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Daily Pan Evaporation Modelling With ANFIS and NNARX

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ABSTRACT- Evaporation, as a major component of the hydrologic cycle, plays a key role in water resources development and management in arid and semi-arid climatic regions. Although there are empirical formulas available, their performances are not all satisfactory due to the complicated nature of the evaporation process and the data availability. This paper explores evaporation estimation methods based on nonlinear dynamic neural network model (NNARX) and adaptive neuro-fuzzy inference system (ANFIS) techniques. It has been found that NNARX and ANFIS techniques have much better performances than the empirical formulas (for the test data set, NNARX R2 = 0.95, ANFIS R2 = 0.94, Meyer R2 = 0.81 and Marciano R2 = 0.68). ANFIS and NNARX models are slightly better albeit the small difference. Although NNARX and ANFIS techniques seem to be powerful, their data input selection process is quite complicated. More studies are needed to gain wider experience about this data selection tool and how it could be used in assessing the validation data.

Keywords: ANFIS, Empirical formulas, Evaporation, NNARX

INTRODUCTION

Evaporation has wide implications amongst hydrological processes and plays a key role in water resources management in arid and semiarid climatic regions. The most common and important factors affecting evaporation are solar radiation, air and soil temperature ,relative humidity, vapor pressure deficit, atmospheric pressure, and wind speed. In one of the earliest published papers, Dalton (27) pointed out that evaporation was proportional to the difference between vapor pressure of the air at the water surface and that of the overlying air, although apparently he never expressed this relationship in mathematical terms. (1) Later concluded that the vapor pressure deficit was a much more sensitive indicator of the water vapor conditions of the atmosphere and underwent greater variations for temperature changes than did the relative humidity. Evaporation losses should be considered in the design of various water resources and irrigation systems. In areas with little rainfall, evaporation losses can represent a significant part of the water budget for a lake or

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reservoir, and may contribute significantly to the lowering of water surface elevation (23) .Therefore, accurate estimation of evaporation loss from the water body is of primary importance for monitoring and allocating water resources, at farm scales as well as at regional scales. Owing to its convenience and cost effectiveness, an evaporation pan is one of the most widely used instruments for the measurement of evaporation, but its performance is affected by instrumental limits and practical issues such as measurement errors and maintenance, which can reduce the accuracy of evaporation measurements. It is also difficult to use the pan by telemetry techniques, hence the human labor cost is high. Alternatively, mathematic models could be used to estimate evaporation from related weather variables. To date, many researchers have developed models for estimating free water evaporation all over the world (27). Mosner and Aulenbach (25) compared four empirical methods of evaporation estimation, including the Priestly–Taylor, Penman, DeBruin–Keijman, and Papa–Dakis equations for Lake Seminole, southwestern Georgia, and northwestern Florida, from April 2000 to September 2001. It has been found that the average monthly lake evaporation estimates derived from the empirical equations were as much as 16% in error. Therefore, there is room for improvement in the conventional evaporation models. In recent years, other methods have been explored by many researchers, such as the mass transfer methods (37, 27, 10) and eddy correlation techniques (36, 2). Despite the large amount of literature published, most of the reported methods are too demanding for observed meteorological data and prone to errors if locally calibrated parameters are not available. In addition, evaporation is an incidental, nonlinear, complex, and unsteady process, so it is difficult to derive an accurate formula to represent all the physical processes involved. As a result, there is a new trend in using data mining techniques such as fuzzy logic, artificial neural networks (ANN), and ANFIS to estimate evaporation. This followed a large number of studies in which some hydrological processes were simulated by nonlinear models based on ANN, support vector machines, fuzzy logical system, polynomial function, local linear regression, Bayesian networks, decision trees, etc. (27, 7, 17, 18). In evaporation estimation, some typical studies reported so far use ANN in modeling daily soil evaporation (8), daily evapotranspiration (19), daily pan evaporation (30, 33, 18, 17), and hourly pan evaporation (32). Using temperature data alone, Sudheer et al. (30) found that a properly trained ANN model could reasonably estimate the evaporation values at their study area in a temperate region. From these reports, it is clear that ANN models are superior to the conventional regression models, as ANN does not require any predetermination of regression forms. This advantage becomes more promising when an engineering problem is too complex to be represented by regression equations (32). In comparison with a wider application of ANN in other fields (such as flood forecasting, 10, 6, 35, 5, 4, 20), the modeling experience of ANN in evaporation estimation is still quite limited and there is a need to study and report trials of this technique in different climate regions so that some generalization of this method could be achieved.

