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Simplified Control Structure for Current Control of Single Phase Rectifiers Using COT-ANN-PWM

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Abstract—**This paper describes a single phase switched rectifier for current control using Model Reference Adaptive Control (MRAC) with a Continually On-Line Trained Artificial Neural Network (COT-ANN). The results obtained with the proposed scheme are similar to the ones obtained in a previous work but using a simpler control structure. Simulations are used to test the validity of the proposed algorithm and the results are later verified by a practical implementation of this system.**

I. Introduction

Several schemes have been proposed for improving the power factor in single phase rectifiers [1]. A common disadvantage in existing schemes is that in general an in-depth knowledge of the process is required for tuning these controllers. A solution to this is the use of intelligent systems that are able to adjust their dynamic response to any operating condition. Additionally, with the use of intelligent controllers, the rectifier can be used to feed completely new systems without the need of cumbersome recalibrations.

From a control point of view, current mode control is a common strategy to ensure unity power factor control at the input of a switched rectifier, and Pulse Width Modulated Voltage Source Inverters (PWM-VSI) are commonly used to achieve this. An advantage of a PWM-VSI based scheme is its operation at a fixed switching frequency, which allows for better filtering and results in a reduction of noise into the utility. PWM based systems make use of the traditional PI controller, embedded in the control software, for the current loop [2], but precise tuning is needed for optimum operation of the controller, and in general this can be achieved only for a particular operating point. The use of artificial neural networks has previously been proposed to obtain an estimated value of the system current used to feed a conventional current controller with a state predictor in a three phase rectifier [3]. A direct current controller has also been proposed [4], but its capabilities were evaluated only by simulations. Figure 2 shows the structure of a Continually On-line Trained-ANN (COT-ANN) PWM rectifier proposed in [5], where the main structure and theoretical background has been borrowed from intelligent machine control [6]. This PWM rectifier is employed to attain a sinusoidal regulation while keeping the ripple at a minimum. The topology proposed in this paper, for controlling the rectifier, is depicted in Fig. 3 and is based on the MRAC scheme proposed in [7]. In the present work, however, a COT-ANN is used to approximate the unknown plant function rather than individually adapting the unknown plant parameters. The proposed scheme requires a COT-ANN with a reduced number of inputs and requires less processing time than the one proposed in [5].

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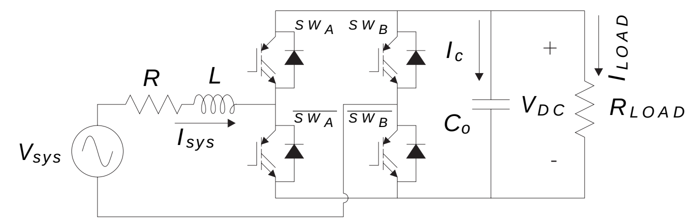

Fig. 1. Typical single-phase controlled rectifier.

II. Continually On-Line Trained Neural Networks

The capabilities of neural-networks to approximate a non linear function can be exploited to estimate and control the current into the rectifier. For the neurocontroller, a multilayer perceptron with one hidden layer is used. The ANN in Fig. 2 has eight inputs, twelve hidden neurons with monopolar sigmoidal (also known as logistic squashing) activation functions, and one linear neuron in the output layer. The ANN in Fig. 3 has two inputs, four hidden neurons with logistic squashing activation function and one linear neuron in the output layer.

A. Neural Networks

From Kolmogorov's theorem [8] it is possible to infer that an ANN with sufficient neurons can approximate any non-linear function. A neural network may be trained to identify and approximate any desired continuous vector mapping function over a specified range. The ANN's accuracy in tracking time varying functions depends not only on their structure, but also on the rate of training. The size of the neural network has to be chosen using a heuristic procedure, depending on the type of application and the processing power available for the neurocontroller.

