(04-003) - Deep Learning Model for Forecasting Average Daily Flows in Mazar Reservoir

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Through the application of the H20 library of the R code, a Deep Machine Learning (DML) model was developed to forecast the daily inflows to the Mazar reservoir, based on the levels monitored in the tributaries of the Paute River. Records from 2014 to 2020 were considered, 80% of the records were for training and 20% for model validation. The neural network architecture consists of 7 inputs representing the water levels monitored by 7 hydrological stations located in the different tributaries of the Mazar reservoir, a hidden layer with 50 learning neurons, and an output layer with 1 neuron representing the corresponding forecast. The average percentage error of the predicted flows in contrast to the observed ones was less than 10% according to the randomly selected parameters within the learning network. The importance of having a tool for flow forecasting to regulate hydroelectric generation in the Paute Integral complex with an installed power of 1757 MW, which represents about 30% of the energy generated in the Republic of Ecuador, is highlighted.

Keywords: Neural Networks; Flow Forecasting; Regulation Reservoirs.

Aplicación de modelos de aprendizaje profundo para la predicción de caudales medios diarios en el embalse de Mazar

Mediante la aplicación de la librería H20 del código R, se desarrolló un Modelo de Aprendizaje Profundo (DML por sus siglas en Inglés) que permite pronosticar los caudales de ingreso diario al embalse Mazar, basado en los niveles monitoreados en los tributarios del río Paute. Se consideraron registros desde el año 2014 al 2020, siendo el 80% de los registros para el entrenamiento y un 20% para la validación del modelo. La arquitectura de la red neuronal consta de 7 entradas que representan los niveles de agua monitoreados por 7 estaciones hidrológicas ubicadas en los diferentes tributarios del embalse Mazar, una capa oculta con 50 neuronas de aprendizaje, y una capa de salida con 1 neurona que representa el pronóstico correspondiente. El error porcentual medio de los caudales pronosticados en contraste con los observados fue menor al 10% de acuerdo a los parámetros seleccionados aleatoriamente dentro del aprendizaje de la red. Se destaca la importancia de contar con una herramienta para el pronóstico de caudales, para regular la generación hidroeléctrica en el complejo Paute Integral con una potencia instalada de 1757 MW, que representa alrededor del 30% de la energía que se genera en la república del Ecuador.

Palabras clave: Redes Neuronales; Pronóstico de Caudales; Embalses de Regulación.

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Agradecimientos: Se agradece el financiamiento de la Universidad Católica de Cuenca dentro del Proyecto de Investigación PICODS21-33, gracias a esta colaboración es posible obtener los resultados presentados y continuar con la investigación de los tributarios de la cuenca del río Paute. Un agradecimiento especial a las empresas públicas del Ecuador INAMHI, ETAPA E.P. y CELEC E.P. por la información brindada

para el desarrollo de los proyectos de investigación planteados por la Universidad Católica de Cuenca.

1. Introduction

River flow prediction has always been a challenge in the areas of hydrology. Predicting the flow of a river contributes to decision making at imminent stages during floods and helps to regulate reservoir flows during low flows for water resources management (Chetan & Sudheer, 2006).

The complexity of the interaction of the hydrological cycle, in some cases has led to the application of hydrological forecasting methods using linear regressions, such models measure the relationship between dependent and independent variables of the phenomenon and use flow rates as input data (Weisberg, 2005). However, due to the non-linearity of these phenomena and the additional need to include other hydrological and morphological variables for these models to be more accurate, these models are not always appropriate and it is necessary to use other types of approaches (Bejár-Chacón et al. 2016).

According to Ahmed et al. (2022), the application of artificial intelligence has gained popularity as an efficient tool for the accurate estimation of a wide variety of hydraulic, hydrological and environmental details (Tsai et al., 2015). The main advantages of this approach over conventional prediction techniques are the ability to consider the nonlinearity of hydrological variables and the ability to deal with large amounts of information (Nayak et al., 2005). Some examples of hydrological parameter estimation using ANN are river flow (Hassan et al., 2015), reservoir levels (Shamim et al., 2016), sediment load in irrigation canals (Ahmed et al., 2018), groundwater level prediction (Lee et al, 2019), application in rainfall-runoff models (Van, 2020) and water quality prediction (Loc et al, 2020).

Models based on neural networks have the characteristic of being potentially capable of learning any function. The speed at which they learn is mainly influenced (although there are many other hyperparameters) by the number of observations, the number of neurons and the number of learning iterations (commonly called epoch). Deep learning frameworks provide machine learning schemes without the need for feature engineering, while at the same time they remain quite flexible. Initially developed for supervised tasks, they are nowadays extended to many other settings (Vakalopoulou et al., 2023).

