

MODÉLISATION DE L'ÉVAPORATION JOURNALIÈRE (EP) DES RÉSERVOIRS DE BARRAGES À L'AIDE D'UNE APPROCHE BASÉE SUR LES RÉSEAUX DE NEURONES À FONCTION DE RÉGRESSION GÉNÉRALE (GRNN) : CAS DU RÉSERVOIR DU BARRAGE D'EL AGRAM, JIJEL, A L'EST DE L'ALGÉRIE

MODELLING DAILY EVAPORATION (EP) FROM DAMS RESERVOIRS USING GENERALIZED REGRESSION NEURAL NETWORK BASED APPROACH: CASE STUDY OF EL AGRAM DAM RESERVOIR, JIJEL, EAST OF ALGERIA

Réception : 28 /10 /2018

Acceptation : 06/11/2018

Publication : 08/01/2019

SEBBAR Abderrazek^{*1}, HEDDAM Salim², DJEMILI Lakhdar³^{*1}Etudiant doctorant, Faculté des Sciences de l'ingénieur, Département d'Hydraulique, Université Badji-Mokhtar, Annaba, Algérie, e-mail: rsebbbar@yahoo.fr.²Maître de conférences (MCA), Faculté des Sciences, Département des Sciences Agronomiques, Section Hydraulique Agricole, Université 20 Août 1955, Route El Hadaik, BP 26, Skikda, Algérie, e-mail: heddamsalim@yahoo.fr.³Professeur, Faculté des Sciences de l'ingénieur, département d'Hydraulique, Université Badji-Mokhtar Annaba, Algérie, Algérie.lakhdardjemili@gmail.com

Résumé : le réseau de neurones à fonction de régression générale (GRNN) a été appliqué pour estimer l'évaporation journalière (EP) du réservoir du barrage EL AGRAM, dans la wilaya de Jijel, dans l'Est de l'Algérie, à l'aide de quatre données de variables climatiques mesurées. Pour démontrer la capacité et la robustesse du modèle GRNN, nous avons utilisé des données pour une période de 13 ans allant de 2003 à 2015. Pour développer les modèles, nous avons utilisé quatre variables d'entrée mesurées au pas de temps journalier, à savoir, la température journalière maximale de l'air ($T_{\max}$), la température journalière minimale de l'air ($T_{\min}$), la vitesse journalière du vent (W_s) et l'humidité relative journalière (H%). Les performances des modèles ont été évaluées à l'aide de la racine carrée de l'erreur quadratique moyenne (RMSE), l'erreur absolue moyenne (MAE), l'indice de Willmott (WI) et le coefficient de corrélation (R). Le modèle GRNN proposé a été comparé aux régressions linéaires multiples (MLR) en ce qui concerne leur capacité à modéliser l'EP journalière. D'après les résultats obtenus, il a été constaté que : (i) l'EP pouvait être estimée avec succès à l'aide du modèle GRNN ; (ii) le modèle GRNN, qui utilise les quatre variables d'entrée, est le meilleur modèle parmi tous les autres modèles testés. Les valeurs de R, WI, RMSE et MAE calculées pour les données de test étaient respectivement de 0.804, 0.879, 1.638 et 1.252.

Mots – clés : Modélisation, évaporation, GRNN, RLM, Barrage, EL AGRAM, Jijel.

Abstract: A generalized regression neural network (GRNN) has been applied to estimate daily evaporation (EP) from EL AGRAM Dam reservoir, Jijel, East of Algeria, by using four measured climatic variables data. To demonstrate the capability and robustness of the GRNN model, we used data for a period of 13 years: 2003 to 2015. For developing the models, we used four input variables measured at daily time step, namely, daily maximum air temperature ($T_{\max}$), daily minimum air temperature ($T_{\min}$), daily wind speed (W_s) and daily relative humidity (H%). The performances of the models were evaluated using the root mean square error (RMSE), mean absolute error (MAE), Willmott's Index (WI), and correlation coefficient (R) statistics. The proposed GRNN model was compared to the multiple linear regressions (MLR) with respect to their capability for modelling daily EP. According to the results obtained, it was found that: (i) the EP could be successfully estimated using the GRNN model; and (ii) the GRNN model, which uses all the four input variables is the best model among all others tested models. The R, WI, RMSE and MAE values calculated for the testing data were 0.804, 0.879, 1.638, and 1.252, respectively.

