

## Estimation of Daily Evaporation Using of Artificial Neural Networks (Case Study; Borujerd Meteorological Station)

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**Abstract.** Evaporation is one of the most important components of hydrologic cycle. Accurate estimation of this parameter is used for studies such as water balance, irrigation system design, and water resource management. In order to estimate the evaporation, direct measurement methods or physical and empirical models can be used. Using direct methods require installing meteorological stations and instruments for measuring evaporation. Installing such instruments in various areas requires specific facilities and cost which is impossible to be specified. Pan evaporation is one of the most popular instruments for direct measuring. In this research, by using daily temperature, relative humidity, wind velocity, sunshine hours, and evaporation data in meteorological station and neural network model, daily evaporation is estimated. Network training using daily data takes three years and network testing takes one year in which data is standardize for training and testing the model. In this model, a feed forward multiple layer network with a hidden layer and sigmoid function is used. The results show the suitable capability and acceptable accuracy of artificial neural networks in estimating of daily evaporation. Best model for estimation of evaporation is ANN (5-4-1), it have MSE 0.006716 and R2 0.725398. Artificial neural networking is one of the methods for estimate evaporation. In this method can use in any area that have only maximum and minimum data for estimate evaporation.

**Key words:** Artificial neural networks, Daily Evaporation, Borujerd.

## Introduction

Mean of precipitation in Iran is 230mm which is 1.3 in the world. Every year millions meter cube of fresh water from tank of dams that was collected by height cost, evaporated and lose and residual salts which result decrease of water quality. In arid land and little water like Iran, for more prevention of water waste, this subject is very important (karamuz *et al.*, 2005). Evaporation need to energy. Each gram water exchange to evaporation need to about 600 calorie heat (Mahdavi M., 2003). But evaporation need to other energy except heat energy. Affect many factors on evaporation which importance's are: daily temperature, relative humidity, wind velocity, sunshine hours, atmosphere pressure, amount of matter solution in water and latitude. All of this factors caused that be evaporation estimation one of the most complexity calculations in meteorology and hydrology sciences. Measurement of evaporation is very complicated. Evaporation is one of the hydrologic cycle Thus in meteorological stations of Iran used A class pan evaporation. Measurement of evaporation by this pan has limitations and it is a index for evaporation of region. In this method in each 24 hour when is out of water pin of pan, add water to pan and measured amount of added water according to diameter and depth of pan and this water will be for evaporation of region. In this method for avoiding error, describe a coefficient, it is 0.7. Thus multiple this coefficient in amount of evaporation and advertise. This coefficient in the entire world has been accepted. Otherwise for estimate evapotranspiration and evaporation have been many formulas in each especial region in the world. This formulas and equations were used in Iran. However happen in each temperature upper than zero centigrade evaporation but most of the evaporation does in warm season. Need of plants to water is in time of growth and germinating synchronize with warm season. Thus this caused high

importance of measurement of evaporation on the other hand in growth seasons in Iran there is no precipitation or is very little. Therefore not only measurement of evaporation is important and representation amount of water lose in unit area but also for measurement of evaporation can determine affected factors in that region. Recognizing of this factors can help to decrease evaporation and will be one of the ways to reduce evaporation. Bruton *et al.* (2000) estimated daily pan evaporation by using artificial neural networking model. Independent variables in precipitation model were temperature, relative humidity, wind velocity and sunshine hours. They study compared neural network with multiple linear regression and Priestley-taylor equation. They showed that when all variable were used in model input best accuracy in pan evaporation will be done. The results of Sudheet *et al.* (2002) showed that the neural computing technique could be employed successfully in modeling the evaporation process from the available climatic data set. However, an analysis of the residuals from the ANN models developed revealed that the models showed significant error in predictions during the validation, implying loss of generalization of ANN models unless trained carefully. His study indicated that evaporation values could be reasonably estimated using temperature data only through the ANN technique. They told ANN (1, 5, and 2) have better potential to Stephen and Stewer linier model. Thus in some region that have no enough climatic data or no, neural network model is suitable for measurement of evaporation. Abtew (2002) estimate evaporation of Lake Okeechobee by using analysis five years' meteorological data in 7 methods. He recommended simple method by using maximum daily temperature and sunshine hour. Also measure mean monthly indexes and annually pan evaporation for 7 stations which have pan evaporation. Kumar *et al.* (2002) told the best ANN architecture was selected on the basis of weighted standard