MATERIALS AND METHODS

Empirical Methods of Estimating Evaporation

Evaporation pans are commonly used to estimate evaporation from lakes and reservoirs. However, there are many problems with them. Many factors can introduce errors in pan evaporation measurement, such as debris in water, animal activity in and around the pan, pan size, materials employed to construct the pan, exposure of the pan, strong winds, and measurement of water depth in the pan (27). In practice, empirical formulas have been derived to estimate evaporation on the basis of field measurements of evaporation pans and reservoir/lake water balances. Those formulas are linked with various weather factors impacting evaporation. As the complexity of the empirical methods increases, data requirements to drive the equations often make the empirical methods hard to apply for field applications. A large number of empirical methods for estimating evaporation based on different meteorological inputs have been suggested during the past decades (27). However, many of them are not applicable in this study due to their limitations in data availability. As a result, only two relevant empirical methods are used in the case study (i.e., they are compatible with the available weather measurements), as listed in Table 1. In this table, for each formula, E=evaporation rate (mm/day); es=saturation vapor pressure (millimeters of Hg); ea=actual vapor pressure (millimeters of Hg); U=average wind velocity (km/h) at a height of 2 m above the lake or surrounding land areas; and C for deep lake=0.36, low lake=0.5

Table 1. Evaporation Formulas for Lakes and Reservoirs

References	Equation	Formula name
Alizadeh, 2004	$E = 0.03U(es - ea)$	**Marciano**
Alizadeh, 2004	$E = (1+\frac{U}{16}) \times C \times (e_s - e_a)$	**Meyer**

Adaptive Neural-based Fuzzy Inference System (ANFIS) and NNARX

The adaptive neuro-fuzzy inference system is a new improved tool and a data – driven model ling approach for determining the behavior of imprecisely defined complex dynamical systems (27) .An ANFIS aims at systematically generating unknown fuzzy rules from a given input–output data set (25). Fig.1 represents a typical ANFIS architecture.

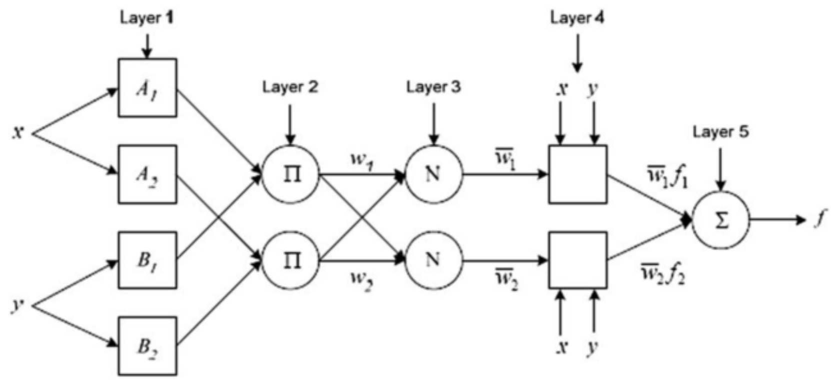

Fig. 1. A typical ANFIS architecture (Jang 1993)

The figure is based on:

Layer 1: every node in this layer is an adaptive node with a node function that may be a generalized bell membership function (Equ.1), a Gaussian membership function(Equ. 2), or any membership functions

$$\mu_{Ai}(x) = \frac{1}{1 + \left[x - \frac{ci}{ai}\right]^{zbi}} \tag{1}$$

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x - ci}{ai}\right)^2\right] \tag{2}$$

