# Journal of Applied Sciences

ISSN 1812-5654

science alert

ANSInet
an open access publisher
http://ansinet.com

Journal of Applied Sciences 7 (7): 1078-1084, 2007
ISSN 1812-5654
© 2007 Asian Network for Scientific Information

# Neural Network Generalized Predictive Control of the Unified Power Flow Controller

[1]Soraya Zebirate, [1]Abdelkader Chaker and [2]Ali Feliachi
[1]Laboratory LAAS, BP 1742 El M'Naouer-Oran-Algeria
[2]Advanced Power and Electricity Research Center,
P.O. Box 6109, West Virginia University, Morgan Town, WV 26506-6109

**Abstract:** The Unified Power Flow Controller (UPFC) is the most comprehensive tool for real time control of alternative transmission systems. It can be used to control the transmitted real and reactive power flows through a transmission line. Different control techniques for the UPFC system have been proposed. This present study investigates an efficient and robust control method for the UPFC in order to improve the stability of the power system, thus providing the security for the increased power flow. It is now becoming clear that only the classical method based on information processing tools issued from artificial intelligence may lead to a new stage in the automatic control technology. With Artificial Neural Networks (ANNs) issues such as uncertainty or unknown variations in plant parameters and structure can be dealt with more effectively and hence improving the robustness of the control system. The basic idea of a Neural Network Generalized Predictive Controller (NNGPC) is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a prediction horizon. The NNGPC performances are compared in terms of reference tracking, sensitivity to perturbations and robustness against line transmission parameters variations.

**Key words:** UPFC system, neural networks, generalized predictive control

## INTRODUCTION

The concept of Flexible Alternating Current Transmission Systems (FACTS) has recently gained much attention in the electric industry community and has been an area of interest and technology development during these last years.

An important FACTS device is the UPFC, which can control all three principal parameters (voltage, impedance and phase angle) that determine the power flow of a transmission line. A UPFC consists of two forced-commutated voltage inverters which are connected through a common dc link provided by a storage capacitor as shown in Fig. 1, (Gyugyi, 1992; Edris *et al*., 1995; Tuttas, 1999). One converter is shunt-connected and the other is connected in series with the transmission line.

Each inverter can independently generate reactive power at its own ac terminal. The dc link allows an active power exchange between both electronic circuits. Inverter 2 operates as a series compensator and injects an ac voltage $V_c$ with variable amplitude and phase angle at power system frequency.

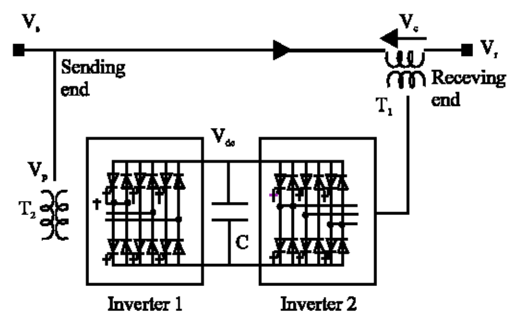


Fig. 1: Basic circuit configuration of a UPFC

The active and reactive power flow of the transmission line can be controlled. Inverter 1 provides the real power demand of inverter 2, regulates the capacitor voltage $V_{dc}$ and provides reactive power.

Sen and Keri (2003) compared field results of the Inez UPFC project to an EMTP simulation. There are no details on the design of the controllers utilized, or the presence of any disturbances or uncertainties. Zhengyu *et al*. (2000) have discussed four principal control strategies for UPFC series element main

**Corresponding Author:** Soraya Zebirate, Laboratory LAAS, BP 1742 El M'Naouer, Oran, Algeria
Tel: 213 41 416420 Fax: 213 41 419806

control and their impacts on system stability. Ma (2003) demonstrated the feasibility of using a centralized optimal control scheme using an evolutionary programming algorithm. Sukumar (2006) has used a Radial Basis Function neural Network (RBFNN) as a control scheme for the UPFC to improve the transient stability performance of a multimachine power system. Schoder *et al.* (2000) have proposed a Fuzzy damping controller. In last years, the application of neural networks (NNs) for adaptive control has been a subject of extensive study (Xie *et al.*, 2006; Chau *et al.*, 2005, 2007; Lin *et al.*, 2006).

