Paper accepted for presentation at 2009 IEEE Bucharest Power Tech Conference, June 28th - July 2nd, Bucharest, Romania

StatCom's Control by Neural Networks: Results on a Lab Prototype

Oliver Perez M., Juan M. Ramirez, Pavel Zuñiga H., Ruben Tapia O.

Abstract-- **This paper presents the Static Synchronous Compensator's (StatCom) voltage regulation by a B-spline neural network. The fact that the electric grid is a non-stationary system, with varying parameters and configurations, adaptive control schemes may be advisable. Thereby the control technique must guarantee its performance on an actual operating environment where the StatCom is embedded. The B-spline neural net (B-SNN) is a convenient tool to execute the power system voltage adaptive control, with the possibility of carrying out such tasks on-line and taking into account non-linearities. The proposed controller presents a simple structure, adaptability, fast response, and robustness. The simplicity and performance of such control are exhibited. The applicability of the proposition is tested on a lab prototype.**

Index Terms **– FACTS, StatCom, Neural Networks.**

I. INTRODUCTION

Power systems are highly nonlinear, with time varying configurations and parameters [1-3]. Thus, PI controllers based on power system's linearized model cannot guarantee a satisfactory performance under wide operating conditions. Thus, in this paper the use of a control, adjustable under different circumstances, is suggested.

Currently, most of the nonlinear control-based methods are intricate and their realization is complex. Additionally, the computational requirements of memory and processing speed may be overwhelming.

StatCom requires an adaptive control law which considers the nonlinear nature of the plant and adapts to variations on the environment for regulating the bus voltage magnitude. The aim of this paper is the utilization of an adaptive B-spline neural network controller. Such one is proposed because of it has a relatively simple and robust design, representing a commitment between the complexity of a conventional nonlinear controller and its performance.

II. B-SPLINE NEURAL NETWORKS: A SUMMARY

The major advantages of ANN-based controllers are simplicity of design, and their compromise between complexity and performance. The B-SNN is a particular case of neural networks that are able to adaptively control a system, with the option of carrying out such tasks on-line, and taking into account non-linearities [4-6]. Additionally, through B-SNN the possibility exists to bound the input space by the basis functions' definition. The most important feature of the B-spline algorithm is the output's smoothness that is due to the shape of the basis functions. Their size, shape and overlap determine how the network generalizes in M-dimensional input space. Some parameters have to be specified as the basis functions and the learning rate. Once the B-spline NN is specified, it is adaptive and able to achieve a satisfactory performance over a wide range of operating conditions. This is due to the weighting vector is updated on-line in each data sampling. The network can adaptively be updated to follow output's modifications when the system's operating point varies or an external disturbance takes place [7-9].

The bus voltage magnitude must attain its reference value through the B-spline adaptive control scheme. That is, control must drive the StatCom's modulation ratio m and the phase angle α to the desired value in order to regulate the injected voltage of the shunt converter.

The B-spline neural network output is [10],

$$y=\sum_{i=1}^{p} a_i w_i \qquad (1)$$

where w_i and a_i are the i^{th} weight and the i^{th} B-spline basis function output, respectively; p is the number of weights. Let us define

$$\mathbf{w}=[w_1\ w_2\ \ldots w_p]^T, \qquad \mathbf{a}=[a_1\ a_2\ \ldots a_p]^T$$

Thereby, eqn. (1) can be rewritten as

$$y=\mathbf{a}^T\mathbf{w} \qquad (2)$$

The input space is normalized by a lattice on which the basis functions are defined. The transformed input vector, **a**, is generally sparse, which means that knowledge is stored and adapted locally. That is, only a fixed number of basis functions participate in the network's output. Therefore, weights are not calculated each time step, thus reducing the computational effort and time, making B-spline NN suitable for on-line adaptive control.

In order to define a lattice of the input space, a set of M knot vectors must be specified; one knot vector for each input axis. These knot values give the positions of the (M-1)-dimensional hyperplanes which are parallel to each other (M-1) axes, and

This work was supported by CONACyT under Grant 88160.

Oliver Perez M. is a M. Sc. student at CINVESTAV. México. Email operez@gdl.cinvestav.mx.

Juan M. Ramirez is with CINVESTAV, México. E-mail jramirez@gdl.cinvestav.mx.