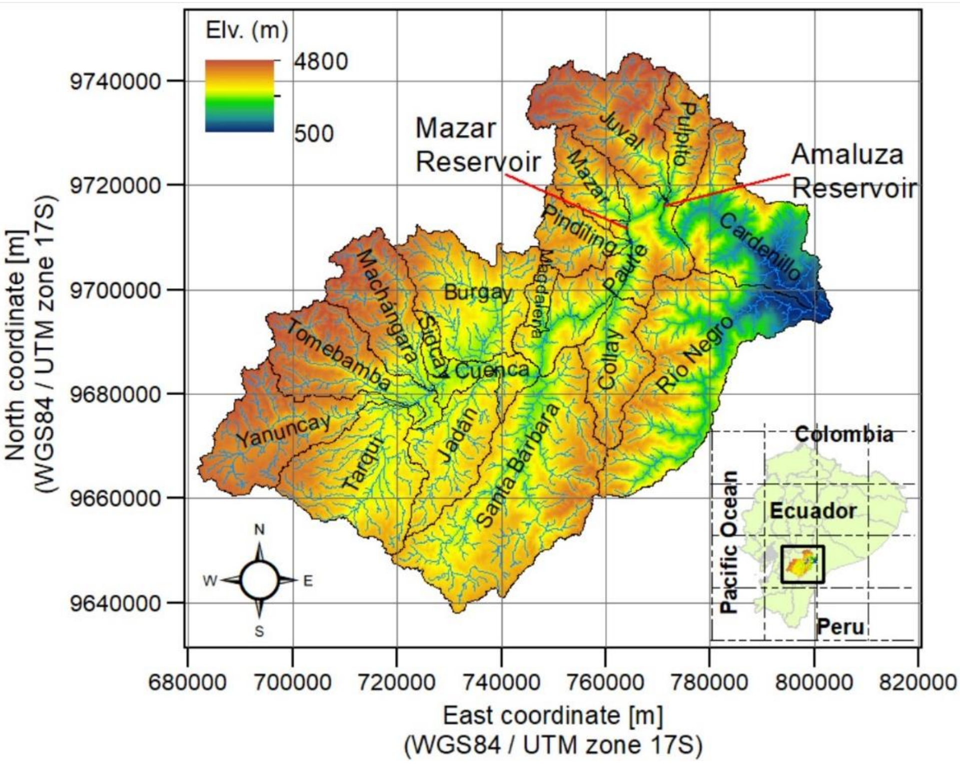
In general, power production in hydropower plants should be planned based on the needs of each country. Specifically, Ecuador has several hydroelectric power plants that plan short-term power generation based on data collected by a flow and water level sensor of the reservoir (Hernández-Ambato et al., 2017). The objective of the study is focused on developing a prediction model of inflows to the Mazar reservoir applied ANN with Deep Machine Learning (DML) model, the domain is focused on the Paute river basin, where about 30% of Ecuador's hydroelectric power is generated with the Paute Integral project (Ochoa-García et al., 2022).

2. Materials and Methods

2.1 Study Area

The study domain is centered on the Paute river basin (Figure 1), where around 30% of Ecuador's hydroelectric energy is generated with the Paute Integral project. The Paute Integral hydroelectric complex is located in the provinces of Azuay, Cañar and Morona Santiago in the foothills of the Andes Mountain range of the Republic of Ecuador, the complex takes advantage of the waters of the Paute river, it develops between heights 2163 meters above sea level and 525 meters above sea level. It has 4 hydroelectric plants arranged in a cascade type system: Mazar (170 MW), Molino (1100 MW), Sopladora (487 MW) and Cardenillo (596 MW). Currently, the project has three power plants (Mazar, Molino and Sopladora) and two reservoirs (Mazar and Amaluza), while the Cardenillo power plant and reservoir is the fourth and last stage of the complex, works that already have studies and designs definitive for its bidding and construction (CELEC EP, 2024).

Figure 1: Application area.



As shown in Figure 1, the main characteristic of the Mazar dam is the formation of a large reservoir (410 Hm^3) that allows regulation of the flow of the Paute River, becoming the reserve for the hydro-energy production of the project. Additionally, the Mazar reservoir was designed to retain the solid materials transported from the upper and middle basins of the Paute river, allowing extend the useful life of the Amaluza reservoir (120 Hm^3) for the operation of the Molino and Sopladora power plants (CELEC EP, 2024). The Mazar reservoir receives flow from 13 of the 18 subbasins of the Paute river basin up to its lower or Cardenillo basin.

