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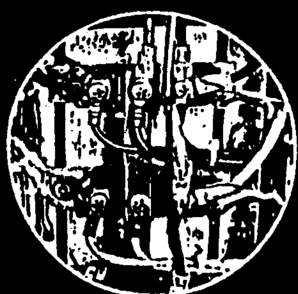

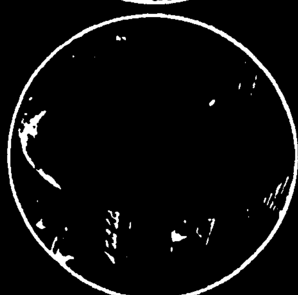

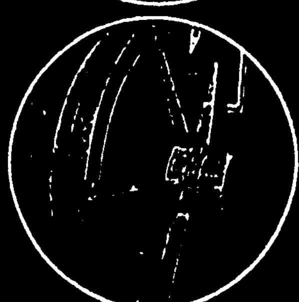

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AUTHORS INDEX

A

Abdelhamid T.H. 340
Abdelkadar S. 399
Abouarkoub A. 479
Adam T. 90
Adjepon-Yamoah D. 505,471
Aggarwal R.K. 115, 420
Aguado J. 300
Ah King R.T.F. 458
Ahmed M.M.R. 509
Al-Ashwal A. 588
Alcorn R.G. 395
Allan R.N. 38, 46, 660
Aller J.M. 600, 612
Ametani A. 9, 127, 521, 543
Andersson G. 46, 660
Andrew D. 316
Asiain T. 26
Atmadji A.M.S. 111, 517, 539
Attaianese Ciro 596
Augugliaro A. 257
Ault G.W. 21, 551, 647
Azoui M. 86

B

Baines G.D. 588
Barbosa F.M. 156
Barnes M. 103
Barrado A. 13
Barry N. 279
Bartlett E.J. 249, 575
Beattie W.C. 395
Belkacemi M. 579
Bentouati S. 181
Benabdallah L. 579
Benfarhi L. 579
Benoudjit A. 267, 288
Bertling L. 660
Bertsch J. 144
Betka A. 86
Bialek J. 450
Billinton R. 189, 632
Birch A.P. 505, 640
Birch T.S. 169, 177, 181
Bish N.B. 303, 356
Bitzer B.E. 217
Bleijs J.A.M. 94, 387
Bo Z.Q. 82, 119, 446, 624, 628
Bollen M.H.J. 588
Bolton H.R. 1, 434
Booth M. 616
Bouakkar R. 271
Bouguechal N. 312
Bousbaine A. 479
Brook D.P. 253
Brown A.D. 420
Brown N. 430
Bueno A. 612
Bumby J.R. 450
Burgos J.C. 403
Burt G.M. 66, 237

C

Cabello A. 612
Cadel O. 438
Campbell H.S. 620
Campero-Littlewood E. 197
Carpenter G.F. 82
Carvalho J.B. 156
Cataliotti A. 283
Celli G. 58
Chaouch S. 312
Chatterton I. 245
Chen L. 652
Chen Z. 119, 241, 446, 624, 628
Chen H. 489
Chen Y.S. 169, 177
Cheong H.W. 360
Chin P.S.M. 624
Chinchilla M. 403
Chung T.S. 42, 62
Cipcigan L. 123
Ciric R.M. 513
Clavert P.A.J. 438
Corbett J. 307

D

Damstra G.C. 517
Darwish M.K. 99, 107, 383
Davies T.S. 135, 592
Devine P.J. 326
Dodds S.J. 164
Dong L.Y. 442
Dorrell D.G. 173
Dujic J.K. 570
Dunn R.W. 253
Duran O. 300
Dusonchet L. 257

E

El Desouky A.A. 229
El-Alayly A.A. 213
El-Ghotmy M.A. 17
El-Habrouk M. 383
El-Kateb M.M. 229, 399, 41
El-Rabaie N.M. 17
El-Sayed Awad H. 539
Elmitwally A. 399
Enache M.C. 296, 556
Escarela-Perez R. 197
Espic P. 551, 647