Pavel Zuñiga H. is with Universidad de Guadalajara –CUCEI. México. E-mail pavel.zuniga@cucei.udg.mx

Ruben Tapia O. is with Universidad Politecnica de Tulancingo. México. E-mail rtapia@gdl.cinvestav.mx

the set of all hyperplanes generates the lattice in the input space. For instance, a two-dimensional multivariate basis function formed from an order-1 (x_1) and an order-2 (x_2) univariate basis function is exhibited in Fig. 1. There are usually a different number of knots on each axis and they are generally placed at different positions. More specifically, a knot vector must be specified for each input axis.

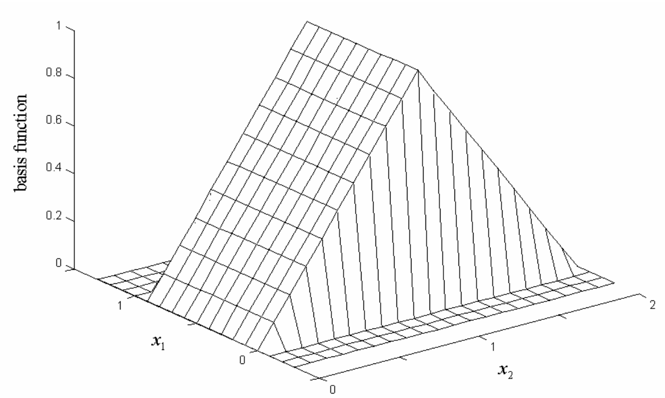


Fig. 1. Two-dimensional multivariate basis function constituted by an order-1 and an order-2 univariate basis function

These knots are required for generating the basis functions of width ki, which are close to the lattice's boundary. Given a knot vector, it is possible to define a univariate basis function. The network's input space is the domain $[x_1^{\min}, x_1^{\max}]\times\cdots\times[x_M^{\min}, x_M^{\max}]$ [8-10].

The j^{th} univariate interval on the i^{th} axis, denoted by $I_{i,j}$, is defined as:

$$I_{i,j} = \begin{cases} [\lambda_{i,j-1}, \lambda_{i,j}) & for\ j = 1,\ldots,r_i \\ [\lambda_{i,j-1}, \lambda_{i,j}] & if\ \ j = r_i + 1 \end{cases} \tag{3}$$

Thus, denoting the j^{th} univariate basis function of order-k by $N_k^j(x)$, the basis functions are defined through the following recurrence relationship,

$$N_k^j(x) = \left(\frac{x-\lambda_{j-k}}{\lambda_{j-1}-\lambda_{j-k}}\right)N_{k-1}^{j-1}(x) + \left(\frac{\lambda_j - x}{\lambda_j - \lambda_{j-k+1}}\right)N_{k-1}^j(x) \tag{4}$$

$$N_1^j(x) = \begin{cases} 1 & if\ x \in I_j \\ 0 & otherwise \end{cases} \tag{5}$$

where λ_j is the j^{th} knot and I_j (=[λ_{j-1}, λ_j)) is the j^{th} interval, eqn. (3).

Since in this paper the ANN is employed as a controller, the proposed input signals are some errors. That is, the difference between a reference and measured values. The B-SNN requires the following a-priori information: the bounded values of e_y and e_z (error signals), for characterizing the size, shape, and overlap definition of the basis function. Such information allows to bound the B-SNN input and to enhance the convergence and stability of the instantaneous adaptive rule. With this information the B-SNN estimates the optimal weights.

Learning in artificial neural networks (ANNs) is usually achieved by minimizing the network's error, which is a measure of its performance, and is defined as the difference between the actual output vector of the network and the desired one.

On-line learning of continuous functions, mostly via gradient based methods on a differentiable error measure is one of the most powerful and commonly used approaches for training large layered networks in general [10], and for nonstationary tasks in particular.

For the voltage magnitude regulation, the controller's quick response is looked for. While conventional adaptive techniques are suitable to represent objects with slowly changing parameters, they can hardly handle complex systems with multiple operating modes. The instantaneous training rules provide an alternative so that the weights are continually updated and reach the convergence to the optimal values. Also, conventional nets sometimes do not converge, or their training takes a lot of time [10-13].

In this paper, the neural controller is trained on-line using the following error correction instantaneous learning rule [9],

$$w_i(t) = w_i(t-1) + \frac{\eta\, e_i(t)}{\|\mathbf{a}(t)\|_2^2} a_i(t) \tag{6}$$

where: η is the learning rate and $e_i(t)$ is the instantaneous output error.

