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Short Communication

Assessment of reference evapotranspiration using ANN at Mulde, Maharashtra

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Evapotranspiration is a complex and non-linear phenomenon because it depends on several interacting climatological factors, such as temperature, humidity, wind speed, solar radiation. In the past decade, ANN intensively used in system modelling, rainfall-runoff modelling, reservoir operation; land drainage design, aquifer parameter estimation etc. shown that ANN is more accurate than conventional methods. Artificial Neural Networks (ANN) is effective tools to model nonlinear systems which may be difficult to present by conventional mathematical equations. The ANN models are well suited under relationships between the input and output variables are not explicit. The ANN models need less data than conventional methods when properly validated and numbers of variables remain constant from one simulation to another. The ANN approach estimates evapotranspiration under limited climatic data conditions. The many researchers are working on ANN applications and some of these applications are reviewed. According ASCE Task Committee (2000) examined the role of artificial neural networks in various branches of hydrology. It was found that ANNs are robust tools for modelling many of the nonlinear hydrologic processes such as rainfall runoff, stream flow, ground water management, water quality simulation and precipitation. Maier and Dandy (2000) reviewed 43 research articles regarding neural network models for the prediction and forecasting of water resources variables in terms of the modelling process adopted. Keskin and Terzi (2006) evaluated the potential of ANN models for daily pan evaporation prediction using meteorological data from Lake Eirdir consisting of 490 daily records from 2001 to 2002 and concluded that there was better agreement between the ANN estimations and measurements of daily pan evaporation than for other model. Kisi (2006b) used two different feed forward neural network algorithms, Levenberg-Marquardt (LM) and Conjugate Gradient (CG)for estimation of daily reference evapotranspiration from climatic data and claimed that neural computing techniques could be employed successfully in modelling evapotranspiration process from the available climatic data. Chauhan and Shrivastava (2011) investigated the potential of artificial neural networks (ANNs) for estimation of monthly crop reference evapotranspiration (ETo) and to compare the performance of ANNs with Penman-Monteith (P-M) method used to estimate ETo. The study found that ANN model trained with the Conjugate gradient algorithm was found to be the best with minimum SEE of 0.225 mm day^{-1}, ASEE of 0.195 mm day^{-1} and maximum model efficiency of 98.8%. Huo *et al* (2012) tested artificial neural network models for reference evapotranspiration (ET0) using 50 years' meteorological data from three stations in northwest China. They found that for different locations and climatic conditions the ANN models exhibited potential advantages for ET_0 estimation with limited meteorological input. Kale et *al* (2013)formulated various ANN architectures using varied input combinations of climatic variables and were trained using backpropagation algorithm i.e. Levenberg-Marquardt with sigmoid function. The study concluded that ANN (2-2-1) topology should be used to estimate fairly accurate ETo when data pertaining to climatic parameters is insufficient to apply standard ETo estimation methods. Reddy (2014) developed artificial neural network (ANN) models for estimating daily, weekly and monthly reference evapotranspiration (ET0) in Rajendranagar region of Andhra Pradesh. The optimal ANN (4-3-1) model showed a satisfactory performance in the daily, weekly and monthly ET0 estimation. These ANN models may therefore be adopted for estimating ETo in the study area with reasonable degree of accuracy. Sibale *et al.* (2016) also studied the reference evapotranspiration for Dapoli station.

From review, it observed that neural computing techniques employed successfully in modelling evapotranspiration process from available climatic data. ANN model developed showed significant error in predictions during the validation, implying loss of generalization properties of ANN models unless trained carefully. ANN also used to fill the gaps in data sets for reliable estimates and could be used to obtain continuous ET data for modelling and water management practices. By viewing these advantages of ANN the present was taken to to assess reference evapotranspiration for short and tall crop reference surfaces for Mulde station of Konkan region of Maharashtra.

