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Novi pristup u upravljanju hidroelektranama zasnovan na neuronskim mrežama

A New Approach in Hydropower Plant Control Based on Neural Networks

Radmila Koleva, Darko Babunski, Emil Zaev, Atanasko Tuneski, Laze Trajkovski
Faculty of Mechanical Engineering, "Ss Cyril and Methodius" University in Skopje
Karpoš II b.b. P.O. Box 464 1000 Skopje, R. Macedonia

Rezime – Novi pristup efikasnoj, bržoj i inteligentnoj hidroelektrani (HE), gde je sastavna oprema opisana visoko nelinearnim matematičkim modelima na osnovu preporuke radne grupe IEEE. Stabilnost HE i visoka efikasnost su važni faktori koji zavise od dinamičkih promena u zahtevima energetskog sistema i vreme na pokretanja postrojenja jer je dobijena energija veoma fleksibilna na te promene u energetskom sistemu. U ovom radu je prikazana i analizirana implementacija kontrolera baziranog na veštačkoj neuronskoj mreži sa PID-om kao pomoćnim kontrolerom koji je pomogao u postizanju boljeg ponašanja, brže stabilizacije postrojenja i rada. Prednosti novih tehnologija i mogućnosti dovele su do poboljšanja upravljanja HP i bržeg rada sistema. Ovo se postiže korišćenjem MATLAB®-a - Deep Learning Toolbox, dok su simulacije pripremljene u Simulink-u. Veštačke neuronske mreže (ANN) kao tehnika koja se koristi u sistemima upravljanja HP ima prednosti u dobijanju stabilnog i bržeg odziva, ali složenost strukture koja stoji iza neuronskih mreža (NN), što znači algoritme, broj skrivenih slojeva, funkciju obuke, pobudna funkcija može da zakomplikuje i destabilizuje proces. U ovom radu fokus je stavljen na odzive i prednosti implementacije novih tehnologija u suprotnosti sa problemima koji se mogu javiti njihovom upotrebom kao što su: destabilizacija postrojenja primenom manjih promena, prilagođavanje parametara, proces učenja i obuke koji neće biti temu ovog rada.

Ključne reči - hidroelektrane, upravljanje, veštačke neuronske mreže, PID

Abstract **-** A new approach to efficient, faster, and intelligent hydropower plant (HPP) control, where constituent equipment is described with highly non-linear mathematical models based on the recommendation from the working group of IEEE on prime movers, is represented in this paper. HPP stability and high efficiency are important factors dependent on the dynamic changes in the energy system demands and the starting time of the plant because the obtained energy is very flexible to those changes in the energy system. This paper is shown and analysed the implementation of the artificial neural network-based controller with PID as an auxiliary controller which helped achieve better behaviour, faster plant stabilization, and operation. The benefits of new technologies and possibilities led to improvements in HPP control and faster system operation. This is achieved by using MATLAB® - Deep Learning Toolbox whereas the simulations are prepared in Simulink. Artificial Neural Networks (ANN) as a technique used in the HPP control systems have advantages in getting a stable and faster response but the complexity of the structure behind the neural networks (NN), meaning algorithms, number of hidden layers, training function, activation function can complicate and destabilize the process. In this paper, the focus is put on the mechanical power responses improvement and the advantages of implementing new technologies contrary to the problems that can occur by using them such as plant destabilization by implementing minor changes, fitting parameters, learning, and training processes, number of hidden layers/neurons, number of epochs, etc.

Index Terms - Hydro Power Plant, Control, Artificial Neural Networks, PID

I INTRODUCTION

Increasing hydropower efficiency besides operational improvements and the electricity market opportunities is possible by implementing new technologies in the plant control process, especially frequency control. Meaning that providing the hydropower plant (HPP) control strategy has a long history of improvement. The foundation is set by the IEEE working group on Prime mover and energy supply where the HPP dynamic model is proposed [1]. This paper has represented the improvement and modernization of the model proposed in [1], utilized, and verified in [2]. Here, the proposed control technique is achieved by the PID controller. By the time of various techniques improvement, different approaches have been implemented and represented.

The Proportional-Integral (PI) controller in HPP frequency control could be found to be a successful strategy in [3] and [4]. While in [5] are studied four types of controller strategies, traditional, PI, PID, and PI-PD but PI is represented as the one which has the best performance over the traditional, PID, and PI-PD within the stability criteria whereas the mechanical power follows the demanded power curve the best.

Besides, [1], [6] [2], and [7] which showed that the PID has the best performance as an HPP control strategy, [8] also represented rapid output response and minimal overshoot using PID.

In frequency control, another approach [9] is represented to highlight the PID performance based on the feedback signal average derivative for obtaining noise-tolerable differential control. Another completely different approach to power plant control is represented in [10] where the tilt-integral-derivative (TID) showed better performances than the PID in order to diminish the frequency variations along with control the tie-line power. This type of controller as shown offered a lesser effect on the closed-loop response for system parameter variations and offered better disturbance rejection.

