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Prediction of reference evapotranspiration using artificial neural network

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■ **ABSTRACT :** The study has been undertaken to predict one month ahead ETo using artificial neural networks (ANNs). Climatic parameters for 35 years (1977-2011) were collected for Akola station. The ETo was estimated by using standard Penman-Monteith method which was further used for development and validation of the ANN models as the observed data on ETo was not available. The ANN models were developed using different input combinations. The models learned to predict one month ahead ETo (*i.e.* $ET_{o,\,t+1}$) for Akola using Levenberg-Marquardt learning method. The training results were compared with each other, and performance evaluations were done for untrained data. Based on results obtained, the ANN model with architecture of 4-12-1 (four, twelve and one neuron(s) in the input, hidden, and output layers, respectively) was found to be the best amongst all the models with minimum standard error (SE) of estimates of 0.74 mm day^{-1} and correlation co-efficient of 0.9260. From the study it is concluded that ANN4 model had given better performance with mean absolute error of estimates (MAE) and root mean square error (RMSE) of 0.20 and 0.27 mm day^{-1}, respectively, mean absolute relative error (MARE) of 5.7 per cent and model efficiency of 0.9745.

■ **KEY WORDS :** Reference evapotranspiration, ANN, Levenberg-Marquardt

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The concept of the reference evapotranspiration was introduced to study the evaporative demand of the atmosphere independently of crop type, crop development and management practices. Evapotranspiration is involved in problems of water supply, water management and in the economics of multipurpose water projects of irrigation, power, water transportation, flood control, urban and industrial water uses and waste water reuse system. Evapotranspiration data are essential for estimating water yields from watersheds, safe yield of ground water basins and streams of flow depletion in river basin. The ability to predict events with reasonable accuracy enables one to plan in advance what course of action to take to get the best out of situations.

The ability to forecast reference evapotranspiration is of utmost importance for water resources development and utilization, project planning, design and management of irrigation systems effectively in agricultural areas where crop production is the principal user of water.

ANNs have found successful applications in the areas of science, engineering, industry, business, economics and agriculture. Studies on ANN application include rainfall-runoff relationship (Hsu Kuo-lin *et al.*, 1995); water table depth simulation (Yang *et al.*, 1996 a and b, Yang, 1995); (Yang *et al.*, 1997 a&b); soil water content_at a given depth prediction (Altendrof *et al.*, 1999); hydraulic roughness co-efficients estimation for overland flow (Lopez *et al.*, 2002); forecasting of reference evapotranspiration (Trajkovic *et al.*, 2003); daily flows modelling (Rajurkar *et al.*, 2004). It is evident from the literature; the study has been carried out to utilize input-output mapping capability of ANN in the prediction of ET.

An ANN is capable of identifying nonlinear relationship between input and output data sets, which may be too difficult to represent by conventional mathematical equations. ANNs are universal approximators which can approximate a large class of functions with a high degree of accuracy (Kumar *et al*., 2002; Sudheer *et al*., 2003; Trajkovic, 2005; Zenetti *et al*., 2007 and Landeras *et al*., 2008). It seems necessary that nonlinear models such as artificial neural networks (ANNs), which are suited to complex nonlinear systems, be used for the analysis of real-world temporal data. There are many applications of ANNs in water resources. Forecasting is mentioned as one of the most promising application areas of ANN. Hence, in this study ANNs are developed to predict one month ahead ETo (*i.e.* $ETo_{,t+1}$) for Akola station.

METHODOLOGY

In order to carry out study, mean monthly meteorological data, *viz.*, maximum temperature (Tmax), minimum temperature (Tmin), maximum relative humidity (RHmax), minimum relative humidity (RHmin), bright sunshine hours (SH) and wind speed (WS) were collected from Agricultural Meteorological Observatory, Dr. Panjabrao Deshmukh Krishi Vidyapeeth, Akola, for the duration of 35 years (1977-2011). Other parameters like geographic locations, *viz.*, latitude and longitude of Akola station also were obtained.

Out of 35 years data first 34 years (1977-2010) data were used for model development and remaining one year (2011) data were used for model validation.

