EVALUATION OF NEURAL PDF CONTROL STRATEGY APPLIED TO A NONLINEAR MODEL OF A PUMPED-STORAGE HYDROELECTRIC POWER STATION

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Abstract: In this paper, a neural Pseudoderivative control (PDF) is applied to a nonlinear mathematical model of the Dinorwig pumped - storage hydroelectric power station. The response of the system with this auto-tuning controller is compared with that of a classic controller, currently implemented on the system. The results show how the application of PDF control to a hydroelectric pumped-storage station improves the dynamic response of the power plant, even when multivariable effects are taken into account.

1 INTRODUCTION

Dinorwig is a large pumped storage hydroelectric scheme located in North Wales that is operated by the First Hydro Company. The station has six 300 MW rated turbines, driving synchronous generators which feed power into the national grid. Dinorwig provides rapid response frequency control when peak demands occur. This hydroelectric station has a single tunnel, drawing water from an upper reservoir into a manifold, which splits the main flow into six penstocks. Each penstock feeds a turbine to generate power using a guide vane to regulate the flow. The electrical power generated is controlled by individual feedback loops on each unit. The reference input to the power loop is the grid frequency deviation from its 50 Hz set point, thus forming an outer frequency control loop. Mansoor et al, have derived a multivariable nonlinear simulation model of this plant, which has provided an improved understanding of its characteristics (Mansoor, Jones, Bradley, & Aris, Stability of a pumped storage hydropower station connected to a power system, 1999) (Mansoor, Jones, Bradley, Aris, & Jones, 2000). Its main features are non-minimum-phase dynamics, poorly damped poles (associated with water-hammer in the supply tunnel and electrical synchronization) and a nonlinear relationship between flow and power. It is also known (Kundur, 1994) (Working group on prime mover energy supply, 1992) that there is a significant hydraulic coupling between the turbines because of the common supply. This makes the plant a good candidate for the application of auto-tuning control.

The paper begins with a brief discussion of the nonlinear mathematical model of the power plant. Then a few concepts of neural network theory are reviewed, followed by a description of the application of neural Pseudoderivative control (PDF) to the model of Dinorwig (Kang, Lee, Kim, Kwon, & Choi, 1991). Finally, results are presented which show the improved response provided by neural PDF.

2 HYDROELECTRIC PLANT MODEL

The hydroelectric plant model can be divided into three subsystems: guide vane, nonlinear hydraulics and turbine/generator (figure 1). Mansoor et al developed a multivariable non-linear model that includes a rate limit and saturation in the guide vane dynamics, as shown in figure 2 (Mansoor, Jones, Bradley, Aris, & Jones, 2000).

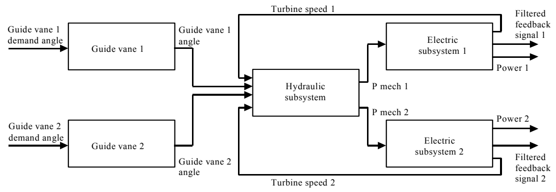

Figure 1: MIMO model of the hydroelectric plant with two penstocks.

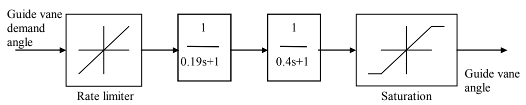

Figure 2: Guide vane subsystem.

In this study a nonlinear model that takes into account the effects of the water column, including water compressibility and pipe wall elasticity, was employed (Working group on prime mover energy supply, 1992). Figure 3 shows the nonlinear elastic model of a single penstock. The coupling effect between the units is included in the model (main tunnel block).

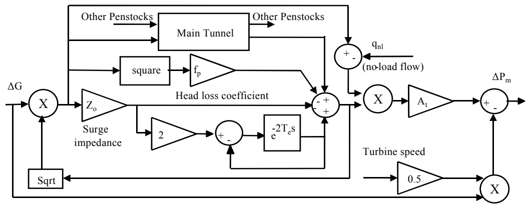

Figure 3: Hydraulic subsystem.

