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# Universal phase shifter regulator system modeling with robust GPC using neural networks for compensation power in transmission line

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**ABSTRACT**

Electricity consumption is increasing gradually and this trend will continue in the future. In addition, rapid network control systems using the resources offered by power electronics and control microelectronics have been recently studied and developed, and are currently in normal application for some, for others, in pilot applications or as prototypes. This paper attempts to show that these systems are referred to by the general acronym flexible alternative current transmission systems (FACTS) similarly dethroned the traditional systems while offering better solutions and solving the energy quality problem such as the hybrid system (unified power flow controller (UPFC), or universal phase shifter regulator (UPSR)) which opens up new perspectives for more efficient operation of networks by continuous and rapid action on the various parameters of the network (voltage, phase shift, and impedance); thus, the power transits will be better controlled and the voltages better held, which will make it possible to increase the stability margins or tend towards the thermal limits of the lines. In this work, we used a classic control (PI-decoupled) and others while offering more flexibility of control thanks to the development of strategies identification/control based on generalized predictive control (GPC) with neural network to ensure robust control with advanced algorithms.



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## 1. INTRODUCTION

As the demand for power increases, the operation of the power system to operate within power quality standards becomes more complex and therefore less secure. The advent of flexible alternating current transmission system (FACTS) technologies has coincided with a major restructuring of power generation; they can provide significant benefits by increasing the transmission capacity of the system as well as the flexibility and speed of power flow control. There are several types of FACTS, and the choice of the appropriate device depends on the goal to be achieved [1]-[3]. The unified power flow controller is one of the most effective FACTS equipment systems for improving power system safety; however, the performance of the UPFC is highly dependent on the parameter settings of the equipment in the system. The utilization of static VAR compensator (SVC) converters in power flow control for AC electric power transmission systems is an established practice, the UPFC is a union of two SVCs one is a static synchronous compensator

(STATCOM) shunt device and the other is a static synchronous series compensator (SSSC) series component, the two devices can operate independently, they act on the control of the voltage and/or the impedance of the line by injecting the amount of active and/or reactive power required, or simultaneously. The unified power flow controller (UPFC) combines both series compensation and parallel compensation, it is the most powerful device in power flow control, where it allows for adjustment of the three network quantities namely, voltage, angle load, and line impedance. The basic structure of a UPFC connected to the electrical power network is represented by Figure 1 [4], [5]. It consists of two three-phase inverters, one connected in series with the network via three single-phase transformers whose primaries are connected, in a star, and the other connected in parallel with the network via a three-phase transformer. The two inverters are interconnected by a DC bus represented by capacitor C.

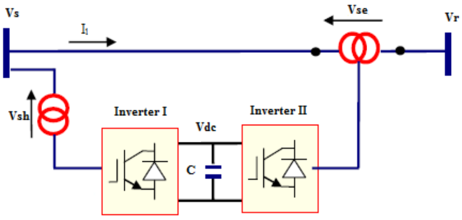


Figure 1. The basic scheme of a UPFC

## 2. MODELING OF THE UPFC

The two-level UPFC is characterized by three systems of equations which are detailed in the following paragraphs [6]: i) the dynamic equations of the series compensator, ii) the dynamic equations of the parallel compensator, and iii) the equations of the continuous circuit. The application of Kirchhoff's laws to meshes of the circuit of Figure 2 and the transformation of PARK, the current in the transmission line can be described by (1) to (3).

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

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

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

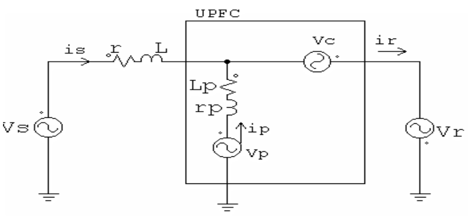


Figure 2. Equivalent circuit of UPFC system

## 3. CONTROLLER DESIGN

This study provides new insights into what was designed to improve the performance of the UPFC the interaction between the real and reactive power flow control system must be reduced. Different control techniques for the UPFC system have been proposed. This paper begins with PI decoupling control (PI-D) and it will go on to a Generalized predictive controller with neural networks to control the UPFC (NNGPC) [7], [8].

