

# Robust stability power in the transmission line with the use of a UPFC system and neural controllers based adaptive control

Abdelkrim Bouanane, Merzoug Yahiaoui, Khaled Benyahia, Abdelkader Chaker

**Abstract:** The aim of this article is to design a regulator which enables a power system to track reference signals precisely and to be robust in the presence of uncertainty of system parameters and disturbances. The performances of the proposed controllers (NEWELM and NIMC) are based neural adaptive control and simulated on a two bus test system and compared with a conventional PI controller with decoupling (PI-D). The studies are performed based on well known software package MATLAB/Simulink tool box. Flexible Alternating Current Transmission System devices (FACTS) are power electronic components. Their fast response offers potential benefits for power system stability enhancement and allows utilities to operate their transmission systems even closer to their physical limitations, more efficiently, with improved reliability, greater stability and security than traditional mechanical switching technology. The most used component of FACTS systems is the Unified Power Flow Controller (UPFC). According to high importance of power flow control in transmission lines, new controllers are designed based on the Elman Recurrent Neural Network (NEWELM) and Neural Inverse Model Control (NIMC) with adaptive control.

**Keywords:** FACTS, UPFC, PI-D, NEWELM, NIMC, Neural Adaptive Control, Synthesis, Stability, Robustness.

## 1. INTRODUCTION

The industrialization and the growth of the population are the first factors for which the consumption of electrical energy increases regularly. In addition we live today in the era of electronics and informatics and any expenses are very sensitive to disturbances that occur on their supplies: a loss of power can cause the interruption of the different processes of the production; and in front of consumers who are becoming more demanding in wanting more energy and best quality, enterprises of production of electrical energy must therefore ensure the regular supply of this request, and without interruption, through a mesh network and interconnected in order to prove a reliability in their service; and increase the number of power plants, lines, transformers etc., which implies an increase of the cost and the degradation of the natural environment (L.Gyugyi, 1994).

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The networks increased continuously And they becomes complex and more difficult to control. This system must drive in large quantities of energy in the absence of control devices and sophisticated adequate, a lot of problems can occur on this network such as: the transit of the reactive power in excess in the lines, the hollow of voltage between different parts of the network...etc. and this fact the potential of the interconnection of the network will not operate properly. Up to the end of the eighties, the electrical networks were controlled by electromechanical devices having a response time of the more or less long, coils of inductance and capacitors switched by circuit breakers for the maintenance of the voltage and the management of the reagent (Praing and al, 2000). However, problems of wear as well as their slow action does not allow to operate these devices more than a few times a day, they are therefore difficult to use for a continuous control of the flow of power. Another technique of adjustment and control of reactive powers, tensions and transits of power using the power electronics has made its evidence. The solution of these problems happening by improving the control of electrical systems is already in place. It is necessary to equip these systems with a certain degree of flexibility allowing them to better adapt to the new requirements. The rapid development of the power electronics has had a considerable effect in the improvement of the conditions for the functioning of the electrical networks in the performance of the control of their settings by the introduction of control devices on the basis of components of Power Electronics very advanced (GTO, IGBT) known under the acronym FACTS: "flexible alternating current transmission systems" (Renz and al, 1999; Gyeongui and al 2008; Johal and al 2007).

The contribution of this technology "FACTS" (Narain G. H .and al 1999) for the companies of the electricity is to open new prospects for controlling the flow of power in networks and to increase the capacity used existing lines similar to extensions in the latter. The Schematic diagram of a UPFC is shown in Fig. 1 .It consists of two voltage-source inverters with fully switchable elements (GTO, IGBT) that are connected through a common DC-link. One, connected in shunt, called STATCOM (Static compensator), and injects an almost sinusoidal current of adjustable magnitude. The second, connected in series, called SSSC (Static Series synchronous compensator) (Sen and al 1998; Mathur and al, 2002), injects in series an almost alternative voltage with an adjustable amplitude and phase angle in the transport line. The active power  $P_s$ , injected by the series converter must come from the DC link, which is in turn drawn from the AC system through the shunt converter. On the other hand, both

the series and shunt converters are capable of absorbing or supplying reactive, power independently. The reactive power of the shunt converter can be used to regulate the voltage magnitude of the bus at which the shunt transformer is connected.

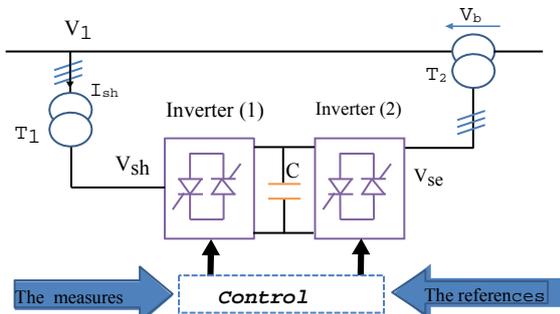


Fig.1. Schematic diagram of a UPFC.

2. MODELING OF A UPFC SYSTEM

The Single- phase equivalent circuit of a UPFC system is shown in Fig. 2. The series and shunt converters are represented by voltage sources  $v_e$  and  $v_p$  respectively. The transmission line is modeled (Jagtab and al, 2010; Zhengyu and al 2000; Bouanane and al, 2013; S. Zebirate and al 2007) as a series combination of resistance  $r$  and inductance  $L$ . The parameters  $r_p$  and  $L_p$  represent the shunt transformer resistance and leakage inductance respectively. The non linearity's caused by the switching of the semiconductor devices, transformer saturation and controller time delays are neglected in the equivalent circuit and it is assumed that the transmission system is symmetrical.