Study area

The study was conducted for Western part of the Maharashtra State namely Konkan region. Mulde station from Sindhurag district was selected for present study. The Mulde station situated on 16°26' N latitude and 73°16' E longitude with 17 m altitude. The meteorological data required for analysis was collected from Agricultural Meteorological Observatories, Dr. B.S.K.K.V., Dapoli. The meteorological data includes daily maximum temperature (Tx.), minimum temperature (Tn.), maximum relative humidity (RHx.), minimum relative humidity (RHn.), bright sunshine hours (SH) and wind speed (WS) for a period of 24 years (1991 to 2014).

Estimation of reference evapotranspiration

The ASCE Technical Committee on Evapotranspiration in Irrigation and Hydrology recommended that two standardized reference evapotranspiration equations adopted for general practice along with *standardized* computational procedures (ASCE, 2005).

Standardized reference evapotranspiration equation, short (ETo):

Reference ET for a *short* crop having an approximate height of *0.12* m (similar to grass). The form of the reference evapotranspiration equation is

$$ET_{O}=\frac{0.408\,\Delta(R_n-G)+\gamma\frac{900}{(T+273)}u_2(e_s-e_a)}{\Delta+\gamma(1+0.34\,u_2)} \quad (1)$$

Standardized reference evapotranspiration equation, tall (ETr):

Reference ET for a *tall* crop having an approximate height of *0.50* m (similar to alfalfa). The form of the reference evapotranspiration equation is

$$ET_{r}=\frac{0.408\,\Delta(R_n-G)+\gamma\frac{1600}{(T+273)}u_2(e_s-e_a)}{\Delta+\gamma(1+0.38u_2)} \quad \ldots (2)$$

Both standardized reference equations were derived from ASCE-PM equation by fixing h = 0.12 m for short crop (ETo) and h = 0.50 m for tall crop (ETr). The short crop and tall crop reference equations are traceable to the commonly used terms grass reference and alfalfa reference.

Modelling using artificial neural network

The multilayer back propagation feed forward networks was used with sigmoid as transfer function. The number of neurons in input layer corresponded to climatological parameters considered in respective combinations while output layer nodes correspond to ET was estimated by both reference surfaces. The available data was divided into a model development set and evaluation data. The data was then normalized in order to train network. The model development data set was further divided into three subsets; training set; cross validation set and testing set in 70:15:15 proportions. The first subset was used for computing and updating network weights and biases. The second subset was cross validation set. The error in validation set was monitored during training process. When validation error increases for a specified number of iterations, the training was stopped, and the weights and biases at minimum validation error were retained.

The most common architecture; composed of input layer, where data introduced, the hidden layer where data processed and output layer where results obtained was used with three learning functions namely Levenberg- Maquardt learning algorithm(LM); Conjugate gradient decent learning algorithm(CG) and Momentum learning algorithm(MOM) with step size 1.0 with momentum rate of 0.8. The network was trained for maximum epochs and with goal for mean squared error of 0.01. The number of neurons in input and output layers was fixed as per combinations. The numbers of neurons in hidden layer were varied as per input parameters in input layer i.e. maximum twice the input parameters (2n) in order to get best performance.

Performance evaluation of ANN Model

The performance of different ANN models tested using statistical indicators such as Root mean square error (RMSE), Mean bias error (MBE), Index of agreement (I.A), Coefficient of correlation (r), and Nash-Sutcliffe Efficiency (NSE). The results of study are described in brief