### 3.1. PI decoupling control (PI-D)

The principle of this method is to transform the measured magnitudes of the current and the voltage of the three phases on the two d-q axes using the park transformation. Next, the values of the active and reactive powers are imposed and the reference currents are calculated from these values (the desired powers) and the values of the voltages measured, by the two equations:

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

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

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

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

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

with $\Delta = V^2{}_{sd} + V^2{}_{sq}$ (8)

where the * superscript defines the reference quantities. The power flow control is then realized by using properly designed controllers to force the line currents to follow their references. It is desired that the UPFC control system have a fast response with minimal interaction between the real and reactive power together with a strong damping of the resonance frequency. However, perfect decoupling is difficult to achieve with a PI controller due to the presence of time delays and other non-linearities in the UPFC system. Figure 3 shows a step response of decoupling control system. It can be seen that the interaction between the $i_{sd}$ and $i_{sq}$ appears and the system has a slower response.

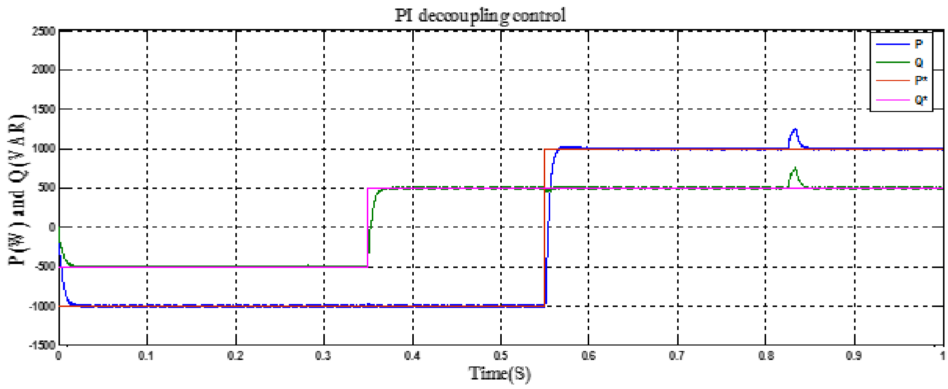


Figure 3. Power step response of PI with decoupling control system

### 3.2. Generalized predictive control (GPC)

#### 3.2.1. The principle of generalized predictive control (GPC)

The principle of GPC owes its name to the fact that it takes into account predictions of process's future outputs and sometimes also of the future inputs [9]-[11]. The outputs and the inputs are predicted over a finite horizon, then on the synthesis of a control system capable of anticipating setpoint variations. The prediction model used is controlled autoregressive integrated moving average (CARIMA), which is an extension of the CARMA model, where an integral effect is incorporated to eliminate the permanent deviation from the effect of constant disturbances.

#### 3.2.2. The prediction model and the cost function

In predictive controllers, several models of the process can be applied, and the implementation of the GPC is carried out from the model represented in the form controlled autoregressive integrated moving average (CARIMA) Figure 4. He is given by (9).

$$A(Z^{-1})y(t) = B(Z^{-1})u(t-1) + x(t) \tag{9}$$

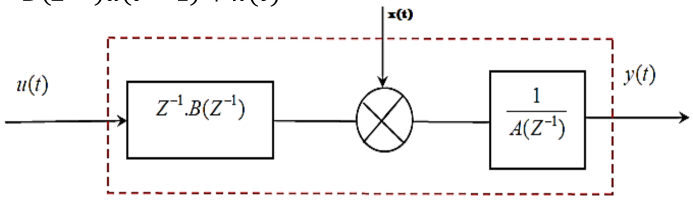


Figure 4. Representation of the CARMA digital model

With: $y(t)$ output from the system, u(t) command applied to the system, $Z^{-1}$ delay operator, and the polynomials are defined by (10).

$$\begin{cases} A(Z^{-1}) = 1 + a_1 Z^{-1} + \cdots + a_{na} Z^{-na} \\ B(Z^{-1}) = b_0 + b_1 Z^{-1} + \cdots + b_{nb} Z^{-nb} \end{cases} \tag{10}$$

$x(t)$term related to disturbances, usually chosen in the form (11).