B. Neuron Model

In its most general form a neuron is composed of the following parts: inputs, a weighted adder, an activation function and an output. The neural network is formed by one or more neurons interconnected in layers, where the

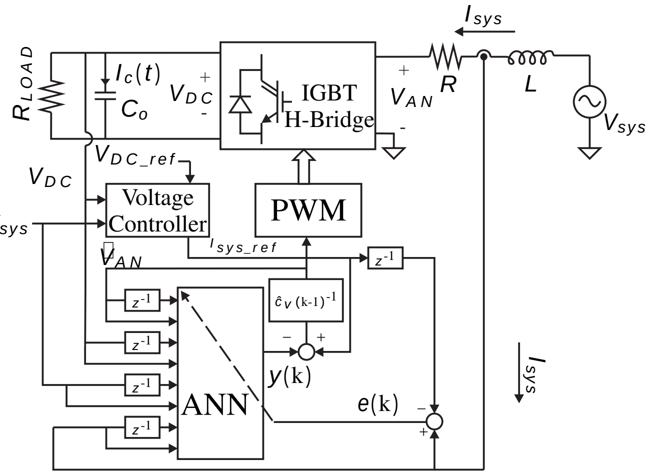

Fig. 2. Topology for the COT-ANN PWM single-phase rectifier.

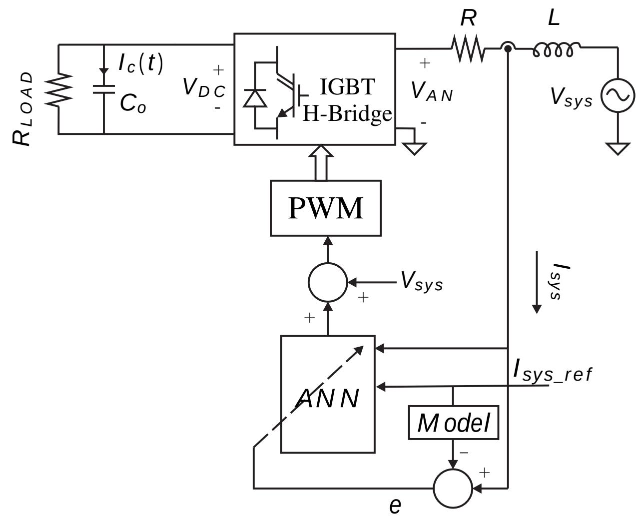

Fig. 3. Proposed topology for the MRAC COT-ANN.

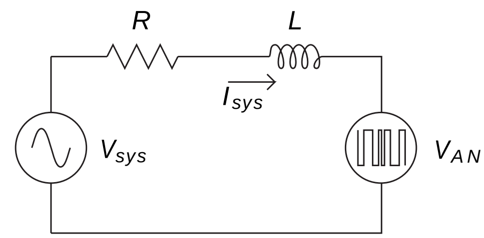

Fig. 4. Equivalent circuit for the current controller.

neurons in the same layer share the same inputs. The output for neuron j in layer k is:

$$y_j^k = S\left(\sum_{i=1}^{N^k} W_{i,j}^k x_i\right) \quad (1)$$

where $S(\cdot)$ is the activation function. The hidden layer neurons employed in the neural network used in this work have non-linear activation functions.

III. Previous Control Scheme

The control scheme proposed in [5] is shown in Fig. 2. The current loop shapes the inductor current (or power system current), I_{sys}. The reference current is set to follow the fundamental component of the line voltage in order to ensure unity power factor. Its magnitude controls the power flow between the utility and the load and is obtained as the division of the power reference by the line voltage. Figure 4 shows a simplified equivalent circuit for the PWM-rectifier used for controlling the system current. Here L and R represent an user inserted reactance, and (2) describes the relationship between the variables in Figs. 2 and 3.

$$I_{sys}(t) = I_{sys}(0) + \frac{1}{L}\int_0^t [V_{sys}(\tau) - V_{AN}(\tau)]\,d\tau \quad (2)$$

where the effect of R is neglected. The DC link voltage is a function of the load current and of the system current (I_{sys}) according to the following equation.

$$V_{DC}(t) = V_{DC}(0) + \frac{1}{C_o}\int_0^t I_c(\tau)\,d\tau \quad (3)$$

where $V_{DC}(0)$ is the initial voltage across the capacitor and the current in the DC link capacitor $I_c(t)$ depends on the bridge connectivity. From Fig. 1 the current into the capacitor is:

$$I_c(t) = \begin{cases} A=0,\ B=0 & -I_{LOAD} \\ A=0,\ B=1 & -I_{sys} - I_{LOAD} \\ A=1,\ B=0 & I_{sys} - I_{LOAD} \\ A=1,\ B=1 & -I_{LOAD} \end{cases} \quad (4)$$

