



Multi-Step Ahead Time-Series Forecasting of Sediment Load Using NARX Neural Networks

Mahmud Iwan Solihin, Gasim Hayder, Haris Al-Qodri Maarif, and Qaiser Khan

Abstract

River sedimentation is a universal issue in a river catchment. It can affect the reservoir ability, the river flow, and dam structure including the hydropower capacity. Therefore, having multi-step ahead forecasting for the sediment load is beneficial in terms of research and applications. This study discusses and presents a case study in multi-step ahead forecasting for the sediment load using non-linear autoregressive with exogenous inputs (NARX) neural networks. We use sediment data that was recorded from 8 locations in the Ringlet reservoir (upstream sections) in Malaysia. The results suggest that the NARX neural networks have good capability to do multi-step ahead forecasting for sediment load in a recursive way (closed-loop mode) based on its past values and the past values of suspended solid and discharge. The model is evaluated with performance metrics yielding NSE = 0.99 (Nash–Sutcliffe efficiency coefficient) for both the training and test dataset, and RMSE (root means square error) of 0.22 and 0.25, respectively, training and test dataset.

Keywords

Sediment load • River system • NARX • Neural networks • Multi-step ahead forecasting

1 Introduction

Estimation and prediction of suspended sediment load is important in water management and monitoring of environmental issues (Melesse et al. 2011). In a prior work, multiple machine learning (ML) techniques were used to estimate sediment load from available input predictor variables (Hayder et al. 2021). The two predictor variables are suspended solid and discharge. The sufficient review on the important of sediment load estimation has also been discussed. However, the study is more focused on revealing the correlation between sediment load in the catchment area with the input variables, namely suspended solid and discharge.

This paper extent this earlier study by introducing multi-step ahead forecasting where artificial neural networks (ANN) will be used to forecast the sediment load based on its past values, the input variables and their historical data. The proposed multi-step ahead forecasting takes the popular time-series forecasting architecture namely non-linear autoregressive with exogenous inputs (NARX) with the internal function based on neural networks. This hybrid approach makes up an architecture known as non-linear autoregressive with exogenous inputs (NARX) neural networks. This architecture has been applied in various task for multi-step ahead forecasting ranging across disciplines not only in hydrology (Guo and Xue 2014; Sarkar et al. 2019).

In the applications of hydrology especially suspended sediment load forecasting, some studies have used that particular NARX architecture with different input variables and different machine learning methods and yielding various interesting results (Mohammadi et al. 2019; Kumar et al. 2017). Some studies use particular neural networks as the prediction engine in the NARX architecture, i.e., NARX neural networks (Bouzeria et al. 2017; Alarcon 2021; Afan et al. 2014; Nivesh and Kumar 2017). These vibrant research interest of using machine learning in the area of hydrology

M. I. Solihin (✉)

Department of Mechanical and Mechatronics Engineering,
UCSI University, Cheras, Malaysia
e-mail: mahmudis@ucsiuniversity.edu.my

G. Hayder · Q. Khan

Department of Civil Engineering, College of Engineering,
Universiti Tenaga Nasional (UNITEN), Selangor Darul Ehsan,
43000 Kajang, Malaysia

H. A.-Q. Maarif

Computer Science Department, Nusa Putra University Sukabumi,
Kabupaten Sukabumi, Indonesia

indicates the potential impact of application and contribution in solving problems in water management and environment systems.

This study aims to further explore and justify the important of this hybrid multidisciplinary approach of computer science and hydrology by presenting the case study of sediment load forecasting using NARX neural networks. The study employs the data was recorded in upstream catchment of Ringlet reservoir, Cameron Highland, Malaysia.

2 Study Area and Data

There are 8 upstream area in Ringlet reservoir catchment located in Cameron Highland, Pahang, Malaysia. This location is taken as the case study where there data was gathered (Hayder et al. 2021). The geographical map is shown in Fig. 1. Within the Cameron Highlands, there are six water catchments: Bertam, Lemoi, Mensun, Terla, Telom and Wi. In addition, the district contains various towns such as Kuala Terla, Kampung Raja, Kea Farm, Teringkap, Brinchang, Tanah Rata and Ringlet as the district's southernmost town (Gasim et al. 2009). The largest reservoirs in the Cameron Highlands district are Ulu Jelai and Sultan Abu Bakar (SAB) Dam. Ringlet Dam is another name for SAB Dam, which was erected in the 1960s with 19,000 m³ of rockfill and 52,000 m³ of concrete standing 39.6 m height and 135 m long.