Where ai, bi and ci are premise parameters .Also x is the input to node i and Ai is the linguistic label (for example, low and high) associated with this node function. Premise parameters change the shape of the membership function. Layer 2: every node in this layer is a fixed node labeled , representing the firing strength of each rule ,and is calculated by the fuzzy AND connective 'product'of the incoming signals by using (Equ. 4).

$$w_i = \mu_{Ai}(x) \times \mu_{Bi}(x) \quad i = 1,2 \tag{3}$$

Every node in this layer is a fixed node labeled N, representing the normalized firing strength of each rule.The ith node calculates the ratio of the ith rule's firing strength to the sum of two rule's firing strengths by using (Equ. 4)

$$w_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{4}$$

Layer 4: every node in this layer is an adaptive node with a node function (Equ. 5), indicating the contribution of the ith rule to wards the over all output.

$$\text{Wizi} = \text{wi}(\text{pix} + \text{qiy} + \text{ri}) \tag{5}$$

Where pi, qi and ri are consequent parameters. Layer 5: the single node in this layer is a fixed node labeled P, indicating the over all output as the summation of all incoming signals calculated by (Equ. 6):

$$Z = \sum_i wizi = \frac{\sum_i wizi}{\sum_i wi} \tag{6}$$

What should be realized when inspecting the above layer sis principally three different types of components that can be adapted as follows (14):

1. Premise parameters as nonlinear parameters that appear in the input membership functions.
2. Consequent parameters as linear parameters that appear in the rules consequents (output weights).
3. Rule structure that needs to be optimized to achieve a better linguistic interpretability.

In this study, three Gaussian membership functions were used to construct the ANFIS model. There are a wide variety of algorithms available for training a network and adjusting its weights. In this study, an adaptive technique called 'momentum Levenberg–Marquardt' based on the 'generalised delta rule' was adopted (25). In this scheme, the adaptive learning rates were used for increasing the convergence velocity throughout all ANFIS simulations.

The ANN is an evolving technique and new progress still being made with time. In recent years, a combination of ANN and ARX (Autoregressive Extra Input) has gained some popularity in the control field. Traditionally, The ARX model has been widely used in control theory for modelling various control processes (22). Its simple structure is basically linear and can be described as

$$A(q)y(t)= B(q)\, u(t-n_k)+e(t) \tag{7}$$

Where *y(t)* is the output(evaporation) *u(t)* is a vector with all the inputs, such as wind, temperature, relative humidity and vapour pressure deficit *e(t)* is the white noise, *A(q)* and *B(q)* are the polynomials in terms of time shift operator, of the n_a and n_b orders respectively and n_k is the time delay. This model's structure is shown in Figure 2(a).

The integrated model of NNARX is a combination of the ANN and ARX. Such a model has recently been explored and studied by researchers in other fields with some successful results (16). The estimated value of *y(t)* shown by $\hat{y}(t \mid \theta)$ is expressed below:

$$\begin{aligned}\hat{y}(t \mid \theta) = f(&u(t-nk),\ldots,u(t-nb-nk+1),\\ &y(t-1),\ldots,y(t-na))\end{aligned} \tag{8}$$

Where f (.) is the nonlinear mapping by ANN, and θ = model parameters. This structure is almost the same as the structure in Figure 2(a) but instead of using a simple summation block, a neural network structure is replaced as shown in Figure 3(b).