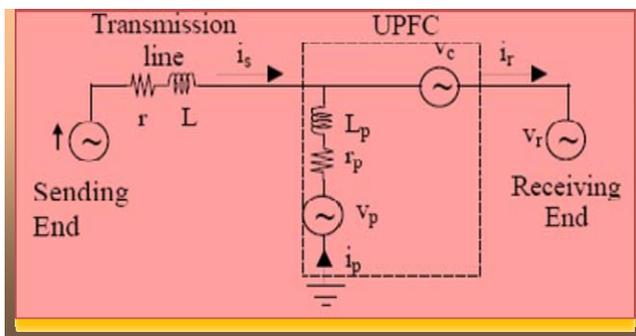


Fig.2. Single- phase equivalent circuit of a UPFC system.

The current through the series and shunt branches of the circuit n be expressed by the following differential equations. The three –phase (a-b-c) differential equations of the system can be transformed into a two-phase (d-q):

$$\begin{cases} \frac{di_{sq}}{dt} = \omega l_{sq} - \frac{r}{L} l_{sd} + \frac{1}{L} (v_{sd} - v_{cd} - v_{rd}) \\ \frac{di_{sd}}{dt} = -\omega l_{sd} - \frac{r}{L} l_{sq} + \frac{1}{L} (v_{sq} - v_{cq} - v_{rq}) \end{cases} \quad (1)$$

Similarly, the shunt inverter can be described by:

$$\begin{cases} \frac{di_{pq}}{dt} = \omega l_{pq} \frac{r_p}{L_p} l_{pd} + \frac{1}{L_p} (v_{pd} - v_{cd} - v_{rd}) \\ \frac{di_{pd}}{dt} = -\omega l_{pd} \frac{r_p}{L_p} l_{pq} + \frac{1}{L_p} (v_{pq} - v_{cq} - v_{rq}) \end{cases} \quad (2)$$

By the use of power balance if one neglects the losses of the inverter it is possible to express the continuous voltage by:

$$\frac{dV_c}{dt} = \frac{3}{2C V_c} (V_{cd} i_{rd} + V_{cq} i_{rq} - V_{pd} i_{pd} - V_{pq} i_{pq}) \quad (3)$$

Here C represents the DC link capacitor. It may he mentioned here that the dynamic equations of the shunt converter are identical to that of the series converted. Thus both the series and shunt converters should have identical control strategy.

3. CONTROLLER DESIGN

The control system of the UPFC consists of the shunt inverter with the control circuit (Papic and al,1997; Hideak and al 1999; Kannan and al 2007), as well as the series inverter. First, we justify the possibility of separation of the two control circuits and similarly we are interested in the adjustment of the inverter for the additional voltage and more particularly to the setting of the active and reactive power transmitted.Then we will develop the different settings considered in this study and we will show the transient behavior of the control circuits using a simulation of the regulators considered in the adjustment of the closed loop UPFC system in order to improve the performances in the case of active or reactive power change. , (change one of the three parameters of the line).

3.1 PI decoupling control (PI-D):

The performance of the UPFC depends on the stability of the DC link voltage between the series and shunt converters. In the case of ideal converters, the shunt converter must be capable of handling the amount of real power that is exchanged between the series converter and the line. Thus the UPFC as a whole exchanges zero real power with the transmission line. However, during dynamic conditions, the input power to the shunt converter should be equal to the sum of series injected power and the rate of change of stored energy in the capacitor on an instantaneous basis.

The principle of this control strategy is to convert the measured three phase currents and voltages into d-q values and then to calculate the current references and measured voltages as follow:

$$P = \frac{3}{2} (v_{sd} i_{sd} + v_{sq} i_{sq}) \quad (4)$$

$$Q = \frac{3}{2} (v_{sd} i_{sq} - v_{sq} i_{sd}) \quad (5)$$

With  $i_{rd} = i_{sd} + i_{pd}$  and  $i_{rq} = i_{sq} + i_{pq}$

$$i_{sd}^* = \frac{2}{3} \left( \frac{P^* v_{sd} - Q^* v_{sq}}{\Delta} \right) \quad (6)$$

$$i_{sq}^* = \frac{2}{3} \left( \frac{P^* v_{sq} - Q^* v_{sd}}{\Delta} \right) \quad (7)$$

With:  $\Delta = V_{sd}^2 + V_{sq}^2$  (8)

The configuration of the overall system with PI control is shown in Fig. 3. The proportional ( $K_p$ ) and integral ( $K_i$ ) gains are obtained via a pole placement method.

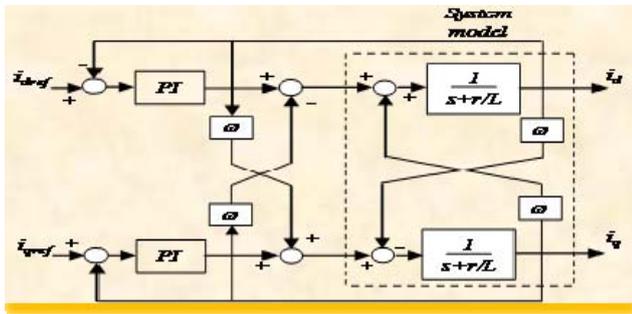


Fig.3. Control design with PI corrector.

To be able to lead to a reliable command of the system, it is indispensable to proceed to a decoupling of the two components. The decoupling of two loops is obtained by subtracting the term ( $\omega$ ) through a reaction against .It is then conducted to a rule which provides a command with decoupling (PI-D) of the currents  $I_d$  and  $I_q$  with a model which can be rewritten in the following form:

$$\begin{cases} \frac{di_d}{dt} = \omega(1 - \sigma)i_{sq} - \frac{r}{L}i_{sd} + \frac{1}{L}(v_{sd} - v_{rd} - v_{rd}) \\ \frac{di_{sq}}{dt} = \omega(1 - \sigma)i_{sd} - \frac{r}{L}i_{sq} + \frac{1}{L}(v_{sd} - v_{rd} - v_{rd}) \end{cases} \quad (9)$$

The classical PI control technique is the most widespread at industrial scale. This is obviously due to the simplicity of its implementation and its acceptable performance. This is obtained by a judicious choice of the parameters  $K_p$  and  $K_i$  representing respectively the proportional gain and the integral action gain.