Ringlet Reservoir contributes 20% of total power generation in West Malaysia as part of the National Electric

Board's Cameron Highlands Hydroelectric Scheme. Ringlet Reservoir, in addition to generating hydropower for Jor Power Plant, it serves as a flood control reservoir for residents in the Bertam Valley. The system was under the care of Malaysian Metrological Department (MMD), Tenaga Nasional Berhad (TNB) and the Department of Irrigation and Drainage (DID). Generally, Ringlet reservoir catchment is equipped with a good hydrological monitoring system including stream flow, rainfall and weather stations (Abdul Razad et al. 2018). Nonetheless, the reservoir storage volume has been depleted because of sedimentation, affecting the power station's energy output. The worst-case situation occurs when the Ringlet Reservoir gradually loses its ability to hold large flood inflows, forcing flood discharge through the spillway to be controlled (Sidek 2013).

Three important variables, i.e., discharge (DC) in mg/L, suspended solid (SS) in m³/s and sediment load (SL) in ton/day units were collected as the raw data. The available information on DC and SS in the 8 (eights) spots neighboring the Ringlet reservoir catchment area are compiled after substantial pre-processing and cleansing; the locations are listed in this reference (Hayder et al. 2021). Many daily data are missing so that only left some hundred instances can be used for this study. From December 12, 1997, to May 12, 2010, 405 data instances were compiled after extreme outliers were removed. Figure 2 shows the boxplot of the data where several outliers are still detected on each variable although the extreme outliers are already removed.

Despite the actual data is not in a uniform temporal time-series sequence, this research assumes that the compiled data is in a uniform temporal time-series sequence so that the NARX neural networks model development is more focused rather than the validity of the data and the model itself. Therefore, on order to have higher applicability impact, the data quality must be improved in the future since the main ingredient of machine learning-based model is the data.

3 Methodology

The architecture of NARX neural networks can be seen in Fig. 3 (Thapa et al. 2020). It is applied as multivariate estimator to perform prediction on a number of step ahead values of the sediment load using the lagged values of both SS and DC as well as the previously estimated values of SL.

The predictive model used in here is NARX neural networks. It is essentially an extension of non-linear autoregressive (NAR) model by combining additional relevant time-series features to the forecasting model. The non-linearity of the model is handled by the neural networks. Here, the standard multilayer neural networks where the architecture and the training algorithms is listed in Table 1.