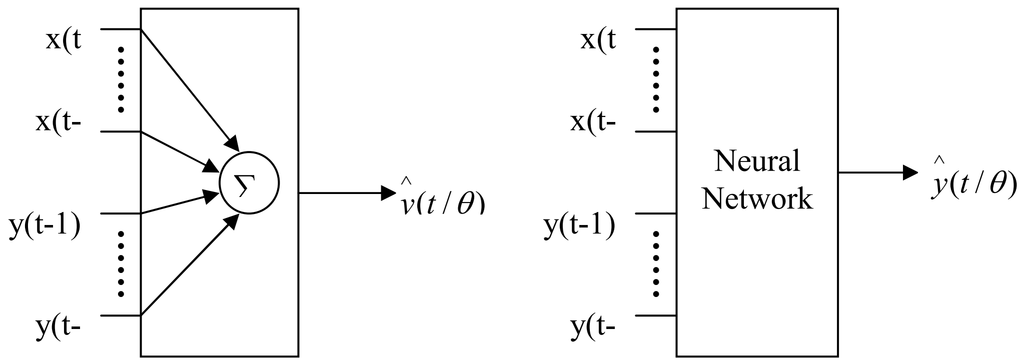

Fig. 2. (a) The ARX block and (b) The NNARX model block

Study Area and Data

The study area is the Sistan plain located in the Southeast of Iran, one of the driest regions of Iran and famous for its "120 day wind" (bād-e sad-o-bist-roz), a highly persistent dust storm in the summer which blows from north to south with velocities of nearly 20 knots. Hirmand River, originated from Afghanistan, is bifurcated into two branches when it reaches the Iranian border, namely Parian and Sistan. Sistan is the only water supply known in Sistan and Baluchistan province. It is the main stream of Hirmand River, which flows through Sistan plain and discharges into the natural swamp of Hamun-e-Hirmand (Figure 3). As can be seen in the figure, Sistan plain is essentially an inland delta with its major watercourses leading to a series of lakes.

The Sistan delta has a very hot and dry climate. In summer, the temperature exceeds 50°C. Rainfall is about 60 mm/year and occurs only in autumn and winter. Open water evaporation is very high and is estimated to be 3200 mm/year. Strong winds in the region are quite unique and are an important contributing factor for the high evaporation. The Chahnime reservoirs are a series of natural depressions used

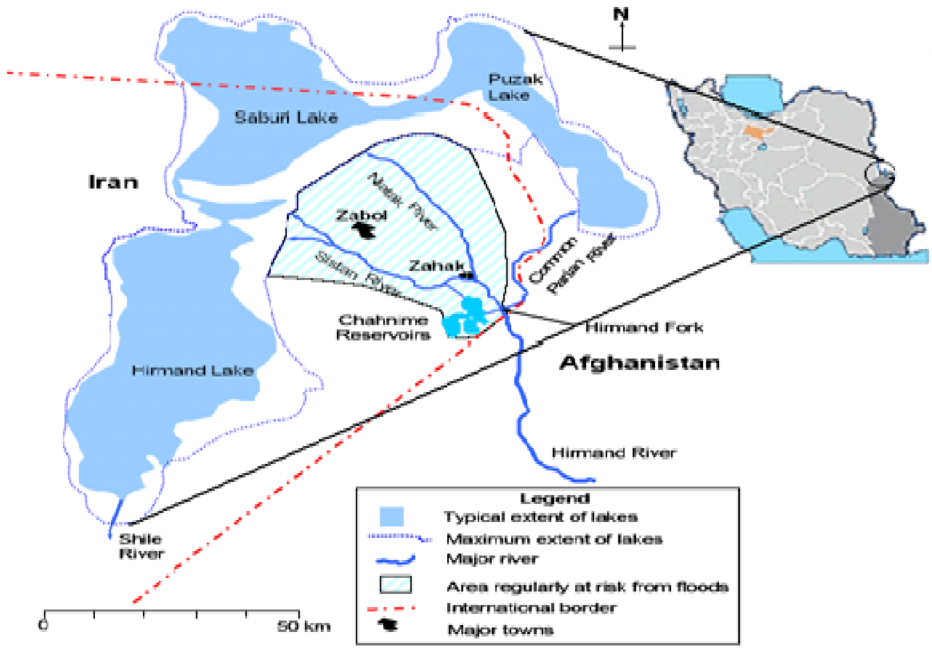

Fig. 3. The Sistan plain and location of the Chahnime reservoirs

Primarily to store water for irrigation. However, they also play an important part in attenuating floods. During periods of high flows, water is diverted to these reservoirs via an intake and canal which has a capacity of up to 1000 m^3 /s.