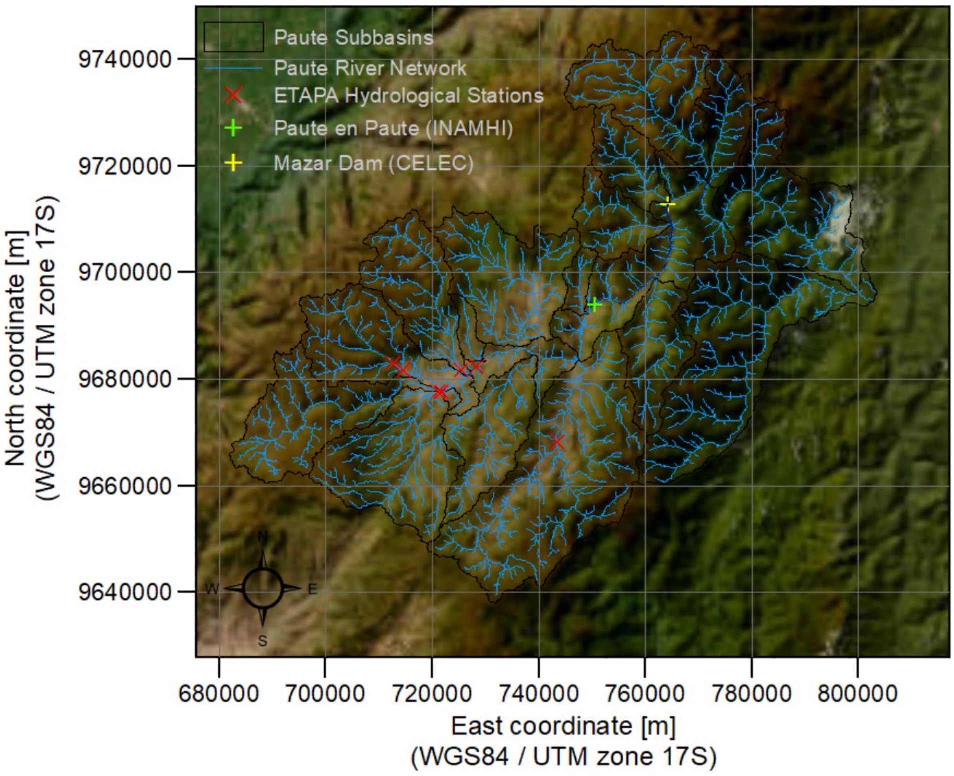
The Paute river basin (Figure 1) forms part of the inter-Andean alley, with slopes that are in the range of 25 to 50%. The steep relief is representative in the middle and lower area, followed by a mountainous relief in the upper area. The Paute river basin has an area of 5066 km^2. The altitudinal ranges vary between 500 and 4800 meters above sea level (Celleri et al., 2007).

The upper basin of the Paute river has a cold semi-humid climate with altitudes between 2600 and 4800 meters above sea level and rainfall that varies from 1000 to 2000 mm/year; mean temperature around 8 °C and mean relative humidity 88%. The middle basin comprises the area between 2200 and 2600 meters above sea level, with a semi-humid temperate climate, this area is the driest in the basin, with rainfall that fluctuates between 500 and 1000 mm/year, average annual temperature of 15 °C, relative humidity means 84%. The most significant populated cities are located in this part of the study area, including the city of Cuenca. The lower part of the Paute river basin develops approximately at altitudes between 500 and 2200 meters above sea level, an area in which the main works of the Paute Integral Hydroelectric Project are located. The climate is classified as humid meso-thermal, with average annual precipitation over 2000 mm reaching up to 4000 mm in the lower part, which defines it as a rainy zone with an eastern regime. The average temperature is 20 °C and the average relative humidity is 91% (Donoso, 2002).

2.2 Available Information

One of the main challenges when implementing flow forecasting models for water resources development is the quantity and quality of the information monitored by governmental institutions. Hydrological information was collected and processed from nine stations monitored by ETAPA EP (Empresa Pública Municipal de Telecomunicaciones, Agua Potable, Saneamiento y Gestión Ambiental del Cantón Cuenca in Ecuador), INAMHI (Instituto Nacional de Meteorología e Hidrología) and CELEC EP (Corporación Eléctrica del Ecuador). Figure 2 shows the geographic location of the hydrological stations considered within the Paute river basin.

Figure 2: Hydrological stations location.



As can be seen in Figure 2, seven hydrological stations with river surface level sensors property of ETAPA EP. Also, the Paute en Paute station of INAMHI, which coincides with the tail of the Mazar reservoir, and the inflow data monitored by CELEC EP from the Mazar dam, which relates the capacity of the reservoir with inflows and outflows based on a SCADA system. The data series was analyzed from 2016 to 2020 (Figure 3), which is the time interval available with the least amount of missing data.

Figure 3: Hydrological series.

