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Artificial Neural Network-based Neuro-controller for Hydropower Plant Control

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***Abstract* – In this paper, the behavior of a system dynamics is represented where neuro-controller is designed, trained, and implemented. The development of the mathematical models is based on suggestions and recommendations from the literature issued by the working group of IEEE. According to the mathematical models, simulation is developed in Simulink software. MATLAB/Simulink software was used to represent the difference between the conventional PID controller and artificial neural network (ANN) neuro-controller. Nonlinear autoregressive-moving average (NARMA-L2) has been used for control simulation of the hydro-power plant (HPP) with neuro-controllers on one hand, and conventional PID control on the other hand.**

***Keywords* – neuro-controller, PID controller, HPP control.**

1. Introduction

New approaches and techniques as a result of the modern-world advances have been developed [1] and used in order to achieve more reliable, energy-efficient, and safer processes where the environmental regulations are stricter and more demanding.

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Considering the above mentioned characteristics, the industrial processes, as well as power plants have become more complex and highly non-linear.

The research which is the focus of this paper covers hydro-power plant (HPP) control when only one turbine is in island operation mode [2]. It does not matter if it is linear or non-linear, the HPP model which is a real case, experimentally verified, used in this paper, is proposed by the working group of IEEE, as shown in Figure 3 [2], [3], [4], [5]. According to the proposed HPP model and the HPP control, previous research was settled with traditional proportional-integral (PI), proportional integral derivative (PID) [5], [6], or proportional integral – proportional derivative (PI-PD) controllers [6]. It is concluded in [6] that with PI controller, the plant represents the best performances, while in [2], [5], [7], PID controller is represented as a more proper and successful HPP control technique.

As described in [2], the gain scheduling technique on PID controller (used especially in non-linear models) has an advantage over the manual or auto-tuning of the conventional PID controller values because gain scheduling can be applied in a complete working area of the plant while using PID controller only, its control is valid in the vicinity of the workstation for which the controller is designed. [8] proposed simple structured PI control results in low cost and fast time response. Moreover, PI control provides poor system dynamics which is overcome by introducing I-PD controller where I-controller parameters are present in feedforward and PD-controller parameters are present in a feedback loop.

Another approach of HPP control [9], [10] is using an intelligent algorithm for system stability and better dynamics performances. When dealing with complex non-linear systems, PID control techniques are prone to overshoot and oscillate, and because of that, fuzzy logic control has proven to be a better solution. Furthermore, in [11] and [12], the combination of fuzzy logic and neural networks (NN) is proposed, especially for high-order non-linear HPP model where random disturbances could be eliminated due to the robustness of the system.

Using intelligent algorithms for better dynamic performance such as neuro-controller implementation into multiple processes: hydro-pneumatic systems, thermal power plants, etc., is a well-known approach. However, such a control technique has not been yet developed/implemented in an HPP. Therefore, neuro-control implementation is the focus of the research presented in this paper. In order to exhibit the plant behavior improvement, meaning faster system stabilization and better dynamic performance, a non-linear autoregressive-moving average (NARMA-L2) is used.

2. Methodology

Customization and design of a conventional PID controller, on one hand, and neuro-controller, on the other, in this paper is utilized in order to achieve more efficient, stable, and reliable HPP control. As a further research goal, the difference in responses with both controlling techniques will be examined.

Neuro-controllers as a modern control technique provides efficient control and faster system stabilization as the most important parameter related to processes and production. Important attention is paid to the design, training, and implementation of the NARMA-L2 neuro-controller. The NARMA-L2 control technique, which is an artificial neural network (ANN)-based neuro-controller, offers an efficient solution to the problem via utilizing a backpropagation training algorithm. NARMA-L2 has been used as a controlling technique that linearizes the model inside the controller and cancels the disturbance dynamics to the input in the system, simultaneously aiming to maintain the original dynamic of the system [13]. The training process is performed offline and uses approximated models which represent the process dynamics.

In the herein proposed model, NARMA-L2 controls the angular velocity of a hydro-turbine rotor depending on a network load. The reference value in the neuro-controller is angular velocity which according to Figure 3 is connected to a controller and the controller is then connected to the servomechanism and a hydro-turbine sub-system [2]. Accepted as the most accurate/efficient way and as the fastest backpropagation algorithm in MATLAB® - Deep Learning Toolbox, the training function for the controlling technique is performed by Levenberg-Marquardt Algorithm (LMA) [14].

