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# Estimation of discharge in rivers by different artificial neural network algorithms: case of the Algerian Coastal basin

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## INTRODUCTION

River discharge estimation is fundamental for a large number of engineering applications. The rating curve of a hydrometric station, which permits the establishment of a relationship between water level $h$ and flow rate $Q$ at a given cross-section, is the methodology most frequently used for continuous river flow measurements. To properly develop rating curves, discharges must be measured at all representative stages, using at least 10 to 12 points covering the range of low to high flows (Kennedy 2001). In the Algerian rivers, the bed is unstable, it is constantly in motion and characterized by a strong rate of sediments transported (Salhi *et al.* 2013), so the stage–discharge relationship is re-callipered more than four times per year (ANRH, 2009). Whenever, the river cross-section changes, the old data and rating curve become useless and discharge calculations must wait until enough new data are collected to establish a new empirical rating. Consequently, long series of levels are frequently available without the corresponding discharge values. During the transition period when the change is occurring, the discharge is calculated from field measurements of velocity and cross-section gauging (WMO 2008). These require much time and effort and are usually not done in flood conditions because of the dangers and the difficulty in activating the measurement team in due time, which is very frequent in Algerian rivers. In these cases, water level–runoff models can be used as an alternative solution. This study compared three artificial neural networks (ANN) algorithms to calibrate a water level–runoff model from two hydrometrics stations in the Algerian Coastal basin. These algorithms, the Levenberg-Marquard (ANN_LM), scaled conjugate gradient (ANN_SCG), and resilient back-propagation (ANN_RP), were applied to the tangent sigmoid transfer function. The input vector consisted of level [H(t)], and antecedents levels [H(t−1), H(t−2) and H(t−3)]. The algorithms were trained and validated by cross-validation using the limnigrammes provided and the realized gauging.

## STUDY AREA AND DATA

The "Coastal Algiers hydrographic basin" (14 500 km$^2$) is located in northern Algeria, and stretches in an east–west direction; its average elevation is 250 m (Zeroual *et al*. 2010). The choice of the two stations was guided by the availability of calibration curves. Data used in this study were obtained from the National Agency of the Hydraulic Resources (ANRH) known rating data reported between 1987 and 2008, and correspond to the best fit calibration curves used by ANRH to convert stage to discharge.

## WATER LEVEL–RUNOFF MODEL

The water level–runoff model (LR) that relates the stream flow $Q_t$ to the water level $L_t$ is given by (Sikorska *et al*. 2013):

$$Q_t = LR\ (L_t,\ \theta_{LR}) + E_t^{LR} \quad (1)$$

where $\theta_{LR}$ is the parameter vector of the LR and $E_t^{LR}$ is an error term. The error term $E_t^{LR}$ therefore represents uncertainties due to the computation of $Q_t$ and due to structural limitations of the LR model. These are always present, if only due to the hysteresis effect, where the same $L_t$ can be observed for different $Q_t$ on the rising and the falling limb of a flood hydrograph. In order to facilitate the extrapolation of the greater discharges in the transition periods and pro-rate them in time to the standard rating to convert the ranges of stage to the range of instantaneous discharges, the water level-runoff model (equation (1)) calibration was tested with three artificial neural networks (ANN) algorithms.

A three-layer fully connected feed forward network was used for all the test cases. This network has one input layer, one hidden layer and one output layer. The number of neurons in hidden layers was selected by trial and error. Networks with varying neuron numbers in the hidden layer were selected and trained with the same data set. The network that yielded the minimum mean square error (MSE) was selected. On this basis, the number of neurons in the networks was kept equal to five in both hidden layers. In each network pure-line, an activation function was used in the output layer, tan-sigmoid functions were used in the hidden layer. After configuring the input parameters of the neural network models, the next step is to train these models with the required settings. The training process requires a set of examples containing proper network behaviour. The training of ANNs was done using the three different algorithms: ANN_LM, ANN_SCG and ANN_RP. For training, validation and testing, the standardized dataset was divided into two separate parts; 60% of the dataset was used for training, 40% for validation with cross-validation. The performance of each model is evaluated using the mean square error (MSE) and correlation coefficient.

## RESULTS AND CONCLUSION

The model with highest accuracy for modelling the level–runoff relationship, is indicated in Table 1, which shows that that Levenberg-Marquard performed better than the other algorithms.

**Table 1** Performance of ANN model with different algorithms.

| Station | Output variables | Validation<br>Input variables | ANN_LM<br>$R^2$ | <br>MSE | ANN_SCG<br>$R^2$ | <br>MSE | ANN_RP<br>$R^2$ | <br>MSE |
|---|---|---|---|---|---|---|---|---|
| RN30 | $Q_{t+1}$ | H t+1 , Ht , H t–1, H t–2 | 0.99 | 0.001 | 0.97 | 0.09 | 0.95 | 0.74 |
| MESDOUR | $Q_{t+1}$ | H t+1 , Ht , H t–1 | 0.99 | 0.005 | 0.96 | 0.40 | 0.97 | 0.08 |

This method presented an efficient and useful model of discharge measurements developed by ANN as a function of variables which are easily measured in the field. The model drastically reduces the time and cost of measurements in Coastal Algierian rivers, regardless of the irregularity of the geometrical shape of river sections.

## REFERENCES

ANRH (National Agency of the Hydraulic Resources) (2009) Hydrometric and rainfall data. Internal document. Algeria.

Kennedy, E. J. (1984) Discharge ratings at gauging stations. In: *Techniques of Water-Resources Investigations Book 3*, Chapter A10. US Geological Survey.

Salhi, C., Touaibia, B., & Zeroual, A. (2013) Les réseaux de neurones et la régression multiple en prédiction de l'érosion spécifique : cas du bassin hydrographique Algérois-Hodna-Soumma. *Hydrological Sciences Journal*, 58 (7), 1573–1580.

Sikorska A.E., *et al.* (2013) Considering rating curve uncertainty in water level predictions. *Hydrology and Earth Systems Sciences* 10, 2955–2986.

WMO (2008) *Guide to Hydrological Practice, Volume I, Hydrology* – From Measurement to Hydrological Information, 6th edn. World Meteorological Organisation, Geneva, Switzerland.

Zeroual, A., Touaibia, B. & Ammari, A. (2010) Application of the neural networks for the rating curves in the ungauged rivers sites: Case of the Algerian Coastal Basin. *In: Global Change: Facing Risks and Threats to Water Resources* (Proc. of the Sixth World FRIEND Conference, Fez, Morocco). IAHS Publ. 340, 409–417.