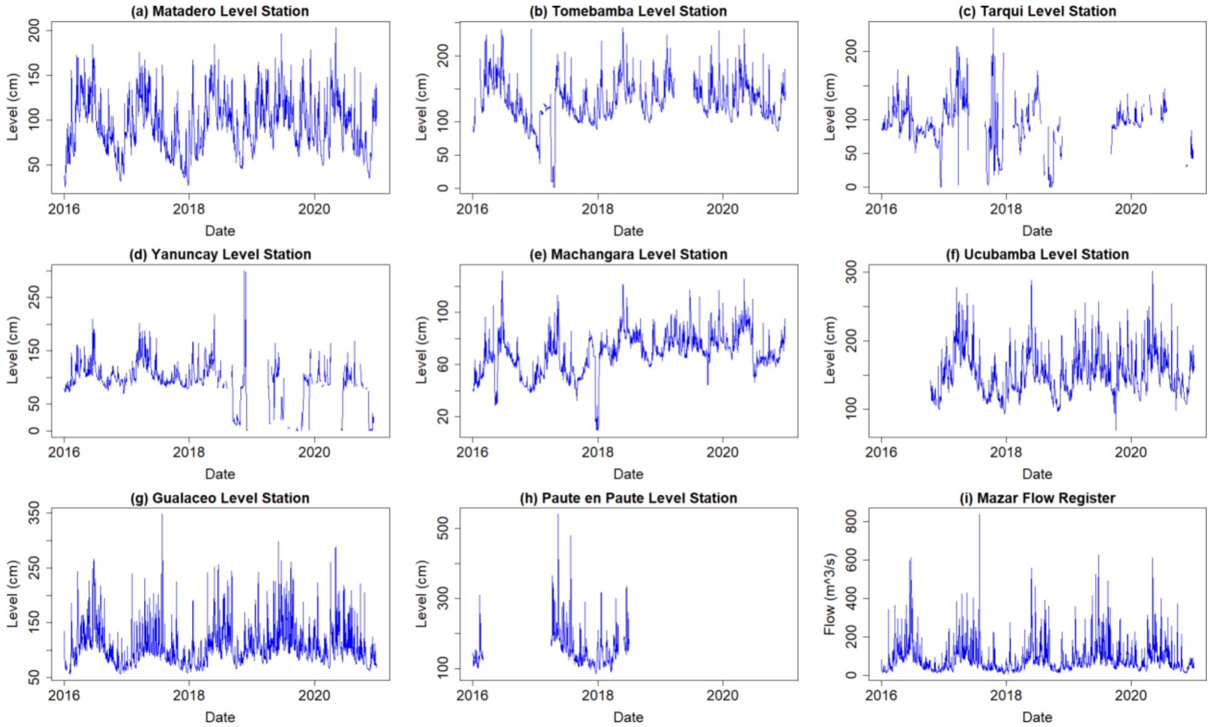


Figure 3 represents the daily average information of the data recorded at the hydrological stations considered. In the 5 years analyzed (2016-2020), the percentage of missing data (NA) due to outliers or unrecorded information of daily average levels varies at each station: (a) Matadero station 0.11%, (b) Tomebamba station 10.18%, (c) Tarqui station 41.11%, (d) Yanuncay station 26.66%, (e) Machángara station 0.99%, (f) Ucubamba station 16.75%, (g) Gualaceo station 1.42%, (h) Paute in Paute station 73.62%. The series of flows over the (i) Mazar dam does not have NA, this is due to the recording of operating flows that CELEC EP performs with a SCADA system to manage hydroelectric generation. Within the information analyzed, the high volume of missing data at the Paute station in Paute (73.62%) and Tarqui (41.11%) was noteworthy. However, the series considered have a minimum of missing data from 05/01/2017 to 06/30/2018, period in which the neural network will be built and validated for the corresponding forecast.

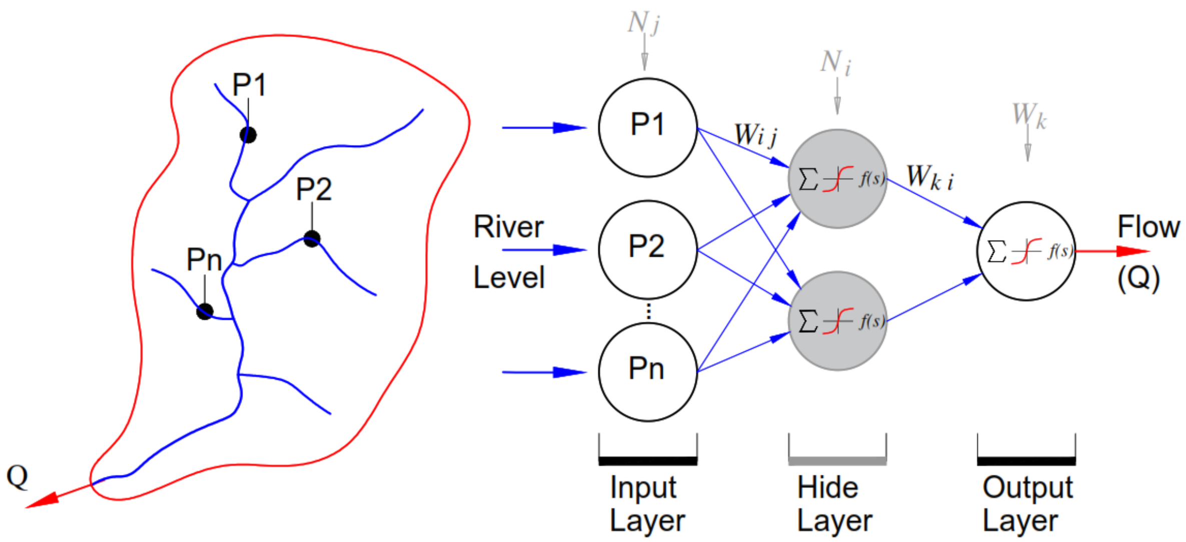
2.3 Deep Machine Learning with H2O library

H2O is an open-source platform that makes it easy for financial services, insurance companies, and healthcare companies to deploy AI and deep learning to solve complex problems. H2O's platform includes interfaces for R, Python, Scala, Java, JSON, and Coffee Script/JavaScript, as well as a built-in web interface, Flow. H2O implements best-in-class algorithms at scale, such as distributed random forest, gradient boosting, and deep learning (Landry et al., 2018).

Concerning the deep machine learning that has been applied, deep learning frameworks have become very popular, attracting a lot of attention from the research community. These frameworks provide machine learning schemes without the need for feature engineering, while at the same time they remain quite flexible. Initially developed for supervised tasks, they are nowadays extended to many other settings. Deep learning, in the strict sense, involves the use of multiple layers of artificial neurons. The first artificial neural networks were developed in the late 1950s with the presentation of the perceptron algorithms (Vakalopoulou et al., 2023).