F

Fang D.Z. 62, 442
Farrag M. 74
Ferguson C. 348
Flynn D. 365
Fotubi-Firuzabad M. 189
Fox B. 365
Frankland J.D. 411
Fukudu N. 127
Fulczyk M. 144
Funabashi T. 9

G

Geerli R.Y.Ms 652
German D.M. 352
Gilmour J.E. 616
Giménez de Guzmán M.I. 60(
612
Goh S.E. 296, 556
Goh M.W. 564
Gouda M.M. 17
Gow J.A. 94

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A DSP BASED PLATFORM FOR A VECTOR CONTROL AC INVERTER WITH A NEURAL NETWORK OBSERVER

Giuseppe Panza[(1)], M.I. Giménez de Guzmán[(2)], V. M. Guzmán[(2)], J. A. Restrepo[(2)] and J.M. Aller[(2)]

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ABSTRACT

This work presents the development of a platform with a DSP based control system intended as a test base for space vector and neural network based control strategies over an AC motor inverter driver. Between the main features of this system are its low cost, adaptability and simplicity, in order to use it in several research and teaching Power Electronics Laboratories. The platform has been tested with scalar, neural network estimator and space vector controller, showing a better performance in comparison with other microprocessor implementations.

INTRODUCTION

A low-cost, versatile, and adaptive DSP based platform has been developed for the implementation of AC machine control algorithms using a neural network estimator. The processing requirement for sophisticate control algorithms, such as vector control, calls for the use of special processing units. The use of microprocessors for the control of AC machines started in the early 80's [1], and now they play an important role in defining the system capabilities. Since the DSP internal architecture has been optimised for performing tasks commonly found in signal processing algorithms [2], It has a processing advantage over conventional microprocessor

For the present work a floating point DSP TMS320C31 was used as the main processing unit. The design of the processing unit has been done considering its future use as a teaching workbench [3]. The DSP programming was performed using C++ and the communication kernel present in the evaluation board DSK3X. An extension board was designed to increase the memory, and to include multi-channel A/D conversion facilities.

Scalar, vector and direct torque control strategies had been tested using this platform, showing the system performance and adaptability. The developed system has proved its usefulness in undergraduate and graduate teaching courses as well as research activities.

PROCESSING AND ADQUISITION SUBSYTEMS

A diagram of the actual test rig is shown in Fig.1. The three-phase AC motor has coupled to its shaft a dynamic load implemented with a DC motor. For some applications, a speed measurement is required, and this is performed with a 1000 pulses per cycle optical-encoder.

Stator current is measured in two of the three motor phases using Hall effect sensors with the analogue output connected to the acquisition module. This card was connected to the PC through the parallel port. The connection between this card and the inverter system was performed through a specially designed extension card described below.

Expansion card

The expansion card, shown in figure 2 and, in block diagram form in figure 3, was designed to complement the DSP card in the motor control tasks. An ADMC-200 motion coprocessor performs most of the power control related tasks [4], and is used to reduce the components count number in the interface card.

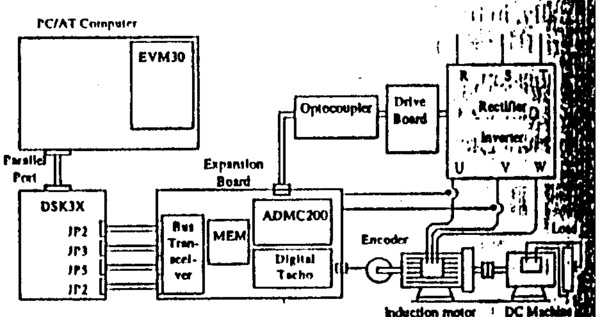

Figure 1. Test rig diagram for the DSP based system.