This learning rule has been elected as an alternative to those that use, for instance, Newton's algorithms for updating the weights [12-13] that require Hessian and Jacobian matrix evaluation. Equation (6) has been obtained through the minimization of the output's mean square error, using descendent gradient rules. That is the reason because it is said that the weights converge to optimal values [10].

Thus, the proposed neurocontroller consists fundamentally on establishing its structure (the definition of basis functions) and the value of the learning rate. Regarding the weights' updating, (6) should be applied for each input-output pair in each sample time; the updating occurs if the error is different from zero. Respect to the learning rate, it takes as initial point one value inside the interval [0, 2] due to stability purposes [10]. This value is adjusted through trial-and-error; with a value close to zero the training becomes slow. However, if such value is large, oscillations can occur; in this application it settles down in 0.55.

Hence, the B-SNN training process is carried out continuously on-line, while the weights' value are updated using the feedback variables. The neural network output is calculated by (2).

The fundamental structure of the StatCom is based on a Voltage Source Converter (VSC), and a coupling transformer that it is used as a link with the electric power system, Fig. 2; $\mathbf{E}_{ST}$ represents the StatCom's complex bus voltage, and $\mathbf{E}_k$ the power system complex bus voltage; all angles are measured respect to the general reference.

The model is represented as a voltage variable source $\mathbf{E}_{ST}$, whose magnitude and phase angle can be adjusted with the purpose of regulating the voltage magnitude. The magnitude V_{ST}, it is conditioned by a maximum and a minimum limit, depending on the VSC's capacitor rating. Ordinarily, the interval of the magnitude, V_{ST}, is settled down within [0.9, 1.1] p.u.; the phase angle, δ_{ST}, may vary within [0, 2π] rad.

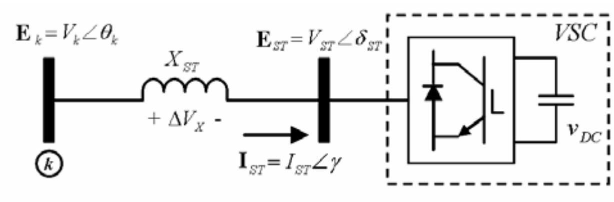


Fig. 2. StatCom's schematic representation.

For tuning parameters, a simplified dynamic model of StatCom may be employed and represented by the capacitor voltage equation ,

$$\frac{dv_{DC}}{dt} = \frac{mk}{C_{DC}}\left(I_{STd}\cos\psi + I_{STq}\sin\psi\right) \quad (7a)$$

$$V_{ST} = mkv_{dc} \quad (7b)$$

$$\delta_{ST} = \psi \quad (7c)$$

where $\mathbf{I}_{ST} = I_{STd} + jI_{STq}$, represent the d and q StatCom's current components, respectively; v_{DC} is the DC StatCom voltage; C_{DC} is the capacitance; m is the modulation ratio defined by the PWM; ψ is the phase angle defined by the PWM, and it determines the phase δ_{ST}; k is the ratio between the ac and dc voltage depending on the inverter structure. Thus, signals V_{ST} and δ_{ST} will be controlled by the proposed B-SNN controller.

III. Results

A lab StatCom's prototype has been implemented in order to validate the appropriateness of the proposition, Figs. 3-6.

