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Artificial Neural Network for Predicting reference Evapotranspiration under Humid Region

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Abstract

Artificial neural network (AN) was used to assess the reference evapotranspiration under missing or limited climatic parameters as input variables. The climatic data from year 1991-2014 i.e. 24 years was used for study. The results indicated that temperature based ANN architecture 2-2-1 and 3-4-1 found suitable for estimation of reference evapotranspiration under humid conditions. For mass based ANN model 4-4-1 and 5-4-1 architectures found appropriate for forecasting of evapotranspiration. The ANN architecture 6-2-1 gives good outcome than other architectures when all climatic variables were considered in the input layers. The study found that the different ANN architectures may be used under limited or missing data conditions. Temperature based, mass based and combination based models can be used for estimation of evapotranspiration by selecting the ideal nodes in hidden layer.

Keywords: FAO Penman-Monteith, ETo, Artificial Neural Networks, Back propagation algorithm, MBE, RMSE, correlation coefficient.

Introduction

Evapotranspiration (ET) has paramount importance for many studies such as irrigation system design and management, hydrologic water balance, crop yield simulation, irrigation scheduling, drainage studies, agricultural and forest meteorology, and water resources planning and management[1]. In order to estimate the evaporation, direct measurement methods or physical and empirical models can be used. The measurement of evapotranspiration is done by direct method such as lysimeter method or water balance method, which are time consuming and labourers. The indirect methods are climatological data based and easily to estimate the evapotranspiration. The indirect methods include empirical or semi-empirical methods developed on the basis of available weather parameters. These semi-empirical are valid only under specific location and climatic situations and not applicable to all locations.ET is a complex and non-linear process depending on different climatic parameters. The different methods need specific weather parameters for estimation of evapotranspiration but under lack of specific parameters the model cannot be used. For estimation of reference evapotranspiration Penman-Monteith as a sole standard model is used. The limitation of the Penman-Monteith model for wide application is that, it needs numerous data parameters, which are not available to all stations or locations. Sometime some parameters are missing or not recorded due to non-functioning of the instruments. Under limited data conditions and missing climatic parameters the artificial neural network system can be used. Many researchers studied the ANN for estimation of reference evapotranspiration.

The ASCE Task Committee examined the ANN performance in various branches of hydrology and found that ANNs are potential tools for modelling nonlinear hydrologic processes such as rainfall runoff, stream flow, ground water management, water quality simulation and precipitation[2].

The utility of ANN was tested for prediction of daily grass reference evapotranspiration (ETo) and compared with Penman-Monteith. The study found that all learning methods of ANN gave less weighted and concluded that ANN predicted ETo better than the conventional method[3]. The ANN was applied to estimating actual crop evapotranspiration (ETc) from limited climatic data and study demonstrated proficiency of ANN in estimating evapotranspiration. The analysis also recommended that ETc can be calculated from air temperature with ANN approach[4].

The RBF network was tested to estimating ETo. It was found that RDF network predicted better ET as that of FAO-56 model than calibrated temperature based models at different locations. The RDF network proven to be most adjustable to local climatic conditions[5].

The Levenberg-Marquardt (LM) and Conjugate Gradient (CG) neural network algorithms may be employed successfully in modelling evapotranspiration from available climatic data[6].

The artificial neural network and conventional techniques like pan evaporation method and multiple linear regressions were compared for estimation of ET at North western Shivalik foothills. The study concluded that ANN can estimate ETo better than conventional techniques and useful for estimating crop water requirements[7]. The capability of Artificial Neural Networks (ANNs) was compared with climatic based methods for estimation of ETo. The better performance of ANN model was observed with addition of all parameters in input layer. As per practical point of view ANN model considered more suitable to serve as a tool to estimate ETo using temperature data as input[8].

The above reviews proved that ANNs performing quite reasonably in evapotranspiration modelling and effective tools for the modelling of nonlinear systems with fewer inputs than conventional methods. An attempt was made to evaluate potential of ANN for estimation of ETo under partial climatic data.