The motion coprocessor is composed of several blocks. Among them, the vector transformation block performs the forward and reverse Clark and Park transformations. The PWM timer block performs several of the tasks involved in the firing pulse generation required to control the voltage source inverter. The analogue to digital block consists of an 11-bits A/D converter, fed from four simultaneously sampled inputs, and a four multiplexed channels extension. Finally, this coprocessor includes a six bits fully programmable I/O.

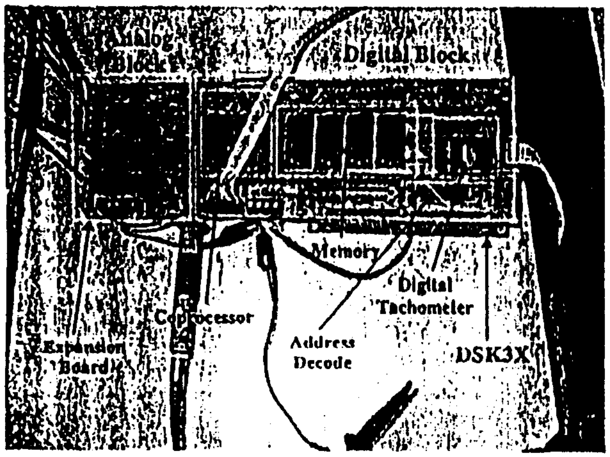

Figure 2. Actual test rig

A FPGA was used for mapping space the different devices in the extension card in the system memory, and also for implementing a digital tachometer, required for machine control.

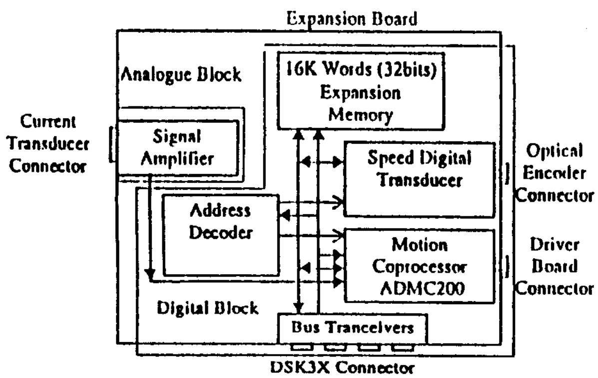

Figure 3. DSP extension card block diagram.

THE INTERFACE PROGRAM

As mentioned before, the PC is used as the developing tool for the control software to be used by the DSP based system. Afterwards, it is also used to monitor the system during normal operation. The DSP board contains a communications kernel for transferring and receiving information from the PC.

The structure of the programme environment is as follows, from the highest level in the PC to the lowest level in the DSP. The main tasks of the supervisory system are:

- Man machine interface.
- Downloading the control algorithms to the DSP board.
- Start and stop the AC machine.
- Data gathering and machine speed control.
- Control variables monitoring and long term storage in disk.

NEURAL NETWORK MODEL

A neural network model of the induction machine is used in this work [5]. This technique can be applied to solve non-linear differential equations in real time, once the neural network has been trained for the task. The learning process adjusts weighs and bias parameters in the neural network in order to minimise the error function as the input-output model is build [6]. The neural network main advantage in this application is that once the learning process is finished, the solution of the problem is practically instantaneous. Recently, neural networks have been used to model and control electric machines by a number of authors [7,8]. The neural network model proposed in this work for of the induction machine is segmented in three parts: the input transform, the non-linear equations, and the non-measurable linear-output variables. This segmentation, shown in Fig. 4, allows for neural network parameter adaptation without on-line training [9].