error of estimate (WSEE) and minimal ANN architecture. The ANN architecture of 6-7-1, (six, seven and one neuron(s) in the input hidden and output layers, respectively) gave the minimum WSEE for all learning methods. This value was lower than the WSEE between the PM method and lysimeter measured ET<sub>0</sub> as reported by Jensen *et al.* (1990). Similarity, ANNs were trained, validated and tested using the lysimeter measured ET<sub>0</sub> and corresponding climatic data. They showed that the ANN can predict ET<sub>0</sub> better than the conventional method (PM) for Davis. Sudheer *et al.* (2003) resulted that his study clearly demonstrates the proficiency of the ANN method in estimating the ET. The analyses suggest that the crop ET could be computed from air temperature using the ANN approach. Also they showed a single crop data for a limited period, therefore further studies using more crops as well as weather conditions may be required to strength these conclusions. Shayannezhad (2006) compared potential evapotranspiration by using two methods such as Penman-Matis and artificial neural networking. His study was done by using 5 years data of Hamedan city metrological station. Climatic data used maximum and minimum air temperature, maximum and minimum air humidity, sunshine hour and wind speed. Results showed that artificial neural networking for determine of potential evapotranspiration is very accurate than Penman-Mantis. Keskin and Terzi (2006) compared amount of pan daily evaporation with neural network model and Penman model. The variable used in neural network model was water and air temperature, relative humidity, wind velocity, sunshine hours and air presser. The comparison showed that there is better agreement between the ANN estimation and measurements of daily pan evaporation than for other model. Also ANN (7, 2, 1), ANN (6, 2, 1) and ANN(3,6,1) have R<sup>2</sup> 0.788, 0.787 and 0.77 respectively. Zanetti *et al.* (2007) tested artificial neural network (ANN) for

estimating the reference evapotranspiration (ET<sub>0</sub>) as a function of the maximum and minimum air temperature in the Campos dos Goytacazes County, State of Rio de Janeiro. They trained multilayer perception type by using independent variables such as maximum and minimum air temperatures, extraterrestrial radiation and the daylight hours. They results obtained in ANN testing phase, it is concluded that when taking into account just the maximum and minimum air temperature, it is possible to estimate ET<sub>0</sub> in Campos dos Goytacazes.

### Material and Methods

First aim of this study is evaluate neural networks capability in estimate evaporation by using available climatic data. The daily data were used from Borujerd metrological synoptic station for four years period. Different structure of artificial neural networking used with different combination of data for estimation of daily evaporation. Neural network was a feed forwarded network with training pattern of back-propagation. In this research, by using daily temperature, relative humidity, wind velocity, sunshine hours, and evaporation data in meteorological station and neural network model, daily evaporation is estimated. Network training using daily data takes three years and network testing takes one year in which data is standardize for training and testing the model. In this model, a feed forward multiple layer network with a hidden layer and sigmoid function is used.

Four function like below have been investigated for this study.

$$E(t) = f(T_{\max(t)}, T_{\min(t)}) \quad 1$$

$$E(t) = f(T_{\max(t)}, T_{\min(t)}, RH_t) \quad 2$$

$$E(t) = f(T_{\max(t)}, T_{\min(t)}, RH_t, N_t) \quad 3$$

$$E(t) = f(T_{\max(t)}, T_{\min(t)}, RH_t, N_t, V_t) \quad 4$$

$$E(t) = f(T_{\max(t)}, T_{\min(t)}, RH_t, N_t, V_t) \quad 5$$

$T_{\max(t)}$  = daily maximum temperature

$T_{\min(t)}$  = daily minimum temperature

$N_t$  = daily sunshine hours

$RH_t$  = daily relative humidity

$V_t$  = daily wind speed

$E(t)$  = daily evaporation

At first data standardized and then network tested and trained with different combination. For example in (1) function which have 2 inputs and 1 output, tested and trained hidden layer with different neurons for receive to best combination. One network ANN (2, 1 and 1) is 2 inputs and one hidden layer and one output. After testing and training estimate in each network error of test and train and determine best network structure.