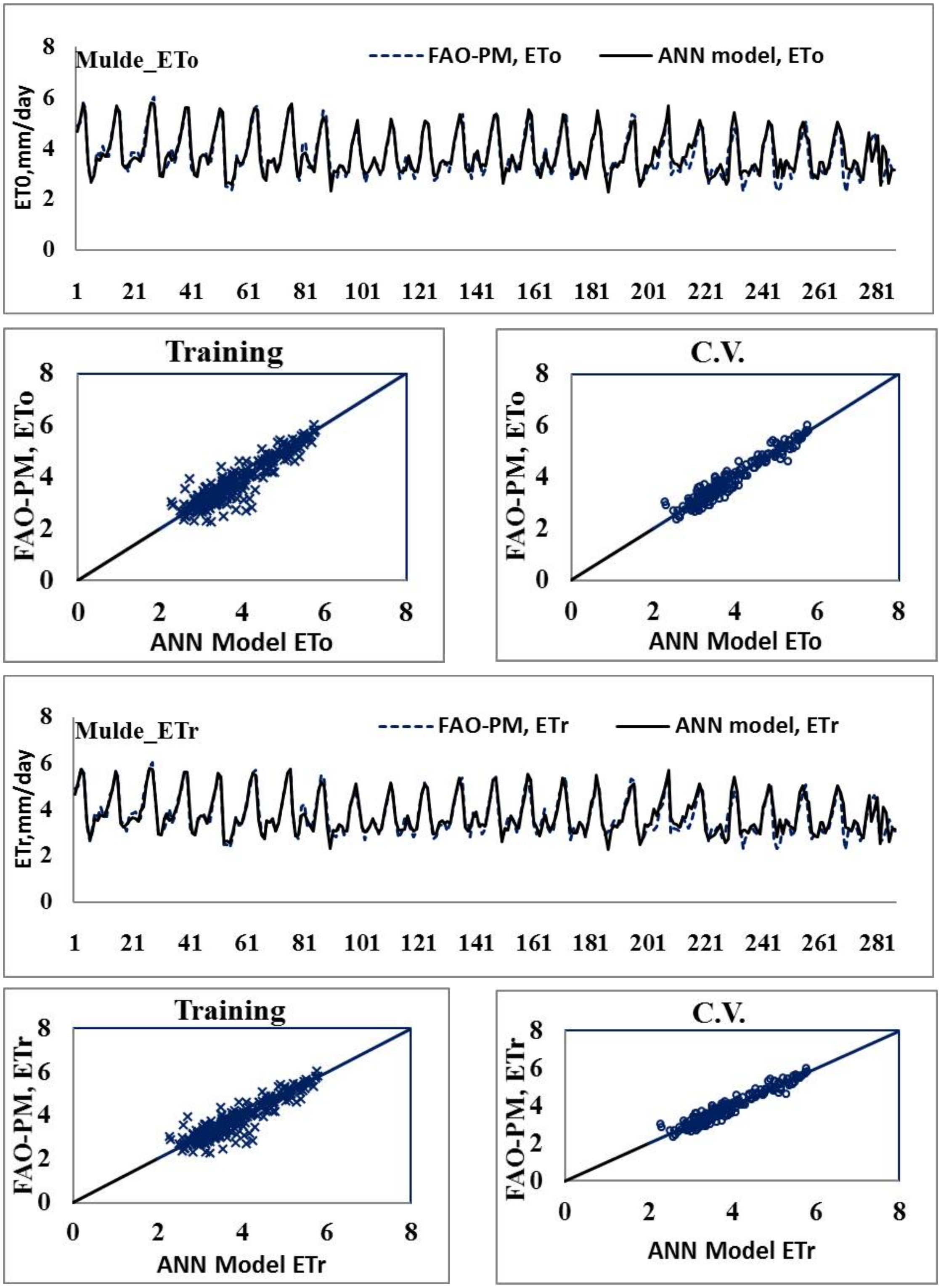

Fig 1: Performance of LM learning algorithm at Mulde station

Selection of learning algorithms

For estimation of ETo using ANN approach with three learning algorithms at Mulde station showed that correlation coefficient, index of agreement was 0.93 and 0.96 for LM and CG learning algorithms. The NSE was also nearly same for both learning algorithms. The minimum MBE and RMSE of 0.051 and 0.330 were found for LM learning algorithm. For tall crop reference evapotranspiration (ETr) LM learning