2.1. Identification and Implementation of NARMA-L2

NARMA-L2 (Figure 1), as linear/non-linear process controller, trained offline, is widely used to achieve accurate tracking reference value. Its working principle is based on the input and output data, whereas the linear function of the plant model output is created by the control input [15].

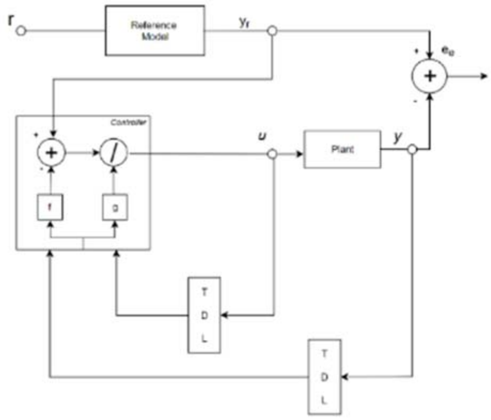

Figure 1. Block diagram of the NARMA-L2 controller [13]

Both, g and f, non-linear functions as a part of NARMA-L2, have $(2n-1)$ inputs, whereas y (output) and u (control effort), are input prior values. Both non-linear functions are eliminated, (1) after the plant approximation procedure and (2) after the training data generation. Then, the system output, defined as $y(k+d)$, is equal to the tracked reference model output defined as $y_r(k+d)$, where (d) is the delay, n is plant output and k is the time index [3] [5]. Once the data are generated inside the neuro-controller, the system is trained repeatedly, until reaching the desired behavior and minimal data output error.

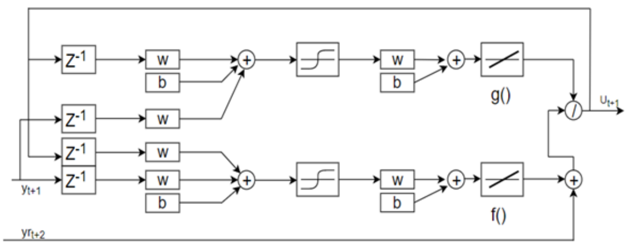

Figure 2. NARMA-L2 neuro-controller structure [13]

Mathematical model of the control law, with a structural representation as in Figure 2, is defined by the following discrete time characteristic equation, where in (1), (2) and (3), variables have the same meaning [16]:

$$u(k+1) = \frac{y_r(k+d) - f[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)]}{g[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)]} \quad (1)$$

were

$$f = F[(y(k),\ldots,y(k-n+1),0,u(k-1),\ldots,u(k-n+1))] \quad (2)$$

$$g = \frac{\partial F}{\partial u(k)}\bigg|_{[(y(k),\ldots,y(k-n+1),0,u(k-1),\ldots,u(k-n+1))]} \quad (3)$$

3. Problem Elaboration

Implementing new control techniques may help with faster system response, faster system stabilization, and avoiding system disturbance.

The system that is research topic is implementing modern control techniques and experiencing their advantages. Since the considered plant is HPP, its mathematical and functional representation combines the following subsystems: servomechanism subsystem, hydraulic turbine, electrical subsystem, and controller (Figure 3).

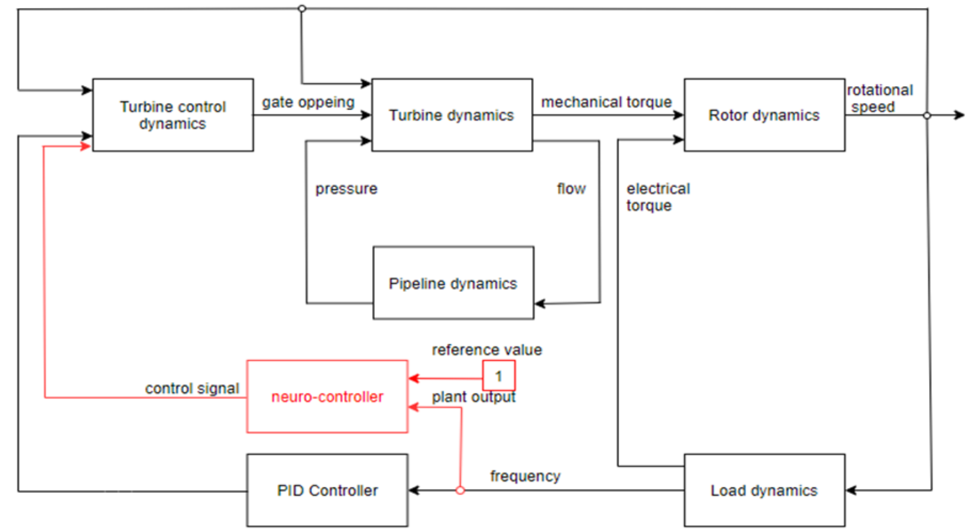

Figure 3. Block diagram of a hydropower plant [2] (amended by authors)

