Time Series Forecasting of Daily Reference Evapotranspiration by Neural Network Ensemble Learning for Irrigation System

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Abstract. Time series forecasting has gained remarkable interest of researchers in the last few decades. Neural networks based time series forecasting have been employed in various application areas. Reference Evapotranspiration (ET₀) is one of the most important components of the hydrologic cycle and its precise assessment is vital in water balance and crop yield estimation, water resources system design and management. This work aimed at achieving accurate time series forecast of ET₀ using a combination of neural network approaches. This work was carried out using data collected in the command area of VEERANAM Tank during the period 2004–2014 in India. In this work, the Neural Network (NN) models were combined by ensemble learning in order to improve the accuracy for forecasting Daily ET₀ (for the year 2015). Bagged Neural Network (Bagged-NN) and Boosted Neural Network (Boosted-NN) ensemble learning were employed. It has been proved that Bagged-NN and Boosted-NN ensemble models are better than individual NN models in terms of accuracy. Among the ensemble models, Boosted-NN reduces the forecasting errors compared to Bagged-NN and individual NNS. Regression co-efficient, Mean Absolute Deviation, Mean Absolute Percentage error and Root Mean Square Error also ascertain that Boosted-NN lead to improved ET₀ forecasting performance.

Key words: Time series; Reference Evapotranspiration; Neural networks.

1. Introduction

Water is a valuable contribution of nature essential for life on earth. The increasing demand of population and climate change makes it necessary to manage water effectively [1, 3, 6, 10]. Evapotranspiration is one of the key elements in the hydrologic cycle. Evapotranspiration rate from a reference surface, not short of water, is known as Reference crop Evapotranspiration (ET₀). The Penman-Monteith (FAO-56) method is method universally accepted for computing ET₀. More accurate forecasting models of ET₀ would enable more efficient water resources management. Time series forecasting of Daily ET₀ based on data and past values is the focus of this work. It is very vital for irrigation scheduling, water-resources distribution planning and cropping-system design, agricultural water use, regulation and planning [2, 13, 17]. In recent years, attention has been paid on...
analyzing time series trends of \( \text{ET}_o \). More recently a number of machine learning techniques were applied to time series forecasting and on a number of occasions they have showed considerable improvement compared to traditional regression models. While there is an extensive knowledge available in machine learning and pattern recognition, it has been rarely used in temporal aspects of time series prediction. This work presents an ensemble based forecasting model that is designed to handle time series in various scenarios and generate accurate predictions. The proposed ensemble model has been found to be more suitable for forecasting \( \text{ET}_o \).

2. Related Work
Time series forecasting has lot of essential applications in modern water resources management, such as environment protection, water supply planning, water quality management, irrigation system, hydropower generation, and sustainable utilization of water resources etc. [21, 25]. Machine learning methods play a major role in water management modeling [10]. New machine learning techniques have been created in practice for increasingly complex computations in the modeling. The key feature of forecasting models are that these models only require data of the time series and the modeling of hydrologic time series can be directly computed [22, 4, 19]. Many researchers have investigated on autoregressive model to establish a time series forecasting to analyze and forecast \( \text{ET}_o \) for various regions and seasons [5, 14, 15, 16, 20]. Meanwhile, some researchers have proven that the forecasting accuracy can be improved by eliminating noise from time series data using appropriate data preprocessing techniques, such as principal component, moving average, singular spectrum analysis, wavelet analysis, Gamma test [7, 12, 23, 24, 18]. Few researchers concluded that the wavelet based time series algorithm can be used to model events such as droughts with reasonable accuracy [8, 9, 23, 24].

However, with the continuous rise of water demand due to economic development, population growth, irrigation needs and industrial uses, modern water resources management would require more efficient techniques for improving accuracy in forecasting. Ensemble learning is one such technique used to improve the performance of the machine learning algorithms in forecasting. This paper investigates time series forecasting of Daily \( \text{ET}_o \) using ensemble techniques. Boosting and bagging ensemble methods are investigated to predict \( \text{ET}_o \) with time series data. The experiments were designed in two phases to evaluate the performance of ensemble techniques. First, various diverse learning techniques such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), M5 model, Decision Tree (DT), k-Nearest Neighbor (k-NN) were employed in forecasting \( \text{ET}_o \). The performances of these models were evaluated to identify the best learning method. In the second phase, Bagged and Boosted NN ensemble models were developed using identified optimum predictor as base learners. The results obtained were evaluated in order to assess the forecasting performance.