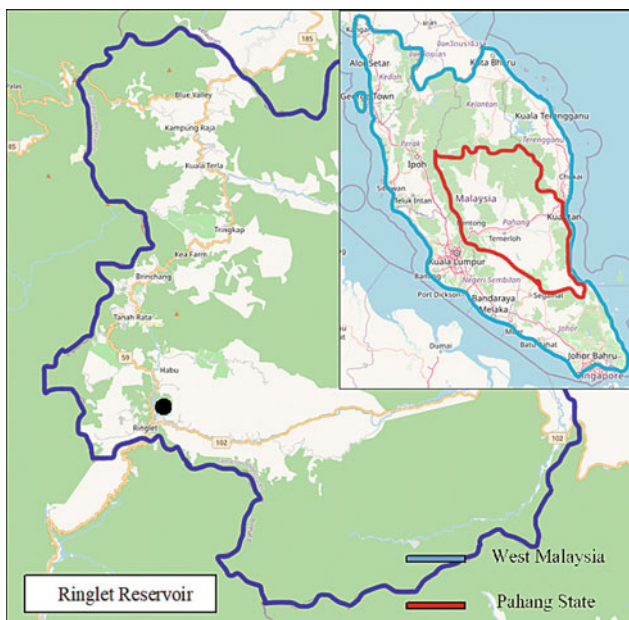


Fig. 1 The map of the study area at Cameron Highlands, Malaysia

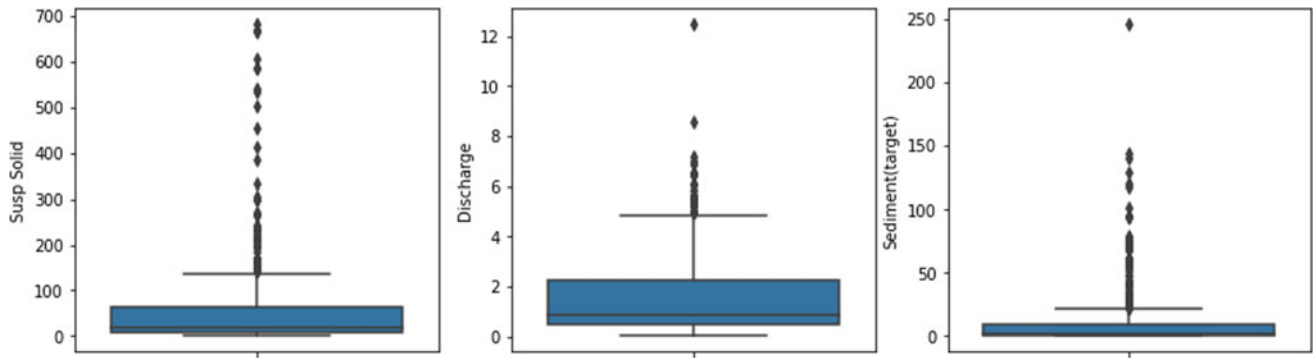


Fig. 2 Boxplot of the data

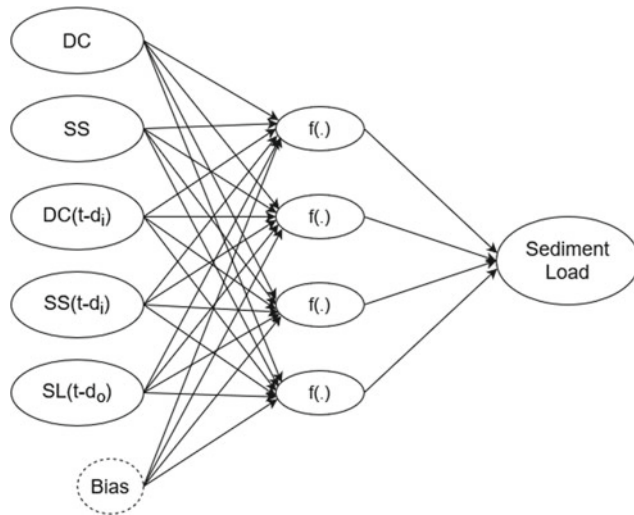


Fig. 3 The architecture of the proposed NARX neural networks

The implementation is performed in MATLAB 2019b software under the university license.

Firstly, the training/learning of NARX neural networks model is performed by feeding the data consisting of input and target variables. Then, the trained model will be evaluated using test dataset once the training performance is satisfactory. Here, we use the first 85% of the daily data for training. The rest 15% proportion is used as test dataset. This proportion is quite common in machine learning model development.

This study performs regressive model development. For regression, the model accuracy can be evaluated using some

common metrics such as presented in Pena et al. (2020). Similarly in this study, the metric used to evaluate the model accuracy are Nash–Sutcliffe efficiency coefficient (NSE) and root mean squared error (RMSE). These two metrics can be expressed as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (1)$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (2)$$

The regression performance of hydrological model is often assessed using NSE. According to Pena et al. (2020), NSE outperforms other metric such as coefficient of determination, (regression coefficient). It is indicated that $\text{NSE} > 0.75$ is substantially very nice fit model while $\text{NSE} < 0.5$ implies poor performance of the model.

4 Results

The first experimentation is to get optimum delay (lag) number for the input (d_i) and the feedback (d_o) as closed-loop mode NARX neural networks architecture is implemented. Here, the auto-correlation and cross-correlation analysis are conducted. As shown in Fig. 4, the sample auto-correlation function for SL has quite significant correlation of its delayed value of 1–5, i.e., previous 1st to 5th months.

Table 1 Architecture of the multilayer neural networks used in the NARX neural networks

Total hidden layer	2 hidden layers
Total neurons in hidden layers	[5 5]; five neurons in each layer
Training algorithm	Bayesian regularization (<i>trainbr</i>)
Activation functions at hidden layers	Tangent sigmoid + sigmoid function
Activation functions at output layer	Linear function (<i>purelin</i>)