Mathematical description of the hydraulic servo mechanism system is as follows:

$$G_v(s) = \frac{1}{(T_1 s+1)(T_2 s+1)} \tag{4}$$

$$\frac{L[y(t)]}{L[u(t)]} = \frac{1}{1+T_p \cdot s} \tag{5}$$

In equation (4), T_1 and T_2 are determined by the pressure characteristics and the flow that enters the plant, for moving the servo-mechanism system, including servomotors [2].

The input in the servo-mechanism system is the signal from the controller u(t) where it strives the error between the reference value of angular speed and the given angular speed, to be as low as possible. In this subsystem, the output is the blade opening position of the wicket gate i.e., wicket gate servomotor stroke, y(t) where T_p is a pilot valve and servo motor time constant [2], [3].

Taking into consideration the parameters, such as: time constant of water (water starting time) T_w, flow, pressure, power near operating point, the transfer function was obtained i.e. the linear mathematical model that describe the hydro-turbine [2]:

$$\frac{\Delta P_m}{\Delta c} = \frac{1 - T_w s}{1 + \frac{T_w}{2} s} \tag{6}$$

where s is Laplace operator.

Transfer function of the system [2]:

$$G(s) = \frac{G_c(s)(1-T_w s)}{\left(1+\frac{T_w}{2}s\right)(T_m s + D)} \tag{7}$$

where $G_c(s)$ is transfer function of a control and could be PI or PID control, depending on whether the system is linear or non-linear, and depending on the parameters that could be controlled. T_m is mechanical time constant in [s] and D is turbine damping coefficient [2].

The characteristics equation of an electrical subsystem [2] which is an essential part of a hydro-power plant, is as follows:

$$P_L = P_0 + P_0 D_{pf} \Delta f \tag{8}$$

$$\Delta P_0 = \Delta P_0 + D \Delta f \tag{9}$$

$$\Delta \overline{P_m} - \Delta \overline{P_e} = 2Hs\Delta\overline{\omega} \tag{10}$$

$$\Delta \overline{P_m} - \Delta P_e = \left(T_m s + \overline{D_f}\right)\Delta\overline{\omega} \tag{11}$$

$$\dot{\omega} = \frac{1}{T_m \omega}(P_m - P_e) \tag{12}$$

$$P_e = P_l + D(\omega - 1) \tag{13}$$

where equation 8 represents active power. Linearizing eq. 8 are defined the load changes which are not sensitive to frequency and those that are sensitive to change frequency which represent equation 9. Combining load equation 9, and 10 -

generator equation, obtained in equation 11, transfer function of mechanical movement of a generator with load damping D_f. Mathematical modeling of rotor dynamics is obtained by combining 9 and 11 and implementing small modification with 12 and 13 [2].

$$G(s) = K_p + \frac{K_i}{s} + K_d s \tag{14}$$

Eq. 14 represents the transfer function of a PID controller where K_p, K_i and K_d are parameters that could be manually calculated or could be auto tuned using $MATLAB^{®}$ software.

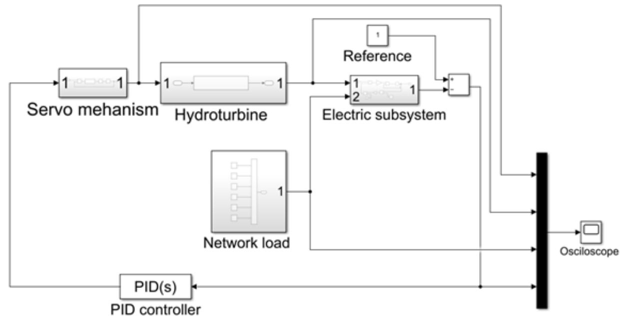

Figure 4. Simulink model configuration for PID models [2]

The most frequently used controller for HPP control is the PID [5], [6]. This type of controller is sensitive to small errors and is more capable of quick response. Emerging new technologies, such as neuro-controllers, are able to speed up the stabilization, no matter whether the process is linear or non-linear. The reason for developing and implementing new controllers lies in the inability of the PID controller to return the system to a stable state, due to its physical limitation and saturation.

4. Results and Discussion

In this section, results obtained are elaborated while using conventional PID controller for HPP plant control, compared to those when using NARMA-L2 neuro-controller, based on the proposed mathematical model (equations 4 to 13).