Sometimes, two control techniques are combined for better plant dynamics behaviour as represented in [11] where PID is included as governor speed control and PI is included as a power control.

Despite the variations in the HPP frequency control strategies, choosing the appropriate PID parameter tuning method as the most suitable controller is represented in [12]. There are obtained two tuning methods Ziegler-Nichols (Z-N) and Ant Colony Optimization (ACO) in which is shown that the ACO PID parameter tuning method gave more accurate frequency responses.

Moreover, gain scheduling [13], [14] as a control technique is used for providing better HPP control because it can be applied in a complete working area of the plant while using the PID controller only, its control is valid in the vicinity of the workstation for which the controller is designed.

A lot of PI, PID, and its combination as an approach could be found in order to represent the plant control improvement. Looking forward to new intelligent control possibilities, the present techniques are Fuzzy-PI controller [15], [16] which showed better load frequency control and stability properties compared to PI/PID.

In the frequency control field, a lot of approaches that include intelligent control could be found such as fuzzy model predictive controller (MPC) [17], fuzzy logic implementation for managing the power over the grid demanding [18], and a lot of other approaches based on the fuzzy logic in HPP control as in [19].

A further step into HPP control is the Fuzzy neural network combination approach [20] which also brings additional system dynamics behaviour improvement. After the fuzzy neural network era, control law based on the neural networks and only neural networks (NN) is the new trend.

The papers for HPP control based on the NN found until now, are about using only NN without the influence of some control law as an approach to system HPP dynamics behaviour improvement. This means that the NN with its input and target data set is used for a plant model behaviour prediction or improvement as represented in [21], [22], [23].

Besides the PI, PID, fuzzy logic, and NN, there are present adaptive methods whose purpose is to achieve stability and flexibility of the power system [24] no matter the conditions or the disturbances influencing the system.

This paper has represented neural network (NN) based control as the latest approach in the control theory [25]. Besides the different control strategies and backgrounds, the achieved results comparing PID and NN-based controllers, are comparable and in this paper are analysed.

Building the NN-based controller parameters and its architecture covers a few steps: selecting the error calculation method, which in this paper is Mean Square Error (MSE), selecting tansig and purelin as the activation function (AC) of the neuron's output in the hidden and output layer, designing the right number of neurons in the hidden layer, selecting Levenberg-Marquardt Algorithm (LMA) as training algorithm, and choosing the right number of epochs. Based on the design and selection of these parameters, simulation results have been represented and discussed in this paper.

The control strategy implemented with the NN-based controller resulted in the HPP dynamics behaviour enhancement when the optimal turbine model has been in use. The non-optimal turbine would not be a discussion point because its working point is not in accordance with the real-case scenario turbine operation as elaborated in IV – Results and discussion.

II METHODOLOGY

To achieve a more stable, efficient, and reliable HPP process, both control techniques have been examined, PID plant control and NN-based control.

Because of the plant and operation complexity, PID plant control is performed as a gain scheduling technique that provides, control in the entire working area of the HPP.

NN-based control as an advanced and modern technique provides options for designing and selecting different types of controllers and parameters that affect plant behaviour in different ways. Each parameter, as part of the controller, and the controller itself contributes to different system behaviour.

Nonlinear autoregressive moving average (NARMA-L2) is the selected type of NN-based neuro controller for HPP control. This type of controller makes an approximation and cancels the process nonlinearity by transforming the nonlinear system dynamics into linear but simultaneously aiming to maintain the original system behaviour and dynamics. This leads to a reduction in the need for large computing power and long computing periods [26]. The training is performed offline because during the computing process, both functions that are part of the NARMA-L2 mathematical representation (Heading III), are eliminated after the approximation and after the training data generation. It is happening after each computation cycle.

In the proposed model [1], the reference value, the feature, which is system input, is the frequency/angular velocity. This is the controlled parameter by the NN-based neuro controller based on the network load. The error between the reference frequency/angular velocity and the real/output frequency/angular velocity is the signal which is processed inside the NARMA-L2. Its output is further HPP model input, according to Figure 1. Besides the design and selection of the parameters that describe the NN-based neuro controller, choosing the right training algorithm is also important. In this paper, Levenberg-Marquardt Algorithm (LMA) is utilized as the most efficient and most accurate training backpropagation algorithm [27] for fast and correct simulation results execution. All equations and parameters set in the NN-based neuro controller are normalized. Also, the equations describing the HPP model are normalized and expressed per unit (pu).

HPP which is elaborated on in this paper works in island operational mode.

III MATHEMATICAL REPRESENTATION

Mathematical representations of both, (A) non-linear HPP and (B) NN-based neuro controller, type NARMA-L2, have been represented.

Figure 1 represents the functional combination of the following subsystems: hydraulic servo mechanics, turbine dynamics, rotor dynamics, and control law.