3. Problem Design
The research design is shown in Fig. 1. The data used in this research work was collected for the period 2004 to 2014. Then collected data was prepared for forecasting by preprocessing. In data preparation, various climatic parameters used for empirical estimation using P-M method were selected. Based on the attributes used for estimation of \( \text{ET}_o \) by P-M method, the data collected were grouped into four data models for forecasting by ensemble methods. Then the results were evaluated and compared to identify the best ensemble approach for forecasting \( \text{ET}_o \).

4. Data Collection and Preparation
The command area of Veeranam tank was taken for the study. Veeranam tank is one of the major irrigation tanks of Tamilnadu which forms part of Cauvery basin, the largest river basin of Tamilnadu. The daily meteorologic and lysimetric data observed at Indian Meteorological Observatory, Annamalainagar of Tamilnadu was taken for computation of Evapotranspiration for Lowland rice.
The FAO Penman-Monteith method is the standard method for computing ET$_{o}$, as recommended by FAO (FAO,1977)since it involves many climatological parameters representative of the location in addition to latitude and elevation. Penman-Monteith method considers the crop physiological factors also, in addition to the meteorological factors considered in the Modified Penman method. The detailed description of the data used is given in Table 1. The dataset contains 9 independent attributes and one calculated dependent attribute for a period of 10 years from 2004-2014. The statistical properties of attributes are listed in Table 2. Forecasting Daily ET$_{o}$ was carried out for 365 days from Jan 2015 to Dec 2015. Four different data models were developed based on the attributes used for ET$_{o}$ prediction. The detailed description of the data used for development of various data models is given in Table 3.

**Figure 1. Problem Design.**

**Table 1. Details of Dataset**

| No. of years of data used | 10 years |
|---------------------------|----------|
| Period                    | 2004 – 2014 |
| Total No. of Samples     | 4018 (Daily ET$_{o}$) |
| Total No. of Attributes  | 9 + 1 (predicted label) |
| Attribute List            | DATE, RHMX, RHMN, WS, TMAX, TMIN, SSH, LAT, ELE, ET$_{o}$ |
Table 2. Statistical Description of Dataset

| Attribute | Description                        | Type  | Mean  | Min ; Max Values             |
|-----------|------------------------------------|-------|-------|-----------------------------|
| ETo       | Reference Evapotranspiration       | Label | 03.725| [1.170 ; 5.485]             |
| DATE      | Day                                | Label | -     | -                           |
| RHMX      | Maximum Relative Humidity          | Regular| 86.985| [8.000 ; 100.000]           |
| RHMN      | Minimum Relative Humidity          | Regular| 58.094| [5.000 ; 100.00]            |
| WS        | Wind Speed                         | Regular| 05.555| [0.000 ; 80.000]            |
| TMAX      | Maximum Temperature                | Regular| 32.847| [1.800 ; 50.700]            |
| TMIN      | Minimum Temperature                | Regular| 23.787| [1.500 ; 35.000]            |
| SSH       | Bright Sunshine hours              | Regular| 07.128| [0.000 ; 12.000]            |
| LAT       | Latitude                           | Regular| 11.400| [0.0 , 11.4]                |
| ELE       | Elevation                          | Regular| 05.790| [0.0, 5.79]                 |

Table 3. Description of Data Models

|                       | Data Model I | Data Model II | Data Model III | Data Model IV |
|-----------------------|--------------|---------------|----------------|---------------|
| No. of samples        | 4018         | 4018          | 4018           | 4018          |
| Attributes used       | 3            | 5             | 6              | 8             |
| Attributes list       | TMAX, TMIN   | TMAX, TMIN    | TMAX, TMIN     | TMAX, TMIN, SSH, RHMN, RHMX, WS, RHMX, WS, LAT, ELE |