Methodology

The detail methodology adopted is described below. The study compared the ANN estimated data with sole standard model to test capability of ANN under limited climatic data.

Study area: The study was conducted for Konkan region. The Konkan region lies between $15^0 60'$ N to $20^0 22'$ N latitude and $72^0 39'$ E to $73^0 48'$ E longitude. The Konkan region is a narrow terrain with width 60 km and length of 500 km with sea coast of 720 km in length. The region comprises districts of Thane, Raigad, Ratnagiri and Sindhu durg. The region spread over in two agro climatic zones of Maharashtra state. In present study the Raigad district is considered. The Alibag meteorological station was selected for analysis. The station lies between latitude 18°38' N and longitude 72°52' E with altitude of 7 m. The climate of station is humid and falls under heavy rainfall area. The costal line soils are black soils with low infiltration.

Collection of meteorological data: The meteorological data includes ambientdaily minimum and maximum temperature (Tmin and Tmax), minimum and maximum relative humidity (RHmin and RHmax.), sunshine hours (SS), and wind velocity (WS) for a period of 24 years (1991 to 2014). The geographic locations, viz, latitude, longitude and altitude were also obtained for respective station.

Standardized Reference Evapotranspiration Equation, Tall (ETr): Reference ET for a tall crop having an approximate height of 0.50 m (similar to alfalfa). The equation is

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

Where: ET_r is reference evapotranspiration [mm day^{-1}], R_n is net radiation at the crop surface [MJ m^{-2} day^{-1}], G is soil heat flux density [MJ m^{-2} day^{-1}], T is mean daily air temperature at 2m height [ºC], u_2 is wind sped at 2m height [m s-1], e_s is saturation vapour pressure [kPa], e_a is actual vapour pressure deficit [kPa], Δ is Slope vapour pressure curve [kPa ºC-1], γ is psychrometric constant [kPa ºC-1].

Artificial neural networks methodology: The multilayer back propagation feed forward networks were trained to estimate ET based on combination of climatological parameters as input to find dependence of climatic parameters. The numbers of neurons similar to input climatological parameters in input layer are considered. The summary of different classes of models is given in Table-1.

In output layer nodes correspond to ET estimated considered. The data was normalized to train network. The data was divided into two parts development set and evaluation set. The development data set was further divided into three subsets; training; cross validation and testing set in 70:15:15 proportions. The first subset was used for computing and updating the 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, training of model was stopped, and weights and biases at lowest validation error were considered.

The most common architecture; composed of input layer, hidden layer and output layer with learning function i.e. Levenberg-Maquardt (LM) learning algorithm along with sigmoid function activation function was used. The detailed procedure is given in Figure-1. The Neuro Solution for Excel software was used for analysis.

Table-1
Different classes of model based on climatic parameters.

S.N.	Class	code	Climatic Parameters					
1	Temperature and Radiation based model	T-1	Tmax	Tmin				
		T-2	Tmax	Tmin	SH			
2	Mass based model	M-1	Tmax	Tmin	RHmax	RHmin		
		M-2	Tmax	Tmin	RHmax	RHmin	SH	
3	Combination model	C-1	Tmax	Tmin	RHmax	RHmin	SH	WS