The perceptron relies on a linear model for performing the classification, in which the elements of the input is described as a neuron and all the elements are combined by weighting with the models' parameters and then passed to an activation function for the final decision. The multilayer perceptron (MLP) consists of input layer, many hidden layers and output layer, it is a type of neural network. Most of the everyday problems are of the nonlinear type, however, through the use of MLP they could be explained. It is for this reason that several authors consider the multilayer perceptron as a universal function approximator (Luna, 2013). For the Mazar reservoir flow forecast, the MLP architecture will be based on the scheme shown in Figure 4.

Figure 4: MPL architecture of flow forecast.



The schematic in Figure 4 is divided into three zones: the input layer, the hidden layers and the output layer. The input layer receives all the inputs and propagates them to the next processing layer. The hidden layers are in charge of doing the processing (generally non-linear) of the data that are sent from the previous layer and the output layer is in charge of providing the results of the network. This type of neural network is trained with the error backpropagation algorithm.

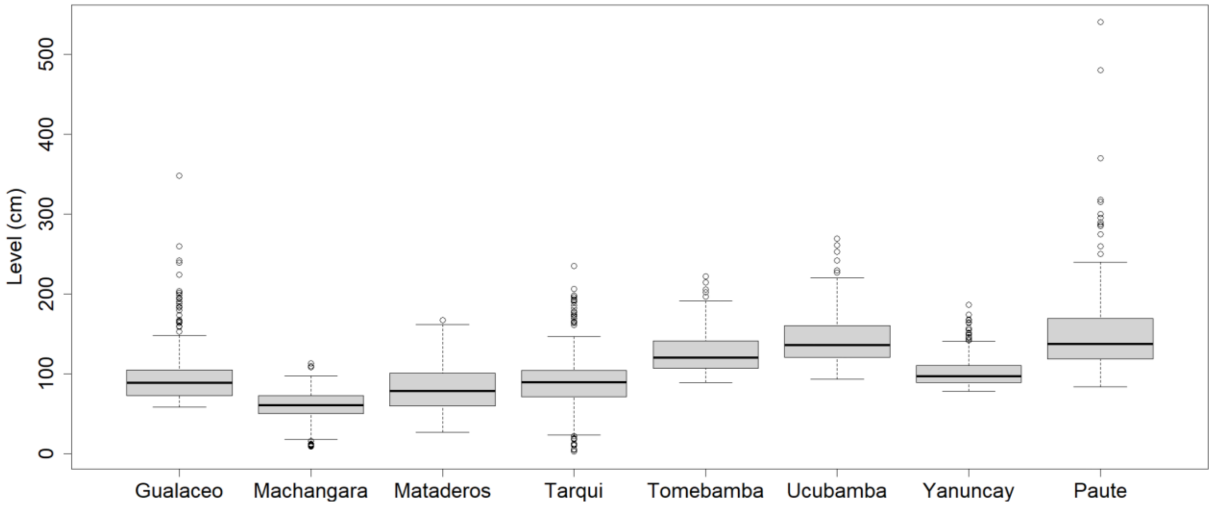
There is no default configuration of input neurons, hidden layers and output neurons that can yield the best results in one model and another. Each neural network and each algorithm is approached differently and based on experience and error evaluation the best configuration is decided. For the data available in the Paute river basin, the best configuration resulted in seven input layers (Independent Variables) with the daily average value of the water level monitored by ETAPA EP stations, a hidden layer with 50 neurons and an output layer with a neuron that relates the flow level of the Paute river at the tail of the reservoir (INAMHI) with the input flows monitored/estimated by CELEC EP.