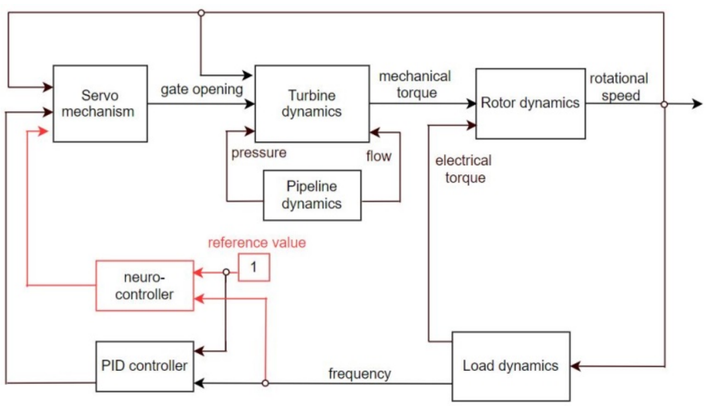

Figure 1. HPP block diagram [1] (amended by authors)

A. *HPP mathematical representation*

The hydraulic servo mechanism is mathematically described as follows:

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

In equation 1, T_1 and T_2 are responsible for the servo mechanism movement including the servo motors. They are determined by the pressure and the flow that enters the HPP [2].

$$\frac{L[y(t)]}{L[u(t)]} = \frac{1}{T_p s + 1} \tag{2}$$

In equation 2, T_p is a pilot valve and servo motor time constant. The signal from the controller $u(t)$ enters the hydraulic servo mechanism, where the output $y(t)$ is the blade opening position of the wicket gate [1] [2].

A non-linear hydro turbine is described as follows:

$$\frac{dq_t}{dt} = \frac{1}{T_w}\left(1 - h_f - h_t\right) \tag{3}$$

$$q_t = c\sqrt{h_t} \tag{4}$$

$$P_m = A_t h\left(q - q_{nl}\right) - Dc\Delta\omega \tag{5}$$

where: h_f - pressure drop, h_t - pressure through a turbine, P_m - mechanical power, D - turbine damping coefficient, T_w - water time constant, A_t - coefficient that brings the equation into a single quantity in relation to the power of the generator, q_{nl} - water flow through a turbine when there is no load and q - turbine water flow, c - wicket gate opening and $\Delta\omega$ - difference between the reference input value and actual output value [2].

Turbine damping coefficient can vary between 0.5 and 1; in the paper its chosen value is 0.5.

The mathematical representation of the electrical subsystem is as follows:

$$\dot{\omega} = \frac{1}{T_m \cdot \omega}\left(P_m - P_e\right) \tag{6}$$

$$P_e = P_l + D\left(\omega - 1\right) \tag{7}$$

Parameters that describe the mathematical model of a single electric generator are: T_m - mechanical time constant in seconds, ω - nominal angular velocity, P_e - electrical power, P_l - electrical load [2].

$$G(S) = K_P + \frac{K_i}{s} + K_d \cdot s \tag{8}$$

The control basic of non-linear HPP is the PID control which is mathematically represented with Eqn. 8, but practically the HPP control is executed with a gain scheduling control technique. It is due to the full HPP operating area.

B. *NN-based neuro controller – NARMA-L2, parameter design, and selection*

Since NARMA-L2 is the chosen type of NN-based neuro controller, its functional block diagram and mathematical representation follow.

The working principle of the NARMA-L2, Figure 2 is based on the input reference data and plant output data comparing and thus creating the control signal that enters the HPP with the minimized error between both input and output values.

Two non-linear functions are in the structure of this neuro-controller, g and f. They have (2n-1) inputs whereas y is plant output and u controlled signal i.e. controller output. After the plant approximation and training data generation, g and f are eliminated. Once the data are generated inside the neuro-controller, the system is trained repeatedly, until reaching the desired behaviour and minimal data output error.

Both non-linear functions g and f are mathematically described as follows:

$$f = F\left[\left(y(k),\ldots,y(k-n+1),0,u(k-1),\ldots,u(k-n+1)\right)\right] \tag{9}$$

$$g = \left.\frac{\partial F}{\partial u(k)}\right|_{\left[\left(y(k),\ldots,y(k-n+1),0,u(k-1),\ldots,u(k-n+1)\right)\right]} \tag{10}$$

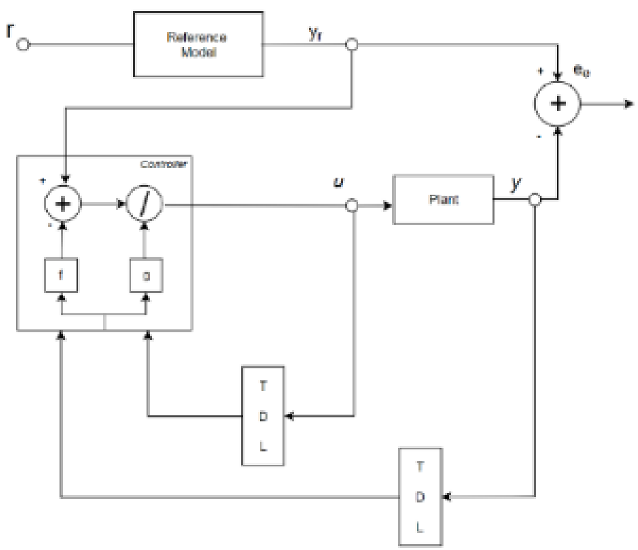

Figure 2. Block diagram of NARMA-L2 [6]