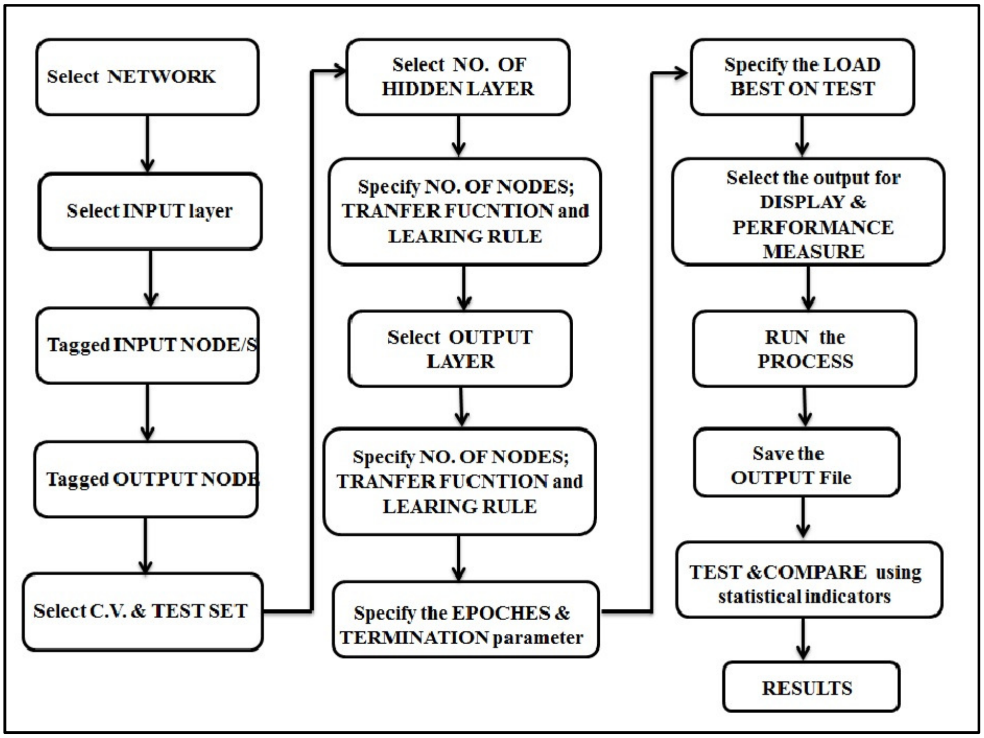

Figure-1
Methodology for Artificial Neural Network

Performance evaluation of ANN model: The evaluation of performance of different ANN model for different station is done using statistical analysis. The some of the selected statistical indicators are as follows:

Root Mean Square Error (RMSE): RMSE measures of mean difference. RMSE involves square of difference and therefore becomes sensitive to extreme values[9]. If the RMSE values are smaller the better is the model performance. The RMSE is represented by equation as

$$\text{RMSE} = \left[\frac{1}{N}\sum_{i=1}^{N}\left(P_i - O_i\right)^2\right]^{0.5} \qquad (2)$$

Where: P_i = Predicted reference evapotranspiration for i^{th} observation; O_i = Targeted reference evapotranspiration for i^{th} observation; N = Number of observations.

Mean Bias Error (MBE): The MBE is good measure of model bias and is simple the average of all differences in the set. It provides general biasness but not of the average error that could be expected[9]. The positive MBE value indicates overestimation and negative value indicates the underestimation. The MBE is given as

$$\text{MBE} = \frac{1}{N}\sum_{i=1}^{N}\left(P_i - O_i\right) \qquad (3)$$

Index of Agreement (I.A.): Index of agreement provides a relative measure of the error alloying cross comparison of the model. The performance of model is good, when value of degree of index of agreement d ≥ 0.95. The Willmott[9] IA is

$$d = 1 - \left[\frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}\left(\left|P_i'\right| + \left|O_i'\right|\right)^2}\right] \qquad (4)$$

Where: N = number of observations,

$$P_i' = P_i - \overline{O}\ ; O_i' = O_i - \overline{O}$$

Results and Discussion

The different ANN architecture were trained using various combinations of weather parameters i.e different climatic parameters as input and reference evapotranspiration as output to develop and evaluate effective ANN model under limited climatic data conditions. The five models namely T1, T2, M1, M2 and COM were developed for Alibag station. For optimization the quantity of neurons in hidden layer, number of neurons diverse up to twice number of input neurons. The minimum mean square was considered the training stopping criteria. From Table-2, it is observed that for model T1 with 2-2-1 architecture, correlation coefficient was varied from 0.47 to 0.63 for training, validation and testing test. The MBE for testing set was -0.1587 and RMSE value fluctuated between 0.77 to 0.98 mm/day for training, tested and validation sets. For T2 model with 2-4-1 architecture, index of agreement was varied from 0.67 to 0.76 for different set of data. Based on these statistical parameters, it observed that T1 temperature model (Tmax and Tmin input), the two neurons in hidden layer are sufficient for predicting the evapotranspiration.