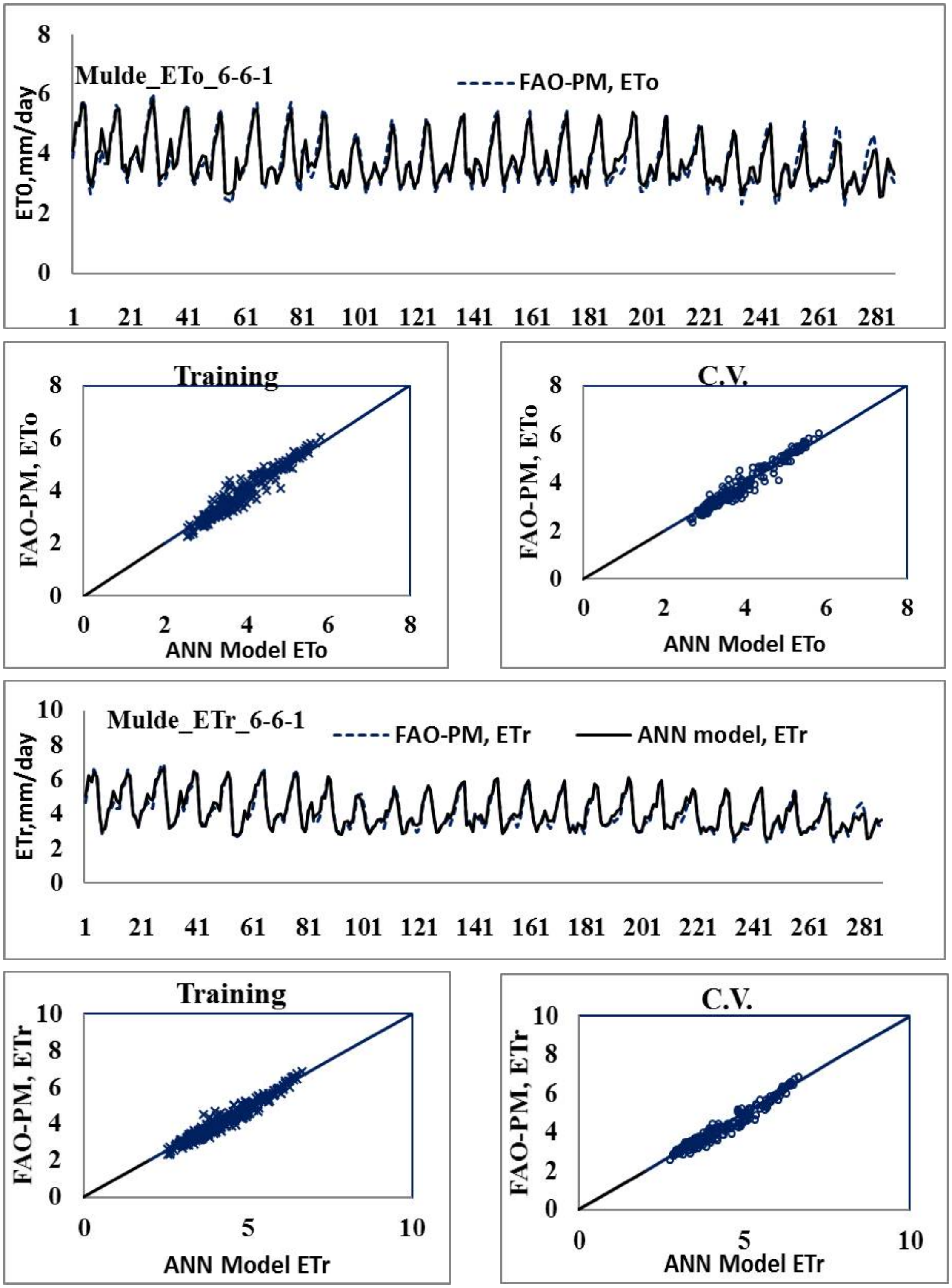

Fig 2: Performance of best ANN architecture at Mulde station

algorithm performed very well as compared to CG and MOM learning algorithm in terms of all statistical indicators. The correlation coefficient, index of agreement, NSE, MBE and RMSE were 0.90, 0.95, 0.81, 0.0334 and 0.46 respectively. The results indicated that LM learning algorithm found appropriate for estimating ETo and ETr at Mulde station. The performance of the best learning algorithm is shown in Fig. 1 shown that line graph and scatter plot between target and predicted ETo and ETr revealed that for both training and cross validation set for all stations predicted ET were very close 1:1 regression line. The curve shows fewer variations over ETo and ETr series. The statistical indictors also confirmed association and close relationship between predicted and estimated ET with less error.

Selection of ANN Architecture

The different ANN architecture was developed by changing number of nodes in hidden layer. The number of nodes varied from 2 to 12 in hidden layer. The selection of suitable ANN architecture for short and tall crop reference evapotranspiration was done. The selection of suitable ANN architecture for short crop reference evapotranspiration was done on the basis of training and cross validation data sets. Statistical indicators such as correlation coefficient, index of agreement, NSE, MBE and RMSE. The highest correlation coefficient of 0.97 was noted for 2,4,6,8 nodes. The maximum index of agreement of 0.98 was observed for 2,6,8,10,12 nodes and lowest of 0.97 for 4 nodes. The NSE ranged from 0.88 to 0.93. The maximum NSE of 0.93 was observed for 6 nodes in hidden layer. The mean bias error (MBE) varied from -0.197 to 0.018, which indicated that 2,4, 6 and 12 nodes in hidden layer underestimated ETo than observed ETo. The node 8 and 10 in hidden layer overestimated ETo. The minimum RMSE of 0.226 was recorded for 6 nodes in hidden layer. The analysis indicated that 4 statistical indicators pointed out that 6-6-1 ANN architecture provides desired ETo.