3. Results and Analysis

3.1 Time Series

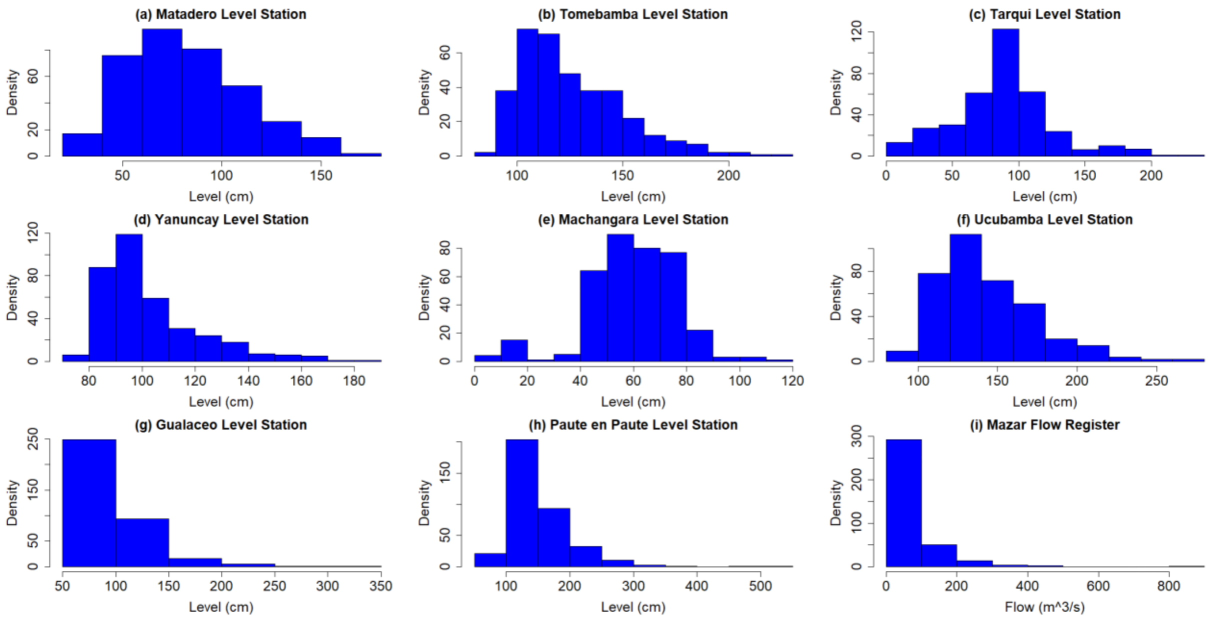
For construction and validation of neural network applied to the forecast of inflows to the Mazar reservoir, the daily hydrological information monitored by nine stations from 01/05/2017 to 30/06/2018 was considered, with a total of 365 data per station, where the Tarqui river station has 154 missing data and Tomebamba 1 missing data that were filled based on a linear correlation with the Ucubamba and Mataderos stations, respectively. It should be noted that the other stations had the complete series in the time period considered. Figure 5 shows the boxplots of the daily average level series monitored by the stations.

Figure 5: Boxplots of hydrological series.



As shown in Figure 5, the series presents extreme data associated with river floods during the rainy season; the extreme flows at the Gualaceo and Paute stations are more recurrent than at the stations located in the upper basins of the Paute River. The station in Ucubamba collects flows from the Tarqui, Yanuncay, Tomebamba and Machángara rivers. According to the analysis, the series with the lowest quality is that of the Tarqui river, both in terms of the number of outliers and the missing data for the period considered. Figure 6 shows the histograms of the stations considered.

Figure 6: Histograms of hydrological series.

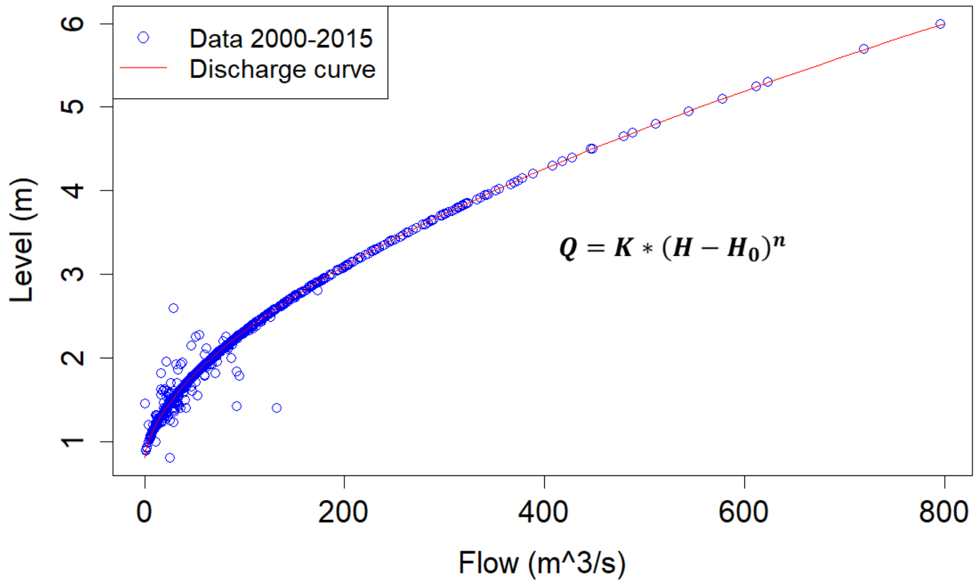


The histograms shown in Figure 6 show that the stations located in the upper Paute river basin (Matadero, Tomebamba, Tarqui, Yanuncay, Machángara and Ucubamba) have a behaviour similar to a normal distribution. However, in the stations of the lower and middle Paute river basin, the histograms show that the daily flows tend to laminate due to the contribution of watersheds with different seasonal floors (Celleri et al, 2007). This highlights the great importance of flow regulation of the Mazar reservoir for the use of the resource in hydroelectric generation