Keywords: Modeling, evaporation, GRNN, MLR, Dams, EL AGRAM, Jijel.

1. Introduction

Evaporation (*EP*) is a physical process requiring two basic conditions (Penman, 1948, 1956): (i) an energy supply to provide heat for vaporization; (ii) some transport mechanism for removing vapor for the evaporating surface (Meyer et al. 1989). Evaporation (*EP*) is a compound term describing the physical process of water transfer into the atmosphere by evaporation from soil and water surface; *EP* constitutes an important component of the hydrologic balance. However, it is difficult to accurately estimate *EP* because of complex interactions between the components of the land and atmosphere systems. Temperature, wind speed, atmospheric pressure, and solar radiation could all influence the amount of evaporation. In hydrological practice, the estimation can be achieved by direct or indirect methods. One of the direct methods for evaporation measurements is Pan Evaporation. Indirect methods, is mainly base on the use of models (Chang et al. 2010). Pan evaporation measurements have been used worldwide as a means of estimating evapo-transpiration and free water surface evaporation. The availability of pan evaporation measurements is critical to many applications including, irrigation scheduling, hydrologic modeling, and irrigation system design. The ability to predict daily pan evaporation based on limited meteorological observations is highly desirable (Cahoon et al. 1991).

During the last few years the use of the artificial neural network (ANN) for modeling hydrological process have gain much popularity. ANN's are capable for mapping a set of inputs variables to an output variable without prior knowledge (Bruton et al., 2000; Kim and Kim 2008; Kim et al., 2009, 2012 ; Kisi 2006, 2009; Arunkumar and Jothiprakash 2013; Guven And Kisi 2011; Sudheer et al., 2002; Jothiprakash et al., 2011; Raza and Jothiprakash 2014). Hence, the main objective of the present investigation is to propose a new kind of model called generalized regression neural network (GRNN) for modeling and estimating daily *EP* using only limited climatic data. EL AGRAM Dam reservoir at Jijel, East of Algeria is selected as a case study.

2. Study Area and data Availability

Daily measured climatic data for 13 years (from 2003 to 2015) period were obtained from EL AGRAM Dam reservoir located in Jijel, east of Algeria country. The location of the EL AGRAM dam reservoir in Algeria is shown in Fig. 1. The daily statistical parameters of each data are given in Table 1. In the table, the X_{mean} , X_{max} , X_{min} , S_x and C_v denote the mean, maximum, minimum, standard deviation, variation coefficient, the correlation coefficient with *EP*, respectively.

Table 1. The daily statistical parameters of data set

Table 1. Paramètres statistiques journaliers de l'ensemble de données

Data set	T_{max}	T_{min}	H (%)	W_s	EP
Unit	°C	°C	m/s	%	mm
X_{mean}	23.52	13.58	72.98	2.54	4.05
X_{max}	43.00	29.20	95.70	14.10	18.30
X_{min}	6.00	0.10	20.50	0.00	0.07
S_x	6.31	5.60	10.20	1.73	2.75
C_v	0.27	0.41	0.14	0.68	0.68
R	0.78	0.69	-0.41	-0.06	1.00

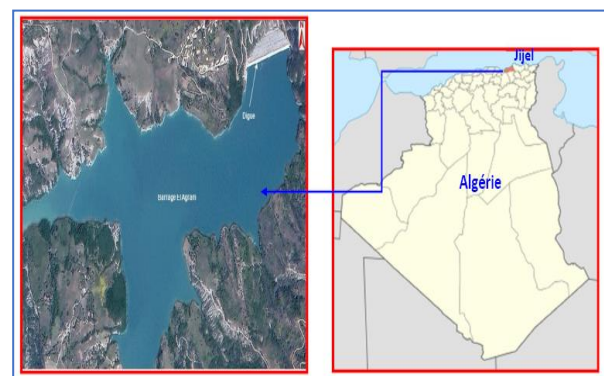


Fig. 1. Location of El Agram dam reservoir at Jijel Northern of Algeria Country

Fig. 1. Localisation du réservoir du barrage EL Agram, Jijel, Nord Est de l'Algérie