Estimation of reference evapotranspiration (ETo):

In this study, the reference evapotranspiration was determined by using standard Penman Monteith (FAO - 56) equation.

Development of artificial neural network models :

The different multilayer back propagation feed forward neural networks were trained to forecast $ET_{o,t+1}$ based on different combinations of $ET_{o,t-11}$, $ET_{o,t-23}$, $ET_{o,t-35}$, $ET_{o,t-47}$ and $ET_{o,t-59}$. Summary of the inputs used for the implementation of each ANN model strategy for prediction of $ET_{o,t+1}$ is as given in Table A.

Thus, five feed forward neural networks were developed for selected station. To avoid overtraining and under training, the available data were splited in three separate data sets: (1) training set, (2) cross validation set, (3) testing set in proportion of 60:20:20. The ANN model implementation was carried out using Neuro-Solution 5 version.

The most common architecture: composed of the input layer, hidden layer and output layer was used in this study, where the number of neurons in the input and output layer (corresponded to $ET_{o,t+1}$) were fixed in each strategy of input combinations and number of neurons in the hidden layer were varied up to three times of number of neurons in input layer in order to get the minimum mean square error (MSE) and high correlation co-efficient. In order to train the network the Levenberg-Marquardt (L-M) algorithm was used, because on function approximation problems it has the fastest convergence and obtain lower mean square errors (Kisi, 2007). Single hidden layer network with linear sigmoid

Table A : Strategies of development of different ANNs using following input combinations

ANN1	ANN2	ANN3	ANN4	ANN5
$ET_{o,t-11}$	$ET_{o,t-11}$	$ET_{o,t-11}$	$ET_{o,t-11}$	$ET_{o,t-11}$
	$ET_{o,t-23}$	$ET_{o,t-23}$	$ET_{o,t-23}$	$ET_{o,t-23}$
		$ET_{o,t-35}$	$ET_{o,t-35}$	$ET_{o,t-35}$
			$ET_{o,t-47}$	$ET_{o,t-47}$
				$ET_{o,t-59}$

$ET_{o, t+1}$=One month ahead ETo
$ET_{o, t-11}$ = Previous 1year's ETo for respective month
$ET_{o, t-23}$ = Previous 2 year's ETo for respective month
$ET_{o, t-35}$ = Previous 3 year's ETo for respective month
$ET_{o, t-47}$= Previous 4 year's ETo for respective month
$ET_{o, t-59}$ = Previous 5 year's ETo for respective month

transfer function in the hidden layer and linear transfer function in the output layer were used. The network was trained for maximum of 5000 epochs and with goal for MSE of 0.001. The number of iterations when training stopped and errors were noted down.

Performance evaluation of developed ANN models:

In the next step the network response was analyzed. The best model architecture was selected from each ANN strategy on the basis of minimum mean square error of the testing set. Then the trained networks were used for predicting the $ET_{o,t+1}$ for the independent data set of year 2011 and predicted $ET_{o,t+1}$ were compared with predetermined ETo of the same year. The variations of the ANN predicted and targets are presented graphically.

The model evaluation results were compared quantitatively using statistically measures and criteria *viz.*, mean absolute error (MAE), mean absolute relative error (MARE), root mean square error (RMSE), co-efficient of correlation (r), co-efficient of determination (R^2), model efficiency (E) used for evaluation and comparisons.

RESULTS AND DISCUSSION

The results obtained from the present investigation as well as relevant discussion have been summarized under the following heads :

Training of ANNs :

It is observed from the Table 1 and Fig. 1 (ANN1) for ANN1 model strategy having only one input (*i.e.* $ET_{o,t-}$