Figure 4 below shows the UPFC adjustment circuit configuration using a PI controller

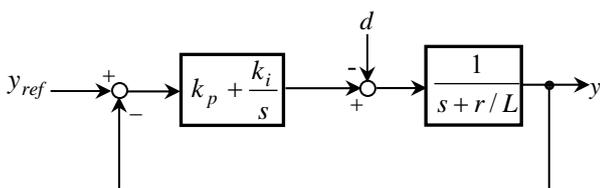


Fig. 4. Adjustment structure of the PI type.

In control, we obtain the following controller, depending on the damping coefficient  $\zeta$  and the frequency  $\omega_N$  :

$$\begin{cases} k_p = 2\zeta\omega_N - a \\ k_i = \omega_N^2 \end{cases} \quad (10)$$

There are two well-known empirical approaches proposed by Ziegler and Tit for determining the optimal parameters of the PI controller Table 1. The method Ziegler-Nichols (Bouanane A. and al 2015; Ziegler and Nichols, 1942) used in the present article is based on a trial conducted in closed loop with a simple analogy proportional controller.

The gain  $K_p$  of the regulator is gradually increased until the stability limit, which is characterized by a steady oscillation. Based on the results obtained, the parameters of the PI controller given by TABLE 2.

Table 1. PARAMETERS OF THE PI CONTROLLER.

Type of	$K_p$	$T_i$	$K_d$
PI	$0.45K_{cr}$	$0.83 P_{cr}$	0

Table 2.PARAMETERS PI CONTROLLER IN OUR SYSTEM

Parameter	$K_i$	$\omega_n$	$K_p$	$\xi$
Valeas	20.000	314.156	0.45	0.200

a. PERFORMANCE EVALUATION:

This simulation study is performed under Matlab/Simulink®. The performance of the proposed controller is evaluated under various operating conditions including model parameters uncertainties and disturbances acting on the power system. For each of the control systems, a simulation model is created which includes the required PWM. The parameters of the simulation model are selected to be equal to the parameters of a laboratory UPFC model (Bouanane and al 2013; Zebirate S. and al 2007), which are listed in TABLE 3.

Table 3. The parameters of the laboratory UPFC model

Parameter name	Symbol	Value	Unit
Network voltage	$V_r$	220	V
Voltage of the receiver	$V_s$	220	V
DC voltage	$V_{dc}$	280	V
Network frequency	$f$	50	HZ
The capacity of the common circuit DC	$C$	2	mF
Inductance 1	$L_1$	1.125	mH
Resistance 1	$R_1$	100	$\Omega$
Inductance 2	$L_2$	1.125	mH
Resistance 2	$R_2$	100	$\Omega$

Simulation results (system UPFC with PI decoupling control):

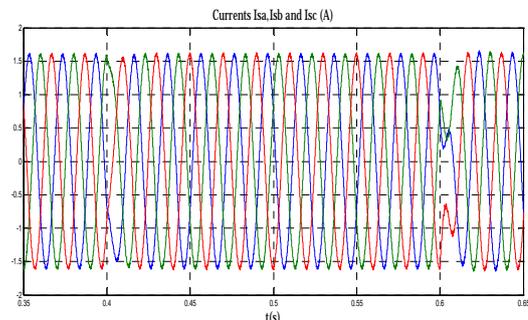
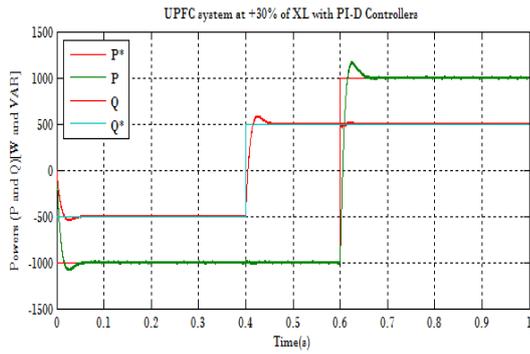
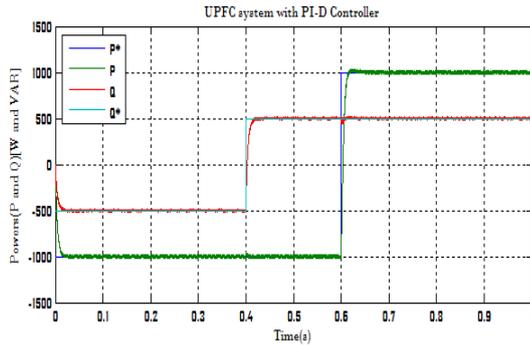


Fig. 5. Currents waveforms  $I_{sa}$ ,  $I_{sb}$  and  $I_{sc}$  (A).

(a)



(b)



(c)

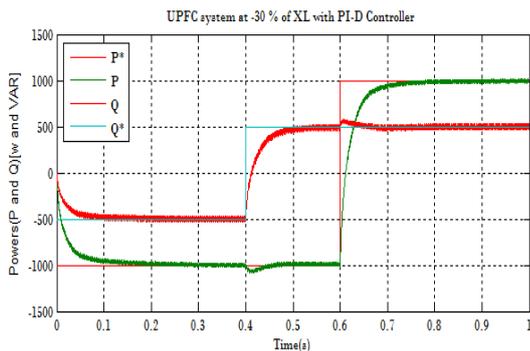


Fig. 6 Powers responses our system with PI-D: (a),at+30% of XL ,(b),at XL and (c),at -30% of XL

The test robustness is observed that the 0.4 s and 0.6 s moments cause an almost zero variation considered as a disturbance of active and reactive power Fig 6., due to the interaction between the two powers. The control system has a fast dynamical response and the same in DC voltage fig7.