The method proposed in this study is novel. It combines two different approaches, namely intelligent techniques that seem to work but do not provide a formal proof and analytical techniques that provide proofs under some restricted conditions and for simple systems. These limitations have been a central driving force behind the creation of hybrid systems (Henriques and Dourado, 1999) where two or more techniques are combined in a manner that overcomes the limitations of individual techniques. So, the hybrid systems are important when considering the control of the unified power flow through a transmission line using a PWM-based UPFC, because, it is a complex application. The present study intends to be a contribution in this direction. It considers the application of a Generalized Predictive Controller (GPC), with neural networks in an electric power system.

## MODELLING OF A UPFC SYSTEM

The series and shunt inverters are represented by voltage sources $V_c$ and $V_p$, respectively. The transmission line is modelled as a series combination of resistance, R and inductance, L, whereas the parameters $R_p$ and $L_p$ represent the resistance and leakage inductance of shunt transformer, respectively. The nonlinearities caused by the switching of the semiconductor devices and transformer saturation are neglected in the equivalent circuit shown in Fig. 2. It is assumed that the transmission system is symmetrical.

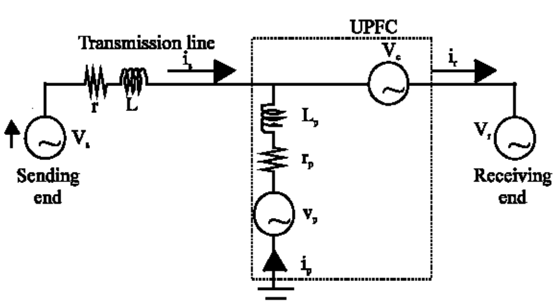


Fig. 2: Equivalent circuit of UPFC system

After the d-q transformation, a mathematical model of the transmission system including the series part of UPFC is given in (1) and (2) where $i_{sd}$, $i_{sq}$ are the transmission line currents (Yu *et al.*, 1996).

$$\frac{di_{sd}}{dt} = \omega \, . \, i_{sq} - \frac{R}{L} \, . \, i_{sd} + \frac{1}{L} \, . \, \left(v_{sd} - v_{cd} - v_{rd}\right) \tag{1}$$

$$\frac{di_{sq}}{dt} = \omega \, . \, i_{sd} - \frac{R}{L} \, . \, i_{sq} + \frac{1}{L} \, . \, \left(v_{sq} - v_{cq} - v_{rq}\right) \tag{2}$$

Similarly, the mathematical model of shunt connection of the UPFC system can be determined from Fig. 2 and is given in Eq. 3 and 4 where $i_{pd}$, $i_{pq}$ are the shunt currents.

$$\frac{di_{pd}}{dt} = \omega \, . \, i_{pq} - \frac{R_p}{L_p} \, . \, i_{pd} + \frac{1}{L_p} \, . \, \left(v_{pd} - v_{cd} - v_{rd}\right) \tag{3}$$

$$\frac{di_{pd}}{dt} = \omega \, . \, i_{pq} - \frac{R_p}{L_p} \, . \, i_{pd} + \frac{1}{L_p} \, . \, \left(v_{pd} - v_{cq} - v_{rq}\right) \tag{4}$$

Using the power balance principle and neglecting the inverter losses, the dc bus voltage can be expressed as (5) .

$$\frac{dv_{dc}}{dt} = \frac{3}{2Cv_{dc}}\left(v_{pd}\, i_{pd} - v_{pq} + v_{pq}\, i_{pq} - v_{cd}\, i_d - v_{cq}\, i_q\right) \tag{5}$$

The dc link capacitor in Fig. 1 must be selected to be large enough to minimize the dc voltage ripple. Having derived the real and reactive power references P* and Q*, the following Eq. 6 can be used to determine the corresponding direct and quadrature axes reference currents at the sending and receiving ends of the two bus power system

$$i^*_d \; \frac{2}{3} \; \frac{P^* v_d - Q^* v_q}{v_d^2 + v_q^2}$$
$$i^*_d \; \frac{2}{3} \; \frac{P^* v_d - Q^* v_d}{v_d^2 + v_q^2} \tag{6}$$

where the * superscript defines the reference quantities.