The turbine gain value of A_t depends directly on the turbine MW rating and inversely on the Generator MVA rating. f_p is the head loss coefficient for the penstock. Z_0 is the surge impedance of the conduit. T_e is the wave travel time; it is defined as the time taken for the pressure wave to travel the length of the penstock (l) to the open surface. v is the velocity of sound in water.

$$T_e = \frac{l}{v} \tag{1}$$

$$Z_0 = \frac{T_W}{T_e} \tag{2}$$

T_w is the *water starting time* of the main tunnel and the penstocks. Kundur defines the *water starting time* as the time required for a head to accelerate the water in the penstock from standstill to a specific velocity (Kundur, 1994). Its value depends directly on the constructional dimensions of main tunnel and penstocks.
In this model G is the per unit gate opening, P *mech* is the mechanical power produced by a single turbine. The value of T_e depends on the length of the penstock and inversely on the wave velocity (equation 1). Z_o depends directly on the flow rate, inversely on the head of water and on the acceleration due to gravity (equation 2). The value of A_t depends directly on the turbine MW rating and inversely on the Generator MVA rating (Mansoor, 2000). The models are expressed in the per-unit system, normalized to 300 MW and 50 Hz. The electrical subsystem is based on the 'swing' equations (Kundur, 1994) and includes the effect of synchronizing torque. For noise reduction a first order filter is included in the feedback loop (fig. 4).

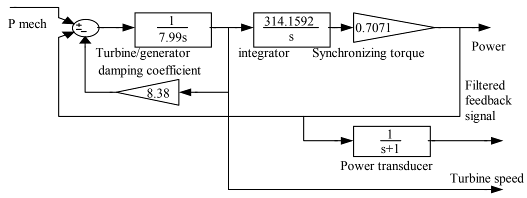

Figure 4: Electrical subsystem.

3 NEURAL NETWORKS

3.1 Basic Theory

Since the early 1980s, there has been a dramatic increase in research on the computational properties of highly interconnected networks of simple processing units called artificial neural networks. These networks are loosely patterned after the structure of biological nervous systems. However, the use of these artificial neural networks (NN) to improve the behavior of several real systems in engineering applications has recently been increased. One of the engineering disciplines that have been enriched with the properties of the NN is the adaptive control theory, because they offer the

possibility to adjust the parameters of the regulator in order to reduce the difference between the set-point and the output of the process.
There are several types of NN can be found in literature (Narendra & Mukhopadhyay, 1996) but in adaptive control, back propagation is used most frequently, because its calculation speed is fast and easy to implement. A back - propagation artificial neural network is a linear combination of nodes interconnected to form several layers of nodes that may or may not have interactions between them, figure 5.

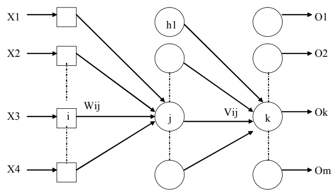

Figure 5: Generic structure for three layer neural network.

The number of layers used in the network plays an important factor during the design stage. Two layers NN have its own limitation but it has a good performance (Minsky & Papert, 1988). Multilayer NN have a wide spectrum of applications and they can deal with problems that are "impossible" to NN with two layers. As was discussed by Rumelhart et al (Rumelhart, McClelland, & group, 1986), the addition of internal layers will allow the back propagation algorithm to develop an internal representation of system dynamics; that feature could be crucial to find a solution. Linear models as the ARX result on internal models of two layers NN with back-propagation.

3.2 Neural PDF

One of the main reasons for using NN in control system is the ability to adjust any non-linear system. A *prior* knowledge about the structure of the system being controlled is very important to tune and improve the performance of PDF controller.

There are several approaches to define a fast and efficient control strategy to calculate and adjust the parameters of discrete PID control systems (Narendra & Mukhopadhyay, 1996) (Garcez & Garcez, 1995). For this work a similar strategy was used to tune a discrete PDF.

Narendra and Mukhopadhyay (Narendra & Mukhopadhyay, 1996) provided a good alternative to make identification on-line of the coefficients using a model on the system. In this situation, the non-linear part of the model is approximated to a linear system. The coefficients of the process are fed back to re-calculate the K's parameters of the PID applied.

There have been several works where the NN have been applied to hydroelectric systems. Garcez applied a PI neural to a linear simulator of a 20 MW hydroelectric power plant (Garcez & Garcez, 1995). Djukanovic, validated an adaptive-network based on fuzzy inference system to control a low head hydropower system (Djukanovic, Calovic, Vesovic, & Sobajic, 1997). Yin-Song, presented a self-learning control system using a PID Fuzzy NN, which was applied it to hydraulic turbine governor system (Yin-Song, Guo-Cai, & Ong-Xiang, 2000). Recently, Shu-Qing, compared a PID controller with a hybridized controller based on genetic algorithms and fuzzy NN for governors of a hydroelectric power plant model (Shu-Qing, Zhao-Hui, Zhi-Huai, & Zi-Peng, 2005).