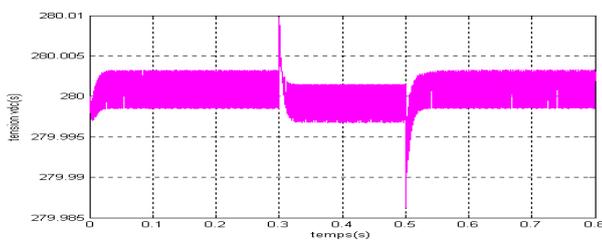


Fig. 7 DC voltage

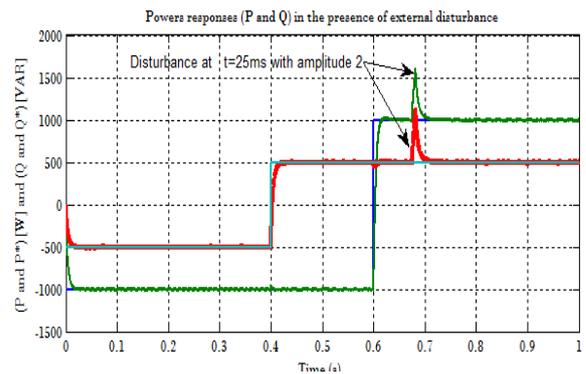


Fig. 8. Power response in the presence of external disturbance

Figure 8 shows when introducing a disturbance of duration 25 ms and amplitude 1.5 in the simulation to further test the stability of our system so we can see that the controller (PI-D) rejected the external disturbance fairly quickly.

### 3.2 NEURAL ADAPTIVE CONTROL:

Adaptive control is dominant in systems with uncertainties, structural disturbances and environmental changes. The main purpose of adaptive control is the synthesis of the adaptation act, for the real-time automatic adjustment of control loop controllers in order to achieve or maintain a certain level of performance when the parameters of the process to be controlled are difficult to determine or vary over time. The interest of adaptive control appears mainly at the level of the parametric disturbance, that is to say that it acts on the characteristics of the process to order, disturb, act on the variables to regulate or to order. The interest of adaptive control appears mainly at the level of the parametric disturbance, that is to say that it acts on the characteristics of the process to order, disturb, act on the variables to regulate or to order. Finally, the combination of adaptive control with other types of conventional automatic controls has paid off and has been the source of many jobs. The adaptive laws implanted in the ideal case could lead to instability in the case of bounded external disturbances.

In this article, we present the hybrid command (classical + neural networks). Neural Network is formed by adaptive learning (Reaz et al, 2004, Xie et al, 2006, Bouanane et al, 2013), the network "learns" to perform tasks, to perform functions according to data given for training. Knowledge acquired during training is stored in synaptic weights. Standard neural network structures (feed forward and recurrent) are both used to model the UPFC system. The main task of this article is to design a neural network controller that keeps the UPFC system stabilized. The Elman network (Xiang et al, 2003) has stated that the hidden layer network is a recurrent network, thus better suited to dynamic system modeling. His choice in the state control neuronal control is justified by its role, this network can be interpreted as a model of nonlinear state space. The standard used for the identification of the UPFC is the back propagation learning algorithm.

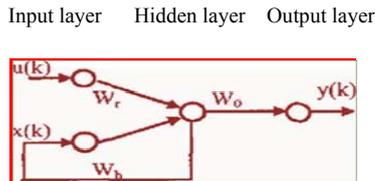


Fig. 9. Structure of the Elman network

A. Neural Adaptive Control of UPFC System (NACSSS-ERNN):

To modify the dynamic behavior of the UPFC system with the use of the hybrid structure it is necessary to apply a counter reaction to the model calculated from the state vector.

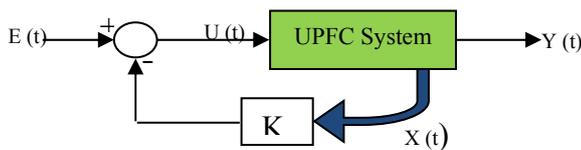


Fig. 10. Diagram of a UPFC control by state feedback

We use the state space to study our structure

Equation of State :

$$\dot{X}^*(t) = A x(t) + B U(t) \tag{11}$$

And observation equation:

$$Y(t) = C x(t) + D U(t) \tag{12}$$

Where

\$u(t)\$ : The control vector

\$x(t)\$ : The state vector

\$y(t)\$ : The output vector of dimension for a discrete system to the sampling process parameters \$T\_e\$ at times of \$T\_e\$ sample \$k\$ are formalized as follows:

$$X(t+1) = A_d X(t) + B U_d(t) \tag{13}$$

$$Y(t) = C_d x(t) + D_d U(t) \tag{14}$$

The system is of order 1, so it requires a single state variable \$x\$. this state variable represents the output of an integrator as shown in Fig.

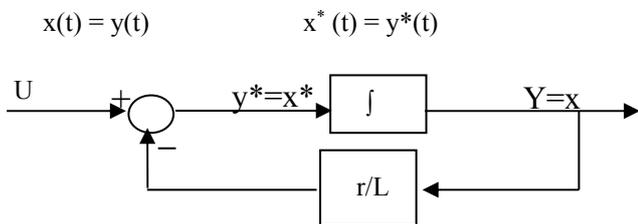


Fig. 11. Block diagram of the state representation of the UPF

The transfer function of our process is written in the form  $G(s) = Y(s)/U(s)$ :

$$G(s) = \frac{1}{s+r/L} \tag{15}$$

The state representation of the UPFC is:

$$\begin{cases} \dot{x}^* = -\left(\frac{r}{L}\right)x + u \\ y = x \end{cases} \tag{16}$$

