FORECASTING RIVER WATER LEVELS INFLUENCED BY HYDROPOWER PLANT DAILY OPERATIONS USING ARTIFICIAL NEURAL NETWORKS

Miloš Milašinović[1], Dušan Marjanović[2], Dušan Prodanović[1], Nikola Milivojević[2]

[1] University of Belgrade, Faculty of Civil Engineering, Bulevar Kralja Aleksandra 73, 11000 Belgrade, Serbia
e-mail: mmilasinovic@grf.bg.ac.rs, dprodanovic@grf.bg.ac.rs
[2] Jaroslav Černi Water Institute, Jaroslava Černog 80, 11226 Pinosava, Belgrade, Serbia
e-mail: dusan.marjanovic@jcerni.rs, nikola.milivojevic@jcerni.rs

Abstract:

Multipurpose water systems are used to deal with multiple objectives related to the usage of water for daily human activities. These activities are often conflicted which creates a challenging water management task. To provide reliable water resources management decision support tools for successful forecasting of hydraulic data (river flows and water levels) are essential. This research presents an approach for forecasting river water levels influenced by hydropower plant operations using artificial neural networks. This approach estimates hourly water level fluctuations at the control location using the water levels and hydropower plant discharge data as input. This tool can be used for fast assessment of different hydropower plant operation plans and help in choosing the optimal one. This water level forecasting procedure is applied and tested on the Iron Gate water system, placed on the Danube River, to deal with multiple objectives in water system management (hydropower production, flood protection, and inland navigation) and shows promising results.

Key words: River water level, Forecasting, Artificial Neural Networks, Danube River, Iron Gate

1. Introduction

Climate change, energy transition and population growth put additional pressure in water resources management. This can lead to making multipurpose water systems too sensitive on different control operations, where inappropriate operation plans by one of the users can significantly reduce other objectives thus reducing the system overall performance. Therefore, operators in charge require reliable tools for fast assessment of the system operations and its influence on system's state. When river water systems are analyzed, water levels at different locations are often used to describe the system's state. Hence, decision support tools must be able to assess water levels affected by different operating scenarios.

Nowadays, forecasting of the river hydraulic data (river flows and water levels) is conducted using data driven techniques, such as artificial neural networks [1]–[4]. These artificial neural networks (ANN) applications show good results in forecasting hydraulic data, but particular focus is placed only on the rivers in natural conditions. To expand the ANN application range, river conditions affected by anthropogenic factors (such as multi-purpose water systems) have to be analyzed. This research focuses on forecasting of river water levels affected by hydropower plant operations. The idea is to analyze the ability of fast estimation of river water levels on a control station using hydropower plant discharge as an input data. The goal of this research is to provide reliable forecasting tool to support optimal hydropower plant (HPP) scheduling [5]–[8]. The proposed method is tested on the transboundary Iron Gate water system, placed on Danube River between Serbia and Romania.

2. Materials and methods

2.1. Case study

Transboundary Iron Gate water system is placed on Danube River between Serbia and Romania. Upstream effects of daily operations (scheduled discharge) have to be evaluated on a specific locations on a daily basis. One of the monitoring locations is Nera control station, placed 132 km upstream from the Iron Gate dam (Fig 1.).