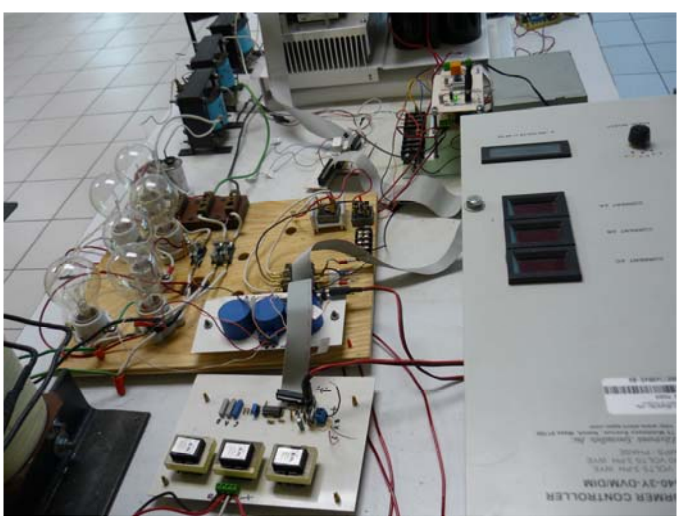


Fig. 3 Lab Prototype overview

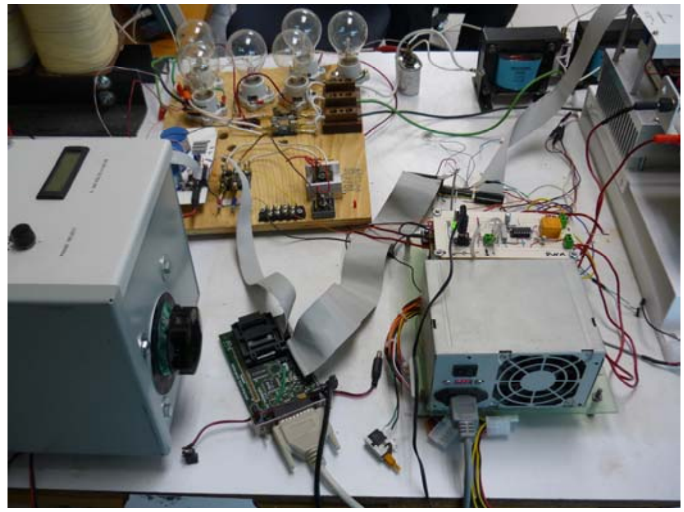


Fig. 4 DSP's connection

Fig. 5 VSC and transformers

The major elements of the scheme are the following, Fig. 6: (*i*) source voltage - 85 volts peak, (*ii*) transmission line – inductance 3.1 mH, (*iii*) LC filter - Capacitors 5 uF and inductors 3.1mH, (*iv*) Asynchronous motor - squirrel cage 0.745 kW.

The Voltage Source Converter (VSC), which is the major component of the circuit, has been controlled by a DSP TMS320F2812, Fig. 4. This DSP has 6.67ns instruction cycle time (150MHz), 16 channel, 12-bit ADC with built-in dual sample-and-hold, and analog input from 0 to 3V which makes the complete system easy to implement. The synchronizing circuit for the twelve-pulses VSC has been already implemented on the DSP, collecting the data with a global Q of 20, which means it has 20 bits as fractional part of the data, and 12 bits as the data's integer part. The selected sampling frequency for the ADC on this application is 2500 Hz, thus 60000 clock cycles available between successive samples can be accomplished. The amount of cycles used for implementing the novel PLL on the DSP, along with the necessary code for refreshing the control signal is 2150.

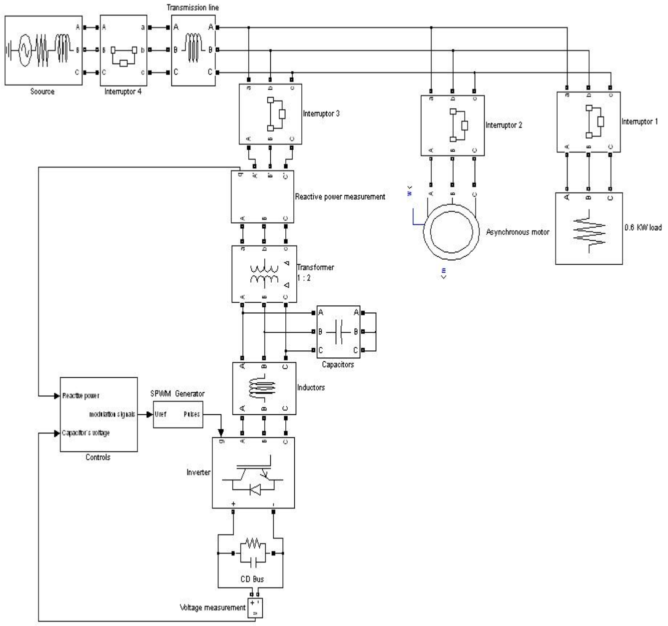
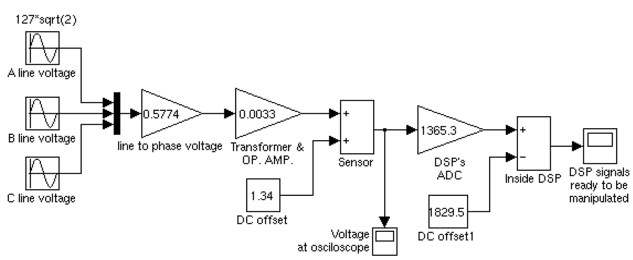


Fig. 6 Scheme of the arrangement

Fig. 7 illustrates details of feeding the line-to-line voltages into the DSP; escalation must be done.