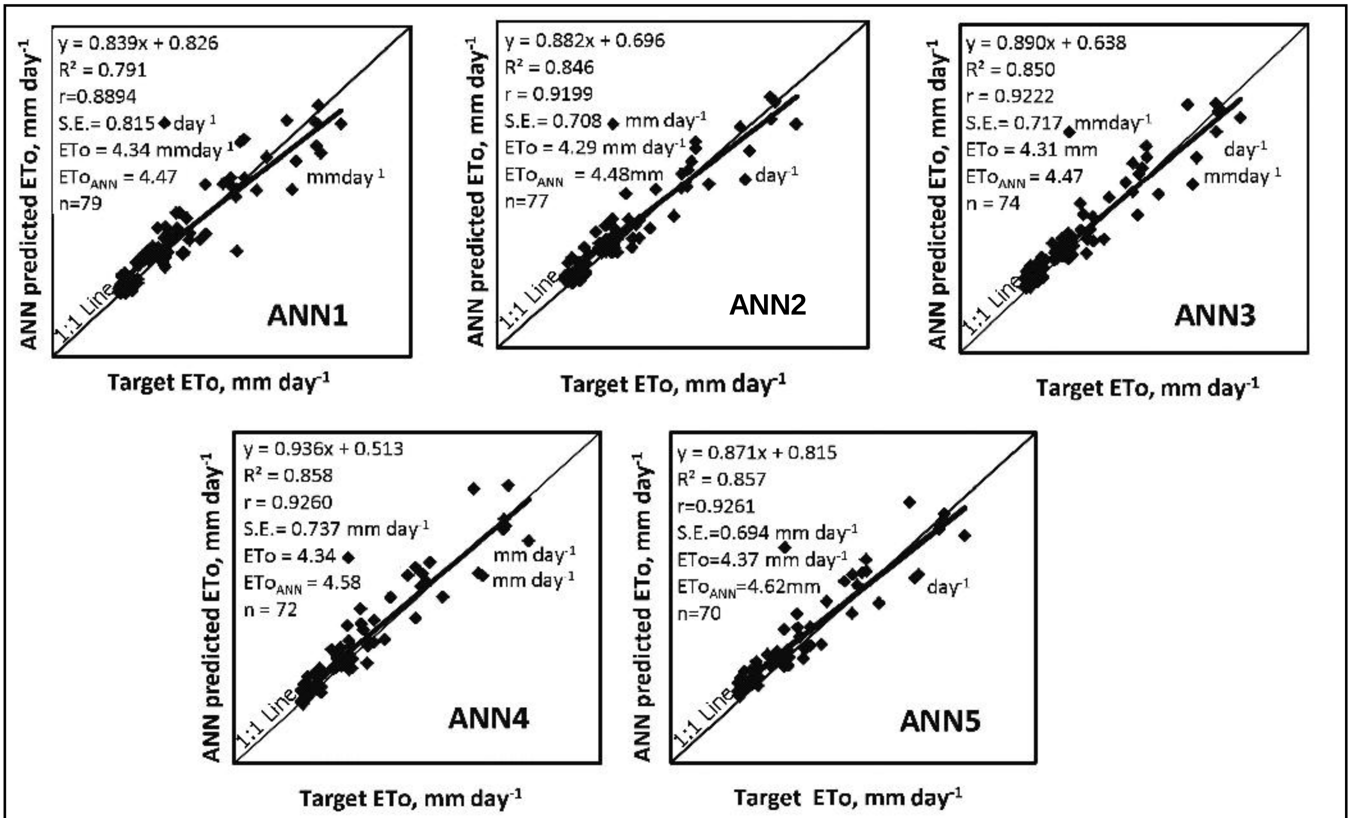

Fig. 1 : Scatter plot between target and ANN predicted Eto values for test data set obtained during training phase of different ANNs

Table 1 : Architectures of neural networks with their performance indices obtained during training phase of ANN1

Sr. No.	Architectures	Number of epochs	Mean square error for test data set	Correlation co-efficient for test set
1.	1-1-1	83	0.7868	0.8857
2.	1-2-1	83	0.8127	0.8857
3.	1-3-1	19	0.7552	0.8894

$_{11}$), that 1-3-1 architecture (1, 3 and 1 nodes in input, hidden and output layer, respectively) was enough for training the network as it resulted in lowest (0.7552) mean square error (MSE) and highest correlation co-efficient (0.8894). Therefore, in ANN1 model strategy, the model with 1-3-1 architecture was selected for validation.

