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Identification of the Conduit Water Starting Time Constant in Hydropower Plants Using LSTM and MLP Machine Learning Algorithms

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Abstract: The accurate determination of the conduit water starting time constant (T_w) is critical for optimizing hydro turbine performance and dynamic control in hydropower plants. Instead of relying on conventional calculation methods, machine learning (ML) techniques, specifically long short-term memory (LSTM) networks and multilayer perceptron (MLP) models, have been employed to identify T_w. The dataset used for model training and validation comprises real operational data collected from two hydropower plants. The effectiveness of both algorithms in T_w identification has been evaluated through simulation, with Python serving as the primary programming environment. The findings indicate that, despite its more complex architecture, LSTM does not necessarily yield superior results. In contrast, MLP, as a relatively simpler model, demonstrates greater accuracy in estimating T_w, suggesting that intricate network structures are not always required for precise identification. Additionally, an optimization function (F_{opt}) has been utilized to assess the reliability of the identified T_w values by comparing them with actual hydro turbine responses. The results underscore the practicality of MLP in hydropower system modeling, providing a computationally efficient alternative for conduit water starting time constant identification. These insights contribute to improving real-time turbine control and enhancing the efficiency of hydropower generation.

Keywords: Time constant identification; Hydropower systems; Machine learning (ML); Long short-term memory (LSTM); Multilayer perceptron (MLP); Optimization function

1 Introduction

In engineering and physics, system identification (SI) is a crucial technique for developing accurate models and control strategies [1]. Based on experimental data, SI involves finding out the mathematical model of a dynamics system. In this paper, the available dataset is for the hydro power plant control system, especially for parameters such as guide vane blade position, active mechanical power, and angular velocity. These data are further used for the identification of the water starting time constant of the conduit – T_w.

The crucial parameter when modeling the hydro power plant is T_w, especially in the Francis turbine and other reaction turbines. This parameter is related to the water inertia in the penstocks and the turbine system. It is important because it influences the plant's dynamic response to load changes, meaning the position of the guide vane blade. Usually, large values for the T_w mean slower response due to the delayed action of the water flow, but smaller values for the T_w mean faster adjustment and stabilization in a steady-state position but increase the possibility of an easy control [2]. Sari et al. [3] examined various turbine technologies and their application on how the initiation of the water flow impacts the system efficiency of the penstock. If penstock dynamics of a hydropower plant are compared, Janevska et al. [4] represented the importance of the T_w. If the T_w is large value, it especially means that the PID controller will require more aggressive tunning. Other control strategies, instead of PID, according to the study conducted by Zoby and Yanagihara [5], could be PI, or combination of PI-PD. Also, in the study conducted by Gangi [6], in a small hydropower plant, where the T_w=0.25 which is a small value makes turbines respond quickly but there are possibilities of overshoots and oscillation. As represented, the control type of the governor is PID. Other than the PID, another control strategies such presented in references [7, 8], involving ML based control that can adapt to different T_w values based on past experiences and responses. As reported by Khaliel and Karrar [9], the importance of the optimal hydropower plant operation through PID tuning for the governor system controlling the guide vane mechanism is presented. Ensuring grit stability and efficiency frequency control, means accurate determination of the T_w constant. It is also important coefficient when it comes to the prediction of the system's behavior during the transient conditions and design of the control strategies. Some standard mandates that T_w must be less or equal to 4 seconds to align with IEC 60308 and IEC 61362, ensuring compatibility with turbine-generator inertia, otherwise some advanced control strategies must be implying design modification, according to the technical guideline [10]. Pérez-Díaz et al. [11] presented another way of determining the T_w constant. In this paper it is calculated by adding two additional elements, tail-race tunnel and penstock. The control type in that case was PI controller.

Saarinen et al. [12] presented standard methods, the prediction-error minimization and MATLAB system identification toolbox technique for system identification of the T_w in various size hydropower plant. System identified are represented with a linear mathematical differential equation. Some hybrid deep learning models such as Temporal Convolutional Networks (TCN), residual LSTM, and Gated Recurrent Unit (GRU) as demonstrated by Ma et al. [13] are used for prediction the operation status of the hydropower plant units, also Wang et al. [14] presented adaptive learning model, recursive least squares (RLS) for modeling the hydropower turbine which is directly connected to T_w identification by determining the state-space and the transfer function model. In this paper, LSTM as a ML method has been used because it successfully captures and processes the time-series data [15]. MLP as a ML method according to the research by Hagan et al. [16], is used for control systems analysis. As reported by Xiong et al. [17], LSTM is presented as a method for turbine operation using time series data. MLP and LSTM methods are selected to be used since both have completely different computational methods.