The daily weather variables of an automated weather station, Chahnime Station of Zabol (latitude 61˚40′ - 61˚49′ W, longitude 30˚45′ - 30˚50′ N) operated by the IR Sistan and Balochistan Regional Water (IR SBRW) were used in this study. The measured daily meteorological data for the Chahnime station were obtained from the IR SBRW (http://www.sbrw.ir). The data sample consisted of eleven years (2005–2009) of daily records of air temperature (T), wind speed (W), sunshine hours (SR), relative humidity (RH) and pan evaporation (E). For the station of interest, the first deta of day nine years (1983–2004) were used for training modes and the remaining data were used for testing. The daily statistical parameters of the weather data are given in Table 2. In the table, the Xmean, Sx, Cv, Csx, Xmax and Xmin denote the mean, standard deviation, coefficient of variation, skewedness, maximum and minimum of the weather factors, respectively.

Table 2. Correlation matrix for input-output variables of ANFIS and NNARX models

Station	Data set	Unit	X_{mean}	Sx	Cv (Sx/X_{mean})	Csx	X_{min}	X_{max}	Correlation with ET
Chahnimeh	T	˚C	23.502	9.928	0.422	-0.381	-3.4	39.9	0.843
	RH	%	31.262	16.122	0.516	0.920	3.5	92	-0.701
	Wind	m/s	6.111	4.046	0.662	0.647	0	21	0.711
	Sun shine hours		9.187	2.971	0.323	-1.412	0	13.2	0.392
	ET	mm/day	12.529	8.687	0.693	0.498	0	35.9	1

The last column in Table 2 represents the correlation vector between the potential input variables for the models (T, SR, W, and RH) and the output variable

(E). In the table, the bold characters highlight the significant factors that affect evaporation. Evaporation losses in the Chahnime station are moderately high due to high temperature and long sunshine hours that show significantly high variations. The data were analyzed with the Minitab program. A similarity matrix was constructed using Jaccard's coefficient of similarity and a dendrogram was obtained as shown in Figure 4. The dendrogram analysis revealed a strong link between evaporation and the two input variables of wind speed and air temperature. The other two weather factors (sunshine hours and relative humidity) played useful but less important roles in the evaporation process. It is concluded that for the ANFIS and NNARX models, all four variables (air temperature, wind speed, sunshine hours, and relative humidity) should be considered as potential inputs.

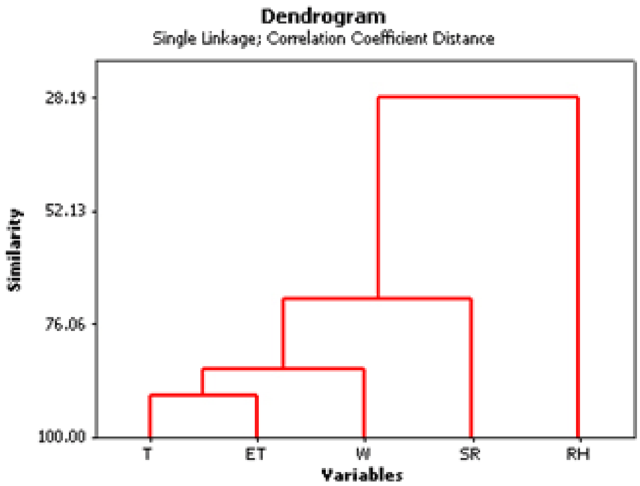

Fig. 4. The rdendrogram of weather variables of interest

RESULTS

Among the four meteorological variables considered, it is clear that some would play more important roles than others and it is important that only the significant ones are used as inputs for the final model. In this study, various combinations of these variables were examined to evaluate the impact of each variable. Root mean square error (RMSE), index of operation (d), mean absolute error (MAE), mean square error (MSE), mean absolute relative error (MARE) and determination coefficient (R2) were all used as evaluation criteria. The RMSE represents the deviation between simulated values and observed values. The parameter d shows the operation of the model which varies between zero and one (best values for d are closer to one). The lower MAE values indicate more accurate estimations. MSE and MARE provide different types of information about the predictive capabilities of the model. The MSE measures the goodness-of-fit relevant to high evaporation values whereas the MARE yields a more balanced estimation of the goodness-of-fit at moderate evaporation (15). R2 measures the degree to which two variables are linearly related. A list of the performance measures are depicted in Table 3.