It is observed from the Table 2 and Fig. 1 (ANN2) for ANN2 model strategy which was having two inputs (*i.e.* $ET_{o,t-11}$ and $ET_{o,t-23}$), that the minimum MSE (0.5726) was found for 2-6-1 architecture with highest correlation co-efficient (0.9199). Therefore, scatter plot of test data set for this architecture was obtained. Hence, in ANN2 model strategy, the model with 2-6-1 architecture was selected for validation.

In ANN3 model strategy, which was having three inputs (*i.e.* $ET_{o,t-11}$, $ET_{o,t-23}$ and $ET_{o,t-35}$), it is observed from Table 3 and Fig. 1 (ANN3) that the architecture 3-9-1 was enough for training the network as it has lowest MSE (0.5707) as well as second highest correlation co-efficient (0.9222). The regression line was more close to 1:1 line, which indicates the closeness of the target and predicted values for test set. Therefore, in ANN3 model strategy, the model with 3-9-1 architecture was selected for further evaluation.

Table 2 : Architectures of neural networks with their performance indices obtained during training phase of ANN2

Sr. No.	Architectures	Number of epochs	Mean square error for test data set	Correlation co-efficient for test set
1.	2-1-1	277	0.6073	0.9141
2.	2-2-1	321	0.6186	0.9175
3.	2-3-1	195	0.5772	0.9195
4.	2-4-1	259	0.5849	0.9179
5.	2-5-1	19	0.5791	0.9198
6.	2-6-1	15	0.5726	0.9199

Table 3 : Architectures of neural networks with their performance indices obtained during training phase of ANN3

Sr. No.	Architectures	Number of epochs	Mean square error for test data set	Correlation coefficient for test set
1.	3-1-1	1091	0.6878	0.9241
2.	3-2-1	94	0.5976	0.9222
3.	3-3-1	195	0.7217	0.9151
4.	3-4-1	275	0.5857	0.9211
5.	3-5-1	183	0.7129	0.9203
6.	3-6-1	275	0.6232	0.9201
7.	3-7-1	358	0.5989	0.9215
8.	3-8-1	1950	0.5850	0.9196
9.	3-9-1	3837	0.5707	0.9222

Table 4 : Architectures of neural networks with their performance indices obtained during training phase of ANN4

Sr. No.	Architecture	Number of epochs	Mean square error for test data set	Correlation co-efficient for test set
1.	4-1-1	5000	0.6068	0.9259
2.	4-2-1	1512	0.6286	0.9238
3.	4-3-1	358	0.6399	0.9232
4.	4-4-1	328	0.7206	0.9163
5.	4-5-1	35	0.5988	0.9263
6.	4-6-1	145	0.6690	0.9232
7.	4-7-1	207	0.6303	0.9245
8.	4-8-1	117	0.6399	0.9253
9.	4-9-1	2017	0.6436	0.9257
10.	4-10-1	1335	0.7750	0.9235
11.	4-11-1	37	0.7503	0.9211
12.	4-12-1	156	0.6561	0.9214

For ANN4 model strategy, in which four inputs were used for training, it is seen from Table 4 and Fig. 1 (ANN4) that MSE (0.5988) obtained during testing of different architectures was lowest with highest correlation co-efficient (0.9263). The regression line was more close to 1:1 line, which indicates the closeness of the target and predicted values. Therefore, in ANN4 model strategy, the model with 4-5-1 architecture was selected for further evaluation.

It is observed from Table 5 and Fig. 1 (ANN5) for ANN5 model strategy with five inputs, that MSE (0.5941) was lowest in respect of 5-12-1 architecture and highest correlation co-efficient (0.9262). Therefore, scatter plot of test data set for this architecture was obtained. The regression line coincides with 1:1 line, which indicates the close fit of the target and predicted values. Therefore, for ANN5 model strategy, the model with 5-12-1 architecture was selected for further evaluation.

Model evaluation :

Independent evaluation data set of 2011 was used for validation of the trained and selected networks. For this purpose the data regarding $ET_{o,t-11}$, $ET_{o,t-23}$, $ET_{o,t-35}$, $ET_{o,t-47}$ and $ET_{o,t-59}$ were given as inputs to the networks developed and $ET_{o,t+1}$ was predicted. For ANN1, only one input was used *i.e.* $ET_{o,t-11}$ which was one year previous data. Likewise each of ANN1, ANN2, ANN3, ANN4 and ANN5 models developed using only inputs from independent evaluation data set. Predicted rates of ETo were then compared with the target values of ETo.