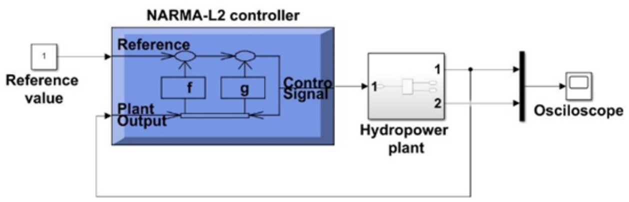

Figure 5. Simulink model configuration for NARMA-L2

Tuning the parameters for the PID controller is done via using the gain-scheduling technique. According to Figure 3, block diagrams and lines in black represent the HPP model with PID controller, while red lines depict the newly implemented neuro-controller.

Simulink model for PID and neuro-controller control techniques are shown on Figure 4 and Figure 5, respectively. NARMA-L2 has a specific block diagram where the parameters for the neuro-controller and the neural network are specified inside the block diagram.

Configuration and generation of the training data for the neuro-controller are according to Table 1, whereby training lasts until the desired responses are obtained and until the regression-R approaches 1.

Table 1. Linear plant identification and controller configuration

Network Architecture			
Size of hidden layer	1	Delayed plant inputs	3
Sampling interval (sec)	0.1	Delayed plant outputs	2
Training data			
Training samples	1000	Minimum interval value	0.01
Maximum plant input	2	Maximum plant output	1
Minimum plant input	-1	Minimum plant output	0
Maximum interval value	1	Simulink plant model	LinearPlant Model
Training parameters			
Training Epochs	500	Training function	trainlm

As per [14] the training function, which in a most accurate and efficient way solves the generic-curve fitting problem, is Levenberg-Marquardt Algorithm (LMA). Hence, herein, this type of algorithm is implemented.

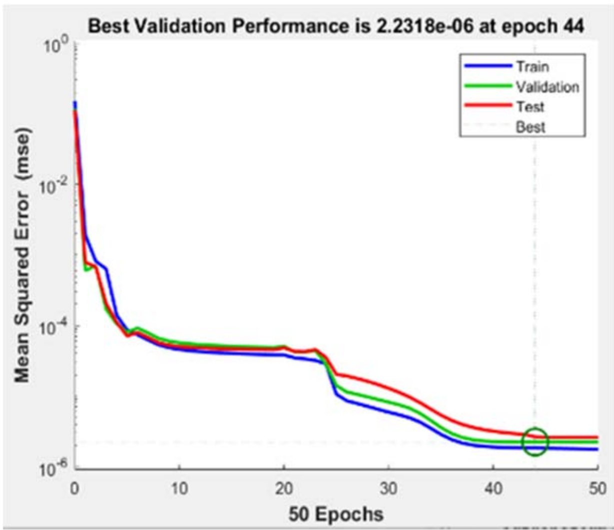

Figure 6. NN training performance graphical representation

The desired response (Figure 6) is reached at epoch 44 when the mean square error is 2.2318 e-06.

Compared to the results when the system is controlled by PID, a significant difference in the responses is noticed after implementing the neuro-controller (Figure 5). As the NARMA-L2 uses linear approximation in the vicinity of u(k)=0, the obtained plant model successfully tracks the signal, it becomes stable in a shorter period, while no response overshoot occurs. The controller input reference signal is the angular velocity, whereas the trajectory that should be tracked is the network load. The negative decline in the mechanical power due to inertia, as a crucial feature in the hydro turbine behavior, is successfully addressed. Short oscillations are still present, but no overshoot occurs.

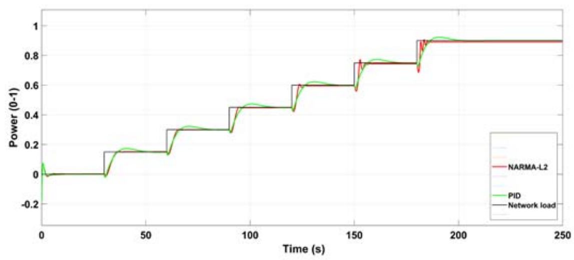

Figure 7. Comparison of the responses given by PID controller and neuro-controller

As shown in Figure 7, the difference in the stabilization period between both responses (PID controller in green and neuro-controller in red) is 10 seconds, where better results are obtained from using neuro-controller rather than the conventional PID controller.