Where O_i and P_i are the observed and predicted evaporation at time i, respectively; $\bar{o}$ is the mean of the observed evaporation; and N is the number of data points.

Table 3. List of the performance criteria

Performance Criteria	Expression
Root mean square error (RMSE)	$RMSE = \left[\frac{\sum_{i=1}^{n}(p_i - o_i)^2}{N}\right]^{1/2} \times \frac{100}{\bar{o}}$
Index of operation (d)	$d = 1 - \frac{\sum_{i=1}^{n}(p_i - o_i)^2}{\sum_{i=1}^{n}(\lvert p_i' \rvert + \lvert o_i' \rvert)^2}$ ($p_i' = p_i - \bar{o}$, $o_i' = o_i - \bar{o}$)
Mean absolute error (MAE)	$MAE = \frac{\sum_{i=1}^{n}\lvert p_i - o_i \rvert}{N}$
Mean square error (MSE)	$MSE = \frac{1}{N}\sum_{i=1}^{N}(o-p)^2$

The combinatory architectures of the ANFS models for the Chahnime station are given in Table 4. This table indicates the number of input variable as well as their corresponding performance criteria of RMSE, d, MAE, MSE, MARE, and R2. It was concluded that the best input combination should include all the variables their order of importance being T, SR, W and RH.

Table 4. A summary of statistic analysis for the ANFIS model (testing period)

Input variables	RMSE	d	MAE (mm/day)	MSE(mm^2/day^2)	R^2
T	**29.19**	**0.950**	**2.859**	**14.47**	**0.828**
T, W	**18.02**	**0.984**	**1.733**	**5.21**	**0.925**
T, W, SR	**16.38**	**0.980**	**1.607**	**5.10**	**0.930**
T, W, SR and	**17.39**	**0.985**	**1.655**	**5.14**	**0.941**

Various input combinations for NNARX model were also tested and the results are displayed in Table 5. It is clear that the performance of NNARX is better than ANFS and the input weather factors should include all four variables.

According to Table 6, the results of empirical equations to simulate evaporation and The artificial intelligence(ANFIS and NNARX), simulation models can be concluded that evaporation results are more acceptable.

Table 5. A summary of statistic analysis for the NNARX model (testing period)

Input variables	RMSE	d	MAE (mm/day)	MSE(mm^2/day^2)	R^2
T	**20.66**	**0.977**	**1.95**	**7.21**	**0.899**
T, W	**17.08**	**0.981**	**1.70**	**5.14**	**0.929**
T, W, SR	**17.40**	**0.985**	**1.65**	**5.09**	**0.94**
T, W, SR and	**15.83**	**0.987**	**1.50**	**4.23**	**0.950**

The evaporation simulations using the final ANFIS and NNARX models are showed in Figure 5 and Figure 6. As shown in the figures (and also through Table 4 & 5), the NNARX estimates are closer to the corresponding observed evaporations than the ANFIS model.

Table 6. A summary of statistic analysis for the estimated values of evaporation for the testing data set of Marciano and Meyer

Formula	RMSE	d	MAE (mm/day)	MSE(mm^2/day^2)	R^2
Marciano	102.49	-0.86	10.53	173.22	0.68
Meyer	82.64	0.82	6.86	104.32	0.81

The evaporation simulations using the final empirical equations (Marciano and Meyer) are shown in Figures 7 and 8. The Meyer estimates are closer to the corresponding observed evaporations than the Marciano equation.

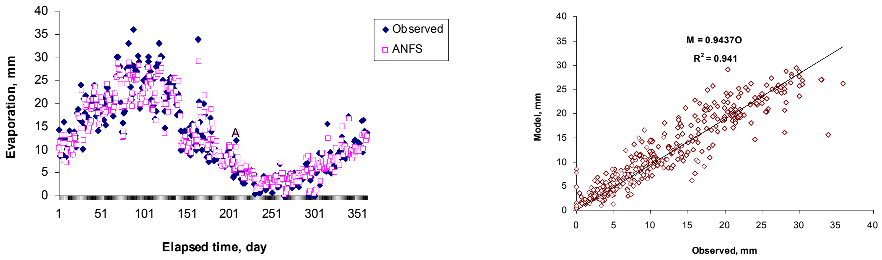

Fig. 5. Comparison of the observed and estimated evaporation for the testing data with the ANFIS model