3. Models development

3.1. Generalized Regression Neural Network (GRNN)

Generalized regression neural network (GRNN) is a special kind of artificial neural network (ANN) proposed by Specht (1991). Figure 2 shows the block diagram of the GRNN architecture. A GRNN consists of exactly four layers. They are (i) input layer, (ii) pattern or radial layer, (iii) summation or regression layer, and a (iv) output layer. The number of neurons in the input layer is equal to the number of inputs variables or regressors, while the number of neurons in the pattern layer is exactly equal to the number of data sets used for the training (Bendu et al. 2016). The pattern layer is connected to the Summation layer. Each pattern layer unit is connected to the two neurons in the summation layer called respectively, S and D summation neurons Specht (1991).

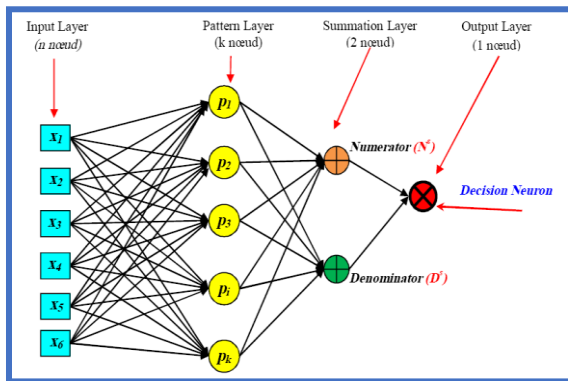


Fig. 2. Architecture of GRNN used for modeling daily EP

Fig. 2. Architecture de GRNN utilisée pour la modélisation EP journalière

3.2. Multiple linear regression (MLR) model

Multiple linear regression (MLR) is a well-known method of mathematically modeling the relationship between a dependent variable and one or more independent variables. In general, response variable Y may be related to n regressor variables (x_i). The following model:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n \quad (1)$$

Is called a multiple linear regression model with n regressor variables. Where β_0 is a constant and β_i , $i = 1 \dots n$ are regression coefficients.

4. Result and discussion

In this study, four statistical indices were selected to evaluate the different models. These indices are: the coefficient of correlation (R), the Wilmot's Index (WI), the root mean squared error ($RMSE$) and the mean absolute error (MAE), calculated as follow:

$$R = \frac{\frac{1}{N} \sum (O_i - O_m)(P_i - P_m)}{\sqrt{\frac{1}{N} \sum (O_i - O_m)^2} \sqrt{\frac{1}{N} \sum (P_i - P_m)^2}} \quad (2)$$

$$WI = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (|P_i - O_m| + |O_i - O_m|)^2} \quad 0 \leq d \leq 1 \quad (3)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - P_i)^2} \quad (4)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |O_i - P_i| \quad (5)$$

In this study, the GRNN and MLR models for the EP were developed and compared. The 4474 daily samples of 4 input variables (climatic data) and one output variable (EP) were used for the models. In both the models, 60% of the data set was randomly assigned as the training set, 20% was used for validation, and 20% was used for testing the performance of the model predictions. The R , WI , $RMSE$, and the MAE as computed for the training, validation and test data sets used for the GRNN and MLR models are presented in Table 2. As seen from Table 2, the GRNN models have shown significant variations based on the four performance criteria. In the training phase, the lowest values of the $RMSE$ and MAE were 1.596 and 1.212 using GRNN; and the highest value of the Rand WI were 0.816 and 0.885, also for GRNN. In addition, in the validation phase the lowest values of the $RMSE$ and MAE were 1.695 and 0.310 also