With:  $U(t) = e(t) - kx(t)$

Let:  $X(t+1) = [A_d - K B_d] x(t) + B_d e(t)$  (17)

$$Y(t) = C_d x(t) \tag{18}$$

Where:  $\begin{cases} \dot{x}^* = Ax + Bu \\ y = Cx + Du \end{cases}$  (19)

$$\left\{ \begin{aligned} A &= \begin{bmatrix} -\frac{r}{L} & \omega \\ -\omega & -\frac{r}{L} \end{bmatrix} & B &= \begin{bmatrix} -\frac{1}{L} & 0 \\ 0 & -\frac{1}{L} \end{bmatrix} & C &= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} & D &= \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \\ u &= \begin{bmatrix} v_{cd} \\ v_{cq} \end{bmatrix} & y &= \begin{bmatrix} i_{sd} \\ i_{sq} \end{bmatrix} & x &= \begin{bmatrix} i_{sd} & i_{sq} \end{bmatrix}^T \end{aligned} \right. \tag{20}$$

a. UPFC SYSTEM IDENTIFICATION USING ERNN (NEWELM) :

The identification makes it possible to obtain a mathematical model that represents as faithfully as possible the dynamic behaviour of the process (Narendra and al, 1990; Delgado and al, 1995). Identification is a procedure that consists of adjusting the parameters of a mathematical model to optimize its output to match the output of the system to be identified. In Neural Networks, the identification is done with the adaptation of the weights of the RNA in order to have an output that emulates the output of the system (minimization of the error).

In the architecture proposed by Elman is recurrent neural network architecture for the phoneme prediction task. The Elman network includes recurring connections of hidden neurons to a layer of contextual units consisting of unit time. These contextual units store the outputs of the hidden neurons for a time step and feed the input neurons with them. Hidden neurons also feed the output layer. In this diagram, the entry of the network is the command \$U(t)\$ and its output is \$Y(t)\$. The vector of state \$X(t)\$ from the hidden layer is injected into the input layer Fig.12.

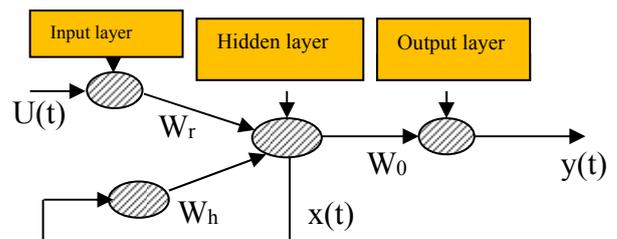


Fig. 12. Structure of the NEWELM

We deduce the following equations:

$$X(t) = W_r X(t-1) + W_h U(t-1) \tag{21}$$

$$Y(t) = W_o X(t) \tag{22}$$

The three weights  $W_o$ ,  $W_r$  and  $W_h$  which are respectively the matrices of the equation of state of the process system (UPFC) [C, A and B] became stable after a rough time  $t = 0.3s$  and several iterations. The Backpropagation through time learning algorithm is a natural extension of standard backpropagation that performs gradient descent on a complete unfolded network; the errors now have to be back-propagated through time as well as through the network.  $t$ , the squared error at the network output is defined as

$$E_t = (y_d(t) - y(t))^2 \tag{23}$$

For the whole training data  $u(t)$ ,  $y_d(t)$  de  $t = 1, 2 \dots N$ , the errors is:

$$E = \sum_{t=1}^N E_t \tag{24}$$

The weights are modified at each time step for  $W_o$  :

$$\begin{aligned} \frac{\partial E_t}{\partial W_o} &= (y_d(t) - y(t)) \frac{\partial y(t)}{\partial W_o} \\ \frac{\partial E_t}{\partial W_o} &= (y_d(t) - y(t)) \cdot X^T(t) \end{aligned} \tag{25}$$

For  $W_h$  et  $W_r$ ,

$$\begin{aligned} \frac{\partial E_t}{\partial W_h} &= -\frac{\partial E_t}{\partial y(t)} \cdot \frac{\partial y(t)}{\partial x(t)} \cdot \frac{\partial x(t)}{\partial W_h} \\ \frac{\partial E_t}{\partial W_h} &= -(y_d(t) - y(t)) \cdot W_o^T \cdot u(t) \end{aligned} \tag{26}$$

$$\begin{aligned} \frac{\partial E_t}{\partial W_r} &= -\frac{\partial E_t}{\partial y(t)} \cdot \frac{\partial y(t)}{\partial x(t)} \cdot \frac{\partial x(t)}{\partial W_r} \\ \frac{\partial E_t}{\partial W_r} &= -(y_d(t) - y(t)) \cdot W_o^T \cdot \frac{\partial x(t)}{\partial W_r} \end{aligned} \tag{27}$$

The latter we obtain:

$$\frac{\partial x_t}{\partial W_r} = X^T(t-1) + W_r^T \frac{\partial x_{t-1}}{\partial W_r} \tag{28}$$

Equation shows that there is a dynamic trace of the gradient. This is similar to back propagation through time. Because the general expression for weight modification in the gradient descent method is:

$$\Delta W = -\eta \frac{\partial E_t}{\partial W} \tag{29}$$

The dynamic back propagation algorithm used to identify a state space model of the UPFC for NEWELM (Elman network) can be summarized as follows:

$$\Delta W_o = -\eta E(t) X^T(t) \tag{30}$$

$$\Delta W_h = \eta E(t) \cdot W_o^T(t) u(t) \tag{31}$$

$$\Delta W_r = \eta E(t) \cdot W_o^T(t) \left( \frac{\partial x(t)}{\partial W_r} \right) \tag{32}$$