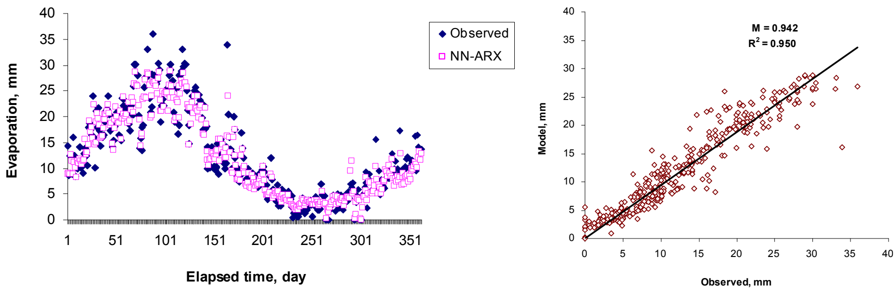

Fig. 6. Comparison of the observed and estimated evaporation for the testing data with the NNARX model

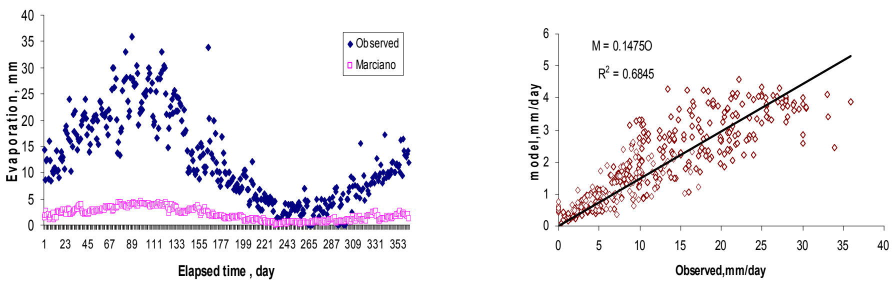

Fig. 7. Comparison of the observed and estimated evaporation for the testing data with the Marciano model

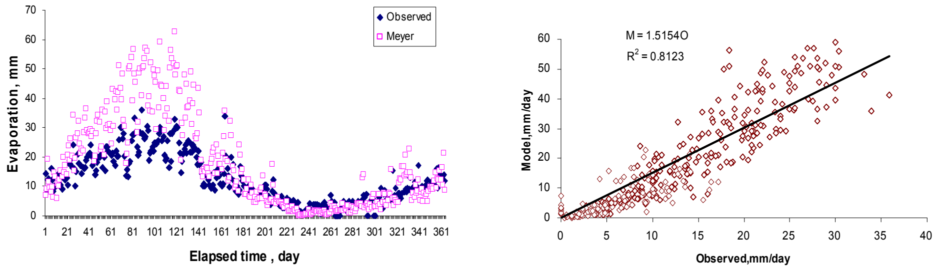

Fig. 8. Comparison of the observed and estimated evaporation for the testing data with the Meyer model