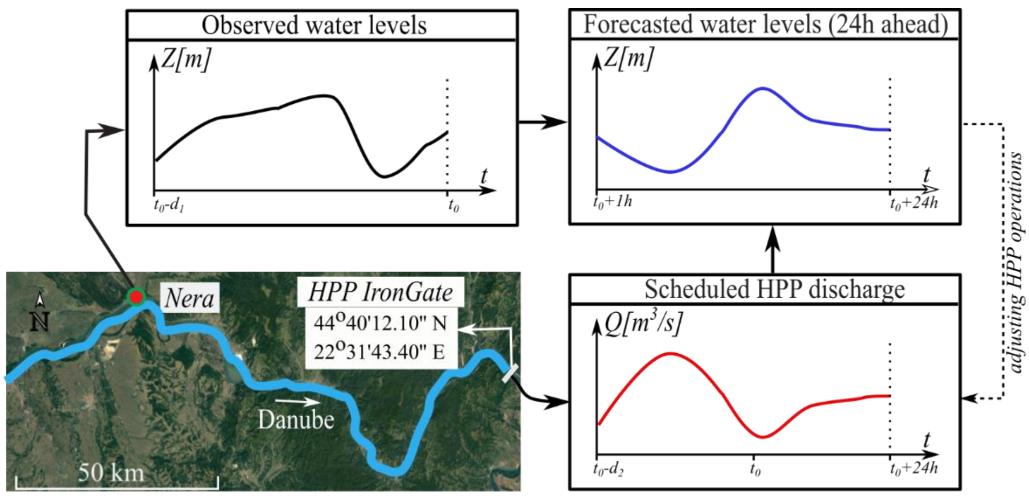

Fig. 1. Iron Gate water system and overview of the water level forecasting methodology

2.2. Artificial neural network for water level forecasting

For 24 hours ahead water level forecasting at Nera station, with hourly timestep, recurrent neural network, in a form of Nonlinear AutoRegressive network with eXogenous inputs (NARX) is used. HPP scheduled discharge is used as an exogeneous input and previous water levels are used as feedback inputs, as presented in the following equation:

$$Z^t = f\left(Z^{t-1}, \ldots, Z^{t-d_1}, Q_{HPP}^{t-1}, \ldots, Q_{HPP}^{t-d_2}\right) \quad (1)$$

In this equation, predicted value of a water level Z^t at time *t* is regressed on given d_1 (feedback delay) past values of water level and d_2 (input delay) past values of an independent (exogeneous) input presented by HPP discharge Q_{HPP}. In this research, d_1 is set to 4h and d_2 is set to 24h.
ANN is created using two hidden layers consisting of 20 neurons each (Fig. 2) in MATLAB programming environment [9]. Number of hidden layers and number of neurons is arbitrary selected to demonstrate the methodology. Effects of different set of ANN parameters should be a analyzed in a separate research. To train the ANN, Levenberg-Marquardt backpropagation algorithm is used, along with hyperbolic tangent sigmoid transfer function and mean squared error (*MSE*) loss function.