3.2 Deep Learning Forecast

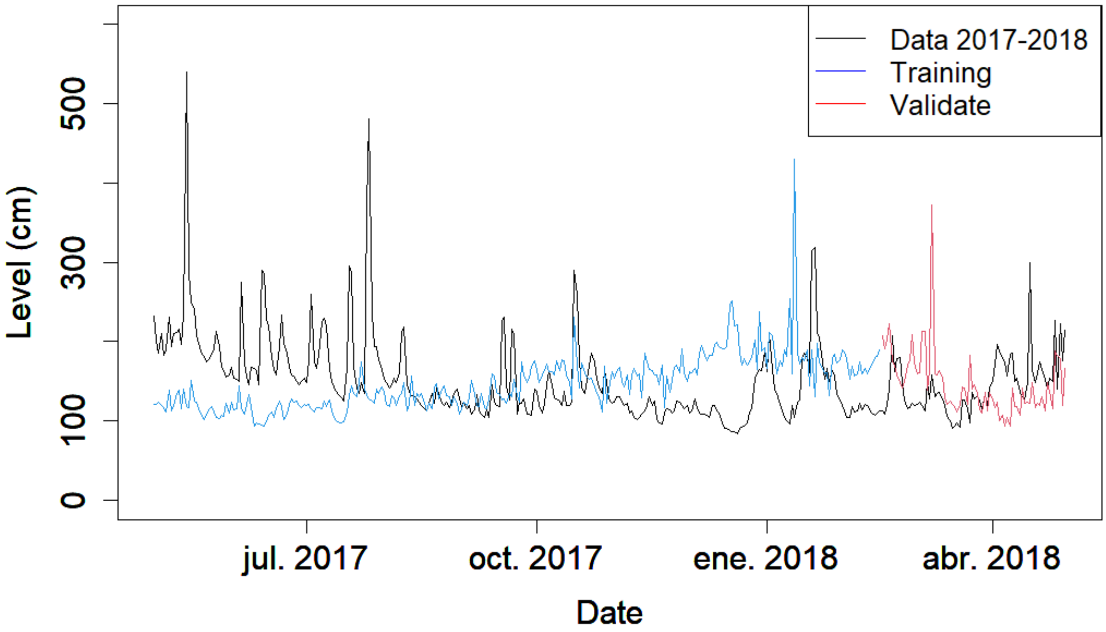
Deep Learning was applied to forecast inflows to the Mazar reservoir. The input information used are the levels monitored in the upper and middle basin of the Paute river of the main tributaries of the reservoir, so the forecast result will consist of an inflow level of the reservoir that coincides with the Paute en Paute station. The forecast level will be converted to a discharge curve obtained based on historical level and flow information. Figure 7 shows the discharge curve of Paute en Paute control section, based on historical data for the period from June 2000 to December 2015.

Figure 7: Paute en Paute discharge curve.



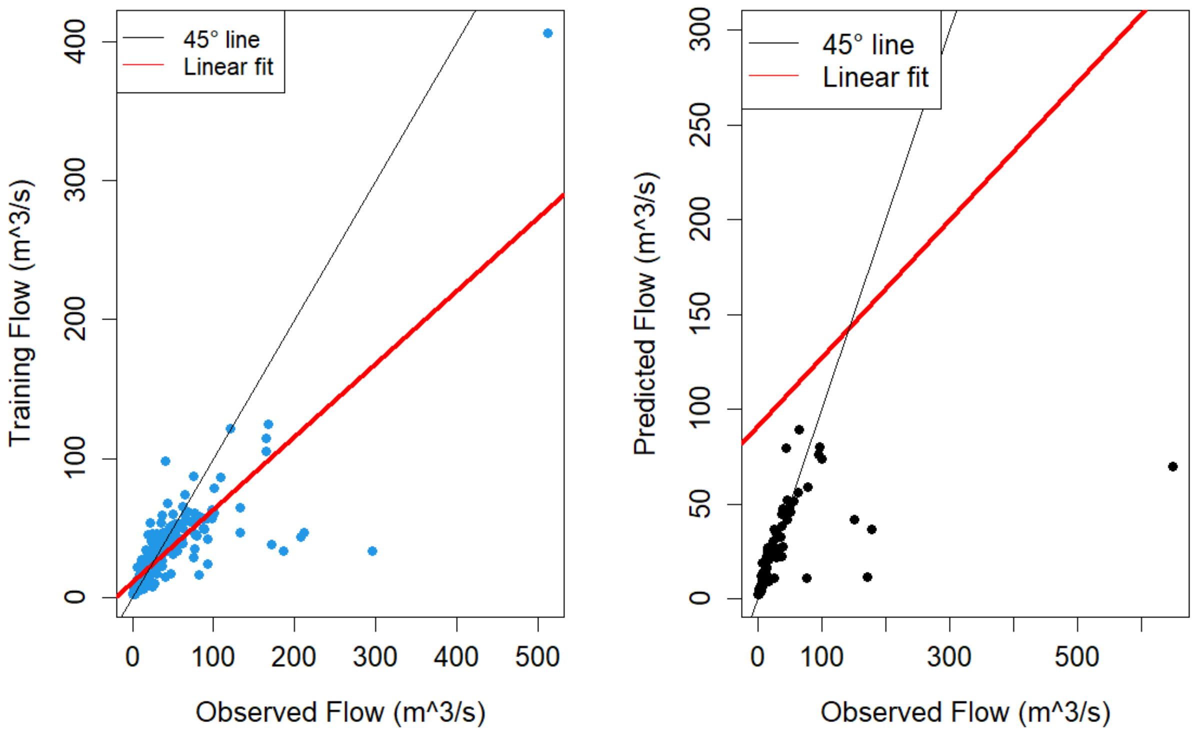
For the prediction of the daily flow level with deep learning methodology, the dataset is divided into training and testing to build the models. The partitioning of the dataset (training and testing) generally varies with the problem of interest. Hence, there is no data division and depend upon problem (Sahoo et al, 2019). We used 80% data for training model and remaining 15% for testing. For the data available in the Paute river basin, the best configuration resulted in seven input layers (Independent Variables) with the daily average value of the water level monitored by ETAPA EP stations, a hidden layer with 50 neurons and an output layer with a neuron that relates the flow level of the Paute river at the tail of the reservoir (INAMHI) with the input flows monitored/estimated by CELEC EP. The best configuration was selected based on the Root-Mean-Square Error (RMSE). The model was run with the Rectifier, Maxout, Hyperbolic Tangent and Rectifier with Dropout activation functions, but the best results were obtained with the Hyperbolic Tangent function. Figure 8 presents the training and validation results in contrast to the data series observed in Paute en Paute station.

