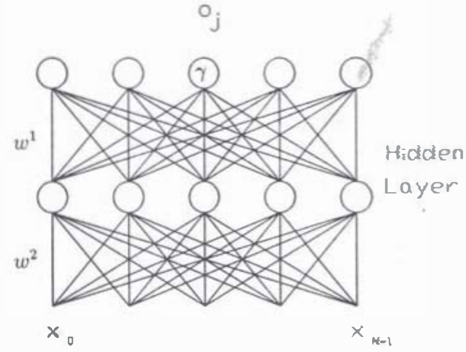

Figure 3: Schematic representation of a two layer network.

The determination of the error signal is a recursive process which starts with the output units,

$$\delta_{pj} = (t_{pj} - o_{pj}) \gamma'_j (\sum_i w_{ij} o_{pi}) \tag{13}$$

where t_{pj} is the jth component of the desired output when the input pattern p is applied to the neural net and $\gamma'()$ is the derivative of the transfer function. The error signal for hidden units for which there is no specified target is

$$\delta_{pj} = \gamma'_j (\sum_i w_{ij} o_{pi}) \sum_k \delta_{pk} w_{kj} \tag{14}$$

IV. CONTROL SCHEME

The proposed control scheme is presented in figure 4. The state variables i_L and v_C and the parameters v_{cont}, v_i and v_o are fed into the ANN, which calculates an approximation of the error signal e given by 10.

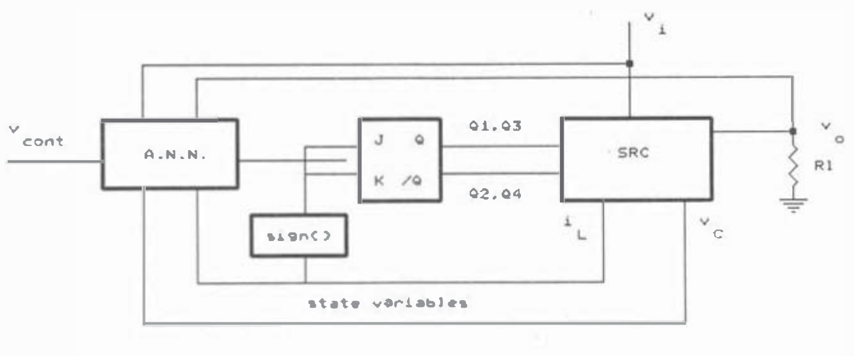

Figure 4: Proposed control scheme.

The ANN is previously configured in a learning phase. This procedure is carried out using random input signals uniformly distributed within the ranges of interest. When this phase is finished, the connections W are networks of resistors and the sigmoidal transfer function can be realized using CMOS inverters, leading to an easy implementation.

V. SIMULATION RESULTS

In order to evaluate the performance of the neural controller, it is applied to a full-bridge series resonant converter. The parameters of the converter are:

$$L = 0.113mH \quad v_i = 30v$$
$$C = 0.120\mu F \quad v_o = 12v$$

The ANN used to implement the controller belongs to class $\mathcal{N}_{3,8,1}$ (three inputs, eight hidden units and one output unit). During the learning process, the following intervals for the generation of random inputs are used:

$$v_{cont} \in [1.0, 4.0] \qquad v_C \in [-100, 100] \qquad i_L \in [-5, 5]$$

The values of the error function e are limited by the maximum and minimum values of the sigmoidal transfer function. Notice that we are only concerned with the zero-crossing of the error function. During the learning phase, the ANN is trained for 100.000 time steps before it is being applied to the SRC.

Hspice is being used to simulate the whole circuitry. The SRC is simulated using a constant f_{er} controller and the proposed neural one in order to compare its responses to a change in the reference. The transient output current of the energy feedback control with $f_{er} = 0.2$ for the step change of v_{cont} from 1.2 to 3.75 can be seen in figure 5, showing a undesirable underdamped behaviour.

In figure 6 an improved transient response is obtained when using the neural controller. The evolution of f_{er} is presented in figure 7. When the transistors are triggered, f_{er} evolves from 0.76 to 0.52, corresponding to the optimal values predicted by 9.