Mathematical representation of the control law is defined by the following discrete-time characteristic equation

$$u(k+1) = \frac{y_r(k+d) - f\left[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)\right]}{g\left[y(k),\ldots,y(k-n+1),u(k),\ldots,u(k-n+1)\right]} \tag{11}$$

System output is $y(k{+}d)$. It is equal to the tracked reference model output defined as $y_r(k{+}d)$, where d is a delay, n is a positive integer, and shows the number of delayed outputs and k is the time index.

Fitting the network is based on a few parameters: activation function (AC), numbers of neurons, training algorithm, error calculation principle.

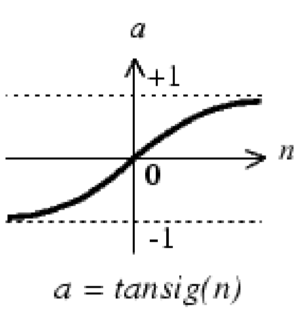

Figure 3. Tansig AC [28]

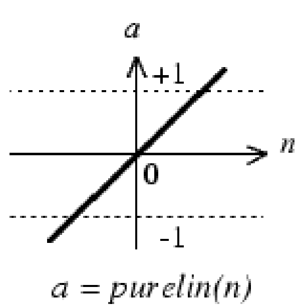

Figure 4. Purelin AC [28]

When choosing the AC, must be taken into consideration that the model/plant is real, verified, and in operation. This directs the selection of Tansig AC (Figure 3) in the first hidden layer. The cancelation of the nonlinearity of the system directs to Purelin AC (Figure 4) selection in the output layer. However, it could be neglected by achieving good design and fitting the controller parameters.

Equation 12 gives the calculation possibilities of the lower and upper limits in neuron number calculation.

$$2\cdot(n_i + n_0) \le n_1 \le \frac{k\cdot(n_i + n_0) - n_0}{n_i + n_0 + 1} \tag{12}$$

Here, where n_i is the number of inputs, n_0 is the number of outputs, k is the number of rows/values, and n_1s the calculated number of neurons.

In this paper, LMA as the most accurate and efficient controller training algorithm [27] is selected and executed.

In (13), N is the average value of all results, y_i is the true value, and $\hat{y}$ is the estimated value of y. Equitation 13 refers to Mean Square Error (MSE), a loss function integrated into the controller.

$$MSE = \frac{1}{n}\sum_{i=1}^{N}\left(y_i - \hat{y}\right)^2 \tag{13}$$

IV Results and discussion

In this paper, the implementation of an NN-based neuro controller, type NARMA-l2 in HPP control is the main research topic. From the very beginning, it was known that NARMA-L2 has its own limitation in the system implementation because of the AC types, the non-linear functions approximation, and even its own structure.

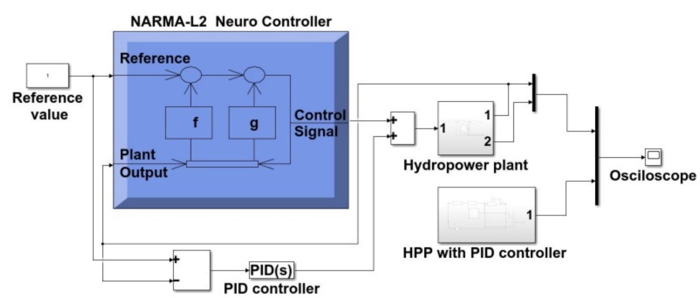

Figure 5. HPP model of Neuro-PID controller

Combining an NN-based neuro controller and PID will give much better results than using PID or NN-based neuro controller only. This is because with NARMA-L2 better dynamics behaviour will be achieved i.e., small behaviour improvement but the error in the tracking signal will be present because of the function approximation and AC that performs inside the controller.

Figure 5 represents a combination of both controllers, where NARMA-L2 is designed, fitted, and trained to track the network load. PID is added with the purpose to minimize the error that could not be reduced by the NN-based neuro controller NARMA-L2, because of the activation function in the layers and because of the non-linear function f and g approximation.

Table 1 represents the network architecture, training data, and training parameters.

Table 1. Plant identification and controller configuration

Network Architecture			
Size of hidden layer	4	Delayed plant inputs	1
Sampling interval (sec)	1	Delayed plant outputs	1
Training data			
Training samples	3000	Minimum interval value	0.1
Maximum plant input	1	Maximum plant output	inf
Minimum plant input	0.9	Minimum plant output	-inf
Maximum interval value	250	Simulink plant model	Model_1
Training parameters			
Training Epochs	2500	Training function	trainlm

According to equation (12), the number of neurons in the layers is calculated to be 4 as its lower limit. This number of neurons calculation must be proper and correct because the behaviour of the system most of the time depends on this parameter which can lead to overfit or underfit. Both conditions are bad for the system dynamics representation. Trainlm means that LMA is the training algorithm. There are 2500 training epochs, and the training samples are 3000. The input limitation is 1 because the reference value in the Simulink model is the angular velocity, which is 1, or 50 Hz. The more the system is operating near the optimal model, the more appropriately the parameters should be selected and designed.