For model T2, which was a temperature based model, the correlation coefficient for different set of data was varied from 0.59 to 0.51. Minimum MBE was recorded for 4 neurons in hidden layer. The index of agreement was more for testing data set for ANN architecture 3-4-1. The root mean square error for 3-4-1 architecture was also less as compared to other architectures. The architecture 3-4-1 is optimum for computing the reference evapotranspiration. It is viewed that, when 3 inputs parameters like Tmax, Tmin and SSH are available, the four neurons are sufficient in hidden layer for estimation of evapotranspiration with 70 per cent of index of agreement in testing set. If the number of neurons increases more than 4 in hidden layer the correlation coefficient reduced considerable for training, validation and testing data set.

The mass based model M1 and M2 also tested and statistical evaluation is given in Table-3. For M1 model four inputs were considered in input layer and neurons in 2n order selected in hidden layer. From Table-1, it is seen that correlation coefficient is decreases as number of neurons are increases in hidden layer. Maximum correlation coefficient for test set was 0.81 for 4-2-1 architecture. The index of agreement was also decreasing as number of neurons increasing more than four in hidden layer. The correlation coefficient for 4-4-1 architecture was ranged from 0.61 to 0.76 for training to testing set. The maximum index of agreement of 87 per cent was observed for 4-4-1. Based on these results it is observed that when four climatic parameters such RHmin, RHmin, Tmax and Tmin are accessible the ANN architecture with four neurons in hidden layer are sufficient for estimation of evapotranspiration with 87 per cent of agreement in testing set. For M2 model the RMSE was less for architecture 5-2-1 than other architectures. The RMSE for training and validation set are 0.79 and 0.92 respectively. The index of agreement was more for training and validation set, but the difference is less between the validation and testing set. The correlation coefficient for testing set was 0.69. The correlation coefficient for training set was decreasing in order when the numbers of neurons in hidden layer are increasing. The 5-2-1 architecture found test when five input parameters are available except the wind speed.

The results of combination model are depicted in Table-4. For COM model, correlation coefficient of training, validation and testing set was reduced when numbers of neurons were increased. The MBE, RMSE were less for 6-2-1 architecture than other architectures. The index of agreement was 0.76 and 0.81 for training and testing sets. The study found that two neurons in hidden layer are sufficient for prediction of reference evapotranspiration.

Based on above results it was seen that number of neurons in hidden layer increased, the performance in terms of coefficient of correlation, MBE and RMSE was decreases for training and testing sets. For temperature based models 2-2-1 and 3-4-1 architecture found suitable for estimation reference evapotranspiration. For mass based model 4-4-1 and 5-4-1 architecture found appropriate for forecasting evapotranspiration. When all climatic parameters were available the 6-2-1 gives good outcomes than other architectures.

Table-2
Statistical evaluation of neural network architectures for temperature based model

Model	Architecture	Statistical parameter	Training	Validation	Testing
T-1	2-2-1	CORREL	0.63	0.53	0.47
		MBE	-0.0077	0.0149	-0.1587
		RMSE	0.77	0.77	0.98
		I.A	0.77	0.72	0.67
T-1	2-4-1	CORREL	0.61	0.53	0.47
		MBE	-0.0080	-0.0158	-0.2286
		RMSE	0.79	0.79	1.01
		I.A	0.76	0.72	0.67
T-2	3-2-1	CORREL	0.63	0.41	0.22
		MBE	0.0046	-0.0878	-0.3806
		RMSE	0.77	0.92	1.29
		I.A	0.78	0.63	0.54
T-2	3-4-1	CORREL	0.59	0.51	0.51
		MBE	-0.0020	0.0521	-0.2523
		RMSE	0.81	0.78	0.99
		I.A	0.75	0.69	0.70
T-2	3-6-1	CORREL	0.58	0.34	0.30
		MBE	0.0021	0.0320	-0.3066
		RMSE	0.84	1.03	1.24
		I.A	0.75	0.59	0.59