2 Mathematical Modeling of a Hydro Power Plant

The hydropower plant represented in Figure 1 consists of a few subsystems such as hydraulic, electrical, and control subsystem. The control subsystem in this case is PID.

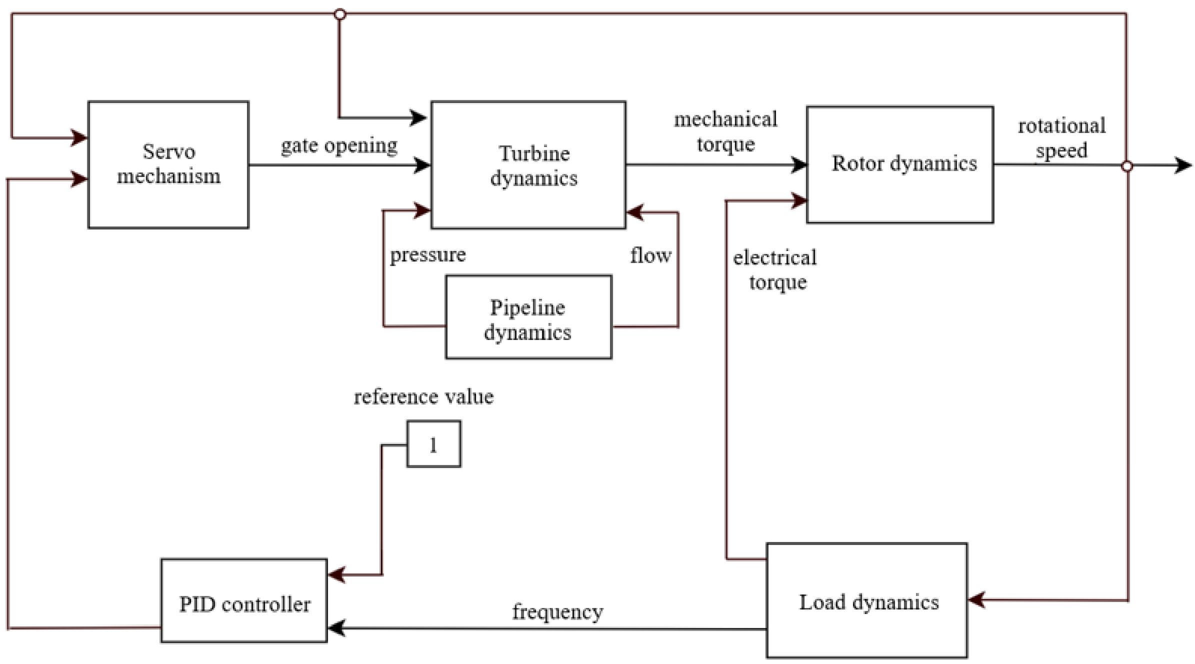

Figure 1. Block diagram of hydropower plant

Based on the analysis presented by Babunski [18], hydro power plant model that includes the guide vane mechanism, the hydraulic turbine, and the electrical subsystem is mathematically represented in this paper according to the equation below.

Eq. (1) gives the water starting time constant of the conduit T_w, and its value depends on several parameters, the length of the pipeline L, the flow through the turbine at a fully open guide vane mechanism q_{base}, the pressure h_{base}, the cross-section of the pipeline A, and the acceleration due to gravity g. Eq. (2) represents the relationship between the generated mechanical power ΔP_m and the guide vane position Δc, which represents the linear model of a hydro turbine. Theoretically, the T_w is defined as the time required for the flow in the pipeline to go from zero q_{base} to when the pressure in front of the turbine will reach a value h_{base}.

$$T_w = \frac{L \cdot q_{base}}{A \cdot g \cdot h_{base}} \tag{1}$$

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

The equation for the turbine mechanical power is represented by Eq. (3), where h_t is the dimensionless unit pressure, q_t is the dimensionless unit flow, q_{nl} is the flow through a turbine when there is no load, A_t is the amplifier factor, D is the turbine damping coefficient, and $\Delta\omega$ is the difference between the reference and actual angular velocity of the hydraulic turbine generator.

$$P_m = A_t h_t \left(q_t - q_{nl}\right) - Dc\Delta\omega \tag{3}$$

The electrical subsystem consists of a power system, a generator, the power transferred between them and the changes in the load on the network. It is represented by Eqs. (4)-(6).