To control the UPFC system, ordinary simple PI-Decoupling (PI-D) controller for UPFC is good enough (Fig. 3).

Unfortunately, The PI-control fails to solve problems where it is not possible to obtain sufficiently precise processes and disturbances models.

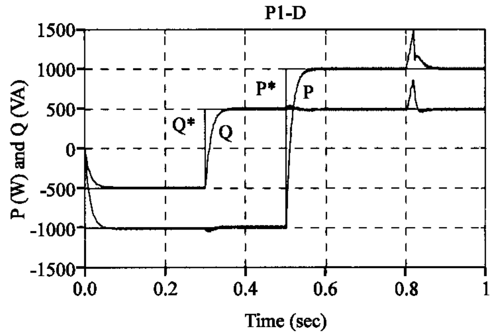


Fig. 3: Current step response of PI with decoupling

## CONTROL DESIGN

This section describes one of the most popular predictive control algorithms: Generalized Predictive Control (GPC) (Peri and Petrori, 1999).

The basic idea of GPC is to calculate a sequence of future control signals in such a way that it minimizes a multistage cost function defined over a prediction horizon (Fig. 4).

A CARIMA model is given by:

$$Ej\,(z^{-1}).\ \Delta.\ A\,(z^{-1}) + z^{-j}.\ Fj\,(z^{-1}) = 1 \tag{7}$$

with

$$\Delta = 1\text{-}z^{-1} \tag{8}$$

A, B and C are the polynomials in the backward shift operator $z^{-1}$. For simplicity, in the Fig. 5 the C polynomial is chosen to be 1.

The Generalized Predictive Control (GPC) algorithm consists of applying a control sequence that minimizes a multistage cost function of the form:

$$J\,(N_u, N, \lambda) = \sum_{j=1}^{N} \left[y\,(t+j) - w\,(t+j)\right]^2 + \lambda \sum_{j=1}^{N_u} \left[\Delta u\,(t+j-1)\right]^2 \tag{9}$$

y(t+j) is an optimum j-step ahead prediction of the system output on data up to time t, where $N_1 \leq j \leq N_2$ (j = 1). There is no reason for choosing it smaller because first predictions depend upon past control inputs only and thus cannot be influenced. On the other hand it is not recommended to choose it bigger since this can lead to quit unpredictable results. $N_1$ is the minimum prediction

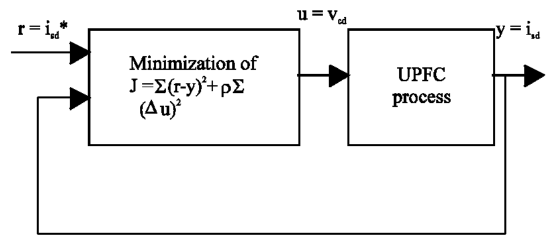


Fig. 4: The principle of predictive control

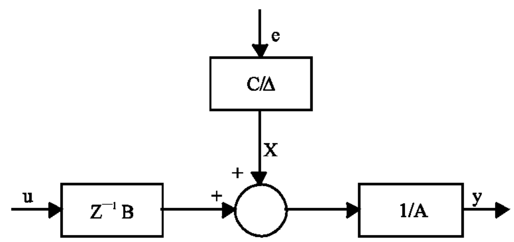


Fig. 5: Representation of the CARIMA model

horizon, $N_2$ is the maximum prediction horizon and $N_u$ is the control horizon, $\lambda$ is the weighting sequence and w(t + j) is the future reference trajectory.