$$x(t) = C(Z^{-1})e(t) \tag{11}$$

Hence $C(Z^{-1}) = 1 + c_1 Z^{-1} + \cdots + c_{nc} Z^{-nc}$ and $e(t)$ uncorrelated random sequence centered. By combining with (9), we obtain the CARMA model:

$$A(Z^{-1})y(t) = B(Z^{-1})u(t-1) + C(Z^{-1})e(t) \tag{12}$$

this model may be inappropriate in several industrial applications in which non-stationary disturbances and in this case, the correct model is:

$$x(t) = C(Z^{-1})e(t)/\Delta(Z^{-1}) \tag{13}$$

$\Delta(Z^{-1})$is the differentiation operator which equals: $\Delta(Z^{-1}) = 1 - Z^{-1}$ coupled with (9) gives the controlled autoregressive integrated moving average (CARIMA) model as (14).

$$A(Z^{-1})y(t) = B(Z^{-1})u(t-1) + C(Z^{-1})e(t)/\Delta(Z^{-1}) \tag{14}$$

For simplicity, we take $C(Z^{-1}) = 1$ which is the case of white noise, (for the case of $C(Z^{-1}) \neq 1$, the model becomes (15).

$$A(Z^{-1})y(t) = B(Z^{-1})u(t-1) + e(t)/\Delta(Z^{-1}) \tag{15}$$

This model constitutes the basic model of the GPC method from which the expression of the control law will be derived. To determine the control to be applied to the system at time t, the GPC method minimizes the following criterion:

$$J(t) = \sum_{j=N_1}^{N_2} [y(t+j) - w(t+j)]^2 + \lambda \sum_{j=N_1}^{N_u} [\Delta u(t+j-1]^2 \tag{16}$$

with $\Delta u(t+j) = 0$ for $j \geq N_u$ or: $N_1$: is the minimum prediction horizon, $N_{12}$: is the maximum prediction horizon, $N_u$: is the command horizon, $\lambda$: is a control signal weighting factor ($\lambda > 0$), $w(t+j)$: is the reference future trajectory known in advance, and $\Delta u(t+j)$: is the control increment.

To simplify the calculation of the GPC control law, we will set: $C(Z^{-1}) = 1$, we show that the predictor is written: in matrix form:

$$\hat{y} = G.\hat{U} + F \tag{17}$$

where: $\hat{y}$, U, and F are vectors of dimension $NXN$ with:

$$\hat{y} = [y(t+1), y(t+2); \dots\dots, y(t+N)]^T \tag{18}$$

$$\hat{U} = [\Delta u(t), \Delta u(t+1), \dots\dots, \Delta u(t+N_u-1)]^T \tag{19}$$

$$F = [f(t+1), f(t+2); \dots\dots, f(t+N)]^T \tag{20}$$

where: G represents the set of terms involved in the future commands and where f represents the set of command terms and past outputs.

$$\text{With: } G = \begin{bmatrix} g_0 & 0 & \dots & 0 \\ . & . & \dots & . \\ . & . & \dots & . \\ . & g_0 & \dots & . \\ g_{N-2} & . & \dots & 0 \\ g_{N-1} & g_{N-2} & \dots & g_0 \end{bmatrix} \tag{21}$$

### 3.2.3. The predictive control law

The control law is calculated to minimize the quadratic criterion $J$ (16) and with $\Delta u(t+j) = 0$ for, $j \geq N_u$. The term $[y(t+j) - w(t+j)]^2$ represents the weighted sum of the future errors between the future outputs and the setpoint signals $w(t+j)$ $(j = 1 \dots \dots N_2)$. The term $\lambda$ $[\Delta u(t+j-1]^2$ represents the cost of the control effort. $J$ can be written in matrix form as (22).

$$J = (Y-W)^T.(Y-W) + \lambda.U^T.U \tag{22}$$

The predictor relation is: $Y = G.U + F$ replacing the latter in equation we obtain:

$$J = (G.U + F\ - W)^T.(G.U + F\ - W) + \lambda.U^T.U$$

$J$ is minimal if $\frac{\delta J}{\delta U} = 0$, which gives:

$$U = [(G^T.G) + \lambda I)]^{-1}.G^T.(F\ - W) \tag{23}$$

where $I$ represent the identity matrix.