In this paper a back-propagation strategy has been used to adjust the parameters of a discrete PDF regulator. This technique was introduced by Aguado (Aguado Behar, 2000). Figure 6 shows the scheme of Neural-PDF. The regulation can be calculated by:

$$v_j(t+1) = v_j(t) + \eta sign(\frac{\partial e_y}{\partial e_u})\delta^1 h_j \quad (3)$$

$$w_{ji}(t+1) = w_{ji}(t) + \eta sign(\frac{\partial e_y}{\partial e_u})\delta^2{}_j x_i \quad (4)$$

$$\frac{\partial E(t)}{\partial v_j} = -\delta^1 h_j \frac{\partial e_y}{\partial e_u} \quad (5)$$

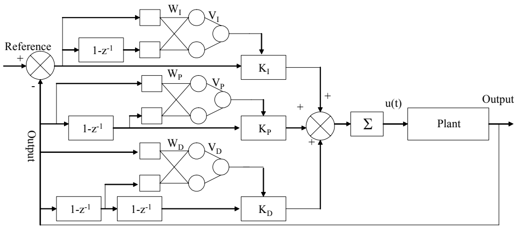

Figure 6: Neural PDF.

4 SIMULINK MODEL AND PROGRAM

A Simulink model was developed to facilitate studies of the power plant under different governors. Libraries of special functions (blocks) and the power plant models were constructed by connecting these functions to the standard Simulink functions. Using a dialog box, the parameters of a specific block can be adjusted, for example, the operating point of linear models may be changed. These models can represent the power plant as SISO or MIMO system and linear or nonlinear behaviour may be selected. Figure 7 shows a schematic of the Simulink power plant model.

The full hydroelectric station model is constructed combining the four sub-systems: Guide vane dynamics, hydraulic subsystem, turbine/generator and sensor filters. Each block is part of the Simulink library developed for this study; they can be selected to represent a diversity of modes of operation. For example there are three models available to simulate the hydraulic subsystem: Linear, nonlinear nonelastic and nonlinear elastic. The guide vane dynamics can be selected with or without rate limitation and saturation. The sensor filters block is a fixed block. The grid model can be adjusted to represent different conditions of the national grid. Through the governor block classic and advanced controls can be selected.

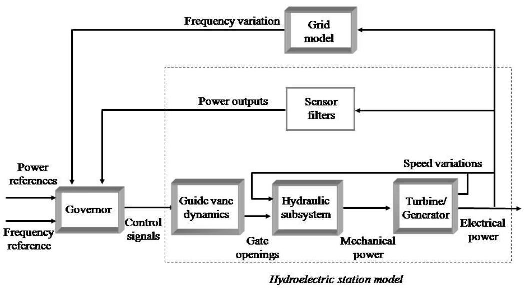

Figure 7: Simulink power plant model.

Simulink S-functions for the neural PDF algorithms were developed. These functions are connected to Simulink plant models. The neural PDF block accepts η (learning parameters) and sample time. The input signals to the PDF block consist of the reference and the output signals of the plant and its output is the plant control signal. The versatility of Simulink is very important to change easily the plant model or even modify the algorithm and quickly see the new results. The neural algorithm calculates the optimal values of the control parameters. The current optimal criterion programmed is quadratic error, where the error is the output deviation from the set-point; however the criterion of optimization can be changed. The algorithm takes some time to find the "best" range of parameter values (training time) when these ranges have been reached the parameters stay constant until the set-point or the plant model change.

5 RESULT OF SIMULATION

The role of a hydroelectric station in frequency control mode is to provide timely and accurate supply of its target power contribution to the power system. The actual form of the power demand is related to Grid frequency variation but, for testing, it can be specified in terms of step, ramp and random input signals. Jones *et al* have proposed a step and ramp response for single unit operation (Jones, Mansoor, Aris, Jones, Bradley, & King, 2004). This step response specification for single unit operation is expressed in Figure 8 and Table 1 (these are not valid for commercial purposes). The most important criterion is usually Test P1 for the *primary response,* which requires that the station, under defined conditions, achieves at least 90% of the demanded step power change within 10s of initiation. Table 1 also shows that the over-shoot P_2 must not exceed 5% and the initial negative excursion P_6 (undershoot), associated with the non-minimum phase response, must not exceed 2%.