$$\dot{\omega} = \frac{1}{T_m \omega} \left(P_m - P_e\right) \tag{4}$$

$$P_e = P_l + D\left(\omega - 1\right) \tag{5}$$

$$P_m - P_e = T_m \cdot s + D_f \tag{6}$$

In these equations, ω is the angular velocity at which the generator rotates, P_l is the load on the network, i.e., the disturbance, P_e is the generated electrical energy, T_m is the mechanical time constant whose value depends on the number of generator revolutions per minute, but is calculated according to the equations defined in reference [19]. Also T_m (mechanical time constant) is represented in Eq. (7), where $G \cdot D^2$ is the moment of inertia, n_r is the number of revolutions per minute, and P_r is the generated power in megawatts (MW).

$$T_m = \frac{2.74 \cdot G \cdot D^2 (10^{-3} n_r)}{P_r} \tag{7}$$

The model for the servo mechanism is represented in formula (8) where T_A is the time constant of the servo mechanism.

$$\frac{1}{\left(1 + s \cdot T_A\right)^2} \tag{8}$$

Because in this paper, two real hydropower plants are going to be of research interest, in Table 1 some details about them are represented.

Table 1. Hydro power plant parameters value

Parameters	**Mark**	**Plant 1**	**Plant 2**	**Unit**
Water starting time constant of the conduit	T_w	1.434	0.479	s
Generator mechanical time constant	T_m	8.3	5.420142	s
Proportional constant	K_p	2	3.4	/
Integral constant	K_i	0.465	0.465	/
Derivative constant	K_d	1.06	3.6	/

The optimization function is also important because it quantifies the accuracy of the turbine model, particularly when identifying the T_w. The more minimal the value for F_{opt}, the more the T_w is optimal, which means that the system's dynamics is better represented. F_{opt} is represented with Eq. (9). In this equation, ω is the angular velocity at which the generator rotates and the ω_{ref} is the referent angular velocity, c guide vane position and c_d is requested guide vane position. The weighting coefficients k1 and k2 determine the influence of the corresponding terms in F_{opt}. The influence of the speed error is greater because the main objective of the speed controller is speed regulation, i.e., ensuring a stable output frequency of the generated energy, which is why the weighting coefficient k1=0.7, i.e., the speed error has an influence of 70%, while the weighting coefficient k2=0.3, which means that the influence of the second term is 30%.

$$F_{\text{opt}} = 0.7 \cdot \int_0^t |\omega_{ref} - \omega| \, dt + 0.3 \cdot \int_0^t |c_d - c| \, dt \tag{9}$$

3 LSTM and MLP Network Modeling and Identification

In this paper, LSTM and MLP have been used as ML methods for T_w identification. The general structure of the LSTM method is represented in Figure 2 and its equations of the signal flow are represented by Deva Sarma et al. [20].

Figure 3 from the study of Salim et al. [21] shows the MLP network architecture and its mathematical representation.

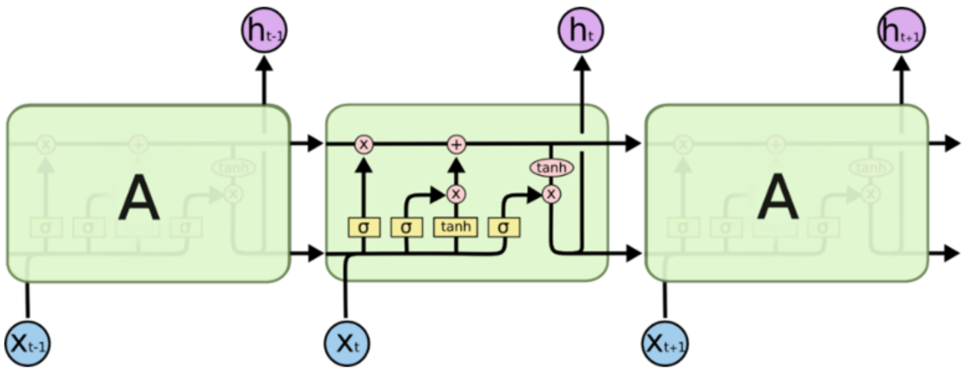

Figure 2. LSTME network architecture [14]