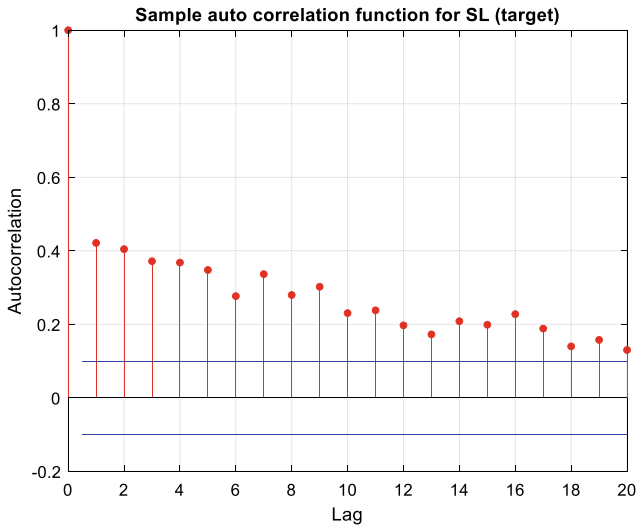


Fig. 4 Graph showing sample auto correlation function (SL)

Likewise, the cross-correlation analysis between SL and SS, and also between SL and DC are also conducted. As shown in Fig. 5, some observation can be drawn as initial assessment for the features/input variable selection for the NARX neural networks model. SL has correspondingly very significant correlation to the present (delay of 0) value of both SS and DC. It extends the correlation between SL and both SS and DC with weaker value up to about lag 2 (past two months). With this observation, the developed NARX neural networks forecasting model can be expressed as:

$$\widehat{SL}(t) = f(SS(t), SS(t-1), SS(t-2), DC(t), DC(t-1), DC(t-2), \widehat{SL}(t-1), \widehat{SL}(t-2), \widehat{SL}(t-3), \widehat{SL}(t-4), \widehat{SL}(t-5)) \quad (3)$$

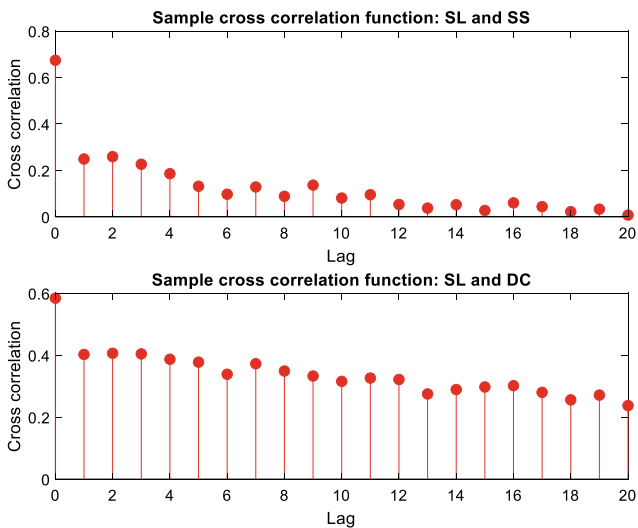


Fig. 5 Graph showing cross-correlation function (SL-SS and SL-DC)

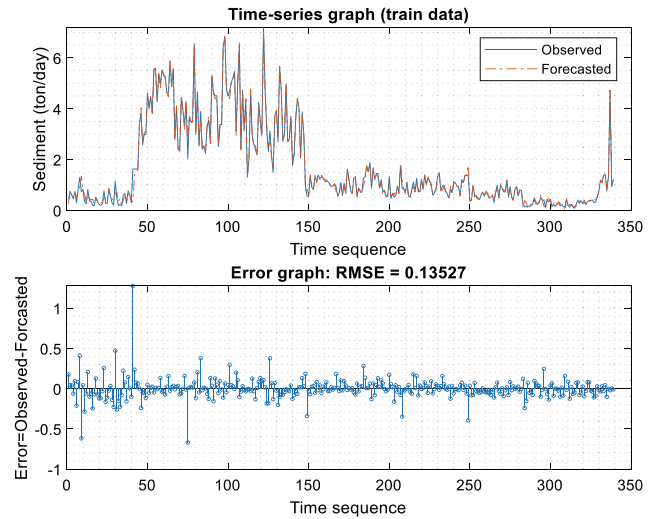


Fig. 6 Graph showing forecasting performance evaluated on training data set

The forecasting result evaluated on training data is presented in Figs. 6 and 7. With the outcome of NSE = 0.99 and RMSE = 0.14, the model fits well the training dataset. The NARX neural networks model produces very high NSE and low RMSE. The blue line (diagonal line) in Fig. 7 indicates the fitting line for regression between the observed and forecasted values.