Table-3
Statistical evaluation of neural network architectures for mass based model

Model	Architecture	Statistical parameter	Training	Validation	Testing
M-1	4-2-1	CORREL	0.61	0.55	0.81
		MBE	-0.0063	-0.3647	-0.7255
		RMSE	0.79	0.83	0.96
		I.A	0.77	0.69	0.75
M-1	4-4-1	CORREL	0.64	0.61	0.76
		MBE	-0.0212	0.0608	0.1487
		RMSE	0.77	0.77	0.77
		I.A	0.79	0.78	0.87
M-1	4-6-1	CORREL	0.57	0.27	0.27
		MBE	-0.0785	-0.3615	-0.6775
		RMSE	0.85	1.09	1.35
		I.A	0.74	0.53	0.53
M-1	4-8-1	CORREL	0.53	0.01	0.54
		MBE	-0.0734	-0.5212	-1.2114
		RMSE	0.91	1.31	1.57
		I.A	0.72	0.39	0.61
M-2	5-2-1	CORREL	0.61	0.49	0.69
		MBE	-0.0067	-0.4419	-0.8556
		RMSE	0.79	0.92	1.15
		I.A	0.77	0.64	0.65
M-2	5-4-1	CORREL	0.59	0.44	0.67
		MBE	-0.0048	-0.3652	-0.6934
		RMSE	0.82	0.91	1.05
		I.A	0.75	0.64	0.65
M-2	5-6-1	CORREL	0.58	-0.38	-0.62
		MBE	-0.0001	0.0807	-0.4895
		RMSE	0.84	1.47	1.81
		I.A	0.75	0.16	0.13
M-2	5-8-1	CORREL	0.57	0.11	0.11
		MBE	-0.0015	-0.4273	-0.8570
		RMSE	0.85	1.38	1.64
		I.A	0.75	0.41	0.45
M-2	5-10-1	CORREL	0.56	0.54	0.44
		MBE	-0.0018	0.1574	0.0133
		RMSE	0.87	0.82	1.04
		I.A	0.73	0.72	0.66

Table-4
Statistical evaluation of neural network architectures for combination model

Model	Architecture	Statistical parameter	Training	Validation	Testing
COM	6-2-1	CORREL	0.59	0.69	0.70
		MBE	0.0017	0.0932	-0.1709
		RMSE	0.81	0.66	0.78
		I.A	0.76	0.81	0.81
COM	6-4-1	CORREL	0.59	0.36	-0.11
		MBE	-0.0051	-0.1896	-0.2645
		RMSE	0.83	0.96	1.43
		I.A	0.75	0.61	0.39
COM	6-6-1	CORREL	0.57	0.37	-0.03
		MBE	-0.0016	-0.2835	0.0356
		RMSE	0.85	0.95	1.66
		I.A	0.74	0.58	0.41
COM	6-8-1	CORREL	0.56	0.58	0.46
		MBE	-0.0022	-0.2128	-0.5722
		RMSE	0.87	0.86	1.19
		I.A	0.73	0.72	0.65
COM	6-10-1	CORREL	0.55	0.38	0.10
		MBE	0.0004	-0.3351	-0.6506
		RMSE	0.88	1.37	1.86
		I.A	0.73	0.52	0.43
COM	6-12-1	CORREL	0.59	0.28	-0.06
		MBE	0.0355	0.2092	-0.4476
		RMSE	0.87	1.52	2.01
		I.A	0.76	0.49	0.35

Conclusion

The study concluded that under limited or missing data conditions different temperature based, mass based and combination based models can be used for estimation of evapotranspiration. The number of neurons in hidden layer increases accuracy of estimation with considerable agreement.

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