These four switching states allow, in a certain range, full control of both the DC link voltage and the AC system current. For microprocessor control, discrete versions of (2) and (3) are required. This can be obtained by using the following first order Euler expansion of (2) and (3).

$$\begin{aligned} I_{sys}(k+1) &= I_{sys}(k) + \frac{T_s}{L}[V_{sys}(k) - V_{AN}(k)] \\ V_{AN}(k) &= V_{AN}(k-1) + \frac{T_s}{C_o}[I_c(k) - I_c(k-1)] \end{aligned} \quad (5)$$

The controlled rectifier is a suitable candidate to be described by the (NARMA) Nonlinear Auto-Regressive Moving Average model. For the single phase controlled rectifier the NARMA model is described by the following equation.

$$\begin{aligned} I_{sys}([k+1]T_s) = &\, y\,(I_{sys}(kT_s), I_{sys}([k-1]T_s), V_{sys}(kT_s), \\ & V_{sys}([k-1]T_s), V_{AN}(kT_s), \\ & V_{AN}([k-1]T_s)) + c_v V_{AN}(kT_s) \end{aligned} \quad (6)$$

where T_s is the control period. An additional delay $(k-1)T_s$ is employed for increasing the order of the continuous-to-discrete mapping of the function, resulting in an ANN that requires eight inputs. Since I_{sys} and V_{sys} are measurable state variables, it is possible to alter V_{AN} to force the system current I_{sys} into any desirable shape, within some limits, depending on the magnitude available for V_{AN}.

IV. Proposed control scheme

The proposed control method is based on the adaptive control with model reference technique [7]. This control scheme requires a model reference whose output is compared with the output of the plant. The error between the plant output and the model output is used to adaptively adjust the ANN. Figure 3 shows the proposed scheme where the current loop can be seen. Equations 2 and 3 can be rewritten as

$$\dot{I}_{sys} = -\frac{R}{L} I_{sys} + \frac{V_{sys}}{L} - \frac{V_{DC}}{L} D \quad (7)$$

$$\dot{V}_{DC} = -\frac{1}{R\,C_o} V_{DC} + \frac{I_{sys}}{C_o} D \quad (8)$$

provided that I_c and V_{AN} can be written as

$$I_c = D\,I_{sys} \quad (9)$$

$$V_{AN} = D\,V_{DC} \quad (10)$$

where D is the duty cycle of the PWM signals. Moreover D is the control signal and must be properly designed to obtain perfect tracking. Using the following expression for D

$$D = \frac{1}{V_{DC}} \left(V_{sys} + (\alpha L - R)\, I_{sys} - \beta L\, I_{sys\_ref} \right) \quad (11)$$

where L and R are, in general, unknown. The reference model is proposed as a first order model

$$\dot{I}_{sys\_m} + \alpha\, I_{sys\_m} = \beta\, I_{sys\_ref} \quad (12)$$

where the constants α and β are positive and are selected such that the model response is similar to the desired plant response. The tracking error between the plant output and the model output is defined as

$$e = I_{sys} - I_{sys\_m} \quad (13)$$

and the quadratic version of this tracking error is used as the cost function to train the ANN. Replacing (11) and (12) in (7) produces.

$$\dot{I}_{sys} - \dot{I}_{sys\_m} + \alpha\,(I_{sys} - I_{sys\_m}) = 0 \quad (14)$$

or equivalently, using (13)

$$\dot{e} + \alpha\, e = 0 \quad (15)$$

This expression correspond to a stable system with an equilibrium point at the origin, that is $e \to 0$ for $t \to \infty$. Even though the expression (11) leads to a system with zero tracking error, the parameters L and R are, as stated before, unknown. Therefore the expression, $(\alpha L - R)\, I_{sys} - \beta L\, I_{sys_{ref}}$, containing the unknown parameters is approximated by the ANN. After that, the resulting output of the ANN is added to V_{sys} and the result divided by V_{DC} to obtain the control signal, D. As a result it is possible to assure that if the learning error tends to zero then the tracking error tends to zero. The algorithm used to train the ANN is momentum backpropagation. Additionally the ANN used in this control scheme requires just two inputs.