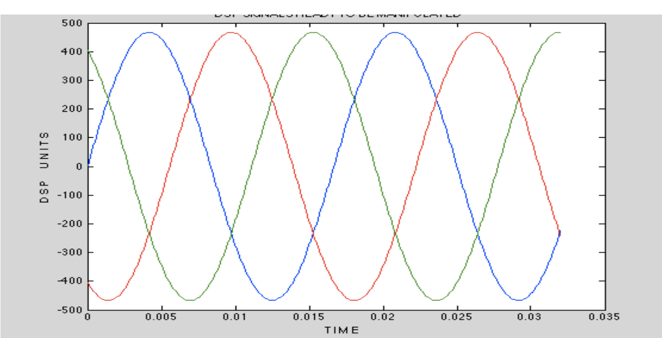


Fig. 7 line-to-line voltages fed into the DSP

Clarke's transformation is utilized for controlling purposes. Thus, three signals result: sine (α), cosine (β), and the integrated one, Fig. 8.

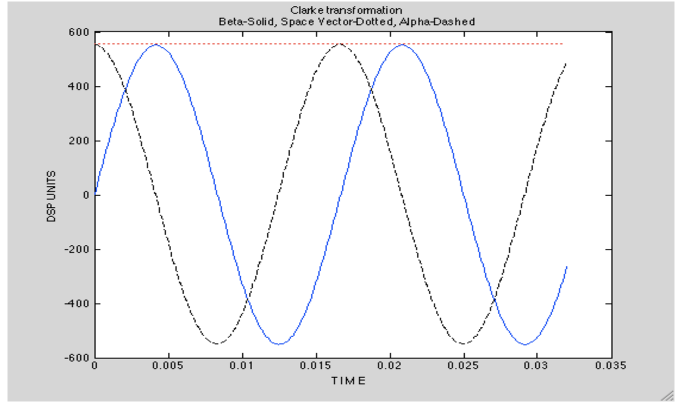


Fig. 8 α-β and integrated signals

The inverse Park's transformation creates three modulating signals, Fig. 9, which are in charge of IGBTs' triggering.

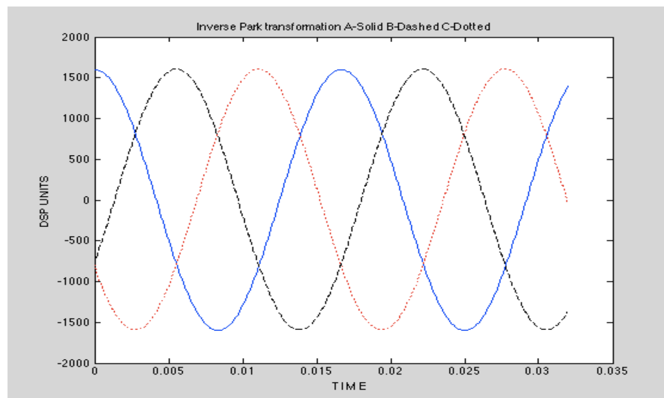


Fig. 9 Modulating signals

Controling the StatCom by two PI controllers (dc voltage and reactive power), Fig. 10 illustrates reactive power at the transformer's primary side (StatCom's side). Likewise, the DC voltage at the capacitor is shown. The reference values are: (*i*) 100 V_{DC}, (*ii*) reactive power 100 Vars.

Under this condition, an induction motor is started (time = 8 s) once the source voltage has been turned on to 87 V_{peak}. The difference between the angle of the StatCom's voltage and the System's one has been ten times amplified in order to notice it, Fig. 11. The desired values are as following: (*i*) 100 V_{DC}, (*ii*) reactive power 100 Vars. In Fig. 11, oscillations can be noticed in both reactive power and voltage capacitors.

As an alternative, a B-spline controller is designed for the StatCom's regulation. Fig. 12 schematizes its corresponding structure.

The induction motor is started at time = 109 s. *I.C.* means initial conditions (on the DSP units, value stored on the term z^{-1} in Fig. 11). *N* means learning, and *D.T.* is disturbance time. The reference values are the aforementioned, Fig. 13.

By modifying the B-spline initial condition, a better behavior can be obtained, Fig. 14.