Data were standardized by below formula:

$$X = 0.8 \left( \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \right) + 0.1$$

Standardization method

$X_i$  = amount of X standardized

$X_{\max}$  = maximum amount in all data

$X_{\min}$  = minimum amount in all data

After standardization of data, were used 75 percent of data for network training and 25

percent for network testing. In this model, a feed forward multiple layer network with a hidden layer and sigmoid function is used. Sigmoid function defines like below:

$$f(x) = \frac{1}{1 + \exp(-x)} \quad 7$$

In during of study, estimate error of testing and training. So for determination of best and better network structure used RMSE and  $R^2$  index.

$$RMSE = \sqrt{\frac{\sum_{i=1}^r (x_{obs} - x_{ann})^2}{r}} \quad 8$$

$x_{obs}$  = observation

$x_{ann}$  = estimation data by network and r number of data.

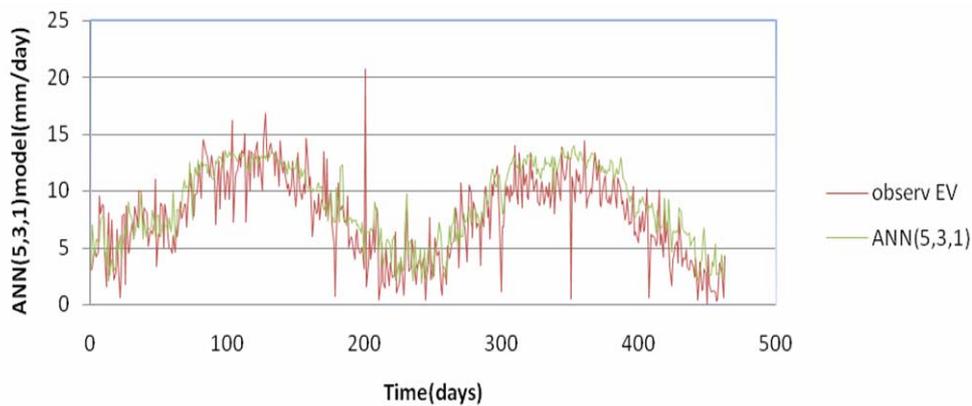
$$R = \frac{\sum_i^n (x_{obsi} - \bar{x}_{obs})(x_{anni} - \bar{x}_{ann})}{\sqrt{\sum_{i=1}^n (x_{obsi} - \bar{x}_{obs})^2 \sum_{i=1}^n (x_{anni} - \bar{x}_{ann})^2}}$$

### Results and Discussion

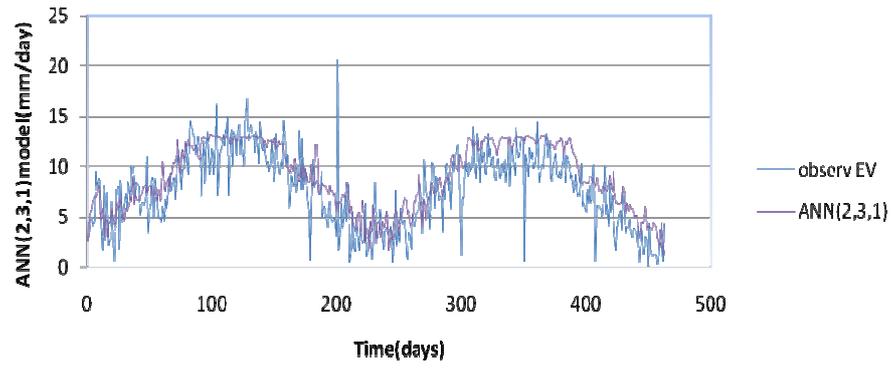
For the purpose of determination of the most suitable network based on defined function with different neurons in hidden layer, done train and test on 31 different structure and selected best network. The results caused from network test and train is in table 1. Also different networks have so near results together but the most suitable networks according to input data for model air maximum and minimum temperature was the ANN (2-6-1) model. For (2), (3) and (4) equations was ANN (3-1-1), ANN (4-5-1 and ANN (5-4-1) respectively. Figures of 1, 2, 3 and 4 showed results of testing and training of the most suitable networks based on defined functions. Finally the most suitable model between networks model is ANN (5-4-1). Figures of 1 showed results estimated evaporation with comparison of observation quantities and artificial neural networking.