Furthermore, the forecasting result evaluated on test dataset is presented in Figs. 8 and 9. The successfully trained model is used recursively to predict 61 step ahead, i.e., prediction in a closed-loop mode. The result indicates excellent capability of the model with NSE = 0.99 and RMSE = 0.25, i.e., only slightly lower RMSE as compared

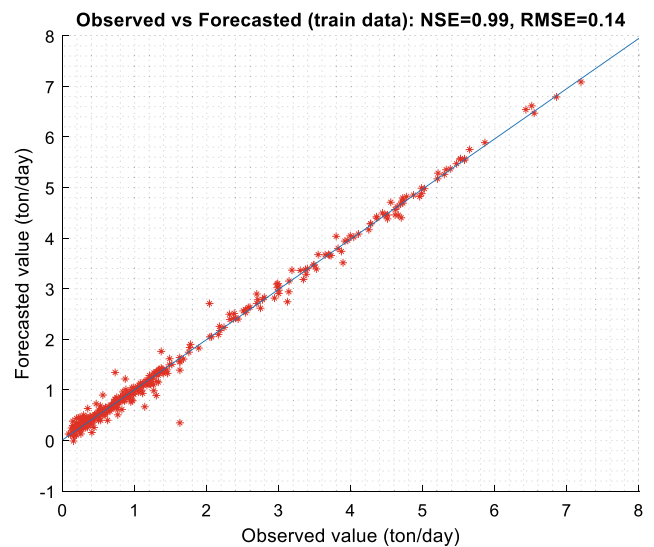


Fig. 7 Graph showing observed versus forecasted value (training dataset)

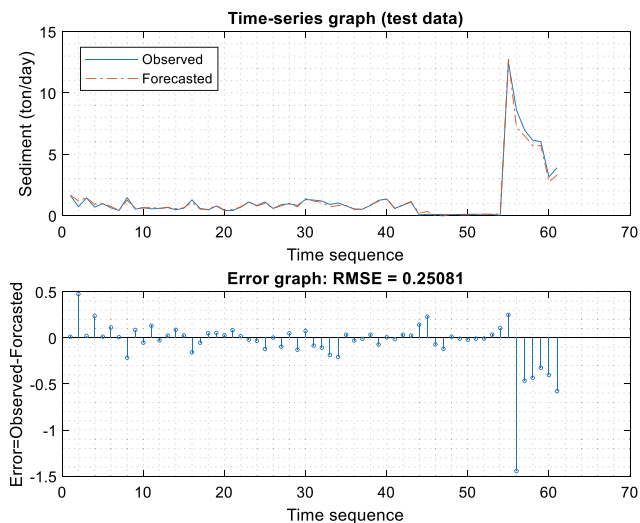


Fig. 8 Graph showing forecasting performance evaluated on test dataset

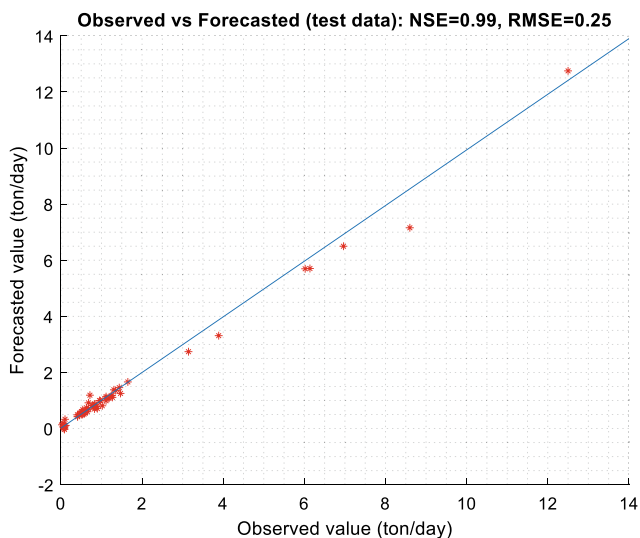


Fig. 9 Graph showing observed versus forecasted value (test dataset)

to that on training data. This means the model can generalize the data very well. This also indicates the good capability of the Bayesian regularization algorithm used in the model training.

5 Conclusion

In this study, sediment load forecasting using NARX neural networks have been proposed. The forecasting is performed in multi-step ahead manner. The study employed the data collected from 8 upstream stations of Ringlet reservoir catchment located in Cameroon Highland, Pahang, Malaysia. The results show the excellent capability of NARX

neural networks to perform multi-step ahead forecasting of sediment load in recursive way based on its past values, the past values of suspended solid and discharge. The model produces low RMSE values for both training and testing data with Nash–Sutcliffe efficiency coefficient ($NSE = 0.99$). In the future, the data quality will be improved as in this study the data is assumed to be in uniform temporal of daily time-series. This to avoid some missing data and non-uniformity of the temporal sequence.