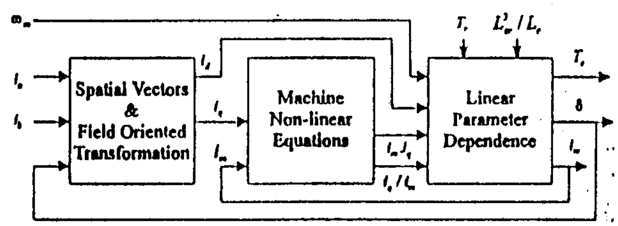

Figure 4. Neural network segmentation of the induction machine estimator.

The input transformation segment is made up by spatial vector and field oriented transformations [9,10]. The first one can be written for the line currents and the line to line voltage using the real variables as:

$$\begin{bmatrix} i_\alpha \\ i_\beta \end{bmatrix} = \begin{bmatrix} \sqrt{3}/2 & 0 \\ \sqrt{2}/2 & \sqrt{2} \end{bmatrix} \begin{bmatrix} i_a \\ i_b \end{bmatrix}$$
$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \begin{bmatrix} \sqrt{2/3} & \sqrt{1/6} \\ 0 & \sqrt{2}/2 \end{bmatrix} \begin{bmatrix} v_{ab} \\ v_{bc} \end{bmatrix} \quad (1)$$

Expressions in (1) are linear transformations and can be modelled by linear neural networks with weights equals to the matrices shown in this equation, and zero activation levels [5]. The field oriented transformation for currents and voltages can be written as [5]:

$$\begin{bmatrix} x_d \\ x_q \end{bmatrix} = \begin{bmatrix} \cos\delta & \sin\delta \\ -\sin\delta & \cos\delta \end{bmatrix} \begin{bmatrix} x_\alpha \\ x_\beta \end{bmatrix}. \quad (2)$$

Equation (2) shows a non-linear transformation, and a non-linear neural network is needed to model this transformation. A two-layer neural network was used to implement this equation. The first layer used sixteen neurones with a tangent sigmoid activation function. The output layer can be constructed with a linear activation function and two neurones. The required behaviour can be obtained using the Back Propagation algorithm and the Widrow – Hoff learning rule after 3240 training cycles (or epochs), with a square error below $0.9x10^{-3}$. The $\sin\delta$ and $\cos\delta$ functions can be obtained using the same technique. The second block reproduces the non-linear dependence on the differential equations of the induction machine model in oriented field co-ordinates. The mathematical model of the induction machine in this co-ordinates frame can be written as [10]:

$$p i_m = T_r^{-1}(i_d - i_m) \tag{3}$$

$$p\delta = \omega_m - T_r^{-1}\left({i_q}/{i_m} \right) \tag{4}$$

$$T_e = \frac{L_{sr}^2}{L_r}\left(i_m . i_q\right) \tag{5}$$

The non-linearity in equations (4) and (5) ($i_m . i_q$ and i_q / i_m) can be modelled with a non-linear neural network similar to the one used in the oriented field transformation. However, in this case it was necessary to employ thirty neurones in the first layer and four neurones in the output layer. The learning process of this network was completed after 853 epochs using the Widrow – Hoff rule with a square error less than $1x10^{-4}$. The learning process is performed off-line only once, since this non-linearity is not machine parameter dependent.

Finally, the non-measured variables of the model can be obtained using a linear neural network with zero bias and a weight matrix calculated directly from the induction machine parameters, as is shown in following equation:

$$W = \begin{bmatrix} 1/T_r & -1/T_r & 0 & 0 & 0 \\ 0 & 0 & 1/T_r & 0 & 1 \\ 0 & 0 & 0 & L_{sr}^2/L_r & 0 \end{bmatrix} \tag{6}$$

EXPERIMENTAL TESTS

Some typical control algorithms, going from standard scalar forms to the more complex vector control were used to test the DSP based platform.

Figure 5 shows the neural network state estimator behaviour when 1000 epochs has been used in the training process. Figure 6 shows the same results after 200.000 epochs has been used in the training process. Neural network training was performed off line in both cases.