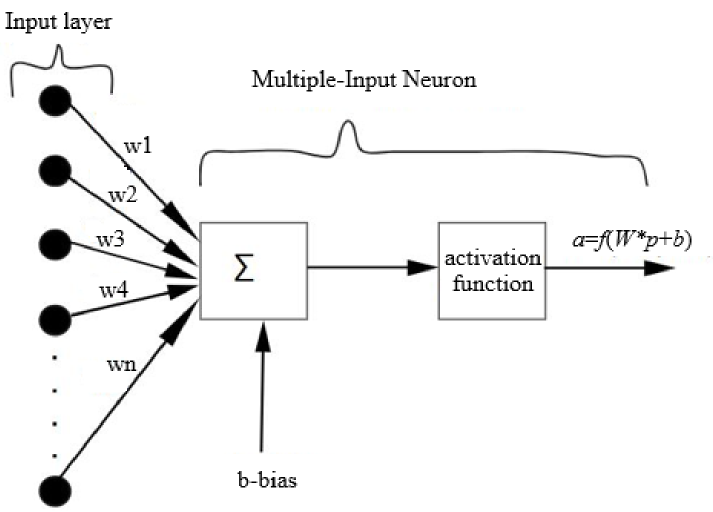

Figure 3. MLP network architecture [21]

Because Python has been used as a programing language, the algorithm for T_w identification is represented through the following order:

1. Definition of the required libraries to perform the calculation.
2. Definition of the inputs (input data set).
3. Definition of the target outputs (target output data set).
4. Definition of the type of ANN with which the data will be processed.
5. Definition of the number of hidden layers and the number of neurons in each layer.
6. Definition of the activation function (AF) for each layer separately.
7. Definition of the type of optimizer.
8. Making a percentage distribution of the data for validation, testing and training.
9. Training the model.
10. Defining the upper and lower bounds of the value of T_w that needs to be obtained.
11. The generated values for the time constant of water are extracted.
12. The obtained values are placed in a simulation model.
13. The obtained outputs are compared with the outputs of the model before applying ML by applying MLP and LSTM.

Because there are going to be represented results from two power plants, the input data set for Plant 1 is the position of the guide vane blades and the output is generated power from Power Plant 1, and the dataset for the Plant 2 is active mechanical power from the second power plant (data taken from supervisory control and data acquisition (SCADA) system) and active mechanical power of the first, referent power plant. The structure of the network for both LSTM and MLP networks used for T_w identification are represented in Figure 4 and Figure 5.

According to Figure 4, the network architecture has one input layer; next is the LSTM architecture, and then is the MLP with three hidden layers. The first one is with 258 nodes, the second one is with 128 nodes and the third one is with 24 nodes and an output layer. The AF are sigmoid, sigmoid and tanh; the learning rate is 0.01, and ADAM is used as an optimizer.

According to Figure 5, the network architecture has one input layer, 2 hidden layers (the first one has 10 nodes and the second one has 4 nodes) and an output layer. The AF is tanh for both hidden layers, and ADAM is used as an optimizer.