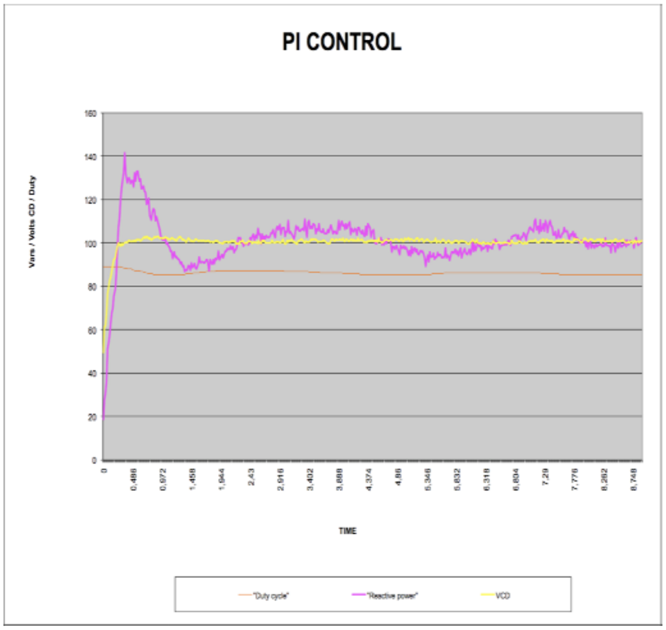


Fig. 10 Reactive power, DC voltage, and duty cycle

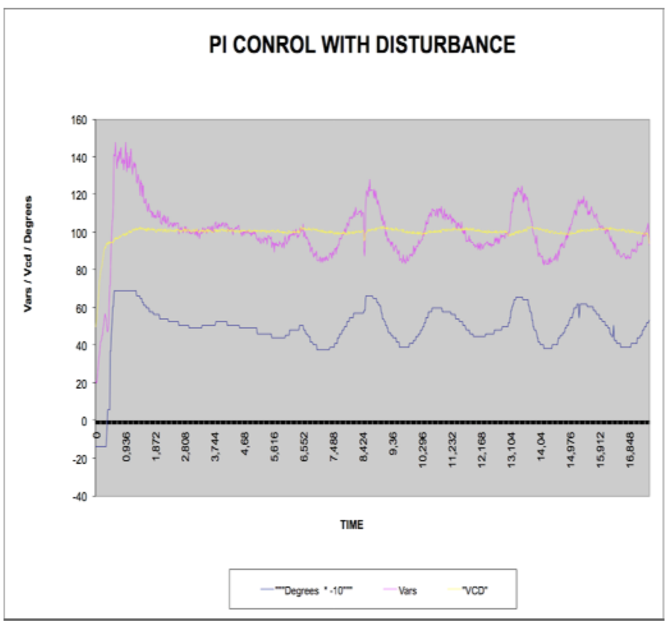


Fig. 11 PI's controllers performance under disturbance

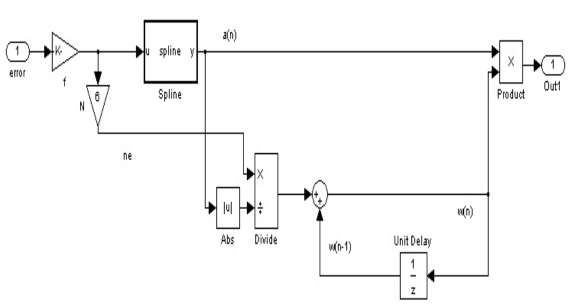


Fig. 12 B-spline neural network structure

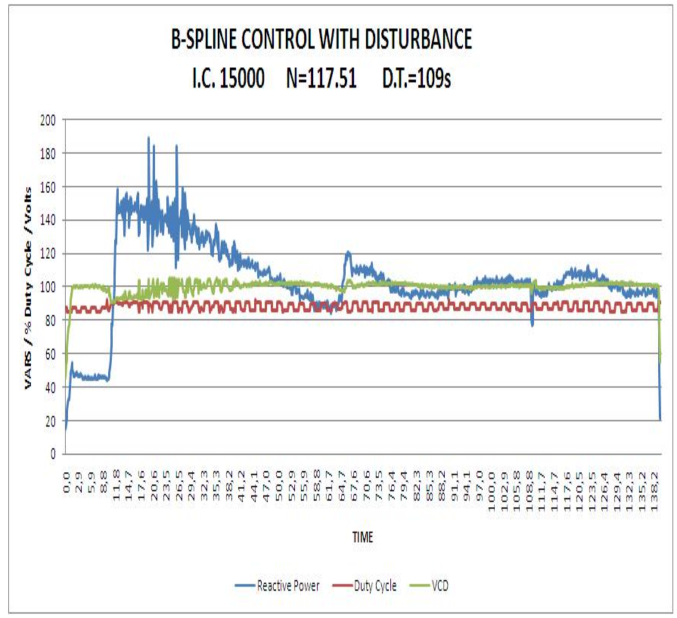


Fig. 13 B-spline neural controller performance

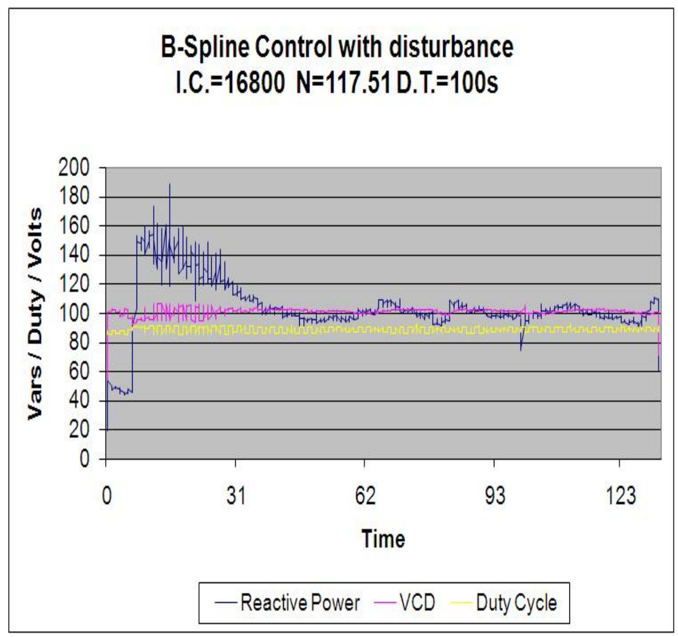


Fig. 14 Behavior under different initial conditions

By an averaging on the error between the desired and measured reactive power, the B-spline performance may be additionally improved, Fig. 15. It is noteworthy that a duty cycle in the B-spline case behaves as a squared signal.

Thus, in this paper results have been shown where it is noticed that a B-spline neural network controller may be an interesting alternative for regulating FACTS devices, which are exposed to variations on the operating point.
This strategy allows appropriately controlling the bus voltage magnitude where the StatCom is connected, but also it helps to limit the oscillations and overshoots in other relevant signals. The proposed control strategy does not depend on the