The objective of predictive control is to compute the future control sequence u(t), u(t+1),... in such a way that the future plant output y( t+j ) is driven close to w(t + j). This is accomplished by minimizing J ($N_u$, N, $\lambda$).

$$u\,(t) = (1 - b_1\, b_2\, (b_1^2 + \lambda)^{-1})\; u\,(t-1) + b_1\, b_2\, (b_1^2 + \lambda)^{-1}\, u\,(t\text{-}2) + b_1\, (b_1^2+\lambda)^{-1}\, c\,(t) + b_1\, (a_1 - 1)\,(b_1^2+\lambda)^{-1}\, y\,(t) - b_1\, a_1\, (b_1^2 + \lambda)^{-1}\, y\,(t\text{-}1) \tag{10}$$

The following set of j ahead optimal predictions can be written as:

$$\hat{y} = G\ \Delta u\,(t) + f \tag{11}$$

$$\Delta u(t) = b1(b_1^2 + \lambda)^{-1}(c - f) \tag{12}$$

Notice that only the first element of u is applied and the procedure is repeated at the next sampling time. The algorithm to obtain the control law described in the previous section will be used on the neural networks GPC (NNGPC). Obtaining numerical results for the parameter values $a_1 = -0.9231$, $b_1 = 9.6095.10^{-4}$ and $b_2 = 2.1617.10^{-7}$, the horizons being: $N_1 = 1$; $N_2 = 2$; $N_u = 1$ and $\lambda = 10^{-9}$.

The control signal is a function of the desired reference and of past inputs and outputs and is given by:

$$u(t) = \alpha_1 u(t-1)+\alpha_2 u(t-2)+\alpha_3 c(t)+\alpha_4 y(t)-\alpha_5 y(t-1) \quad (13)$$

$$u(t) = [\alpha_1 \alpha_2\ \alpha_3\ \alpha_4\ \alpha_5] \begin{bmatrix} u(t-1) \\ u(t-2) \\ c(t) \\ y(t) \\ y(t-1) \end{bmatrix} \quad (14)$$

The training of the network consists in modifying the weights and bias in order to minimize the quadratic errors at the output by using the Windrow-Hoff law (Nguyen and Widrow, 1990). The reason for this specification choice of network is justified by the fact that in general recurrent networks are considered more suitable for modelling dynamical systems. With each step of training, the error at the output is calculated as the difference between the required target y and the estimate output y of the network. The quantity to be minimized, with each step of training k, is the variance of the error at the output of the networks. Equation 13 can be expressed as:

$$u(t) = W_x + W_o \quad (15)$$

where,

$$W = [\alpha 1\ \alpha 2\ \alpha 3\ \alpha 4\ \alpha 5] \quad (16)$$

$$p = \begin{bmatrix} u(t-1) \\ u(t-2) \\ c(t) \\ y(t) \\ y(t-1) \end{bmatrix} \quad (17)$$

P, w et $w_0$ design, respectively, the input vector, the weight and the bias.

## CONTROL PERFORMANCE

Simulations are performed on a Pentium PC under MATLAB/Simulink. The transmission line and the UPFC (series and shunt inverters) system are implemented with Simulink blocks.

The neural network generilized predictive controller (NNGPC) are implemented as a C-coded S-functions as shown in Fig. 7.

For each of the control systems, a simulation model is created which makes use of PWM-inverters as interface to the power system.

The parameters of the simulation model are selected to be equal to the parameters of a laboratory UPFC model (Yu *et al*., 1996), which are listed in Table 1.