Figure 8: Deep learning forecasting of Paute en Paute station.



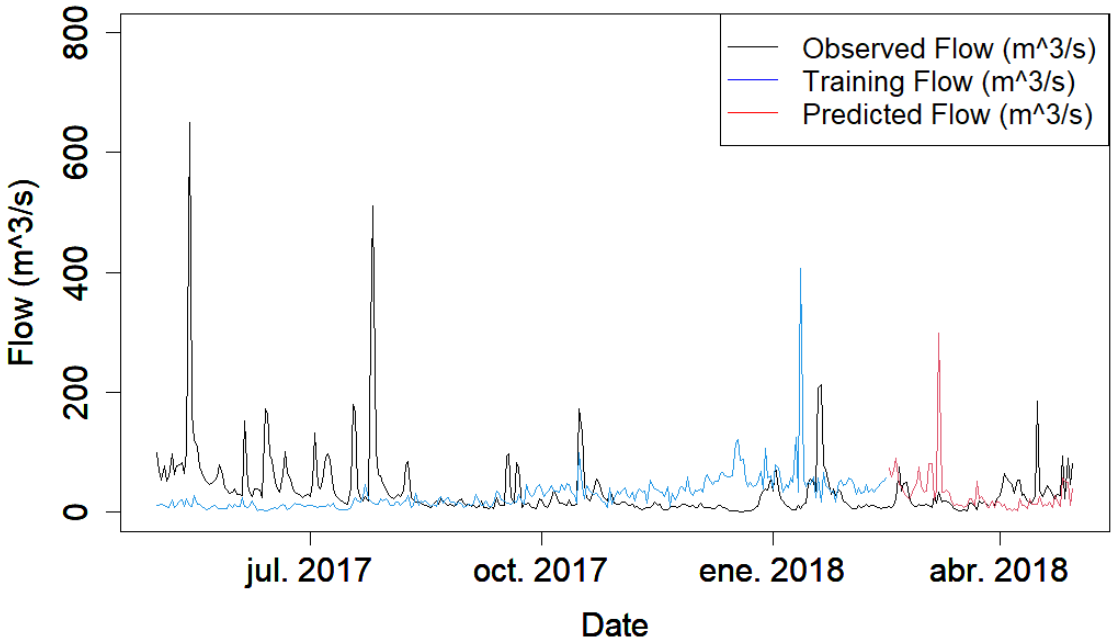
For the model presented in Figure 8, the mean percentage error (MPE) in training was approximately 9% and in the validation stage 11%. The forecasting model performs a random adjustment but in all cases the errors remain around 10%. With the discharge equation presented in Figure 7, the flow rates of the Paute en Paute station were obtained. Figure 9 shows a scatter plot of flow rates according to the levels obtained in the training and validation of the model developed.

Figure 9: Scatterplots of deep learning forecasting.



In general, there was a good correlation between the observed and modelled flow with the proposed methodology. Figure 9 shows some scattered points but the majority of model vs. observed points fall close to a linear trend of 45°. The series of daily mean flows observed and modelled with the deep learning methodology is presented in Figure 10.

Figure 10: Deep learning daily mean flows forecasting.



The learning ability of the networks can be observed as it trains its neurons with the available information. In the first months of the year there is an underestimation of the flow, but as training progresses the model improves in its base flows and some flow peaks. Finally, in the prediction process, the modelled flow trends are much more realistic with respect to the observed flows.

4. Conclusions

Deep Learning was applied to forecast of daily mean flows to the Mazar reservoir. According to the series of average daily levels of the tributaries of the Paute River between 2017 and 2018, the best configuration resulted in seven input layers (Independent Variables) with the daily average value of the water level monitored by ETAPA EP stations, a hidden layer with 50 neurons and an output layer with a neuron that relates the flow level of the Paute river at the tail of the reservoir (INAMHI) with the input flows monitored/estimated by CELEC EP.

In general, there was a good correlation between the observed and modelled flow with the deep learning forecasting. The mean percentage error (MPE) in training was approximately 9% and in the validation stage 11%. The forecasting model performs a random adjustment but in all cases the errors remain around 10%.

The results of the study are encouraging, considering that deep learning neural network approaches can be used in hydrologic time series modeling, to provide some insights for researchers and engineers applying data-driven AI approaches to model streamflow forecasting. A difficulty in the work performed was the lack of continuous series of hydrological information in the tributaries of the Paute River, so the importance of constant monitoring with hydro-meteorological stations for the development of different prediction models is highlighted.

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