FACTS location, since the neurocontroller is able to adapt by itself to different operating conditions.

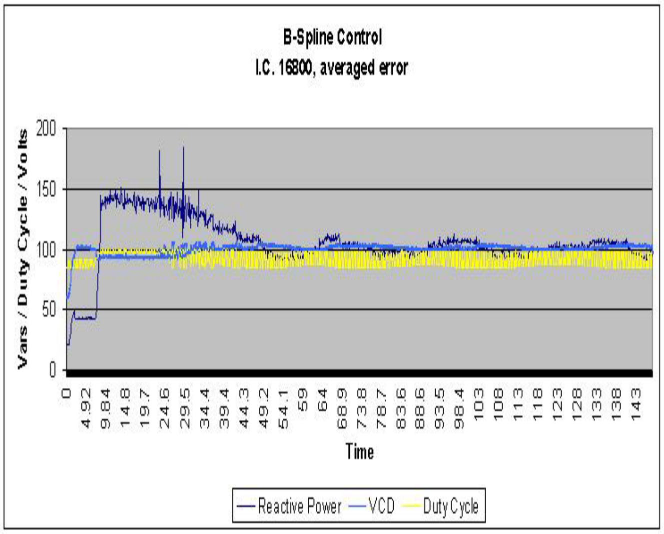


Fig. 15 B-spline performance by an error averaging

IV. Conclusions

By the proposed neural control the possibility to implement the on-line control is potential due to it has learning ability and adaptability, robustness, simple control algorithm and fast calculations. These are desirable characteristics for practical hardware implementation on the power station platforms.

Unlike the PI control technique, the B-spline NN control exhibits adaptive behavior since the weights can be adapted on-line responding to inputs and error values as they take place. Also, it may take into account nonlinearities, non modeled dynamics, and non measurable noise. Lab results for different disturbances and operating conditions demonstrate the effectiveness and robustness of the NN control. Likewise, they show the appropriate performance of the controller, while rapid reference tracking is achieved; also, a satisfactory transient response is obtained.