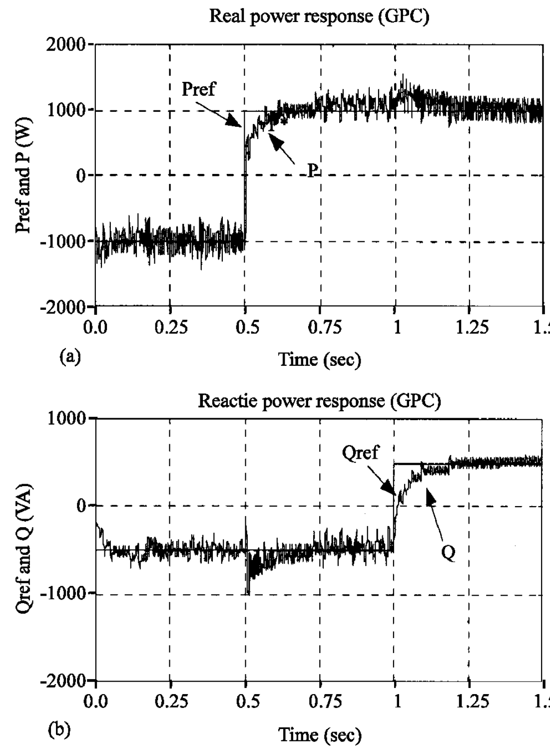


Fig. 6: Simulation result of step response of the series UPFC system

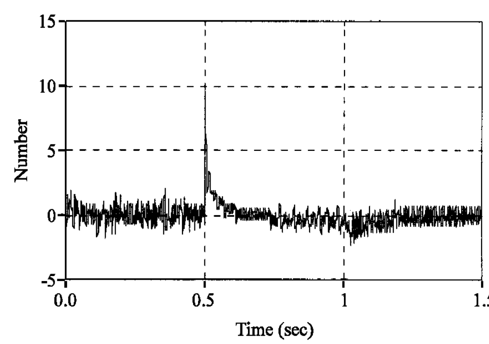


Fig. 7: Error prediction (GPC)

Table 1: The parameters of the laboratory UPFC model

| | | | |
|---|---|---|---|
| $V_r$ | 220 V | $R_P$ | 0.4 Ω |
| $V_s$ | 220 V | R | 0.8 Ω |
| C | 2 mF | $L_P$ | 10 H |
| V*dc | 280 V | L | 10 H |

The PWM switching frequency is selected to be 750 Hz. The control system described above was derived by assuming that the series and shunt inverters are ideal controllable voltage sources.

Simulation results show the behaviour of the closed-loop system.

The Fig. 6 shows the step response of the UPFC system. Initially the system is in steady state

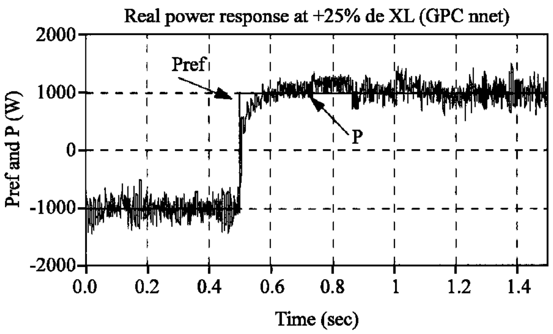


Fig. 8: Real power response of UPFC variables

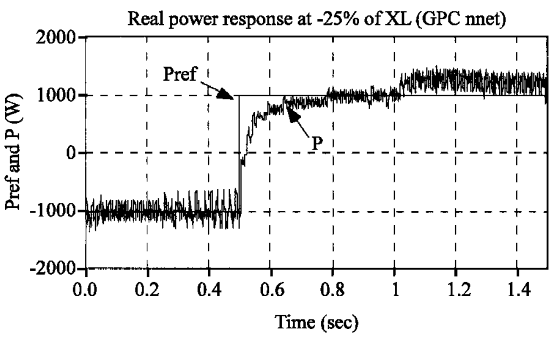


Fig. 9: Reactive power response of UPFC variables

with a real power of the receiving end of -1000 W and reactive power of -500 VA.

At a time 1 sec, the reactive power reference Q* is changed to 500 VA while the real power reference P* is kept constant at -1000 W until t = 0.5 sec where the real power reference P* is changed to 1000 W.

The control system has a fast dynamical response. The error prediction is equal to 0.0002 Fig. 7.

One major advantage of NNGPC is its robustness against parameter variations. This is demonstrated by change the UPFC line impedance by±25% Fig. 8 and 9.

A repeating sequence is added to the system UPFC as a perturbation. The time of this perturbation is equal to 0.02 sec with amplitude 2.

As can be seen, the controller rejected the external perturbation quite rapidly Fig. 10 a and b.

The PI-D control for UPFC has been used successfully with precise models and no disturbances. In cases of model uncertainties and disturbances, the PI-control fails as shown in Fig. 11; hence, the proposed controller is designed to handle these conditions.