**Table 1. Values of Average Test Errors of Different ANN Architectures.**

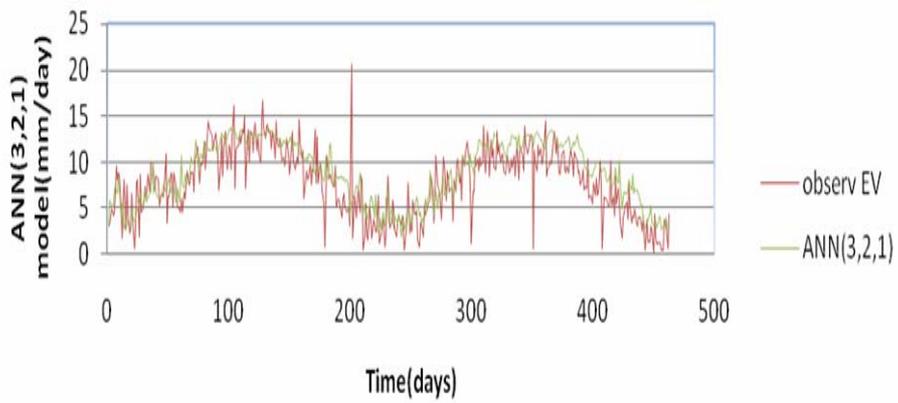
No.	Network structure	Average train(MSE)	Average test(MSE)
1	ANN(2,1,1)	0.00752616	0.00967236
2	ANN(2,2,1)	0.00729264	0.0098548
3	ANN(2,3,1)	0.00712526	0.00964949
4	ANN(2,4,1)	0.00704029	0.01000116
5	ANN(2,5,1)	0.00701453	0.00994456
6	ANN(2,6,1)	0.00693253	0.0097486
7	ANN(2,7,1)	0.00674128	0.01016705
8	ANN(2,8,1)	0.00673556	0.01004854
9	ANN(2,9,1)	0.00665457	0.01000649
10	ANN(2,10,1)	0.00669963	0.00984486
11	ANN(2,11,1)	0.00752616	0.00991963
12	ANN(2,12,1)	0.00729264	0.01028064
13	ANN(3,1,1)	0.007006	0.00931822
14	ANN(3,2,1)	0.00671	0.00931874
15	ANN(3,3,1)	0.006603	0.0096415
16	ANN(3,4,1)	0.006466	0.00938111
17	ANN(3,5,1)	0.00618	0.00998879
18	ANN(3,6,1)	0.006359	0.00970956
19	ANN(3,7,1)	0.006312	0.00983087
20	ANN(3,8,1)	0.006288	0.0094189
21	ANN(3,9,1)	0.006224	0.00968907
22	ANN(3,10,1)	0.006236	0.0097165
23	ANN(4,1,1)	0.006804	0.00924385
24	ANN(4,2,1)	0.006434	0.00868138
25	ANN(4,3,1)	0.006472	0.00918302
26	ANN(4,4,1)	0.006137	0.00912032
27	ANN(4,5,1)	0.006075	0.00904199
28	ANN(4,6,1)	0.005837	0.01011017
29	ANN(4,7,1)	0.005797	0.00944309
30	ANN(4,8,1)	0.005727	0.00907614
31	ANN(4,9,1)	0.005755	0.00918785
32	ANN(4,10,1)	0.005589	0.01310207
33	ANN(5,1,1)	0.00680426	0.0092457
34	ANN(5,2,1)	0.006804285	0.00924606
35	ANN(5,3,1)	0.006146112	0.0089628
36	ANN(5,4,1)	0.006069898	0.00909927
37	ANN(5,5,1)	0.005913921	0.00909232
38	ANN(5,6,1)	0.005748534	0.00903334
39	ANN(5,7,1)	0.005791493	0.00932263
40	ANN(5,8,1)	0.00619223	0.0092457