Responses of the HPP control model represented in Figure 5 follow in Figure 6 and Figure 7.

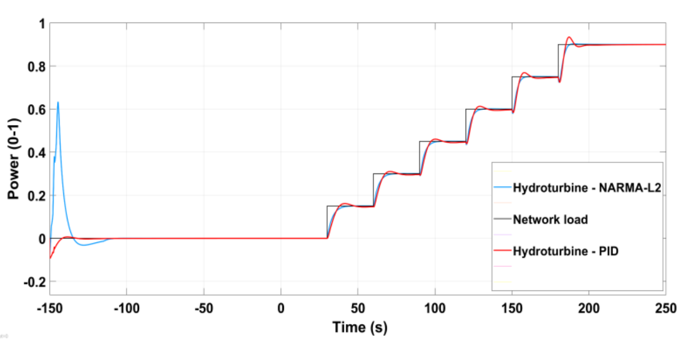

Figure 6. System response of a non-linear HPP model

Responses in Figure 6. represent the system behaviour when the optimal turbine model is in use.

The blue line represented the response when the NARMA-L2 combined with PID is in use while the red one represents the response when the PID controller only is in use.

According to Figure 6 and Figure 7, the mechanical power is in balance with the network load. The blue line response represents a critically damped system while the red line represents the stable system with oscillations that are increased as the system approaches equilibrium.

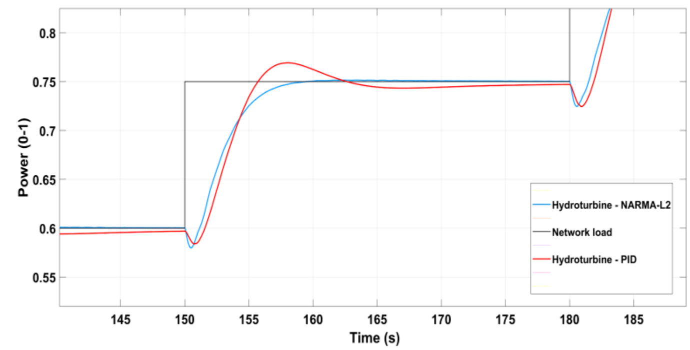

Figure 7. Detailed view of a non-linear HPP response

A small improvement in the system behaviour can be noticed between the PID and the NN-based neuro controller.

The presented model and its simulations refer to an HPP at the black start which means starting the plant operation without an external supply of electricity. In such a case it is very important for the balance between the network load and the generated power to be established. According to the responses, the network load is tracked by the generated power.

According to the non-optimal turbine model using, analysis and simulation results showed that the improvement in system dynamics behaviour when implementing an NN-based neuro controller is incomparably greater than the optimal one. That is because the non-optimal turbine model, whose operational point is not a real-case scenario, has greater performance improvement based on the simulation results. Having a non-optimal turbine in operation is not a usual case. [29].

In theory, an NN-based neuro controller can adapt to a different case, but the adaptation depends on the system's mathematical complexity. Due to the controller limitation, sometimes it would not work as well as expected because every system has its own dynamics features and properties in terms of NN-based neuro controller creation and preparation for implementation.

NN structure may be different for the same input and target data set. The important approach in this paper is to build a NN structure that helps the system to enable better system dynamics behaviour. According to [30], the NN behaviour depends on the hyperparameters data set combination. It means that different training NN data sets would provide different results. Since the different system performances are based on the data set configuration, [30] proves the statement while in this paper is made an additional check to complement the claim.

In this paper is made additional check when only the number of hidden layers/neurons is changed. The number of epochs, training function, and input and output data set remained the same.

Table 2: NN-based neuro controller configuration [30]

Network Architecture – First case	
Size of hidden layer: 10	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
Training Epochs: 600	Training function: trainlm
Network Architecture – Second case	
Size of hidden layer: 20	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
Training Epochs: 10	Training function: trainlm
Network Architecture – Third case	
Size of hidden layer: 4	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
Training Epochs: 2500	Training function: trainlm

Table 3: NN-based neuro controller configuration

Network Architecture – First case	
Size of hidden layer: 2	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
raining Epochs: 2500	Training function: trainlm
Network Architecture – Second case	
Size of hidden layer: 50	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
Training Epochs: 2500	Training function: trainlm
Network Architecture – Third case	
Size of hidden layer: 100	Delayed plant inputs: 1
Sampling interval (sec): 1	Delayed plant outputs: 1
Training samples: 1000	Minimum interval value: 0.1
Maximum interval value: 250	Simulink plant model: Model
Training Epochs: 2500	Training function: trainlm

According to the calculation and proposal in [30], the minimal number of neurons for the available data set is 4 and the maximum is above 100.