The objective is to keep the sending bus voltage at its pre-specified value and to keep the reactive power constant-0.15 p.u while tracking the step changes in the real power: at time 0.2 sec real power flow reference is changed from 1.6 -1.8 p.u, at time 0.35 sec reference is set

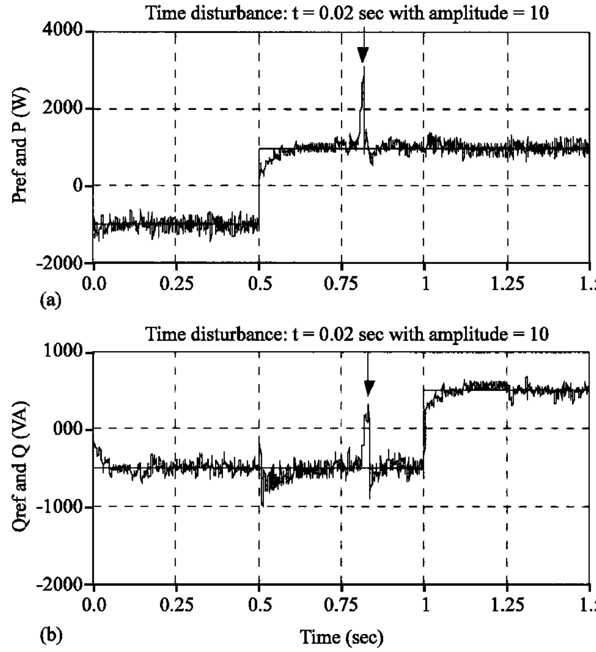


Fig. 10: System response in the presence of external disturbance

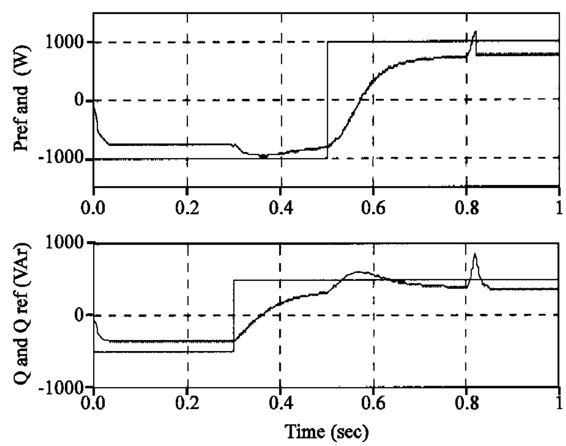


Fig. 11: PI-D power responses at - 15% $X_L$

to 1.3 pu and at time 0.8 sec system returns to the initial operating condition as shown in Fig. 12. A step at the reactive power affects slightly the measured real power in Fig. 12. It can be seen that the NNGPC controller acts correctly with a quite perfect decoupling between real power, reactive power and dc-link voltage.

It is natural that disturbances at both voltage and current affect the power flow, as seen in Fig. 12, despite of keeping the power reference values constant.

However, phase control voltage and phase currents responses (Fig. 13 and 14) performs well since it is able to maintain the outputs P, Q and $V_{dc}$ at the desired values.