The variation and scatter plot between target and predicted ETo using selected ANN model are presented in Fig. 2 and 3. It is seen from Fig. 2 and 3 (ANN1), that ANN1 model having only one input ($ET_{o,t-11}$), yields fairly accurate estimates of ETo for the most of periods of year. The correlation co-efficient between target and predicted ETo was obtained significantly high (0.9730) with 0.47 mm day^{-1} standard error (SE) of estimate. It is observed from Table 6 (ANN1) that low MAE, RMSE and MARE were obtained with good co-efficient of determination and model efficiency of 0.9366. Results of ANN1 model suggest that only previous one year data

Table 5 : Architectures of neural networks with their performance indices obtained during training phase of ANN5

Sr. No.	Architecture	Number of epochs	Mean square error for test data set	Correlation co-efficient for test set
1.	5-1-1	78	0.6548	0.9247
2.	5-2-1	189	0.8957	0.9085
3.	5-3-1	334	0.6502	0.9232
4.	5-4-1	40	0.6669	0.9216
5.	5-5-1	119	0.6368	0.9251
6.	5-6-1	95	0.6378	0.9231
7.	5-7-1	146	0.7300	0.9205
8.	5-8-1	149	0.6550	0.9261
9.	5-9-1	411	0.6285	0.9238
10.	5-10-1	437	0.6584	0.9227
11.	5-11-1	205	0.6741	0.9241
12.	5-12-1	90	0.5941	0.9262
13.	5-13-1	313	0.6487	0.9243
14.	5-14-1	438	0.6519	0.9212
15.	5-15-1	2335	0.6347	0.9261

Table 6 : Comparative performances of different ANN models developed

Sr. No.	Performance index	ANN1	ANN2	ANN3	ANN4	ANN5
1.	Mean absolute error, mm day^{-1}	0.2773	0.3617	0.2410	0.2061	0.2211
2.	Root mean square error, mm day^{-1}	0.4703	0.4538	0.3351	0.2778	0.2983
3.	Mean absolute relative error, %	6.8763	9.7664	6.7039	5.7772	6.8122
4.	Correlation co-efficient	0.9730	0.9850	0.9920	0.9940	0.9910
5.	Co-efficient of determination	0.9467	0.9700	0.9840	0.9880	0.9820
6.	Model efficiency	0.9366	0.9410	0.9678	0.9779	0.9745