A faster estimation was obtained using differential equations instead of neural networks. The time required for the DSP to execute the sequential neural network algorithm was around 40 μs. Using differential equations the time required is less than 10 μs. Figure 7 shows the stator current space vector during the vector control strategy using the neural network observer.

CONCLUSIONS

In this work a control system for AC machines has been implemented using vector control with neural network observer estimation. The controller was programmed using a high level language mixed with some critical routines written in machine language. An extension board was developed for interconnecting the TMS320C3X DSP STARTER KIT with the power stage.

It was shown that the neural network is useful for emulating state estimators and its implementation using DSP is practical. Nevertheless other traditional solutions can be faster. The implemented system is very adaptive, flexible and can be easily used for training undergraduate and graduate students.

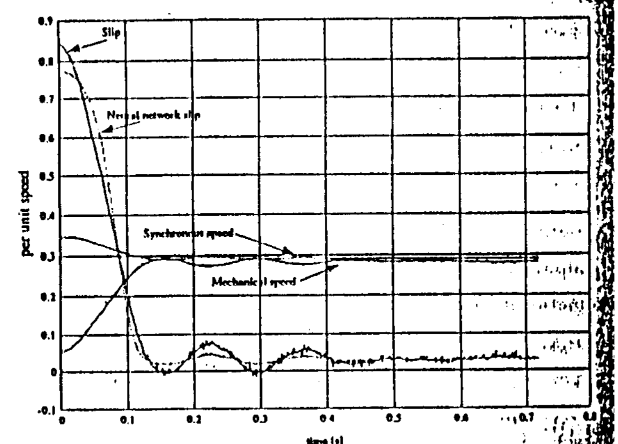

Figure 5. Neural network response using 1000 epochs on training process

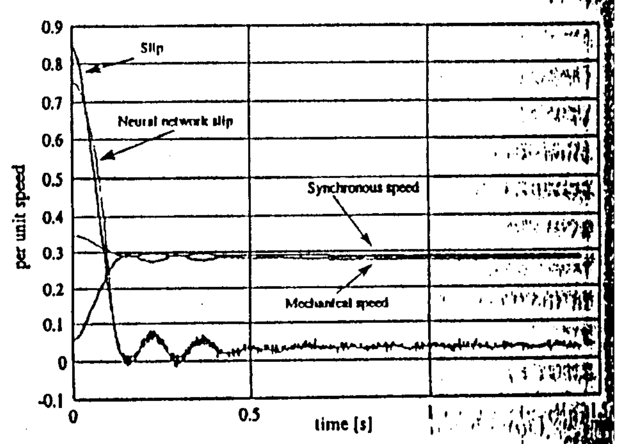

Figure 6. Neural network response using 200.000 epochs on training process

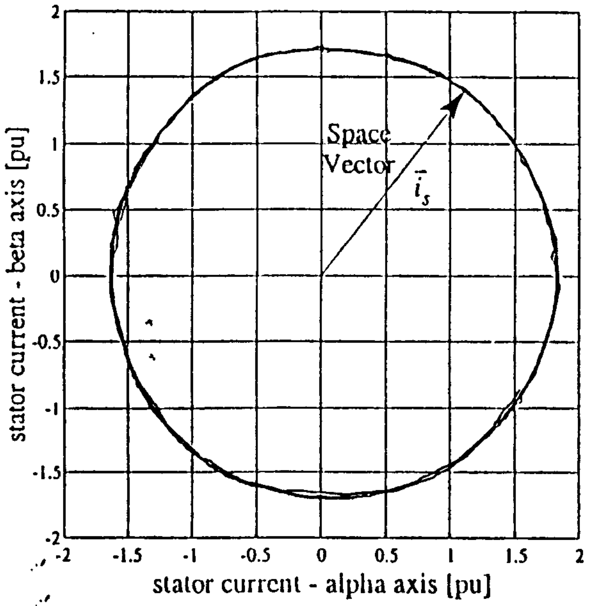

Figure 7. Stator current spatial vector

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