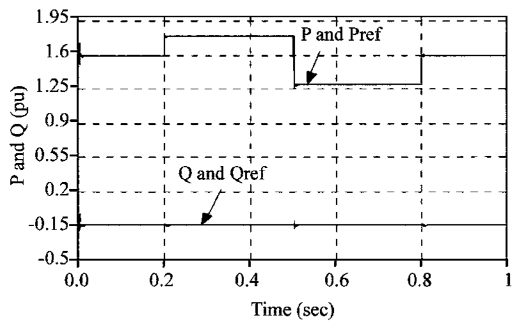


Fig. 12: Step change in receiving end active and reactive power

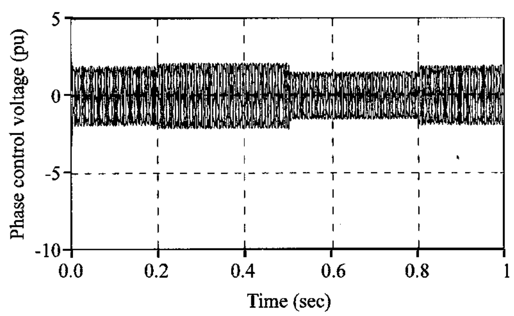


Fig. 13: Phase control voltage response

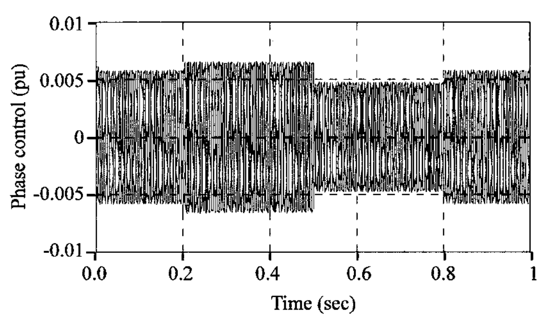


Fig. 14: Phase currents response

## CONCLUSION

The performance of the UPFC under classical and hybrid method control was investigated. A UPFC located at the middle of the transmission line was modeled realistically by transforming its variables into a rotating synchronous reference frame. The developed control concept shows an excellent dynamic behaviour and behaves robust to parameter changes of the power system. Hybrid control systems may contribute to the establishment of an unifying control theory merging traditional analytic-algebraic methods with artificial intelligent tools. It is believed that neural networks can be effectively used for control design of non-linear systems and they must be seen as an extension, rather than replacement, of linear identifiers and controllers that may be already working.

## REFERENCES


Chau, K.W., C.L. Wu and Y.S. Li, 2005. Comparison of several flood forecasting models in Yangtze River. J. Hydrol. Eng. ASCE., 10: 485-491.

Chau, K.W., 2007. Reliability and performance-based design by artificial neural network. Adv. Eng. Software, 38: 145-149.

Edris, A., L. Gyugi, T. Riedman and D. Torgerson, 1996. The unified power flow controller (UPFC) for multiple power transmission compensation. ETG- FACHBERICHT, 60: 61-78.

Gyugyi, L., 1992. Unified power flow control concept for flexible AC transmission systems. IEE Proc., C139: 323-331.

Henriques, J., A. Dourado, 199. A hybrid neural-decoupling pole placement controller and its application. Accepted for Presentation in ECC99. 5th European Control Conference, Karlsruhe, Germany.

Lin, J.Y., C.T. Cheng and K.W. Chau, 2006. Using support vector machines for long-term discharge prediction. Hydrol. Sci. J., 51: 599-612.

Ma, T.T., 2003. Enhancement of power transmission systems by using multiple UPFCs on evolutionary programming. Power Tech Conference Proceedings, IEEE Bologna, 4: 23-26.

Nguyen, D. and B. Widrow, 1990. Neural networks for self-learning control systems. IEEE Control Syst. Mag., pp: 18-23.

Peri, A.M. and N.I. Petrovi, 1999. Generalized predictive controller applied in boost converter input current control. CD-Rom Proceedings of the 8th European Conference on Power Electronics and Applications-EPE'99, Lausanne, Switzerland, pp: 537.

Schoder, K., A. Hasanovic, A. Feliachi, 2000. Fuzzy damping control for the unified power flow controller (UPFC). Proceedings of North American Power Symposium (NAPS), Waterloo, Canada, 2: 5-21-5-27.

Sen, K.K. and A.J.F. Keri, 2003. Comparison of Field results and digital simulation results of voltage-sourced converter-based facts controllers. IEEE Transactions on Power Delivery, 18: 300-306.

Sukumar, M., 2006. Neural-network-based adaptive UPFC for improving transient stability performance of power system. IEEE Trans. Neural Networks, 17: 461-470.

Tuttas, C., 1999. Power Flow control of series compensated transmission lines with an UPFC. European Power Electronics Conference (EPE '99), Lausanne, pp: 1-10.

Xie, J.X., C.T. Cheng, K.W. Chau and Y.Z. Pei, 2006. A hybrid adaptive time-delay neural network model for multi-step-ahead prediction of sunspot activity. Int. J. Environ. Poll., 28: 364-381.

Yu, Q., S.D. Round, L.E. Norum and T.M. Undeland, 1996. Dynamic control of a unified power flow controller. IEEE., pp: 508-514.

Zebirate, S., A. Chaker and A. Feliachi, 2004. Neural network control of the unified power flow controller. Proceedings of the IEEE Power Engineering Society General Meeting, 1: 536-541.

Zhengyu, H., N. Yinxin, C.M. Shen, F.F. Wu, C. Shousun and Z. Baolin, 2000. Application of unified power flow controller in interconnected power systems-modeling, interface, control strategy and case study. IEEE Trans. Power Syst., 15: 817-824.