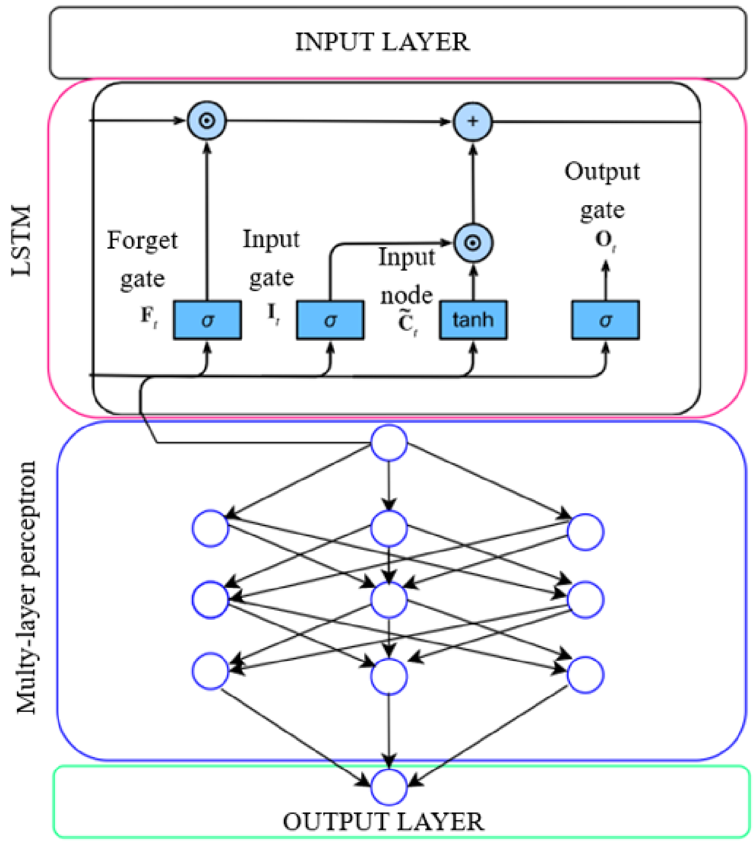

Figure 4. LSTM network architecture

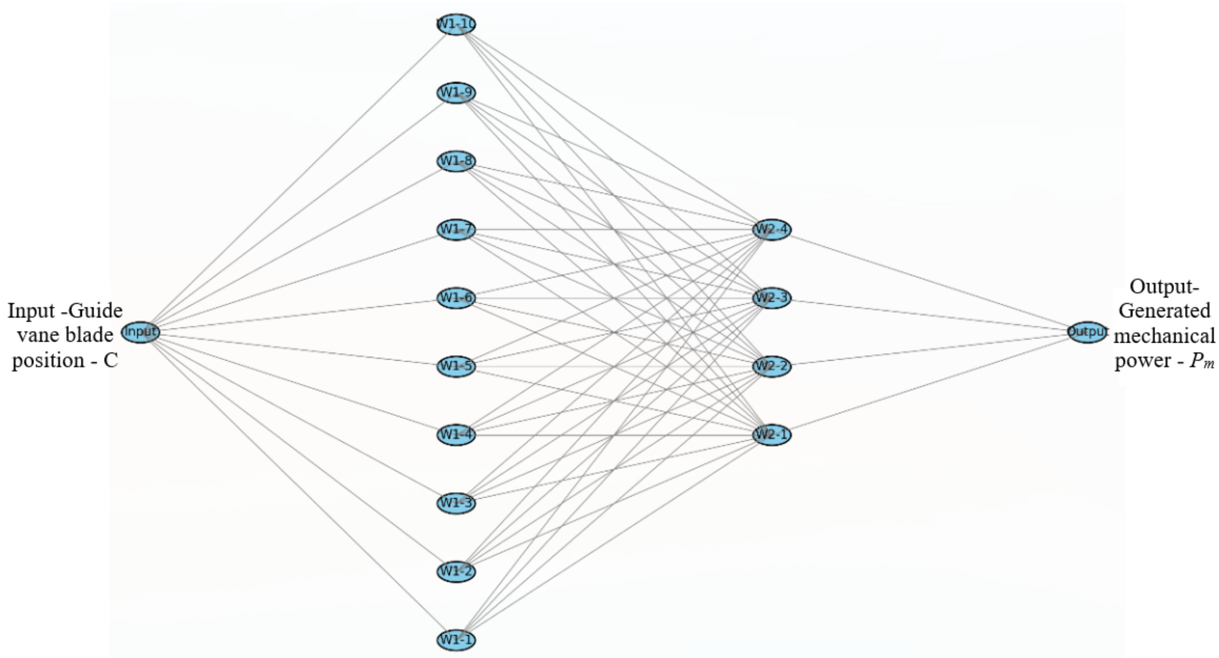

Figure 5. MLP network structure

4 Results and Discussion

According to Table 1, T_w=1.434 (s) for Power Plant 1, while for Power Plant 2, T_w=0.479 (s). The obtained values for T_w by using MLP and LSTM are defined in Table 2 if the available dataset is a guide vane blade position and active mechanical power.

Another T_w identification is done by using a different dataset. It is a combination of a dataset of mechanical power inputs whose values (static parameters) are taken from the SCADA system of the hydro power plant itself, while the output dataset is experimental measurements made by the referent plant, Power Plant 1 (dynamic parameters). The reason for such a dataset is that when the identification for the T_w coefficient is in process, the dynamics of Power Plant 2 are to be approximted to the dynamics of Power Plant 1 as a fast response and stable system. The network structure remains the same as in Figure 5 and the results are represented in Table 3.

Table 2. Identified T_w coefficients and its F_{opt} for the data set of guide vane blade position and active mechanical power (Power plant 1)

	Guide Vane Blade Position and Active Mechanical Power	**RMSE (%)**	F_{opt}
MLP	0.6322 (nonlinear model of the hydro turbine)	0.4%	0.02858 0.02586
	0.76774798 (nonlinear model of the hydro turbine)	0.4%	0.02563 0.02564
	0.8791 (nonlinear model of the hydro turbine)	0.4%	0.02552 0.02553
	0.1571 (nonlinear model of the hydro turbine)	0.3%	0.02622 0.02626
LSTM	0.5822 (nonlinear model of the hydro turbine)	0.7%	0.02221 0.02443
	0.93149 (nonlinear model of the hydro turbine)	0.9%	0.02187 0.02409
	0.2753 (linear model of the hydro turbine)	0.07%	0.00355 0.00357