VI. CONCLUSIONS

A neural controller utilizing the resonant tank energy as an adaptive control law is proposed to improve the stability and dynamic characteristic of the series resonant converter. The controller supervises the state of the converter and generates the switching schedule that provides optimal trajectory control. Simulation results confirm the validity of the controller. The electronic implementation of the neural controller is based on the integration of a set of inverters interconnected with constant resistors. Although the proposed controller is being applied to an specific converter, the design can be easily generalized to any kind of resonant converter.

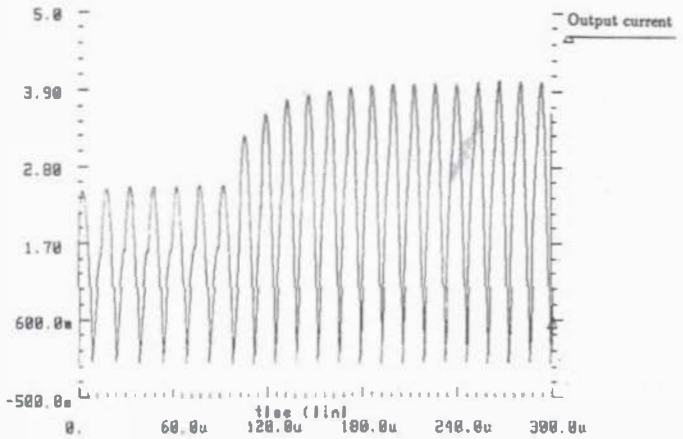

Figure 5: Transient output current response to a change of v_{cont} from 1.2 to 3.75 when using constant $f_{er} = 0.2$.

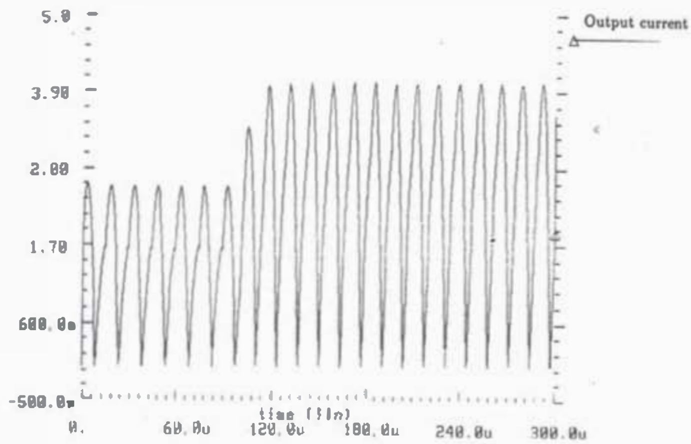

Figure 6: Transient output current response to a change of v_{cont} from 1.2 to 3.75 when using the neural network controller.

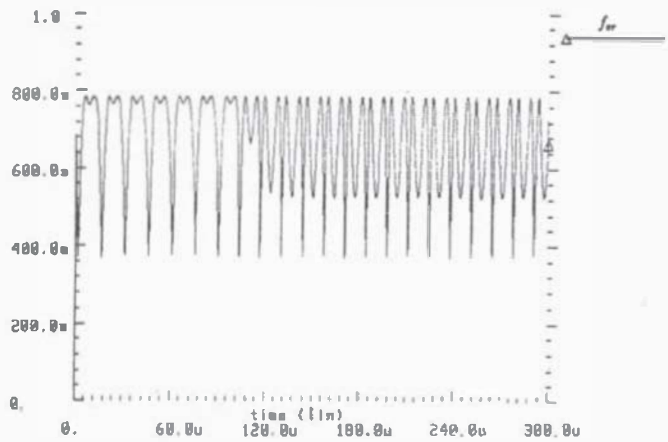

Figure 7: Evolution of f_{er} when the state variables change.

VII. NOMENCLATURE

T_s	Switching period.
i_L	Current in resonant tank inductor.
v_C	Voltage on resonant tank capacitor.
L	Resonant tank inductance.
C	Resonant tank capacitance.
k	Subscript used to indicate the K-th event
v_i	Input voltage.
v_o	Output voltage.
$x_i(t_k)$	Discrete state variables.
Z	Characteristic impedance $Z=\sqrt{L/C}$
f_{er}	Energy feedback gain ratio
o_j	Output of neuron j.
w_{ij}	Connection between neuron i and j
p	Pattern currently presented to the network.
η	Learning step size.
δ	Difference between the target and the output of the network (t-o).
t	Desired output.
γ	Sigmoidal transfer function.

VIII. REFERENCES

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