This last equation provides the future increments of control for instants *'t'* at *(t+$N_u$-1)*, based on the information available at instant *'t'*. Only $\Delta u(t)$ will be applied to the system and the command is then such that: $u(t) = \Delta u(t) + u(t-1)$. The minimization of the criterion will be repeated at each sample for the calculation of the new command to be applied to the system Figure 5 [12]-[16]. Or: *($y_r$ = $i^*_{s\ d}$ ; $u$=$V_{cd}$ ; (estimated parameters +controller)=minimization of J and y=$i_{sd}$)*. For the transfer function of our UPFC system, the predictive current regulator is synthesized for the adjustment parameters of the $N_1$, $N_2$, $N_u$, and $\lambda$. The objective of predictive control is to compute the future control sequence u(t), u (t+1),………in such a way that the future system output y(t+j) is driven close to w(t+j).

$$u(t) = (1 - b_1 b_2 \left(b_1{}^2 + \lambda\right)^{-1} u(t-1) + b_1 b_2 \left(b_1{}^2 + \lambda\right)^{-1} u(t-2) + b_1 \left(b_1{}^2 + \lambda\right)^{-1} c(t) + b_1(a_1 - 1)\left(b_1{}^2 + \lambda\right)^{-1} y(t) - b_1 a_1 \left(b_1{}^2 + \lambda\right)^{-1} y(t-1) \tag{24}$$

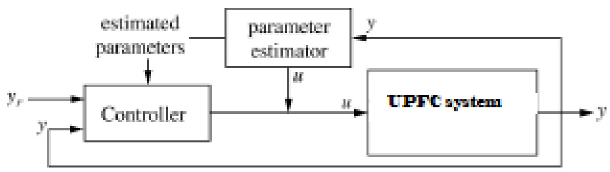


Figure 5. Block diagram of the GPC system for UPFC system

### 3.3. Neural network generalized predictive control (NNGPC)

This study seeks to obtain data that will help to address these research gaps for the application of the neural generalized predictive control (NGPC) [17]-[21] we follow two steps the first is the identification of the system and the second is the design of control. So, in the first step, you develop a neural network model system you to control as can you want to see in Figure 6. So, u is our control parameter and it is input to our system which will give some output.

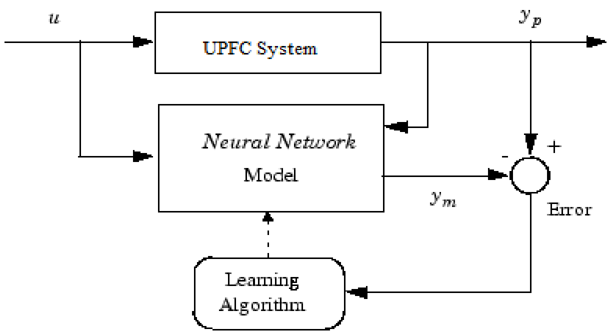


Figure 6. Neural network model predictive control system identification (NNMPCSI)

We can create this neural network then the error is calculated using the usual method and the apply propagation using any of the learning algorithms that we have already chosen. As you can see this is similar to our time series neural network so this is the complete model that will be looking into so in the first step, we have created the NN model of our system and in the second we will be using this neural network model (NNM) to predict the future value.

The optimization block is also which is the reference signal which we want from the system then the optimization block uses some optimization algorithm that optimizes the future system performance. So basically, we will have our output from a system which matches nearly with the reference signal Figure 7. In this article, the abbreviation will be used to refer to our work. So, these two are the same, one is input to NNM, and the second is input to the system to predict.

The optimization of the controller required the significance of online computation because the optimization is performed at each single time step to compute the optimal control. The optimization block tries to minimize the performance which is shown in (25).

$$J(t) = \sum_{j=N_1}^{N_2} [y_r(t+j) - y_m(t+j)]^2 + \lambda \sum_{j=N_1}^{N_u} [\acute{u}(t+j-1) - \acute{u}(t+j-2)]^2 \tag{25}$$

Where:

$N_1, N_2, N_u$ : Horizon over which the tracking error and the control increment are evaluated.
$\acute{u}$ : tentative control signal
$y_r$ : Desired response
$y_m$ : neural network model response
$\lambda$ : determines the effect of control increment on performance

Data for this study were collected using simulation. Coming back to MATLAB type in the command window, write predictor and press enter this will open up the Simulink model Figure 8 [22]-[25]. So first let's look at plant we are using. So, a plant is a set of the equation that represent a dynamic model of system (UPFC).