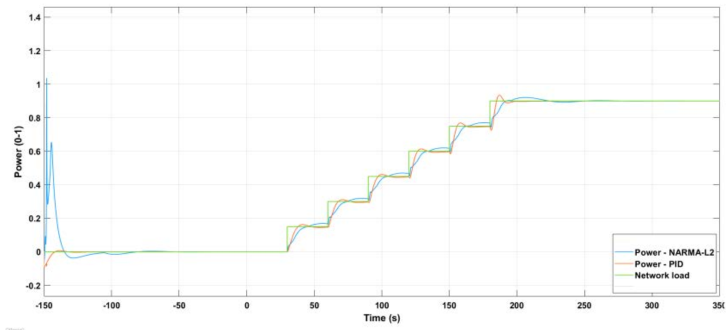

Figure 8. HPP response with 2 neurons – first case

The first case, Figure 8 is when the number of neurons is lower than the minimum calculated. If the response is analyzed, could be concluded that the generated power response when the NN-based neuro controller has the control role, blue line, tracks the network load with a very big error. Even more, the system is very slow compared with the response when the PID has the control role. This indicates that 2, which is below the calculated number of neurons is not suitable for training the proposed controller and NN.

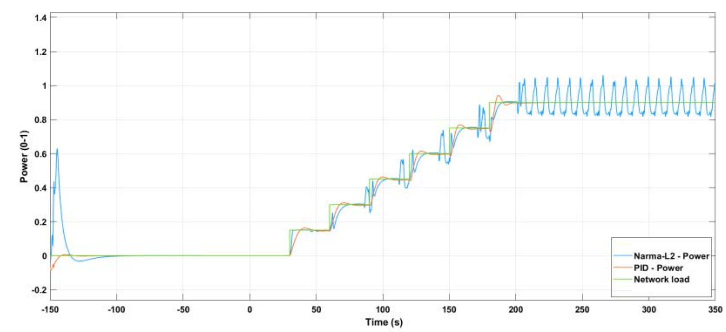

Figure 9. HPP response with 50 neurons – second case

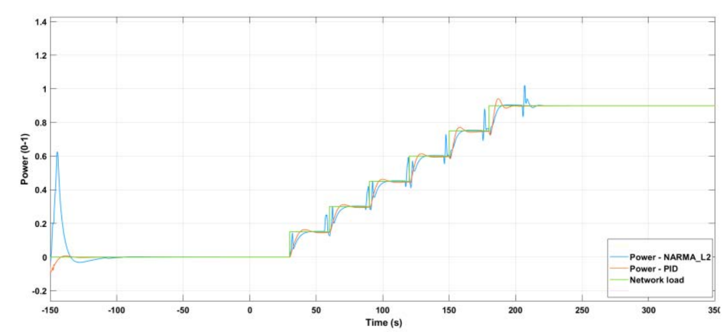

Figure 10. HPP response with 100 neurons – third case

Figure 9 and Figure 10 are the second and third cases, meaning 50 and 100 neurons in the NN.

Training the network with 50 hidden layers/neurons, according to Figure 9, acts as the system is overtrained. The generated power, the blue line tracks the network load but with a lot of oscillations and damping during the transition from one to another load level which is also not good for the power plant. Figure 9 shows that in the steady-state position there would be constant oscillations.

According to Figure 10, with 100 hidden layers/neurons, the mechanical power tracks the network load, but at the moment of transition from one to another load level, there are disturbances in the system. At the steady-state position, the response gets stable with a sudden unexpected pick and then the plant remains stable. However, with 100 neurons, the system with implemented NN-based neuro controller has slower properties, response with blue colour, than the response with red colour, when PID has the control role.

Should be mentioned that this is not an adaptive control, but the control law based on the NN with possibilities to enable better dynamics behaviour, and faster and more efficient plant performance. But since the training data set is not prepared adequately, the plant response would not have any improvements. This shows that every training data set could not bring the system into the desired condition no matter the training period or other system properties.

V CONCLUSION

A mathematical representation of non-linear HPP and the control law of the NN-based neuro controller has been made, and the implementation of the NN-based neuro controller with its control law has been successfully exhibited.

According to the simulations, at black start mode conclusion is made that the frequency i.e. the angular velocity of the turbine at island operational mode can be successfully controlled when new technologies, as a controller based on NN, will be implemented in the system.

The NN training data set configuration is a crucial feature in system stability and dynamic behaviour. Inappropriate training data sets can easily destabilize the plant properties.

The benefits when NARMA-L2 is implemented in the system control when the hydro turbine model is optimal are small but evident. A critically damped, fast, and stable system is achieved when an NN-based neuro controller is in control of the HPP, meaning a more efficient operation process.