V. Simulations

The PWM circuitry was simulated for an 8-bit resolution digital double slope carrier PWM; this closely resembles circuitry found in practical implementations. In the experimental hardware the maximum available resolution for the PWM was 12 bits, however the actual resolution depends on the clock frequency used to feed the PWM circuitry and on the desired carrier frequency [9]. For the present implementation the clock frequency was 8 MHz, and for a 10 kHz carrier frequency the PWM register (defining the duty cycle range for each phase) goes from zero to eight hundred. This can be represented using a 10 bit number. The value of the voltage at the rectifier, fed to the PWM block, was scaled to fit the carrier waveform in the digital PWM. For both the simulations and the practical implementation, the ANN was tested for pre-trained and untrained conditions. For the test with no pre-training the ANN's weights matrix were initialized with pseudo-random values in the range $(-1.0 \leftrightarrow +1.0)$. The simulations were executed on a Digital Signal Processor (DSP) ADSP-21061 running at 40 MHz and were programmed using the manufacturer's compiler for that DSP, VisualDSP++ 4.5 [10] on an IBM compatible PC. The executable file was downloaded into the DSP board through a serial interface. When the simulation was ready the data was transferred back to the PC for storage. The conditions for the simulation were: V_{sys}=37 V_{rms}, resistive load at the DC bus is 100 ohms, and for testing the neuro controller behavior during power regeneration a DC current source was connected to the load at t=92 ms. The learning coefficient or learning rate used for the backpropagation algorithm was η =0.05 and the momentum coefficient was μ =0.15. Figure 5 shows the results of the simulation.

VI. Experimental results

A DSP based test rig [9] was used to verify the simulations performed previously. The test-rig uses a 40 MHz Digital Signal Processor (ADSP-21061) that was used in the previous section. An interface card provides communication between the DSP board and the rest of the driver. It houses a motion controller ADMC-201 used to provide the PWM signals required to control four 50 A, 1200 V IGBTs present in the inverter. The IGBT switching frequency was 10 kHz. The conditions for the test were: V_{sys}=37 V_{rms}, $L \approx$ 4.8 mH, the DC link capacitor C_O=2200 μF and R_{LOAD}=100 ohms and the control cycle period was 100 μs. Figure 6 shows the conditions in the supply when the current loop neuro controller was disabled. In this figure channel 1 shows the line voltage and channel 4 shows the system current. In this case the system current has a high harmonic content shown in Fig. 7. In Fig. 8 channel 4 shows the resulting current taken by the controlled rectifier when the current loop was

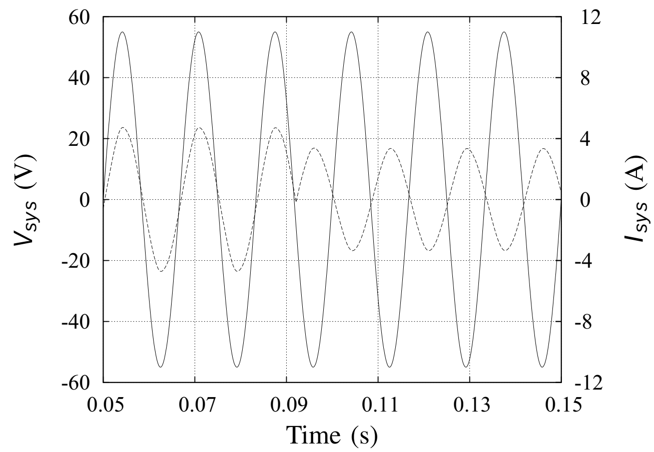

Fig. 5. Simulated line voltage and system current for a change in the sign of the power reference.

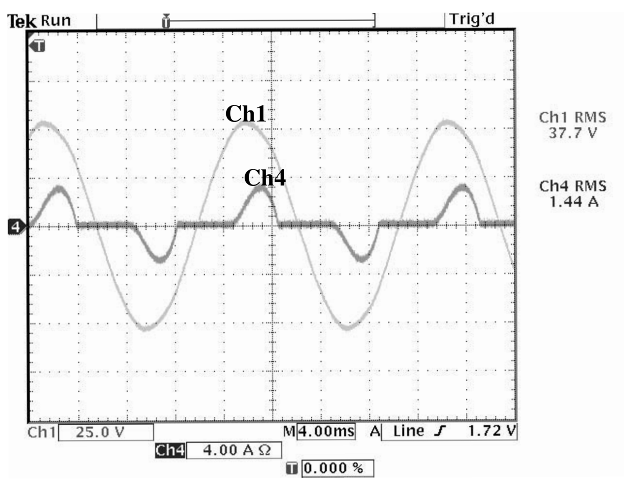

Fig. 6. Line voltage and system current when the current control is disabled.