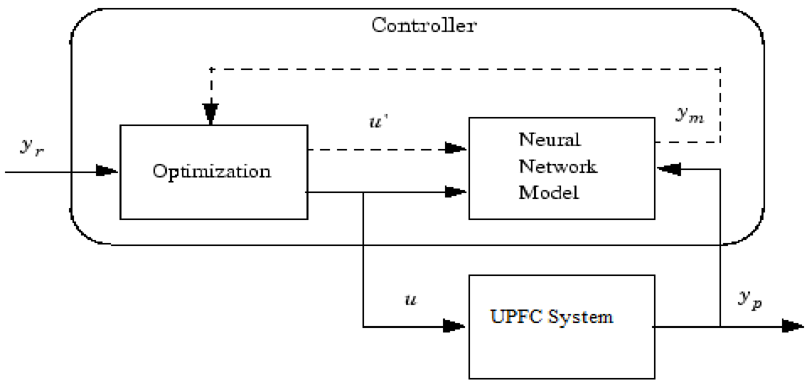


Figure 7. Neural network model predictive control system (NNMPCS)

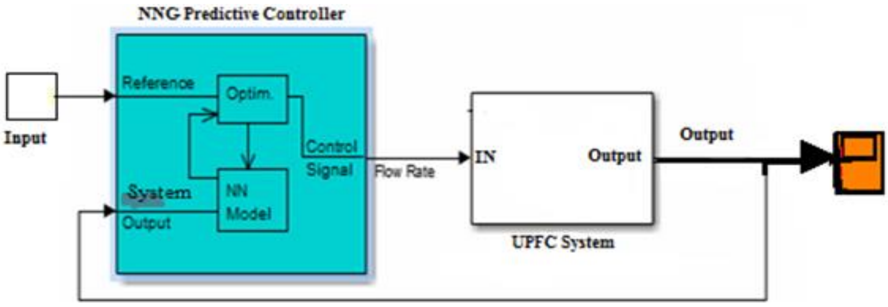


Figure 8. NNGPC MATLAB model with system (UPFC)

This cost function minimizes not only the mean squared error between the reference signal and the UPFC system model, but also the weighted squared rate of change of the control input. When this cost function is minimized, a control input that meets the constraints is generated that allows the system to track the reference trajectory within minor tolerance relying on both configured search parameter (α) and non-configured neural network modeling error (ε). The following set of $J$ ahead optimal predictions can be written by (17) as (26) and (27).

$$\hat{y} = G.\Delta u(t) + f \tag{26}$$

$$\Delta\grave{u}(t) = b_1(b_1^2 + \lambda)^{-1}(c - f) \tag{27}$$

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 generalized predictive control (NNGPC). Obtaining numerical results for the parameter values $a_1 = -0{,}9231$ , $b_1 = 9{,}6065\ 10^{-4}$ , and $b_2 = 2{,}1617\ 10^{-7}$ the horizons being: $N_1 = 1, N_2 = 2, N_u = 1$ and $\lambda = 10^{-9}$, and to know the function of the control signal for the desired reference with the previous inputs and outputs, which are given by a numerical function or in the form of an array:

$$u(t) = \alpha_1\, u(t-1) + \alpha_2\, u(t-2) + \alpha_3\, c(t) + \alpha_4\, y(t) + \alpha_5\, y(t-1) = [\alpha][u] \tag{28}$$

(28) can be expressed as (29).

$$u(t) = w_x + w_0 \tag{29}$$

It is known that generally recurrent neural networks (RNN) are considered more suitable for modeling dynamical systems and their choice allows us that the training of the network consists in modifying the weights and the biases to minimize the quadratic errors in output by using the law of Windrow-Hoff. So, with each step of training, the error at the output is calculated as the difference between the required target y and the estimated 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.

$$y = wP + w_0 \text{ with } w_0 = 0 \tag{30}$$

From which by analogy we obtain:

$$w = [\alpha_1\ \ \alpha_2\ \ \alpha_3\ \ \alpha_4\ \alpha_5\ ] \tag{31}$$

$$P = \begin{bmatrix} u(t-1) \\ u(t-2) \\ c(t) \\ y(t) \\ y(t-1) \end{bmatrix} \tag{32}$$

so, $P,\ w\ and\ w_0$ design, respectively, the input vector, the weight, and the bias. Learning takes place according to the Widrow-Hoff law. therefore, remember that at each learning step, the output error is calculated as the difference between the target sought and the network output.

## 4. SIMULATION RESULTS

The study was conducted in the form of a survey, with data being gathered via MATLAB/Simulink. In the simulation below, in MATLAB neural network and control toolboxes were used and are carried out on a Pentium PC under Simulink with model data are chosen equal to the parameters of a laboratory UPFC model (Table 1). The NNGP Controller is implemented as C-coded S-functions as shown in Figure 8, and of course, with a careful choice of a controller for the inverters.