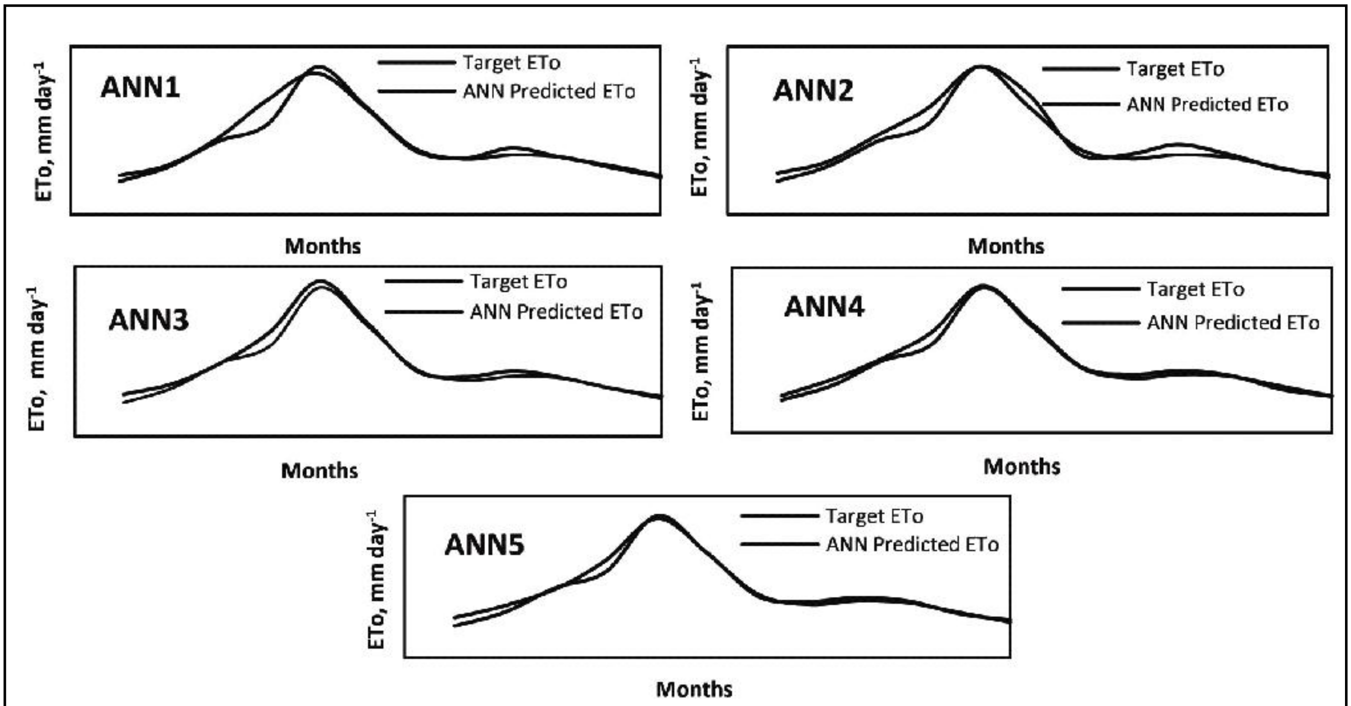

Fig. 2 : Variation between target and ANN predicted Eto using ANNs model for the independent evaluation data set