References

- A.Z. Abdul Razad, L.M. Sidek, K. Jung, H. Basri, Reservoir inflow simulation using Mike Nam rainfall-runoff model. *J. Eng. Sci. Technol.* **13**(12), 4206–4225 (2018)
- H.A. Afan, A. El-Shafie, Z.M. Yaseen, M.M. Hameed, W.H.M. Wan Mohtar, A. Hussain, ANN based sediment prediction model utilizing different input scenarios. *Water Resour. Manag.* **29**(4), 1231–1245 (2014). <https://doi.org/10.1007/s11269-014-0870-1>
- V.J. Alarcon, Hindcasting and forecasting total suspended sediment concentrations using a NARX neural network. *Sustain.* **13**(1), 1–18 (2021). <https://doi.org/10.3390/su13010363>
- H. Bouzeria, A.N. Ghenim, K. Khanchoul, Using artificial neural network (ANN) for prediction of sediment loads, application to the Mellah catchment, northeast Algeria. *J. Water I. Dev.* **33**(1), 47–55 (2017). <https://doi.org/10.1515/jwld-2017-0018>
- M.B. Gasim, S. Surif, M.E. Toriman, S.A. Rahim, R. Elfithri, P.I. Lun, Land-use change and climate-change patterns of the Cameron highlands, Pahang, Malaysia. *Arab World Geogr.* **12**(1–2), 51–61 (2009). <https://doi.org/10.5555/ARWG.12.1-2.L2P14J2833G2Q4L7>
- W.W. Guo, H. Xue, Crop yield forecasting using artificial neural networks: a comparison between spatial and temporal models. *Math. Probl. Eng.* **2014**(January), 2014 (2014). <https://doi.org/10.1155/2014/857865>
- G. Hayder, M.I. Solihin, K.F. Bin Kushiari, A performance comparison of various artificial intelligence approaches for estimation of sediment of river systems. *J. Ecol. Eng.* **22**(7), 20–27 (2021). <https://doi.org/10.12911/22998993/137847>
- S. Kumar, A. Pandey, B. Yadav, Assessing the applicability of TMPA-3B42V7 precipitation dataset in wavelet-support vector machine approach for suspended sediment load prediction. *J. Hydrol.* **550**, 103–117 (2017). <https://doi.org/10.1016/j.jhydrol.2017.04.051>
- A.M. Melesse, S. Ahmad, M.E. McClain, X. Wang, Y.H. Lim, Suspended sediment load prediction of river systems: an artificial neural network approach. *Agric. Water Manag.* **98**(5), 855–866 (2011). <https://doi.org/10.1016/J.AGWAT.2010.12.012>
- B. Mohammadi, Y. Guan, R. Moazenzadeh, M. Jafar, S. Safari, Catena Implementation of hybrid particle swarm optimization-differential evolution algorithms coupled with multi-layer perceptron for suspended sediment load estimation. *Catena*, December 2019, 105024 (2020). <https://doi.org/10.1016/j.catena.2020.105024>
- S. Nivesh, P. Kumar, Modelling river suspended sediment load using artificial neural network and multiple linear regression: Vamsadhara River Basin, India. *Int J. Chem. Stud.* **5**(5), 337–344 (2017)
- M. Pena, A. Vazquez-Patino, D. Zhina, M. Montenegro, A. Aviles, Improved rainfall prediction through nonlinear autoregressive network with exogenous variables: a case study in Andes High Mountain region. *Adv. Meteorol.* **2020** (2020). <https://doi.org/10.1155/2020/1828319>

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- R. Sarkar, S. Julai, S. Hossain, W.T. Chong, M. Rahman, A comparative study of activation functions of NAR and NARX neural network for long-term wind speed forecasting in Malaysia. *Math. Probl. Eng.* **2019** (2019). <https://doi.org/10.1155/2019/6403081>
- L. Sidek, Hydropower reservoir for flood control: A case study on ringlet. *J. Flood Eng.* **4**(June 2013), 87–102 (2013)
- S. Thapa et al., Snowmelt-driven streamflow prediction using machine learning techniques (LSTM, NARX, GPR, and SVR). *Water (Switzerland)* **12**(6) (2020). <https://doi.org/10.3390/w12061734>