If the dependence of  $X(t-1)$  on  $W_r$  is ignored, the above algorithm degenerates to the standard back propagation algorithm:

$$\frac{\partial x_t(t)}{\partial W_r} = X^T(t) = X^T(T-1) \tag{33}$$

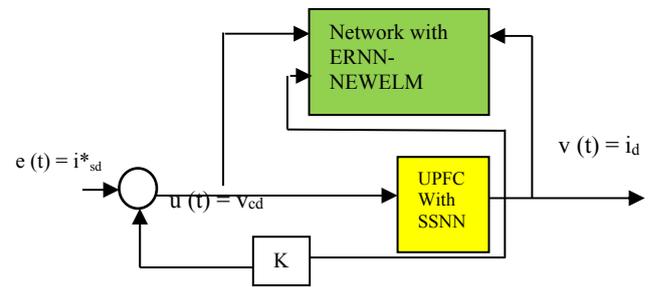


Fig. 13. UPFC system presentation with state space and (ERNN-NEWELM).

a. Estimation of the parameters:

The input used ladder type is considered for identification systems (M. I. Marei, 2012). It is obvious that the input is better than other (ramp, sinusoid .....) from the point of view of identification. In order to allow an identification by inputs allowing to excite the maximum of modes of the system without disturbing its normal operation too much, if one wants to draw a lot of information, in particular to excite it in all the interesting frequency band, one uses in general a slot-like variation of pseudo-random binary sequence (SBPA) superimposed on the wanted signal (PRBS). The design of a system of efficient regulation and robust requires knowing the dynamic model of the process, which describes the relationship between the variations of the command and the variations of the measure. The dynamic model can be determined by direct identification.

- ✚ The classic method type "Response Level" requires signals of excitation of large amplitudes; its accuracy is reduced, and does not allow the validation of the model.
- ✚ The current methods with recursive identification algorithms offer better accuracy and operate in open or closed loop mode with excitation signals of very low amplitude (0.5 to 5% of the pseudo random binary sequence op (PRBS), and in frequency.

The Pseudo Random Binary Sequence (PRBS) is a signal consisting of rectangular pulses modulated randomly in length, which approximate a white noise discrete, therefore rich in frequency and average value of zero, not amending the operating point of the process. Easy to generate; it is commonly used in the identification procedures and posed on useful signal.

In this article, we used the three-layer Elman network system. Note that the identification performance is better when the input signal is sufficiently rich in frequencies to excite the different process modes. To obtain its results, a pseudo random binary sequence (PRBS) is used as the

excitation signal and are of the estates of rectangular pulses modulated in width, which are approximate to a white noise discrete which have a rich content of frequencies.

For the simulation it was chosen:

- Network Elman (NEWELM) to three layers [Entry, hidden and output] is respectively [vector command, the vector of state and output vector]
- A rich signal of frequency pseudorandom binary sequence is of languor in 1023 and of amplitude 1V.
- A PRBS signal fig 14. Is input to system to provide reasonable convergence of the neural network weights for the controller to start with.

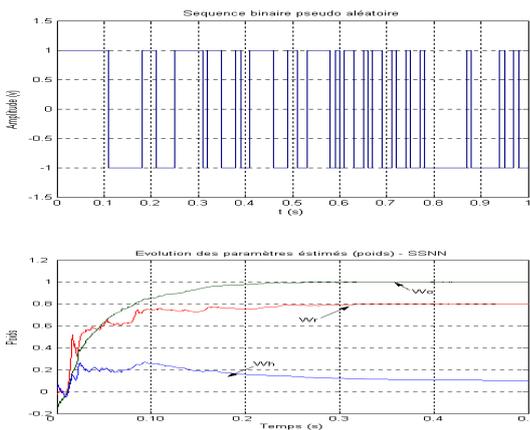


Fig. 14. PRBS signal and changing weights

In Elman Recurrent Neural Network learning, identification, synthesis and correction are done one after the other, where the correction of the numerical values of the parameters is done recursively so the error of estimation puts about one second (t = 1s) to converge to zero Fig. 15.

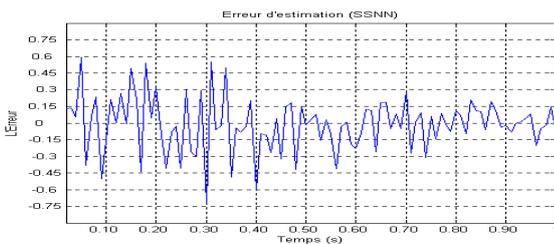


Fig. 15. Estimation error

**B. Neural adaptive control by internal model of a UPF system (NACIMS):**

Several techniques can be envisaged in order to improve the performance. In this work, we use the command by internal model, which belongs to the family of commands in a closed loop (feedback). Its principle is call to a model of the system and has the property to operate in quasi open loop as long as the system and their models are identical, which reduces the risks of instability encountered in the technical standards of counter-reaction. This solution can be used on any architecture or technology of the chain because the only

elements to be added are a couple and a demodulator to the issuance to retrieve information on the distortions introduced. In order to assess the performance of this technique, we have applied in simulation on our system UPFC.

*a. Internal Model Control:*

Figure 16 represents the basic scheme of IMC. For reasons of simplicity, it illustrates the general principle on a linear system in the field of Laplace knowing that this representation can be extended to the discrete domain.

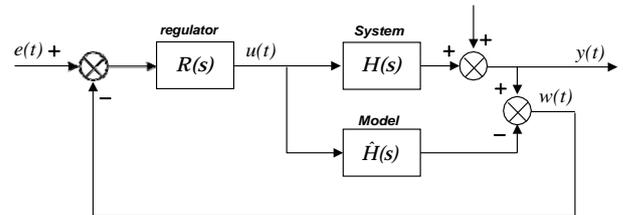


Fig. 16. Basic scheme of IMC

In this figure, we find the main elements of a feedback loop: The system  $H(s)$ , output  $y(t)$ ,

- The model of the  $H(s)$  system, obtained by prior identification of the system,
- The corrector  $R(s)$ ,
- The set point or the excitation  $e(t)$ ,
- A disturbance  $d(t)$ .