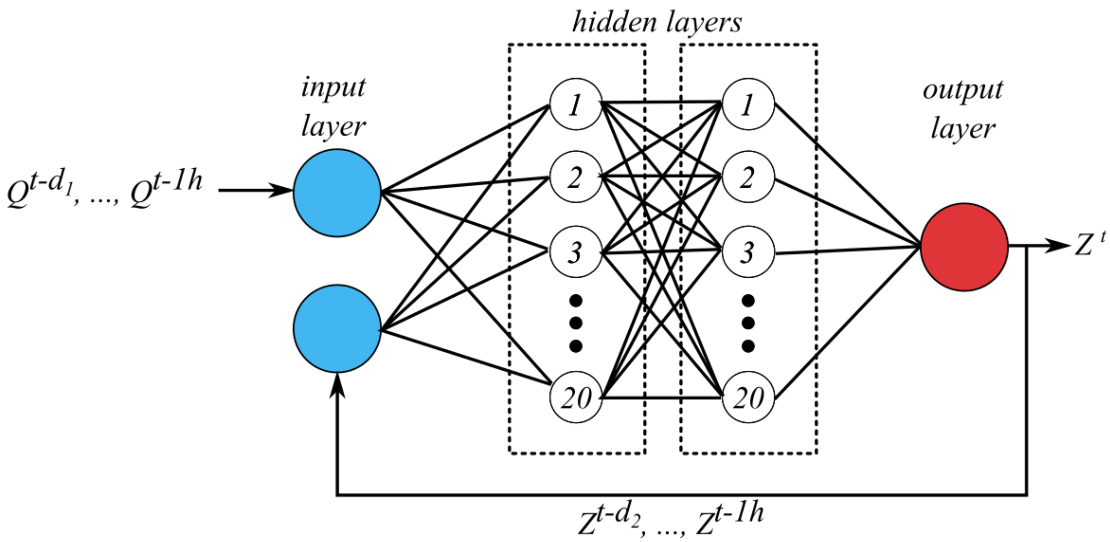

Fig. 2. ANN configuration

3. Results and discussion

HPP discharge and Nera water levels historical data for the period between June 4th 2017 and November 2nd 2019 are used as the training and validation sets. To test the ANN, data for period between November 3rd 2019 and November 19th 2019 is used. The proposed ANN (eq. 1 and Fig. 2) is used to forecast daily water level timeseries for each day in training set, and the results are merged into one timeseries for the entire test period (Fig. 3). Results show that ANN can reproduce trends in water levels fluctuations well according to root mean square error values (*RMSE*). Daily *RMSE* values vary between 1.6 and 9.2 cm, while average *RMSE* value for the entire test period is 4.4 cm. Even though the proposed ANN performed well, for further improvement of the forecasting procedure, thorough analysis of the ANN parameters (input and feedback delays, ANN hyperparameters) has to be conducted along with enriching the training set with more recent data.

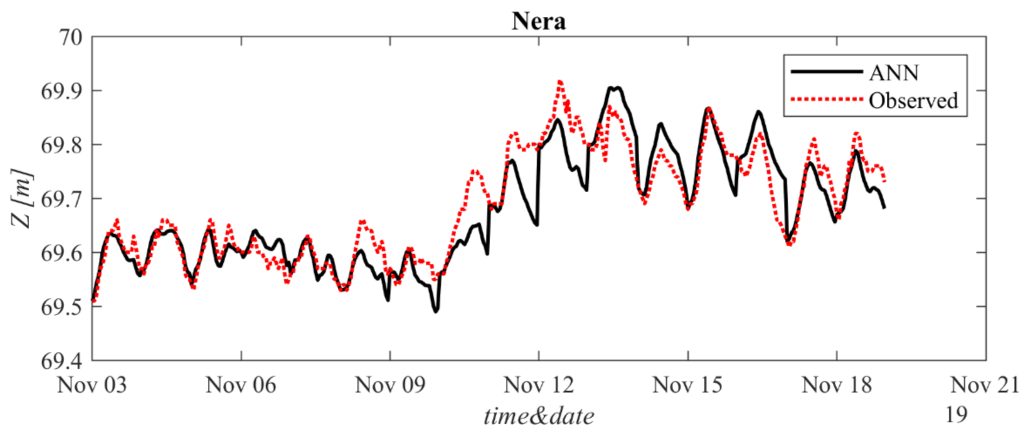

Fig. 3. Water levels at Nera hydrological station for the period November 3rd – November 19th 2019

4. Conclusions

This research presents the potential of using ANNs to forecast river water levels at specific control locations affected by daily hydropower plant operations. Recurrent neural network has been utilized for 24 hours ahead water level forecasting at Nera station, 132 km upstream from the Iron Gate dam. Hydropower plant discharge is used as the independent (exogeneous) input to ANN, along with past values of the water level. This research shows good results considering the *RMSE* indicator, but further investigations have to be conducted to improve forecasts.

Even though water levels across the river domain can be estimated using physically based (hydraulic) models, this approach requires a large set of data considering boundary conditions and model parameters. This approach can produce bad results due to numerous uncertainties in the input data. When there is necessity to assess water levels only at specific control points at the river section, and historical water level and hydropower plant discharge data is available, data driven techniques, such as artificial neural networks (proposed in this research), can be used instead. Finally, data driven techniques shouldn't be considered as a substitute for physically based models. Real world problems, such as complex river water system management, require hydraulic data forecasting on additional locations, where historical data for training data driven models is not available. In that case, physically based models and data driven methods have to be coupled into a hybrid model that can provide reliable forecasting on the entire river domain (data driven forecasting used as a boundary condition for hydraulic model). Proposing the framework for coupling these approaches for river water level forecasting will be a subject of forthcoming research.

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