Table 3. Identified T_w coefficient and its F_{opt} for the data set of active mechanical power form SCADA and active mechanical power from the referent power plant (Power plant 2)

	Active Mechanical Power from Second Power Plant (Data Taken from SCADA) and Active Mechanical Power of the First, Referent Power Plant	RMSE (%)	F_{opt}
MLP	0.195 (nonlinear model of the hydro turbine)	0.3%	0.02644 0.02649
	0.52615 (nonlinear model of the hydro turbine)	0.3%	0.026107 0.026123
	0.60458 (nonlinear model of the hydro turbine)	8%	0.49587 0.02617
LSTM	0.829 (nonlinear model of the hydro turbine)	76%	0.00238 0.00457
	0.8602 (nonlinear model of the hydro turbine)	0.9%	0.02195 0.02417
	0.87875963 (nonlinear model of the hydro turbine)	0.9%	0.02193 0.024149

If the values obtained are analyzed for root-mean squared error (RMSE) and for the F_{opt}, the results for points 1 to 4 of Table 2, by applying the MLP method, the datasets for the guide vane blade position and the active mechanical power are combined; it could be noted that the closer the predicted value of T_w is to the real one, the lower the RMSE is. As the value of T_w increases, the RMSE increases, which is expected because it moves away from the value of the already existing T_w. At the same time, if the F_{opt} is analyzed, it could be noted that the difference appears in the fourth or fifth decimal place if the F_{opt} value is compared for the existing T_w (first value) and the ML predicted one (second value), which means that the predicted T_w values are close to the real ones and identify the new system with the requested dynamics.

If the values of T_w obtained by ML are analyzed (values for no. 5 do 13), it could be noted that when applying the MLP method, obtained results are also closer to the real one, and are with a lower RMSE, compared to the results obtained when applying the LSTM method. MLP as a method is far simpler compared to the LSTM method, therefore, from Table 2 and Table 3, it could be noted that the RMSE value when applying the MLP method as a simpler method is smaller compared to the LSTM method. That is expected because data processing does not require large computational power where the information moves in one direction without considering the influence of previous information. It could be concluded that it is not always necessary to use the strongest ML method or a complicated NN (neural network) consisting of more than one hidden layer or a huge number of neurons because it does not always guarantee the calculation of the best solution to the given problem.

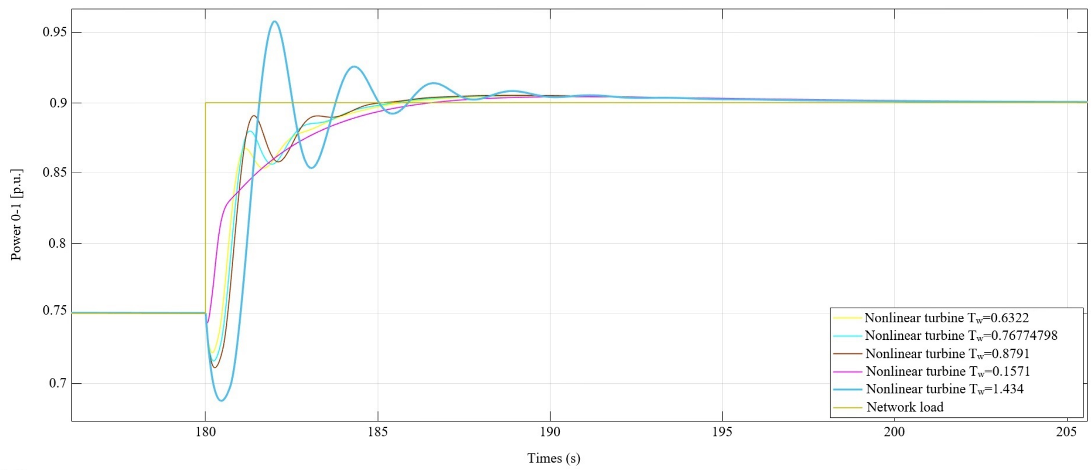

Figure 6. MLP for T_w identification - T_w=0.6322, T_w=0.76774798, T_w=0.8791, T_w=0.1571 obtained with ML (Power Plant 1)