LITERATURA/REFERENCES

[1] Working Group Prime Mover and Energy Supply, Hydraulic turbine and turbine control models for system dynamic studies, IEEE Transactions on Power Systems, Vol. 7, No. 1, pp. 167–179, Feb. 1992. https://doi.org/10.1109/59.141700

[2] Babunski, D., Tuneski, A. Simulation of Control Plant Dynamic Characteristics in the Case of Hydraulic Turbine, IFAC Proceedings Volumes, Vol. 37, No. 19, pp. 301–305, 2004, https://doi.org/10.1016/S1474-6670(17)30701-2

[3] Saxena, S., Hote, Y.V. PI Controller Based Load Frequency Control Approach for Single-Area Power System Having Communication Delay, IFAC-PapersOnLine, Vol. 51, No. 4, pp. 622–626, 2018, https://doi.org/10.1016/j.ifacol.2018.06.165

[4] Strah, B., Kuljaca, O., Vukic, Z. Speed and Active Power Control of Hydro Turbine Unit, IEEE Transactions on Energy Conversion, Vol. 20, No. 2, pp. 424–434, 2005. https://doi.org/10.1109/TEC.2004.837278

[5] Zoby, M. R. G., Yanagihara, J.I. Analysis of the primary control system of a hydropower plant in isolated model, Journal of the Brazilian Society of Mechanical Sciences and Engineering, Vol. 31, No. 1, 2009. https://doi.org/10.1590/S1678-58782009000100002

[6] Babunski, D., Tuneski, A., Zaev, E. Simulation of load rejection on a nonlinear Hydro Power Plant model with mixed mode nonlinear controller, in Proc. *Mediterranean Conference on Embedded Computing (MECO)*, Bar, Montenegro, pp. 275–278, 19-21 June 2012. https://ieeexplore.ieee.org/document/6268977 [pristupljeno 02.04.2022]

[7] 125-2007 - IEEE Recommended Practice for Preparation of Equipment Specifications for Speed-Governing of Hydraulic Turbines Intended to Drive Electric Generators, in: *Revision of IEEE Std 125-1988*, pp. 1–55. https://doi.org/10.1109/IEEESTD.2007.4383553

[8] Hammid, A.T., Hojabri, M., Sulaiman, M., Abdalla, A., Kadhim, A.A. Load Frequency Control for Hydropower Plants using PID Controller, Journal of Telecommunication, Electronic and Computer Engineering, Vol. 8, No. 10, pp. 47–51, 2016.

[9] Moon, Y-H., Ryu, H-S., Lee, J-G., Kim, S. Power system load frequency control using noise-tolerable PID feedback, in Proc. *ISIE 2001. 2001 IEEE International Symposium on Industrial Electronics Proceedings (Cat. No.01TH8570)*, Pusan, South Korea, pp. 1714–1718, 12-16 June 2001. https://doi.org/10.1109/ISIE.2001.931967

[10] Khamari, D., Sahu, R.K., Gorripotu, T.S., Panda, S. Automatic generation control of power system in deregulated environment using hybrid TLBO and pattern search technique, Ain Shams Engineering Journal, Vol. 11, No. 3, pp. 553–573, 2020, https://doi.org/10.1016/j.asej.2019.10.012

[11] Kawkabani, B., Nicolet, C., Schwery, A. Modeling and control of large salient-pole synchronous hydro generators and stability issues in isolated production mode, in Proc. *2013 IEEE Workshop on Electrical Machines Design, Control and Diagnosis (WEMDCD)*, Modena, Italy, pp. 148–157, 11. March 2013. https://doi.org/10.1109/WEMDCD.2013.6525175

[12] Singh, O., Verma, A. Frequency Control for Stand-Alone Hydro Power Plants using Ant Colony Optimization, in Proc. *2020 IEEE International Conference on Advent Trends in Multidisciplinary Research and Innovation (ICATMRI)*, Buldhana, India, pp. 1-6, 30. December 2020. https://doi.org/10.1109/ICATMRI51801.2020.9398417

[13] Orelind, G., Wozniak, L., Medanic, J., Whittemore, T. Optimal PID gain schedule for hydrogenerators-design and application, IEEE Transactions on Energy Conversion, Vol. 4, No. 3, pp. 300–307, 1989. https://doi.org/10.1109/60.43228

[14] Babunski, D. *Optimal control systems in hydro power plants Faculty of Mechanical Engineering* , Ss. “Cyril and Methodius” University, Skopje, 2012.