Figure 9 shows the step response of the GPC system. It can be seen that the interaction between the real force and the interaction with the signals is a bit oscillatory with almost zero prediction error Figure 10. Which forces us to apply the recurrent type neural networks to the generalized predictive control for improvement Figure 11. So it can be said that the dynamic performance of NNGPC is much better than GPC in rising time, set time and overshoot for only in which parameter was tested following a step signal of powers (real and reactive). The learning gain of the neural network is fixed at the value of the prediction error between the output of the process and the setpoint saturates around a not very large value during a sudden variation of the latter, it is equal in absolute value at 0.0258. To verify the effectiveness of the designed controllers, different test cases were carried out.

The test case 1 (robustness test), the inductance of the transmission line is increased by +35% compared to the real system. The response of the active and reactive powers to +%35 of XL could not be detected, the error message given by "MATLAB command" indicated the saturation of the command to infinity during sudden variations of the setpoint signals Figure 12. In test case 2 (stability test), we can check the servo response not only in tracking but also in regulation by adding a disturbance. We simulated this time by introducing a disturbance of duration 0.02 s and amplitude 10 to once again test the robustness of NNGPC. We note that the disturbance does not influence the responses of the powers, on the other hand, its action is slightly felt in Figure 13, where the rejection is done gradually and is accompanied by a slight overshoot at the external disturbance.

Table 1. The performance of a Laboratory UPFC model

| Parameters | Value | Parameters | Value |
|---|---|---|---|
| $v_r$ | 220 V | $r_p$ | 0.8Ω |
| $V_s$ | 220 V | $L_p$ | 10 H |
| $V_{cd}^*$ | 280 V | r | 0.4Ω |
| C | 2 mF | L | 10 H |

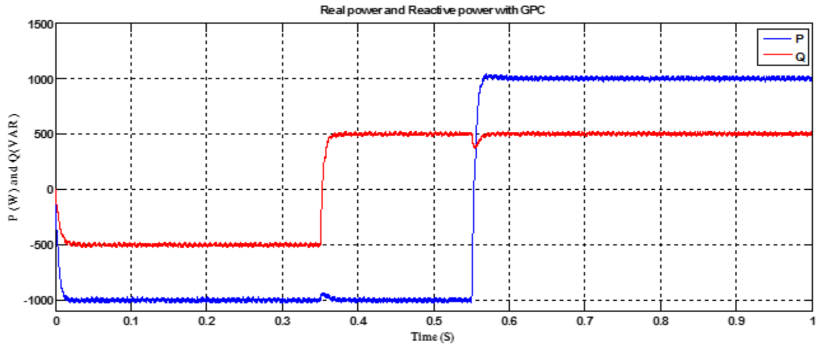


Figure 9. Simulation result of step response of system UPFC with GPC

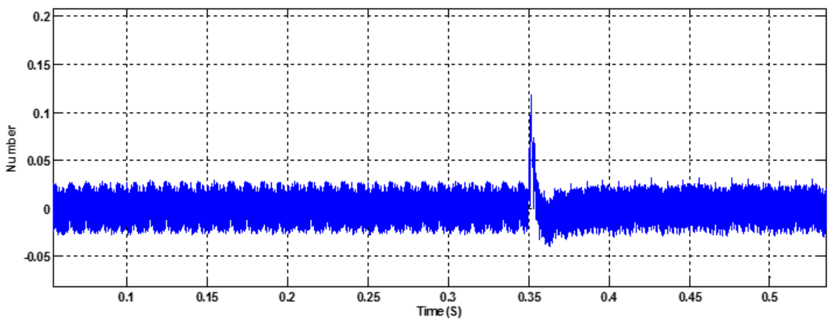


Figure 10. Error prediction (GPC)