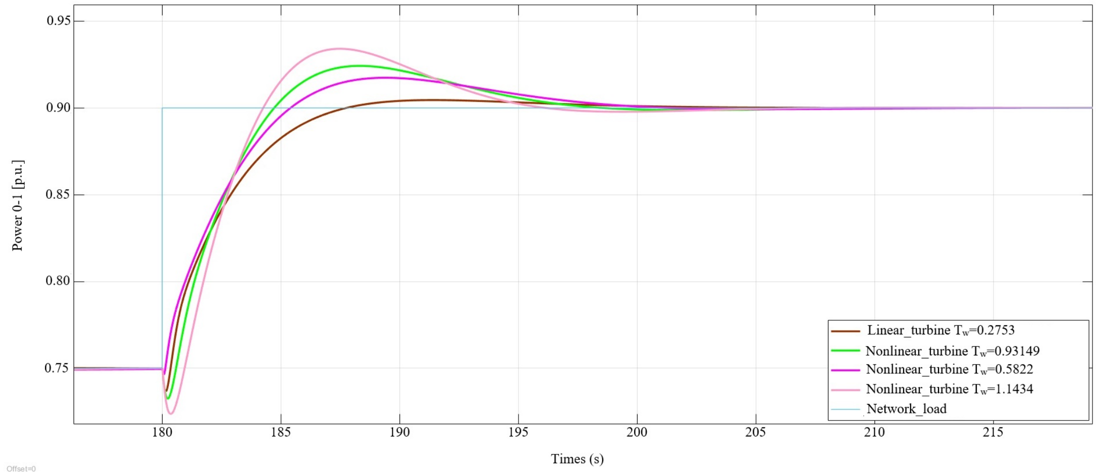

Figure 7. LSTM for T_w identification - T_w=0.5822, T_w=0.93149, T_w=0.2753obtained with ML (Power Plant 1)

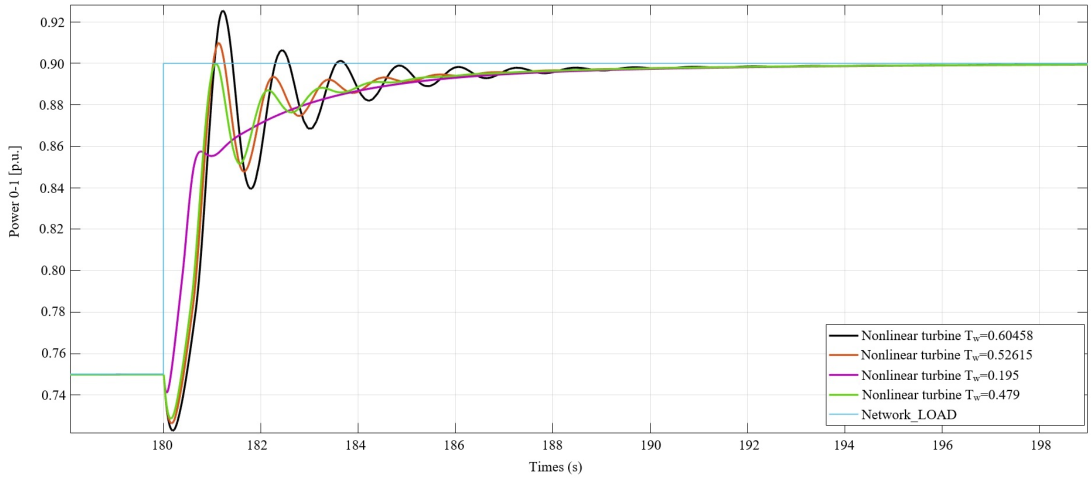

Figure 8. MLP for T_w identification - T_w=0.195, T_w=0.52615, T_w=0.60458 obtained with ML (Power Plant 2)

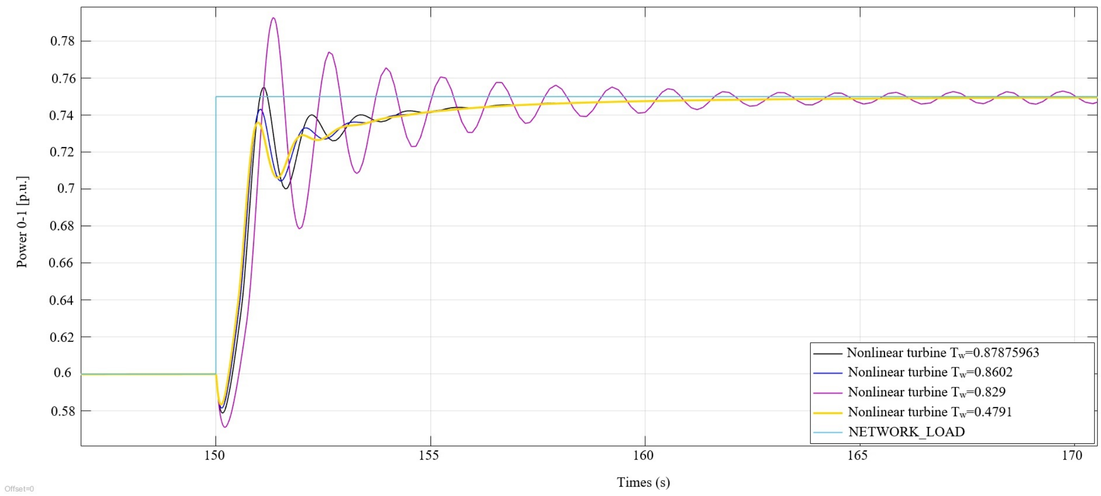

Figure 9. LSTM for T_w identification - T_w=0.829, T_w=8602, T_w=87875963 obtained by applying ML (Power Plant 2)