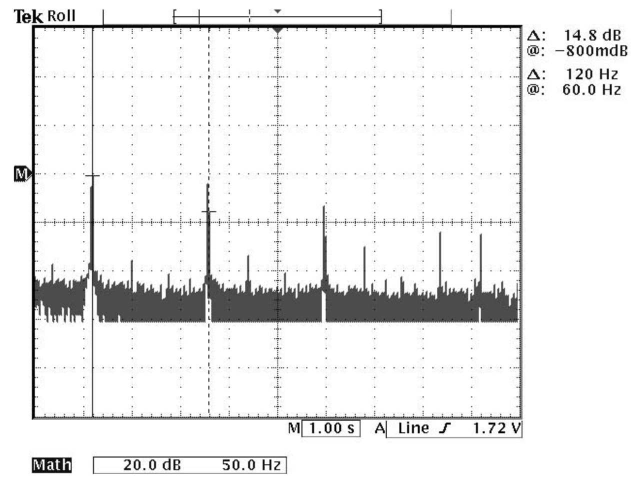

Fig. 7. Harmonic content for the system current when the current control is disabled.

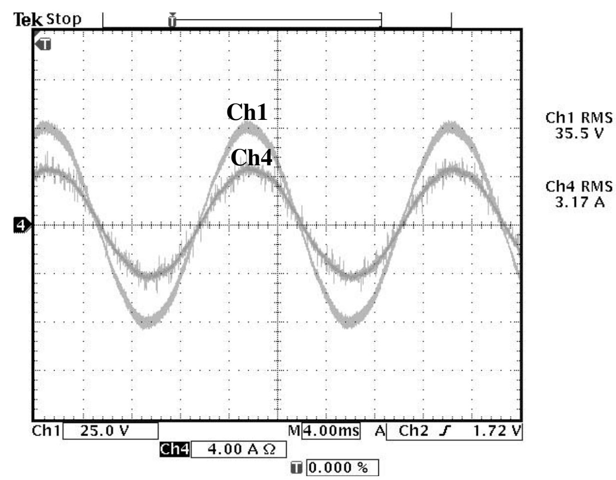

Fig. 8. Line voltage and system current for a positive power reference.

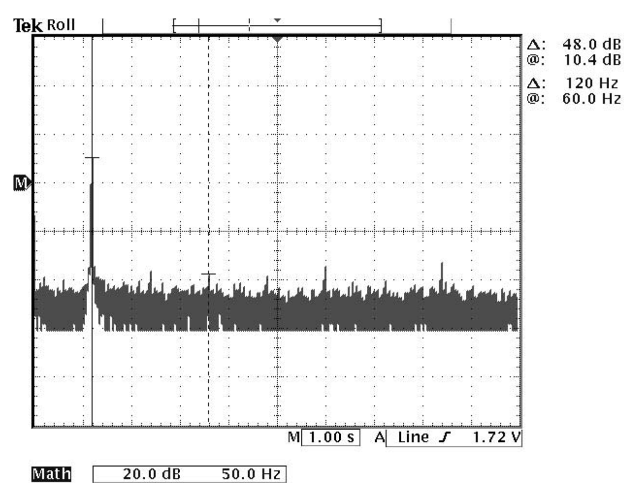

Fig. 9. FFT for the system current when the current control is enabled.

enabled with a 110 W power reference. In this case the system current follows a sinusoidal shape in phase with the line voltage, shown in channel 1, thus providing a power factor close to one. Figure 9 shows the harmonic current content. Figure 10 shows the behavior of the controlled rectifier during power regeneration. In this figure channel 1 shows the line voltage and channel 4 the system current. For this test a DC source was connected to the DC link, with a negative power reference, as a consequence the power flow direction is reversed and the power factor magnitude remains close to one. Figure 11 shows the change in the power flow direction, caused by a change in the power reference. In this figure channel 1 was the line voltage and channel 4 was the system current.

VII. Conclusions

This paper has presented an implementation of a current loop neurocontroller suitable for real time applications. For the proposed neuro-controller, the ANN was trained with the backpropagation method taking 9.1 μs for the forward prop-