5. Forecasting Models
Models were developed using single classifier methods like SVM, ANN (MLP), M5 model trees, k-NN, Decision tree and Ensemble methods. An ensemble is a set of individual models taking a decision by averaging the results of individual models. Depending on the way the ensemble is designed, it can be classified into boosting, bagging or other algorithms. In Bagging a model is fit for all potential data points, on the original training set (Fig. 2). Original training set of size upto the size of the training set was replaced by generating Bootstrap samples. Some of the data points can appear more than once while others don’t appear at all. The instability of the decision rule is effectively removed in bagging by averaging across re-samples. The purpose of boosting is to increase the strength of a weak learning algorithm.

Build the model for m=1 to M
a. Bootstrap sample $D_m$ of size N with replacement from the original training set $D$.
b. Train a prediction model $G_m(x)$ to the bootstrap sample $D_m$.

Figure 2. Bagging Algorithm.

A weak learner is trained a number of times, using a reweighted version of the original training set in Boosting (Fig. 3). Boosting trains the first weak learner with equal weight on all the data points in the training set, then trains all other weak learners based on the updated weight. Heavier weight is given to the data point wrongly classified by the preview weak learner, and lighter weight is given to the correctly classified data point. By such a process, the next classifier attempts to fix the errors made by the previous learner.
Further validation criteria of forecasting models were evaluated and compared by standard metrics like Root Mean Squared Error (RMSE) selected as the performance criterion of ETo prediction. RMSE is defined as:

\[ RMSE = \sqrt{\frac{\sum_{i=1}^{N} (ET_{i,\text{calculated}} - ET_{i,\text{predicted}})^2}{N}} \]  

(1)

where, \( ET_{i,\text{calculated}} \) represents the \( ET_o \) computed by FAO-56 PM method and \( ET_{i,\text{predicted}} \) represents the model predicted ETO. Mean Absolute Percentage Error (MAPE) is selected as the accuracy criterion of ETo prediction. MAPE is defined as:

\[ MAPE = \frac{1}{N} \sum_{i=1}^{N} \frac{|ET_{i,\text{calculated}} - ET_{i,\text{predicted}}|}{ET_{i,\text{predicted}}} \times 100 \]  

(2)

Mean Absolute Deviation (MAD) of a set of data is the average distance between each data value and the mean. The coefficient of correlation (R) is selected as the degree of collinearity criterion of \( ET_o \) prediction. R is defined as:

\[ R^2 = 1 - \frac{\sum_{i=1}^{N} (ET_{i,\text{calculated}} - ET_{i,\text{predicted}})^2}{\sum_{i=1}^{N} (ET_{i,\text{calculated}} - \text{mean}ET_{i,\text{predicted}})^2} \]  

(3)

6. Performance of Forecasting Models

6.1. Individual Forecasting Models

All the forecasting methods were implemented using WEKA machine learning tool with default parameters available. Table 4 gives the RMSE and MAPE error values of all forecasting models on various data models. The results show that ANN model has least error measure in terms of RMSE and MAPE for the entire four data models. For Data model I, a minimum RMSE value of 0.184 was obtained for ANN model compared to other forecasting models. For data model II, a minimum RMSE value of 0.176 was obtained for ANN predictor compared to other forecasting models.
Table 4. Performance measure of individual Forecasting models

| Data Model - I | Data Model - II | Data Model - III | Data Model - IV |
|----------------|----------------|-----------------|----------------|
| MAPE  | RMSE  | MAPE  | RMSE  | MAPE  | RMSE  | MAPE  | RMSE  |
| SVM   | 0.092 | 0.183 | 0.082 | 0.177 | 0.066 | 0.175 | 0.074 | 0.179 |
| ANN   | 0.091 | 0.184 | 0.078 | 0.176 | 0.069 | 0.167 | 0.069 | 0.169 |
| DT    | 0.181 | 0.322 | 0.142 | 0.267 | 0.136 | 0.244 | 0.14  | 0.250 |
| M5    | 0.091 | 0.185 | 0.076 | 0.175 | 0.058 | 0.171 | 0.062 | 0.173 |
| k-NN  | 0.186 | 0.325 | 0.135 | 0.233 | 0.121 | 0.212 | 0.19  | 0.227 |

The MAPE value of 0.05 obtained for ANN predictor of Data model III is the least among other forecasting models. The highest RMSE value was observed for decision tree method for all data models. Similar observation was noted for MAPE values also. Thus ANN performs better than other forecasting models in all data models. Thus, ANN model was chosen as the base learner for developing the ensemble methods proposed in the next phase of this work.