Table 1: Specification of step response for advanced control design at Dinorwig.

Test	Specification for single unit operation.	Single unit response with current governor.
P1	$P_1 \geq 90\%$ at $t_{p1} = 10s$	81% at 10s, 90% at 13.7s
P2	$P_2 \leq 5\%$ and $t_{p2} \leq 20s$	No overshoot
P3	$t_{p3} = 25s$ for $P_3 \leq 1\%$	25.9s
P4	$t_{p4} = 60s$ for $P_4 \leq 0.5\%$	29.2s
P5	$t_{p5} = 8s$	12.1s
P6	$P_6 = 2\%$	1.75%
P7	$t_{p7} = 1.5s$	0.88s

The neural PDF controller was connected to the nonlinear model of the hydroelectric power plant. The model is expressed in the per-unit system, normalized to 300 MW and 50 Hz, and assumes a Grid system with infinite busbars. A PI controller with parameters fixed at K=0.1 and T_i=0.12 (as currently implemented in practice) is used as a basis of comparison. Figure 9 shows small step responses (0.04 p.u.) of hydroelectric plant under PI and neural PDF controllers for one unit operational. Figure 10 shows small step responses (0.04 p.u.) of the power station when six units are connected. In both cases, the hydroelectric plant shows a better performance under neural PDF controller; the response under the neural PDF controller is 10% and 30% faster in one unit operational and six units operational, respectively. The undershoot is also reduced in both cases when a PDF controller is driven the process.

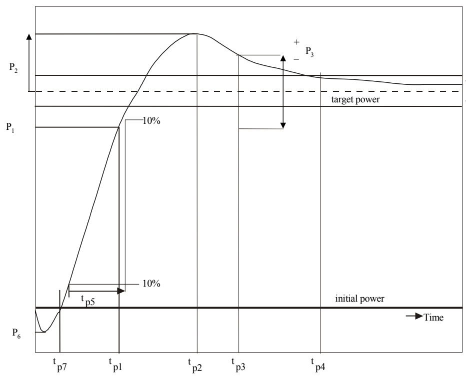

Figure 8: Specifications for a response to a step change in demanded power.

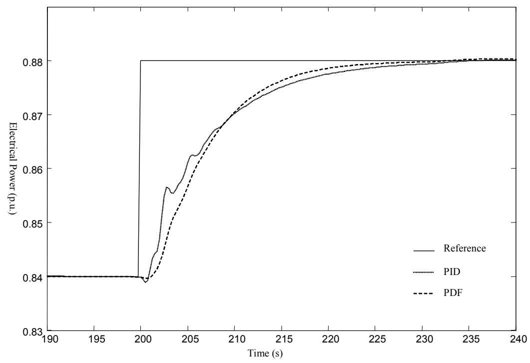

Figure 9: Step response of hydro plant under neural PDF and PI controllers with one unit operational.

The ramp response specification for single unit operation is expressed in Figure 11 and Table 2. Again, the most important criterion is usually Test Q1 for the *primary response (t_{q1}),* which requires that the station, under defined conditions, achieves at least 90% of the demanded power change, ramp amplitude (A_r), within 15s of initiation. Table 2 also shows that the maximum rate Q_2 must not be less than 90% of the ramp rate and the steady-state accuracy Q_3 must not be longer than 30s. Test Q_4 shows the effective under-delivery of power over the period of the ramp (Jones, Mansoor, Aris, Jones, Bradley, & King, 2004). The ramp response of the nonlinear elastic model of Dinorwig is shown in Figure 11.

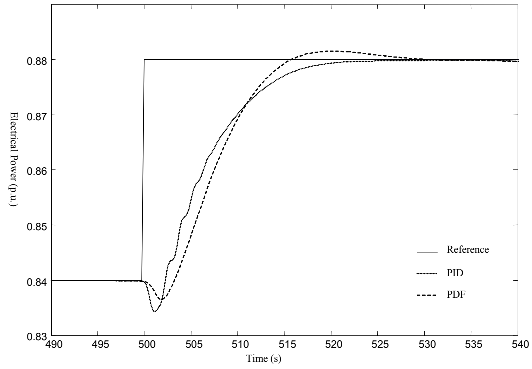

Figure 10: Step response of hydro plant under neural PDF and PI controllers with six units operational.

Table 2: Specification of ramp response for advanced control design at Dinorwig.