References

[1] Mohagheghi, S., Jung-Wook Park, Harley, R.G., Venayagamoorthy, G.K., “Adaptive critic design based neurocontroller for a STATCOM connected to a power system”, IEEE Industry Applications Conference, 38th IAS Annual Meeting, vol. 2, pp. 749-754, 2003.

[2] Mohagheghi, S.; Venayagamoorthy, G.K.; Harley, R.G., “Adaptive Critic Design Based Neuro-Fuzzy Controller for a Static Compensator in a Multimachine Power System.” IEEE Transactions on Power Systems, Vol. 21, Issue 4, Nov. 2006 Page(s):1744 – 1754.

[3] Abido, M.A.; Abdel-Magid, Y.L.; “Radial basis function network based power system stabilizers for multimachine power systems,” International Conference on Neural Networks, 1997, Volume 2, 9-12 June 1997, Page(s): 622 626.

[4] Shuang Cong, and Ruixiang Song, "An Improved B-Spline Fuzzy-Neural Network Controller", in Proc. 2000 3rd World Congress on Intelligent Control and Automation, pp. 1713-1717.

[5] K. W. E. Cheng, H. Y. Wang, and D. Sutanto, "Adaptive directive neural network control for three-phase AC/DC PWM converter", IEE Proc. Electr. Power Appl., vol. 148, pp. 425-430, Sep. 2001.

[6] D.S. Reay, "CMAC and B-spline Neural Networks Applied to Switched Reluctance Motor Torque Estimation and Control", IEEE Industrial Electronics Society 29th Annual Conf., pp. 323-328, 2003.

[7] Cao B, Dodds G and Irwin GW, "Constained time-efficient and smooth cubic spline trajectory generation for industrial robots." IEE Proc. - Control Theory and Applications, Vol. 144, No. 5, pp. 467-475, 1997.

[8] Menken G.-J, "Modularly structured B-spline networks for internal model control", in Proc. 1997 IEEE Control Systems Society, American Control Conf., pp. 2001-2005.

[9] K.F. Cedric Yiu, S. Wang, K.L. Teo, and Ah Chung Tsoi, "Nonlinear System Modeling via Knot-Optimizing B-Spline Networks", IEEE Trans. Neural Networks, vol. 12, pp. 1013-1022, Sep. 2001.

[10] Brown, and C. Harris, Neurofuzzy Adaptive Modelling and Control, Prentice Hall International, 1994.

[11] David Saad, “*On-line learning in neural networks,*” Cambridge University Press 1998.

[12] A. H. Osman, Tamer Abdelazim, , and O. P. Malik, “Transmission Line Distance Relaying Using.” IEEE Transactions on Power Delivery, Vol. 20, No. 2, April 2005, pp. 1257-1264.

[13] A. Osman, T. Abdelazim, and O. P. Malik, “Adaptive distance relaying technique using on-line trained neural network,” in Proc. IEEE PES General Meeting, Toronto, ON, Canada, Jul. 2003.

Biographies

Oliver Perez M. received the B.S. in Electronics and Digital Systems in Electrical Engineering from Universidad de Guadalajara, Mexico, July 2007. He is currently working toward his M. Sc. degree at Guadalajara Campus of CINVESTAV in México. His research interest is power electronics including FACTS devices, power converters, PWM control schemes.

Juan M. Ramirez (M’ 1985) obtained his BS in Electrical Engineering from Universidad de Guanajuato, México in 1984; M. Sc. in Electrical Engineering from UNAM-México in 1987; Ph. D. in Electrical Engineering from UANL-México in 1992. He joined the department of Electrical Engineering of CINVESTAV in 1999, where he is currently a full time professor. His areas of interest are: FACTS devices, and operation and control of electric power systems.

Pável Zúñiga H. obtained his M.Sc. and Ph. D. in Electrical Engineering in 2001 and 2006, respectively. He is with the Graduate Program in Electrical Engineering at CUCEI, University of Guadalajara, Guadalajara, Jalisco, México. His primary areas of interest are in modeling and control of FACTS devices and the application of power converters.

Rubén Tapia O. obtained his BS in Electrical Engineering from Instituto Tecnológico de Pachuca, México in 1999; M.Sc. and Ph. D. in Electrical Engineering from CINVESTAV Guadalajara, México in 2002 and 2007, respectively. He is currently with Universidad Politécnica de Tulancingo. His primary area of interest is in modeling and control of FACTS devices with computational intelligence techniques.