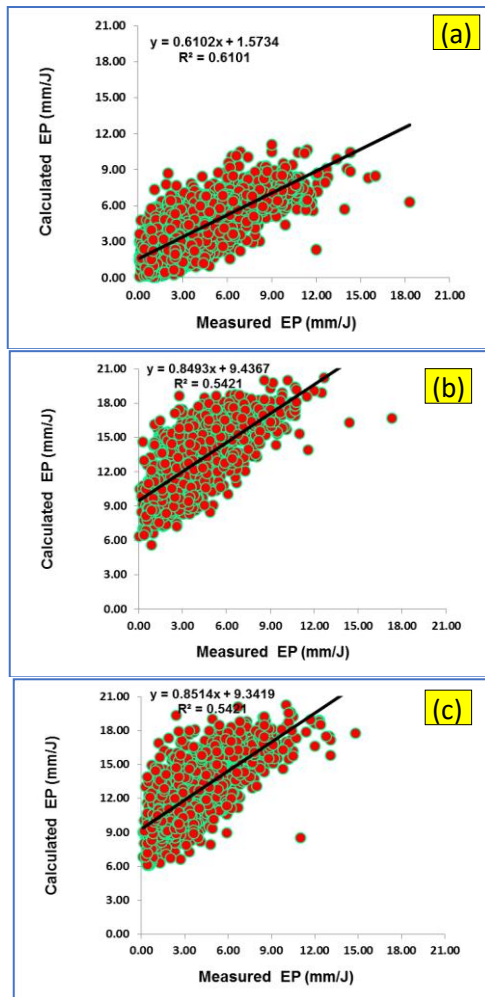


Fig. 3. Scatter plots of calculated versus observed values of EP for the MLR model (a) training, (b) validation and (c) testing.

Fig. 3. Diagramme de dispersion des valeurs calculées et observées de EP pour le modèle RLM : (a) apprentissage, (b) validation et (c) tests.

for GRNN. Finally, in the test phase, the highest value of the R and WI were 0.804 and 0.879, also for GRNN. Therefore, the accuracy of a GRNNs model in prediction is clearly demonstrated by its performance on the testing dataset. The Scatterplots of observed versus calculated values of EP for the GRNN and MLR models are shown in Figure 3 and 4.

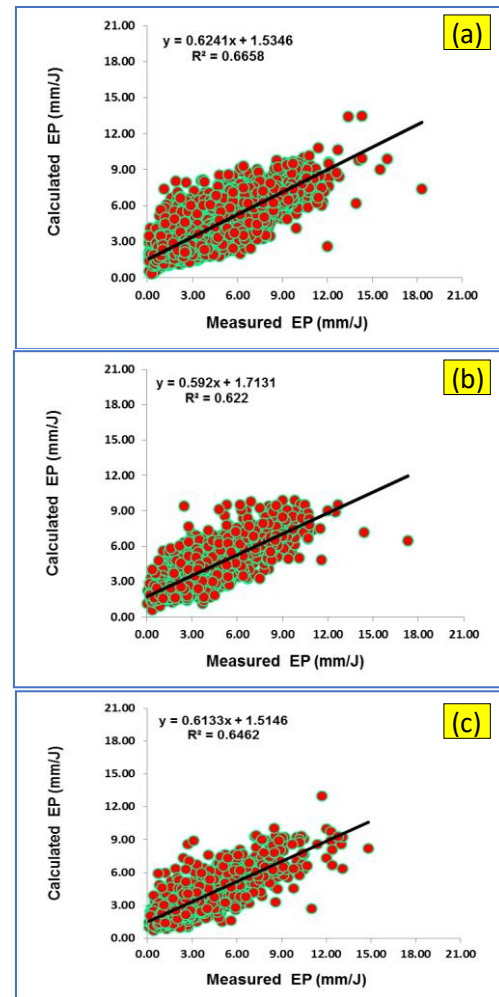


Fig. 4. Scatter plots of calculated versus observed values of EP for the GRNN model: (a) training, (b) validation and (c) testing.

Fig. 4. Diagramme de dispersion des valeurs calculées et observées de EP pour le modèle GRNN : (a) apprentissage, (b) validation et (c) tests.