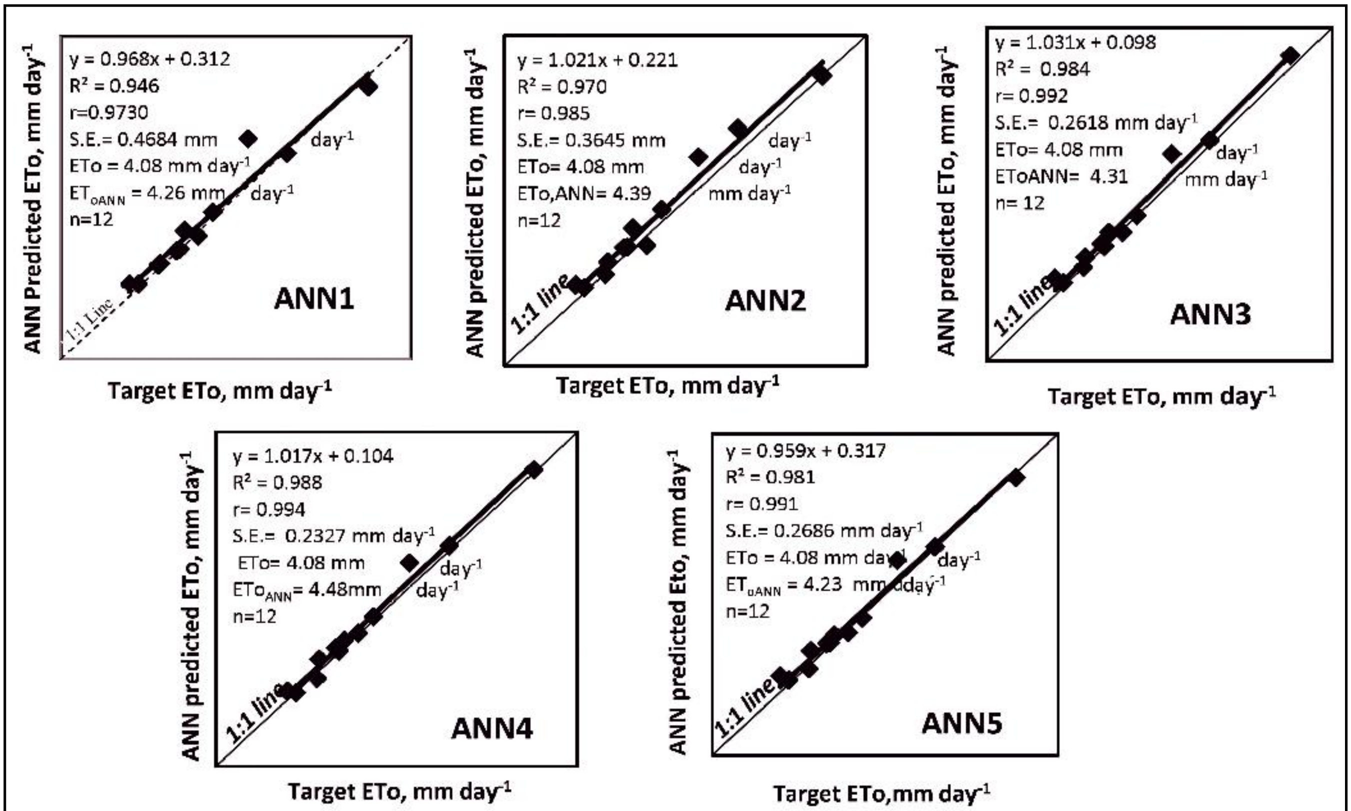

Fig. 3 : Scatter plot between target and ANN predicted Eto values for the independent evaluation data set using ANN1 model

can approximate the model for forecast of ETo and is suitable for fairly accurate prediction of ETo.

It is observed that ANN2 model having only two inputs, has accurately predicted ETo throughout the year. The correlation between target and predicted ETo was highly significant. The regression line is parallel to 1:1 line with low SE of estimate (0.36 mm day^{-1}) which shows slight overprediction that MAE, RMSE and MARE were low of ETo. Table 6 (ANN2) shows with high co-efficient of determination (0.9700). The model efficiency was also high (0.9410). ANN2 model indicates that even with only two inputs *i.e.* previous two years data, it is possible to predict ETo with good accuracy.

It is observed that ANN3 model having three inputs, predicted fairly accurate estimates of ETo for the most of the periods of the year. The regression line deviated from 1:1 line at the higher rates. The significantly high correlation between target and predicted ETo was obtained with 0.26 mm day^{-1} SE of estimate. It is observed from Table 6 (ANN3) that low MAE, RMSE and MARE were low with good co-efficient of determination. The model efficiency was obtained high enough (0.9678). These results of ANN3 model indicate that ANN3 model is suitable for prediction of ETo with good accuracy, where data of even only previous three years are available.

It is observed that ANN4 model having four inputs, has accurately estimated ETo throughout the year. The correlation between target and predicted ETo was highly significant. The regression line coincides the 1:1 line, with 0.23 mm day^{-1} SE of estimate. Table 6 (ANN4) reveals that MAE, RMSE and MARE were also low with high co-efficient of determination. The model efficiency was high (0.9779) enough. The results of ANN4 model indicate that it can approximate the prediction function of ETo with past four years data.

ANN5 model has predicted ETo accurately. The correlation co-efficient between target and predicted ETo was highly significant (0.9910). The regression line coincides with 1:1 line for whole range of values of ETo with low standard error of estimate (0.27 mm day^{-1}). Table 6 (ANN5) reveals that MAE, RMSE and MARE were very low with high co-efficient of determination (0.9820) and model of efficiency was also high (0.9745). Results of ANN5 model indicate that it is possible to predict ETo using ANN5 network model with high degree of accuracy.

Comparative performances of different developed ANNs :

Comparative performances of different ANN models developed are represented in Table 6. From Table 6, results indicate that MAE, MARE, RMSE, r, R^2 and E recorded in respect of all ANN models developed were found to be acceptable and reveal that all are suitable for forecasting the ETo with accuracy. Out of five developed and evaluated ANN models, ANN4 forecasted ETo with highest accuracy among all, with lowest MAE, MARE, RMSE and highest r, R^2 and E.

Conclusion :

Developed ANN models were found to be suitable for prediction of one month ahead ETo and can be used according to the availability of historical data. Whereas ANN4 is suggested to be best among ANN1 to ANN5 models for prediction of ETo.

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