The study of the structure makes it possible to establish the following operating equation, linking the output Y to the input E and the perturbation D:

$$Y(s) = \frac{R(s) \cdot H(s)}{1 + R(s) \cdot (H(s) - \hat{H}(s))} \cdot E(s) + \frac{1 - R(s) \cdot \hat{H}(s)}{1 + R(s) \cdot (H(s) - \hat{H}(s))} \cdot D(s) \tag{34}$$

The error of characterization (or modeling) the system that represents the difference between the system and its model is represented by the term:

$$\Delta H(s) = H(s) - \hat{H}(s) \tag{35}$$

The errors signal  $w(t)$  rebuilt the disturbance  $D(t)$  and the error of characterization following the command  $u(t)$ :

$$W(s) = \Delta H(s) \cdot U(s) + D(s) \tag{36}$$

So we can say that the stability of the whole when  $R(s)$  and  $\hat{H}(s)$  are stable.

For an ideal model  $\hat{H}(s) = H(s)$  and  $R(s) = \hat{H}(s)^{-1}$  a perfect pursuit of trajectory

$$w(t) = 0, \forall d(t)$$

An online estimate of unmeasured disturbances

$$\hat{d}(t) = d(t) \tag{37}$$

*b. Neural Inverse Model Control Design:*

It is quite obvious that this excludes many cases, and thus the effective implementation of the IMC structure goes through techniques which are in two general principles:

- Minimize the sensitivity of the IMC structure for maximum disturbance rejection
- Maximizing the complementary sensitivity for a better pursuit

In the basic principle of the internal model control, the closer the model is to reality the more the structure approaches an open-loop structure.

A closed loop type corrector can therefore compensate for this handicap while enlarging the class of systems for which the structure is applicable. On the other hand, the gap between the actual system and its behavioral model may be due to multiple reasons, so it is more reasonable to consider this signal as exogenous to the control. The structure of Figure 16. is modified as shown in Figure 17 (Alf Isaksson,1999).

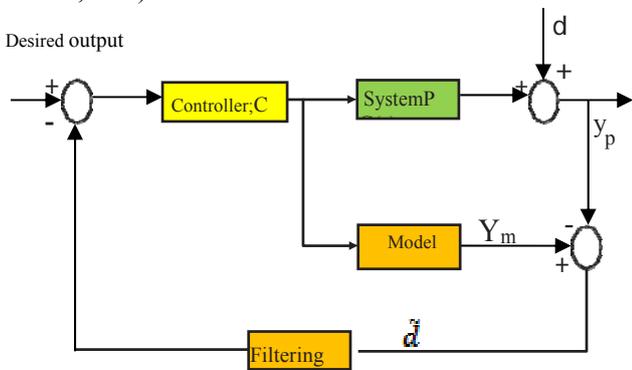


Fig. 17. Block diagram of IMC with input disturbance

The low-pass filter (Filtering model), obviously has an impact on the behavior of the closed-loop system; on the model-following as well as on the disturbance rejection ability.

The model M is determined by the Widrow-Hoff learning law (Widrow and al, 1990; Zebirate S.).The training of the network consists in modifying, with each step, the weights and bias in order to minimize the quadratic errors at output by using the law of Windrow-Hoff. With each step of training, the error at output is calculated as the difference between the required target t and the 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 network.

$$E_k = \mathbf{s}_k^T \mathbf{s}_k = \frac{1}{2} (t_k^T t_k + y_k^T y_k - 2y_k^T t_k) \quad (38)$$

$T_c$ : The sampling time is equal to 1ms .This time will be maintained throughout this study.

The estimation of output and the error are calculated by:

$$\mathbf{z}(k) = [-y(k-1) \quad u(k) \quad u(k-1)] \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} + b_1; \quad \mathbf{s}(k) = y(k) - \mathbf{z}(k) \quad (39)$$

The learning of the network of neuron is to modify, at each sampling, the weight and bias (estimation of parameters) in order to minimize the quadratic criterion of the squares of the errors in the output.

The inverse model controller y (t) is given by the following equation:

$$y(t) = \frac{b_1 + b_2 z^{-1}}{1 + b_2 z^{-1}} u(t-1) \quad (40)$$

Where

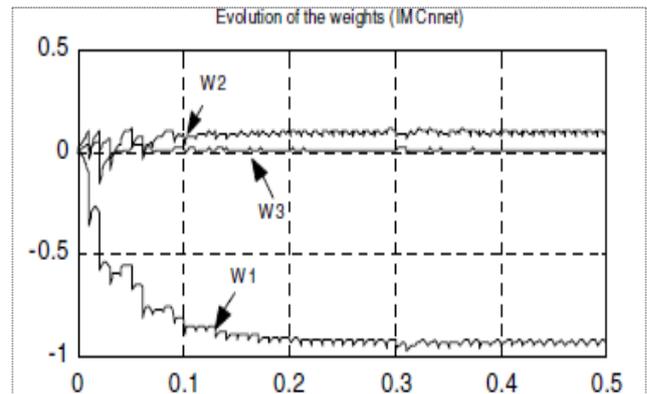
$$\hat{u}(t) = \frac{1}{b_1} y(t) + \frac{a_1}{b_1} y(t-1) - \frac{b_2}{b_1} u(t-2) \quad (41)$$

So the weights and the bias fig. 18 are calculated as follows:

$$w_1 = \frac{1}{b_1}, w_2 = \frac{a_1}{b_1} \text{ and } w_3 = \frac{b_2}{b_1}$$

The control law is described by:  $u(t) = w_c \varphi$  with

$$w_c = [w_1 \quad w_2 \quad w_3] \text{ and } \varphi = [r(t) \quad y(t-1) \quad u(t-2)] \quad (42)$$