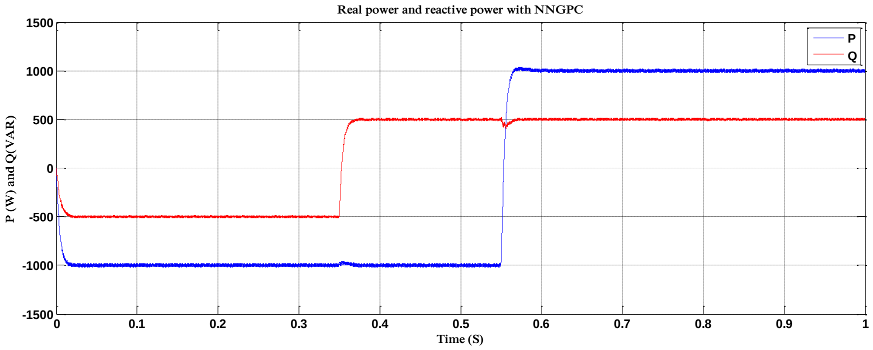


Figure 11. (Real and reactive) powers responses of UPFC with NNGPC

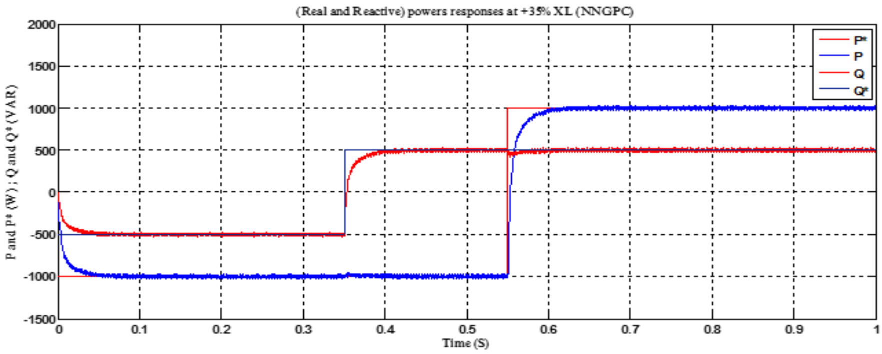


Figure 12. Robustness test of NNGPC (at +35% of XL)

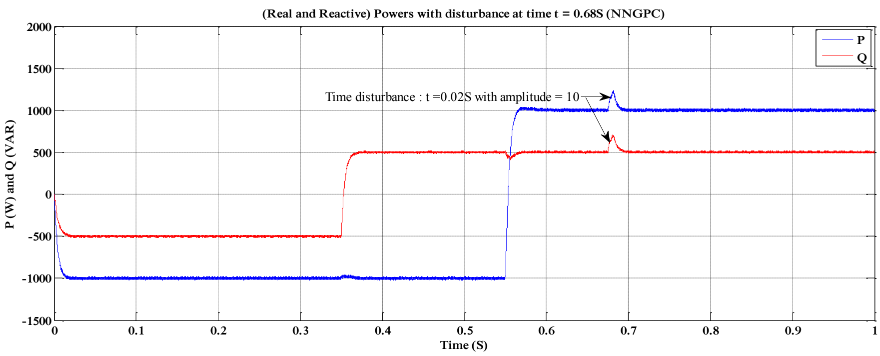


Figure 13. Stability test of NNGPC (external disturbance)

The characteristics of the responses of the UPFC system, Table 2 are deduced graphically from the scope block (MATLAB/Simulink). The quality of the adjustment is sometimes specified utilizing certain characteristic values of the output of the looped process in slaving. So, the characteristics of the table are those of the output of the UPFC system. Thus, for the response time $t_r$ (s), we find that it is more or less important in the methods using the classical approach than in the methods using neural networks and less small in the predictive GPC method using the classical approach than the predictive method using NNGPC neural networks.

Table 2. Characteristics of the different commands

| Command | $t_r$ (s) System response time | $t_p$ (s) Disturbance rejection time | $e_t$ Quadratic error |
|---|---|---|---|
| PI-D | 0.4281 | 0.0600 | 0.4096 |
| GPC | 0.3823 | 0.0598 | 0.0025 |
| NNGPC | 0.3530 | 0.0250 | 0.0016 |

## 5. CONCLUSION

This paper proved the quality of robustness and stability characteristics when neural network identifier is used with GPC in the UPFC system. It is proved by simulation that NNGPC has satisfied the reference pursuit conditions if the appropriate algorithm is used, good offline training is performed, and the line search parameter verifies the derived conditions. The simulation results show the quality of the NNGPC controller compared to the PI-decoupled controller and the traditional GPC algorithm in terms of meeting the required closed-loop performance while stabilizing the system and ensuring robustness. The choice of recurrent neural networks with GPC to improve both tracking and disturbance rejection performance of the system.

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