[15] Asoh, D. A., Mbinkar, E. N., Moutlen, A.N. Load Frequency Control of Small Hydropower Plants Using One-Input Fuzzy PI Controller with Linear and Non-Linear Plant Model, Smart Grid and Renewable Energy, Vol. 13, No. 1, pp. 1-16, 2022. https://doi.org/10.4236/sgre.2022.131001

[16] Çam, E. Application of fuzzy logic for load frequency control of hydroelectrical power plants, Energy Convers Manag, Vol. 48, No. 4, pp. 1281-1288, 2007. https://doi.org/10.1016/j.enconman.2006.09.026

[17] Kayalvizhi, S., Vinod Kumar, D.M. Load Frequency Control of an Isolated Micro Grid Using Fuzzy Adaptive Model Predictive Control, IEEE Access, Vol. 5, pp. 16241-16251, 2017. https://doi.org/10.1109/ACCESS.2017.2735545

[18] Angalaeswari, S., Swathika, O.V.G., Ananthakrishnan, V., Daya, J.L.F., Jamuna, K. Efficient Power Management of Grid operated MicroGrid Using Fuzzy Logic Controller (FLC), Energy Procedia, Vol. 117, pp. 268–274, 2017. https://doi.org/10.1016/j.egypro.2017.05.131

[19] Mahmoud, M., Dutton, K., Denman, M. Design and simulation of a nonlinear fuzzy controller for a hydropower plant, Electric Power Systems Research, Vol. 73, No. 2, pp. 87–99, 2005. https://doi.org/10.1016/j.epsr.2004.05.006

[20] Kareem, H.J. Control on Hydropower Plant using Fuzzy Neural Network based on Right-Angle Triangle Membership, Journal of Advanced Research in Dynamical and Control Systems, Vol. 10, No. 10, pp. 1239-1250, 2018.

[21] Syan, S., Biswal, G.R, Frequency control of an isolated hydro power plant using artificial intelligence, in Proc. *2015 IEEE Workshop on Computational Intelligence: Theories, Applications and Future Directions (WCI)*, Kanpur, India, pp. 1-5, 14-17. December 2015. https://doi.org/10.1109/WCI.2015.7495537

[22] Barzola-Monteses, J., Gómez-Romero, J., Espinoza-Andaluz, M., Fajardo, W. Hydropower production prediction using artificial neural networks: an

Ecuadorian application case, Neural Computing and Applications, Vol. 34, No. 16, pp. 13253-13266, 2022. https://doi.org/10.1007/s00521-021-06746-5

[23] Elgammal, A., Boodoo, C. Optimal Frequency stability Control Strategy for a Grid-Connected Wind/PV/FC/BESS Coordinated with Hydroelectric Power Plant Storage Energy System Using Variable Structure Control, European Journal of Energy Research, Vol. 1, No. 4, pp. 1-7, 2021. https://doi.org/10.24018/ejenergy.2021.1.4.17

[24] Gezer, D., Taşcıoğlu, Y., Çelebioğlu, K. Frequency Containment Control of Hydropower Plants Using Different Adaptive Methods, Energies, Vol. 14, No. 8, pp. 2082, 2021. https://doi.org/10.3390/en14082082

[25] Ma, J., Xu, S., Li, Y., Chu, Y., Zhang, Z. Neural networks-based adaptive output feedback control for a class of uncertain nonlinear systems with input delay and disturbances, Journal of the Franklin Institute, Vol. 355, No. 13, pp. 5503-5519, 2018. https://doi.org/10.1016/j.jfranklin.2018.05.045

[26] The MathWorks, *Design NARMA-L2 Neural Controller in Simulink*, https://www.mathworks.com/help/deeplearning/ug/design-narma-l2-neural-controller-in-simulink.html

[27] Lv, C., Xing, Y., Yhang J., Na, X. Levenberg–Marquardt Backpropagation Training of Multilayer Neural Networks for State Estimation of a Safety-Critical Cyber-Physical System, IEEE Trans Industr Inform, Vol. 14, No. 8, pp. 3436-3446, 2018. https://doi.org/10.1109/TII.2017.2777460

[28] Sharma, S., Sharma, S., Athaiya, A. Activation functions in neural networks, International Journal of Engineering Applied Sciences and Technology, Vol. 04, No. 12, pp. 310-316, 2020. https://doi.org/10.33564/IJEAST.2020.v04i12.054

[29] Koleva, R., Lazarevska, A.M., Babunski, D. Artificial Neural Network-based Neurocontroller for Hydropower Plant Control, TEM Journal, Vol.11, No.2, pp. 506-512, 2022. https://doi.org/10.18421/TEM112-02

[30] Koleva, R., Babunski, D., Zaev, E. System dynamics behaviour based on the hyperparameters impact in hydropower plant control, in Proc. *SimTerm*, Niš, Serbia, 18-21. October 2022.

AUTORI/AUTHORS

Radmila Koleva - assistant, Saints Cyril and Methodius University in Skopje, radmila.koleva@mf.edu.mk, ORCID 0000-0001-9089-2214
Darko Babunski - professor, Saints Cyril and Methodius University in Skopje, darko.babunski@mf.edu.mk, ORCID 0000-0003-2133-4301
Emil Zaev - associate professor, Saints Cyril and Methodius University in Skopje, emil.zaev@mf.edu.mk, ORCID 0000-0003-4041-8789
Atanasko Tuneski - professor, Saints Cyril and Methodius University in Skopje, atanasko.tuneski@mf.edu.mk, ORCID 0000-0002-0719-0543
Laze Trajkovski - professor, Saints Cyril and Methodius University in Skopje, laze.trajkovski@mf.edu.mk