In Figure 6, a summary diagram is presented for different values of T_w obtained by applying the MLP method for the first real hydropower facility where the real value of T_w=1.1434 and the green line represents the grid load. According to the simulation results for the generated mechanical power, angular velocity, RMSE and F_{opt}, it can be noted that if the value of T_w as part of the hydraulic subsystem is 0.175, the lowest value of RMSE=0.3% is obtained, but the value of F_{opt} is also in the middle between the highest and lowest. If the responses for the turbine power are analyzed, it can be said that for T_w=0.157, a response without oscillations is provided, and the speed of reaching a steady state is identical with the remaining values of T_w. According to the results, in the design process, hydro turbines with T_w=0.8791 should be taken into consideration.

If responses from Figure 7 are analyzed, the hydraulic subsystem with T_w=0.5822 is considered, the generated mechanical power at a steady state approaches the requested value (in this case, the step function that represents the network load – blue line) will be slower, but with smaller dumping compared to the real value, T_w=1.434, and also with the smallest F_{opt}.

The responses shown in Figure 8 refer to Power Plant 2, where the same ML methods, MLP and LSTM, have been applied. For Power Plant 2, the real T_w=0.479. Figure 8 shows the responses from the MLP method. When analyzing, it could be noted that for T_w=0.195, a response with the smallest error is obtained, without oscillations when approaching, and at the same time for stabilizing the system in a steady state compared to the responses with other values of T_w. For T_w=0.60458, where the RMSE is as much as 8% and is the largest of the given values, it gives a response with the largest oscillations and the same time for achieving the steady state as for all other values of T_w.

If the results in Figure 9 are analyzed, for all new T_w values, similar responses are obtained, from which T_w=0.8602 or T_w=0.87875963 can be chosen as the most appropriate because they generate a similar response, but slightly faster in approaching the steady state, and the time for settling the oscillations is similar to that of the existing value for T_w. From Table 3, it could be noted that for T_w=0.829, RMSE=76%, which means that the response constantly oscillates around a steady state with a tendency for the oscillations to decrease, but after a very long period of time.

If all identified values for T_w are analyzed, it could be noted that the values obtained by applying MLP and LSTM are in the range of the real value, which is 0.479. This is also a good example from which we can say that not always the most powerful method and network will give the best results, sometimes a simpler method such as MLP is quite enough to obtain satisfactory results that will introduce improved dynamic characteristics of the control system.

According to the results in Figure 6, Figure 7, Figure 8 and Figure 9, could be noted that reverse power of the active power signal is still present after T_w coefficient identification which means that using ML algorithm does not idealize the signal or neglect some physical conditions, because in some cases, ML can try to eliminate that part of the signal making it to look like it does not exist, which is not correct. According to references [8, 18], the reverse power should exist when analyzing the mechanical power and is experimentally verified.

5 Conclusions

This paper represented the importance of two ML algorithms, MLP and LSTM, in the SI purpose. These two were chosen because they are processing the signal/dataset in a completely different way. The model that has been worked on was two different hydro power plants. Because the T_w – water starting time constant of the conduit is an important parameter for the hydro turbine definition, instead of its calculation, based on the available dataset, learning rate value, and optimizer type, the identification of the T_w has been done by using MLP and LSTM.

According to the results represented in the figures above, it could be concluded that ML can do SI using different algorithms, meaning that its algorithms can be used in the systems design process. It should be noted that not every time the complicated and big network will give better results compared to a simpler network. In this paper, MLP has appeared as an algorithm whose capacities are enough for obtaining results that introduce improved dynamics of the controlled system. Another important part is that the results obtained by using the ML algorithm represent the signal with all its characteristics, such as reverse power, which means that the represented signals from the simulation could be compared with the measured and experimentally verified results.

Further work is needed for the laboratory measurement results to be represented. Also, to be presented is how ML methods are affecting the system control and how the problem is solved.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflict of interest.

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