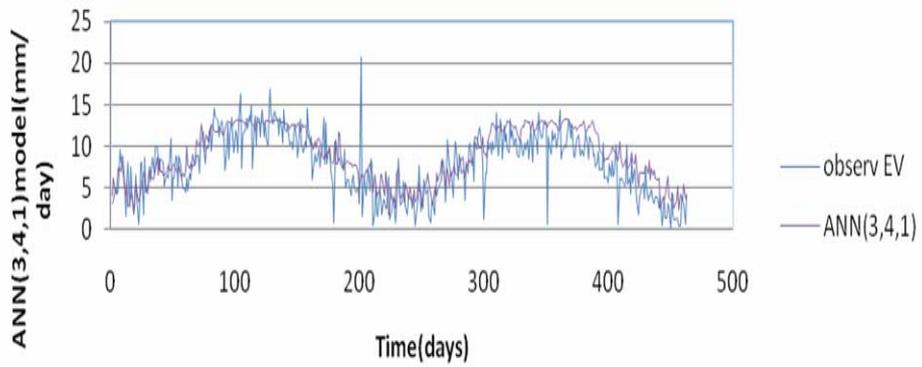
**Fig. 1. Modeled and Measured Evaporation ANN (5-3-1)**



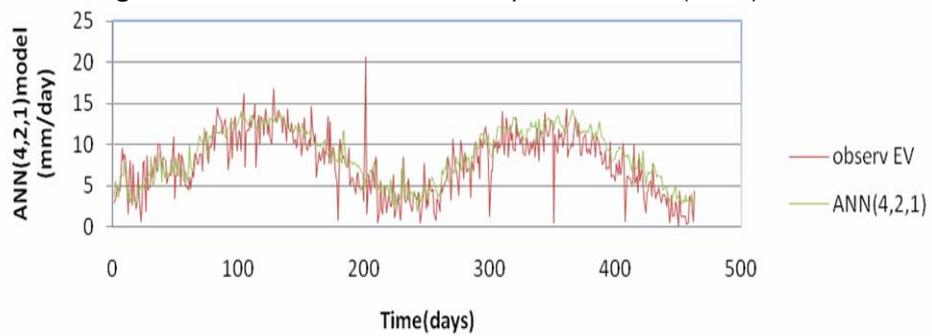
**Fig. 2.** Modeled and Measured Evaporation ANN (2-3-1)