Table 2. Non-linear plant identification and controller configuration

Network Architecture			
Size of hidden layer	10	Delayed plant inputs	3
Sampling interval (sec)	0.01	Delayed plant outputs	2
Training data			
Training samples	3000	Minimum interval value	30
Maximum plant input	1	Maximum plant output	inf
Minimum plant input	0	Minimum plant output	-inf
Maximum interval value	300	Simulink plant model	Non-linearPlant Model
Training parameters			
Training Epochs	2500	Training function	trainlm

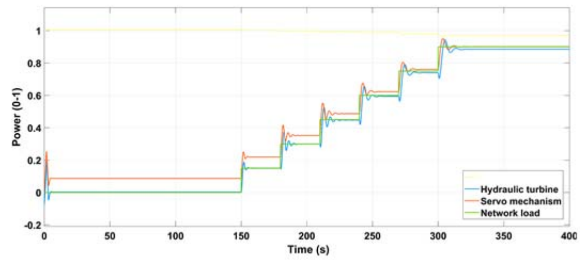

Figure 8. Response of a non-linear model of a turbine tracking the input signal using NARMA-L2

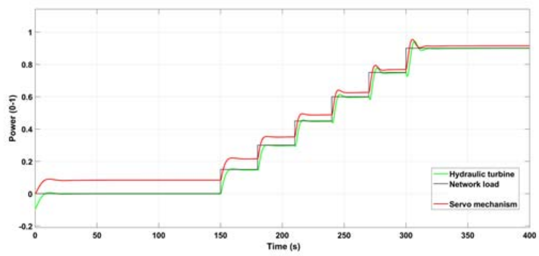

Figure 9. Response of a non-linear model of a turbine tracking the input signal using gain scheduling PID [2]

Configuration of the NARMA-L2 controller parameters is performed either by trial-error method or by realizing the manner of effect that specific parameters have on the system. Using NARMA-L2 as a controller in non-linear systems, indicates that it linearizes the model because of the controller's architecture. Configuration and generation of the training data for the neuro-controller are according to the Table 2.

Comparing Figure 8 and Figure 9, it could be concluded that implementing a neuro-controller results in a shorter rise time, in overshoots, and in oscillations, which stabilize swiftly. According to Figure 8, after more than 1000 trials of network training of the non-linear plant model, a response error compared to the network load in the last two steps is still not eliminated, i.e., the turbine does not follow the network load; while in Figure 9, where the gain scheduling technique is used, the system is stable and the mechanical power is tracking the network load, but the system's response is slower (i.e., larger rise time). Additional research is required to explain why after so many trials when using a neuro-controller that gives better dynamic responses, the error in the last two steps remains.

5. Conclusion

A comparison in the HPP dynamic behavior has been successfully elaborated while using a conventional PID controller and a NARMA-L2 neuro-controller.

The study of both control approaches shows that NARMA-L2 neuro-controller is more beneficial in providing fast rise time, stable response, and a faster system stabilization than the conventional PID control technique.

In contrast to the resolved network load tracking problem in the linear model, in the non-linear model the error in the last two steps still pertains. Thus, initial results are promising, although the actual aim of successful tracking has not yet been achieved. Further research, in order to reach the desired dynamic behavior of the non-linear system is foreseen, whereby a combination of NARMA-L2 and PID controller emerges as a possible solution.

Nomenclature

Table 3. Table with important variables

T_i	Integral time constant	[s]
T_w	Water starting time	[s]
T_m	Mechanical time constant	[s]
P_m	Mechanical power	[kW]
P_e	Electrical power	[kW]
D_f	Load attenuation	[-]
ω	Angular speed	[rad/s]
K_p	Proportional gain	[-]
K_i	Integral gain	[-]
K_d	Derivative gain	[-]
c	Opening of the wicket gate	[pu]
g	Non-linear function	[-]
f	Non-linear function	[-]
y	Output from neuro-controller	[-]
u	Control effort	[-]
k	Time index	[-]
n	Plant output	[-]
T_p	Pilot valve and servo motor time constant	[s]
d	Control error	[-]
w	Vector of real-values weights	[-]
x	Vector of input values	[-]
m	Number of inputs to the Perceptron	[-]
b	Bias	[-]
P_L	Active power	[MW]
P_0	Power load (not sensitive to changes in frequency)	[W]
D_{pf}	Frequency sensitivity parameter	[%]
H	Rotational mass moment of inertia	[kgm]
P_l	Electric load	[kW]
j	Number of neurons	[-]
N_u	Tentative control signal	[-]
y_r	Desired response	[-]
y_m	NN response	[-]
ρ	is sum of the squares of the control increments	[-]
u'	Control increment	[-]
t	Time index	[-]

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