Evolution of the Weights NACIMS

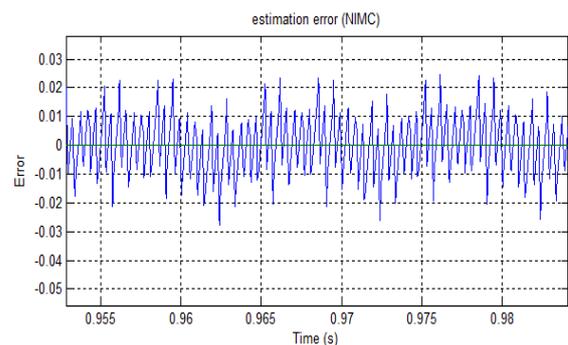


Fig. 18. Evolution of the weights and Estimation error (NACIM)

a. simulation with NACSS-NEWELM and NACIMS

(a)

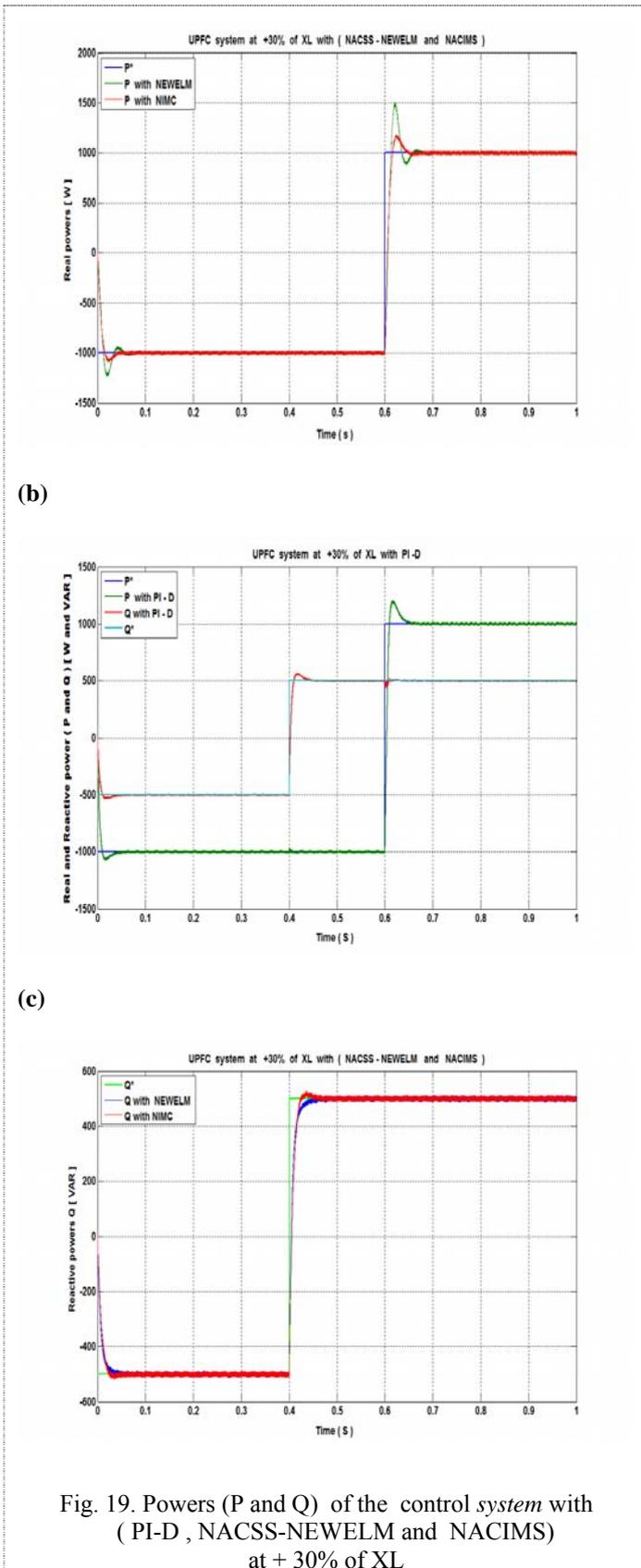


Fig. 19. Powers (P and Q) of the control system with (PI-D, NACSS-NEWELM and NACIMS) at + 30% of XL

#### 4. Comparative simulation studies between PI-D, NACSS-NEWELM and NACIMS:

Adaptive Neural Feedback Control (ANFC) is a hybrid control that was allowed to control any variation in monitoring, regulation or stability. The results of the simulation showed the strength of our neural adaptive controller (NAC). We can say that the decoupled PI regulator would be ideal for the UPFC system control if the +30% variation of the reactance did not degrade its dynamic performance, as pointed out in this article. The process model is never perfect.

The results of this analysis of the three controls by (PI-D, NEWELM AND NIMC) at + 30% of XL fig.19 are summarized in the following points:

- ✓ All control strategies indicate that the proposed regulators have better dynamic performance and are much more robust than the traditional PI controller. They seem to be very high performance dynamic regulators.
- ✓ Thanks to the generalization capacity of network neurons, the use of a neural identification regulator allows an improvement in the dynamic performance of the regulator approached. It has even been demonstrated by simulation that a neural identification regulator can solve the problem of the incapacity of parametric variations regulator PI of the line.

## 5. CONCLUSION

In this article, our UPFC system based on three robust control methods has been proposed [(PI-D), (NEWELM and NIMC) based neural adaptive control]. These control strategies introduce enough flexibility to set the desired level of stability and performance. Practical constraints were considered by introducing appropriate uncertainties. The methods above have been applied to a typical test of a single-phase power system bridge. Simulation results showed that designed regulators were able to ensure a robust stability and performance a wide range of uncertainty of parameters of transmission. But line orders two hybrid (NACSS-ERNN and NACIMS) in case of modification of the parameters of the system and an excellent ability to improve the stability of the system under small disturbances.

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