**Fig. 3.** Modeled and Measured Evaporation ANN (3-2-1)



**Fig. 4.** Modeled and Measured Evaporation ANN (3-4-1)



**Fig. 5.** Modeled and Measured Evaporation ANN (4-2-1)

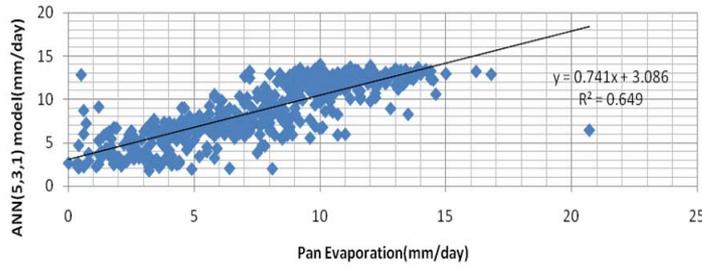


Fig. 6. Comparison of Daily Pan Evaporation with Different ANN (5-3-1) Model

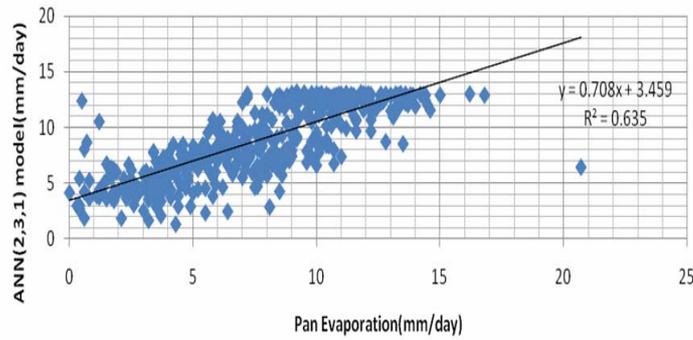


Fig. 7. Comparison of Daily Pan Evaporation with Different ANN (2-3-1) Model

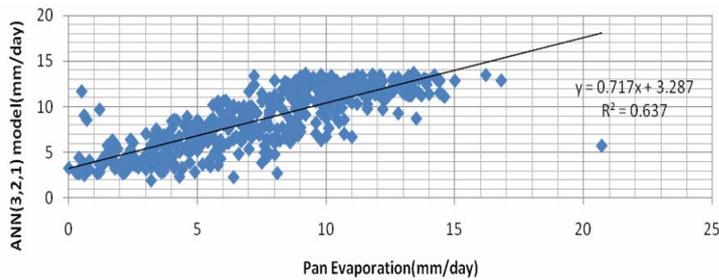


Fig. 8. Comparison of Daily Pan Evaporation with Different ANN (3-2-1) Model

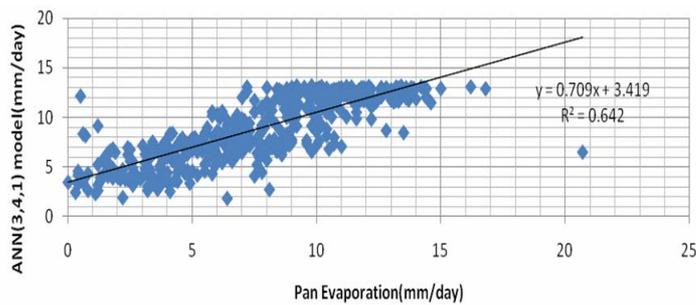


Fig. 9. Comparison of daily Pan Evaporation with Different ANN (3-4-1) Model

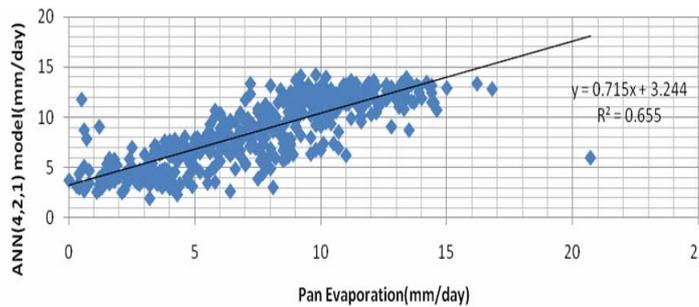


Fig. 10. Comparison of Daily Pan Evaporation with Different ANN (4-2-1) Model

All of the researches showed that artificial neural networking models can compare and compete with direct method like daily pan evaporation for measurement and estimation of evaporation. If used more metrological factors in ANN model, it can cause more accuracy for estimate but that cause more cost. So ANN models can select best according to cost and accuracy. Best model for estimation of evaporation in Borujerd metrological station according to less MSE (0.006716) and height  $R^2$  (0.725) is ANN (5-4-1).

### Conclusion

Artificial neural networking is one of the methods for estimate evaporation. In this method can use in any area that have only maximum and minimum data for estimate evaporation. Thus farmers can estimate needs of water for irrigation of farms. If there is more factors of climatic such as relative humidity, wind velocity and sunshine hours estimation of evaporation will be more accuracy. This method can use for rangeland plants too. If determine amount of evaporation in rangeland, can decrease grazing of livestock for conservation of plants. Also can estimate amount need of water for grazing of livestock in rangeland by this method.

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