Test	Specification for a single unit operation	Single unit response with current PI control
Q_1	$Q_1 \geq 90\%$ at t_{q1}=15s	14.7
Q_2	Q_2=90% of 6 MWs^{-1}	1.8 MWs^{-1}
Q_3	t_{q3}=30s for $Q_3 \leq 1\%$	27
Q_4	None specified	E(RMS)=3.09 MW for t_{q4}=50s

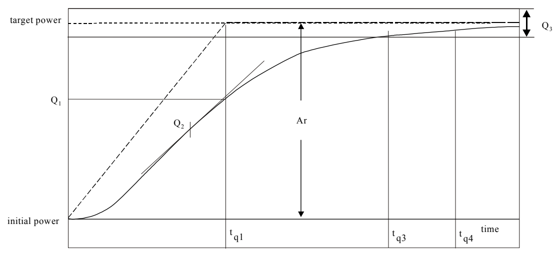

Figure 11: Specification for a ramp input power target.

Figure 12 shows large ramp responses (0.3 p.u.) of hydroelectric plant under PI and neural PDF controllers for one unit operational. Figure 13 shows large ramp responses (0.3 p.u.) of the power station when six units are connected. In both cases, the hydroelectric plant shows a better performance under neural PDF controller; the response under the neural PDF controller is 15% and 13% faster in one unit operational and six units operational, respectively. When a PDF controller is driven the plant, the under-shoot is also reduced for both cases.

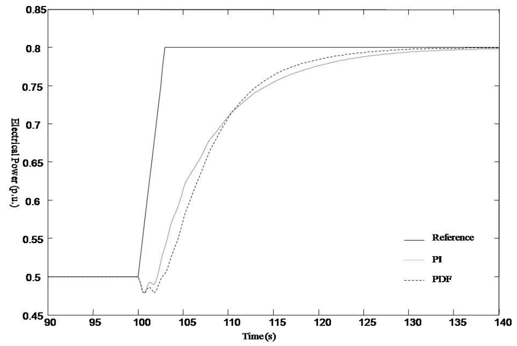

Figure 12: Large ramp response of hydro plant under neural PDF and PI controllers with one unit operational.

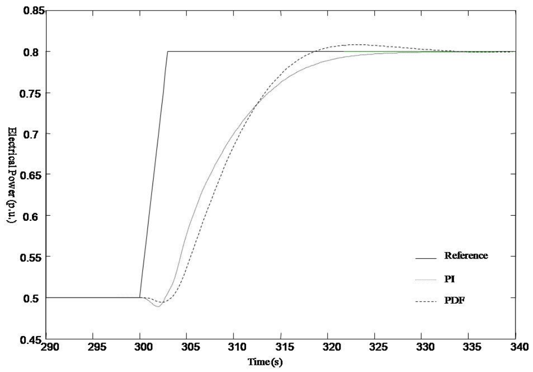

Figure 13: Large ramp response of hydro plant under neural PDF and PI controllers with six units operational.

To evaluate the cross coupling interaction a 0.04 step was applied simultaneously at t=500 to units 2-6 and the perturbation of unit 1 were observed. Figure 14 shows that although the neural PDF response has a higher overshoot, the PI response has a longer settling time and a higher undershoots.

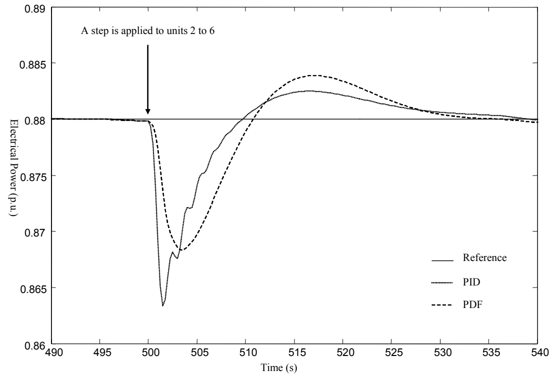

Figure 14: Cross coupling of hydro plant under PI and neural PDF controllers.

6 CONCLUSIONS

The results have shown how the neural PDF can be applied to a hydroelectric pumped-storage station to improve its dynamic response. In particular, this paper has shown that the step response of the system with neural PDF is improved. Multivariable effects have been taken into account to represent closely the real plant. The close relation between penstocks has been included into the nonlinear model. These are promising results for the use of neural PDF in this application and encourage us to address the issue of robustness of the response in future work.

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