5. Conclusion

Regarding the importance of the evaporation estimation and quantification, especially in the arid and semi-arid country as Algeria, an attempt is made in the present investigation to propose an alternative method to the standard and well know pan evaporation, for estimating daily evaporation using only the easily measured climatic variable. As results of the study, we have demonstrated that GRNN model is a good alternative and provide results higher than the standard MLR model. Finally, it will be

much appreciated if the proposed model can be generalized to others dams reservoirs across Algeria country.

Table 2. Performances of the GRNN and MLR models in different phases

Table 2. Performances des modèles GRNN et RLM dans les différentes phases

Model	Training (60%)			
	R	WI	RMSE	MAE
GRNN	0.816	0.885	1.596	1.212
MLR	0.781	0.867	1.718	1.324
	Validation (20%)			
	R	WI	RMSE	MAE
GRNN	0.789	0.866	1.695	1.31
MLR	0.736	0.401	9.074	8.808
	Testing (20%)			
	R	WI	RMSE	MAE
GRNN	0.804	0.879	1.638	1.252
MLR	0.736	0.379	9.025	8.761

Reference

- [1] Specht, D.F. (1991). A general regression neural network. IEEE Transactions on Neural Networks, 420 2, 568-576.
- [2] Bendu H., et al., (2016). Application of GRNN for the prediction of performance and exhaust emissions in HCCI engine using ethanol. Energy Conversion and Management 122 165-173.
- [3] Chang F.J., et al., (2010). Assessing the effort of meteorological variables for evaporation estimation by self-organizing map neural network. Journal of Hydrology 384 118-129.
- [4] Cahoon, J.E., et al., (1991). Estimating pan evaporation using limited meteorological observations. Agric. For. Meteorol. 55:18 1-190.
- [5] Meyer, S.J., et al., (1989). Estimating potential evapo-transpiration: the effect of random and systematic errors. Agric. For. Meteorol. 46: 285-296.
- [6] Penman, H.L., (1948). Natural evaporation from open water, bare soil, and grass. Proc. R. Soc. London, Ser. A, 193: 120-145.
- [7] Penman, H.L., (1956). Estimating evaporation. Trans. Am. Geophys. Union, 37: 43-50.
- [8] Bruton J.M., et al., (2000) Estimating daily pan evaporation with artificial neural networks. Trans ASAE 43(2):491-496.
- [9] Kim S., Kim H.S., (2008). Neural networks and genetic algorithm approach for nonlinear evaporation and evapotranspiration modeling. J. Hydrol. 351(3-4):299-317.
- [10] Kim S., et al., (2009). Statistical learning theory for the disaggregation of the climatic data. Proc. 33rd IAHR Congress 2009, IAHR, Vancouver, Canada, 1154-1162.
- [11] Kim S., et al., (2012) Pan evaporation modeling using neural computing approach for different climatic zones. Water Resour Manag 26(11):3231-3249.
- [12] Kisi O., (2006). Daily pan evaporation modeling using a neuro-fuzzy computing technique. J Hydrol 329 (3-4):636-646.
- [13] Kisi O., (2009). Modeling monthly evaporation using two different neural computing technique. Irrig. Sci. 27 (5):417-430.
- [14] Arunkumar, R., Jothiprakash, V., (2013). Reservoir evaporation prediction using data driven techniques. J. Hydrol. Eng. 18(1), 40-49.
- [15] Guven A., Kisi O., (2011). Daily pan evaporation modeling using linear genetic programming technique. Irrig. Sci. 29 (2), 135-145.
- [16] Sudheer K.P, et al., (2002) Modeling evaporation using an artificial neural network algorithm. Hydrol. Process. 16(16), 3189-3202
- [17] Jothiprakash.V., et al., (2011). Prediction of meteorological variables using artificial neural networks. Int. J. Hydrol. Sci. Technol. 1(3/4), 192-206 (2011)
- [18] Raza K., Jothiprakash V., (2014). Multi-output ANN model for prediction of seven meteorological parameters in a weather station. J. Inst. Eng. Ser. A 95, 221-229.