For estimation of tall crop reference evapotranspiration, ANN architecture 6-6-1 showed that maximum correlation coefficient, index of agreement and NSE was 0.98, 0.99 and 0.95 as compared to other nodes. The lowest MBE was noted for 6-12-1 architecture. The lowest root mean square error was noted by 6-2-1 architecture (0.235). The results showed that out of five statistical indicators 3 showed suitability of 6 nodes in hidden layer. The scatter plot and line graph as shown in Fig. 2 also shown association between predicted and observed ETr.

Based on the above results, it is summarized that the performance of best learning algorithm for ETo and ETr revealed that for both training and cross validation sets for all stations predicted ET showed close association with standard ET. The statistical indictors such as correlation coefficient were more than 0.95, index of agreement was also more than 0.95 and NSE was more than 0.90 confirmed relationships between predicted and estimated ET with less error. The result represents suitability of Levenberg-Marquardt learning algorithm (LM) for estimation of ETo and ETr at different stations.

The ANN architectures were developed by changing number of nodes in hidden layer for estimation of ET at different stations. The different architectures were compared with statistical indictors and found that correlation coefficient was more than 0.90, index of agreement was also more than 0.90 and NSE was more than 0.85. The MBE indicated that some of ANN model overestimated or underestimated ET. The RMSE revealed less error in observed and target ET.ANN architectures analysis for ETo and ETr indicated that for Mulde station 6 nodes in hidden layer were sufficient in hidden layer for prediction with minimum error and high degree of association.

Based on different statistical indicators it is concluded that performance of Lenvenberg-Maquardt learning algorithm found best for both reference surfaces. The study established the suitability of LM learning algorithm for estimation of ETo and ETr. The analysis confirmed that 6-6-1 ANN architecture i.e. 6 nodes in hidden layer found sufficient for prediction of ETo and ETr at Mulde station.

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