DISCUSSION AND CONCLUSION

Overall, the objectives of this study were to evaluate the ANN model for evaporation estimation under a hot and dry climate, to improve the ANN model by incorporating ARX component, and to investigate the suitable input data for the ANFIS model in comparison with those from previously published works. It is quite clear that all the planned objectives have been achieved resulting in some interesting findings about weather variable selections. This paper is the first attempt in applying this model in a Middle Eastern region. It is confirmed that ANFIS works well for a hot and dry place such as Iran. The improved performance by integrating ANN and ARX is not only novel (the first application of such a model in evaporation research field) but is also quite mind broadening since it indicates that there is still room for improving the existing ANN model despite its being a universal nonlinear regression tool. Another interesting finding in this study is the unique combination of the contributing variables. It has been demonstrated that the important weather factors to be included in the model input are: air temperature, sunshine hours, wind speed and relative humidity. This result is different to all others reported in the literature. In the USA, Han and Felker (27), used three weather input variables to estimate evaporation from the soil, relative air humidity, air temperature, wind speed. Kumar et al. (19) selected six input variables, minimum and maximum temperature, minimum and maximum relative humidity, wind speed, and solar radiation. In India with its hot and humid climate, Sudheer et al. (30) found that their model worked best with six inputs: minimum and maximum temperature, minimum and maximum relative humidity, and wind speed (although the improvement of using minimum and maximum temperature over the mean temperature was quite small). In Turkey, there were mixed results from the published papers. Terz and Kesk (34) investigated the evaporation at Lake Egirdir and found that important weather factors were (in order of their importance): air temperature, solar radiation and air pressure. It is surprising to note that they found the influences of relative humidity and wind were negligible but the air pressure was included. One year later, the authors reported that only two weather input variables (air temperature and solar radiation) were good enough and air pressure was dismissed. Another paper by the authors(33) reported three contributing weather factors to be considered in their model: solar radiation, air temperature, and relative humidity (wind and air pressure were ignored). The capricious choice of the weather variables may indicate that their model input selection schemes were not very stable. Tan et al. (32) found the important variables were: sola radiation, relative humidity, air temperature and surface wind speed.

The results in the testing of NNARX and ANFIS are listed in Table 4, 5, 6 along with the empirical methods. It is observed that NNARX and ANFIS have much better performances than the empirical equations. The best result for the empirical formula Marciano is R2 = 0.68 and for Meyer it is R2=0.81 for the test data set. In contrast, the R2 is 0.95 for NNARX and 0.94 for ANFIS both significantly better than all the three empirical formulas. Between NNARX and ANFIS, NNARX has a slightly better performance, which indicates that the fuzzy approach has not helped improve the evaporation modeling results. Figs. 5 and 6 illustrate the scatter plots for all the models (since no training is needed for the empirical models, only the estimation results on the testing data are presented in Fig. 6).This phenomenon could also occur in other climate regions and we hope this paper will inspire more researchers to explore this in their future evaporation studies.

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مدل سازی تبخیر روزانه تشتک با استفاده از ANFIS و NN_ARX

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چکیده- تغییر و تحول کمی و کیفی منابع آب تحت تأثیر فعالیت‌های مختلف در هر حوزه هیدرولوژیکی رخ می‌دهد که با توجه به محدودیت منابع آب، جلوگیری از آن بسیار مهم و حیاتی می‌باشد. در زمینه تبخیر، مدل‌های زیادی ارائه شده است که بیشتر این مدل‌ها نیازمند پارامترهای ورودی هستند که یا دسترسی به آن‌ها مشکل است و یا اندازه‌گیری آن‌ها محتاج صرف هزینه و زمان زیادی می‌باشد. در بحث شناسائی سیستم، مدل‌های آماری قوی برای مدلسازی فرآیندهای اتفاقی و سری‌های زمانی وجود دارد. به طور کلی مدل‌های دینامیک در بررسی‌های کوتاه مدت، دقیق‌تر از مدل‌های استاتیک پاسخ می‌دهد. در این تحقیق ما از دو مدل ANFIS و NN-ARX (ترکیبی از مدل ARX با ساختار شبکه عصبی) جهت پیش‌بینی تبخیر استفاده شده است. پس از اجرای برنامه مذکور نتایج تحلیل آماری که روش‌های NNARX و ANFIS عملکرد بسیار بهتر از فرمول‌های تجربی (برای تست مجموعه‌ای از داده‌ها، NNARX R2=0.95، ANFIS R2 =0.94، مایر R2 = 0.81 و Marciano R2=0.68). مدل ANFIS و NNARX کمی بهتر است. مدل‌های NNARX و ANFIS به نظر می‌رسد عملکرد بهتری نسبت به معادلات تجربی دارند. برای به دست آوردن تجربه گسترده‌تر در مورد این ابزار انتخاب داده و اینکه چگونه می‌توان آن را در ارزیابی اعتبار سنجی داده‌ها استفاده کرد مطالعات بیشتری مورد نیاز است.

واژه‌های کلیدی: تبخیر، فرمول‌های تجربی، NNARX، ANFIS

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