6.2. Ensemble Forecasting Model

Bagged Neural Network model (Bagged-NN) was constructed using 10 MLP learners. Each iteration was constructed by employing multiple learning methods with k value as 10, the learning models were evaluated using 10 fold cross validation. For Boosted-NN, % of weight mass to base training was set to be 100. The number of iterations was set as 10. MLP was used as the base learner for boosting. Table 5 shows the results obtained for Bagged and Boosted NN models in terms of various error metrics such as MAD, RMSE and MAPE. Among ensemble models, Boosted-NN performed better than Bagged-NN for all data models. A minimum RMSE value of 0.049, MAD of 0.107 and MAPE of 7.228% were observed for Boosted-NN of Data model III.

Among all data models, Data model III was identified as the best with minimum error values for both ensemble data models. The performance of Data model III was much better than Data models I and II, but it was observed that Data model IV did not perform better than Data model III. Thus, including all nine attributes was not an optimum attribute set for forecasting ET<sub>o</sub>. At the same time, the six attributes grouped under Data model III play a significant role in obtaining ET<sub>o</sub>. This indicates that including the latitude and elevation does not influence ET<sub>o</sub> prediction.

The simulation results of the various data models developed with Boosted-NN and Bagged-NN in comparison with those of the FAO-56 PM ETo are shown in Figures 4 to 11 for all four data models. The predictions made by the Bagged-NN and Boosted-NN methods for Data model I are shown in Figures 4 & 5 respectively. It was clear that the estimates of the Boosted-NN models were less scattered than those of Bagged-NN models. Similar observation was noted for all the other data models such as Data model II, Data model III and Data model IV. Figures 6 to 11 show that data points in the plot of Boosted-NN are much closer towards the diagonal line. Thus Boosted-NN predicts more data points effectively than Bagged-NN for all data models. This is also proved by the fact that R value is higher (0.991) for Boosted-NN than Bagged-NN (0.989) as seen in Table 6.
Table 5. Performance of Ensemble Forecasting Models

| Data | MAD  | RMSE  | MAPE  |
|------|------|-------|-------|
|      | Boosted NN | Bagged NN | Boosted NN | Bagged NN | Boosted NN | Bagged NN |
| I    | 0.079 | 0.081 | 0.132 | 0.135 | 11.72 | 11.99 |
| II   | 0.065 | 0.072 | 0.118 | 0.126 | 9.59  | 10.60 |
| III  | 0.049 | 0.057 | 0.107 | 0.116 | **7.228** | 8.387 |
| IV   | 0.054 | 0.063 | 0.112 | 0.191 | 7.921 | 8.856 |

Table 6. Regression Co-efficient of Ensemble forecasting model

| Data Model | Boosted R | Bagged R |
|-----------|-----------|----------|
| I         | 0.987     | 0.986    |
| II        | 0.989     | 0.987    |
| III       | **0.991** | 0.989    |
| IV        | 0.989     | 0.987    |

Figure 4. Regression plot for Bagged-ANN of Data Model I

Figure 5. Regression plot for Boosted-ANN of Data Model I

Figure 6. Regression plot for Bagged-ANN of Data Model II

Figure 7. Regression plot for Boosted-ANN of Data Model II
Fig. 12 illustrates the forecasted and estimated ET$_o$ values of Data model III by Boosted-NN, which were identified as best by model evaluation.

The forecasting plot shows the Daily ET$_o$ obtained for the year 2015 from the past time series data i.e. from 2004 to 2014. It is clear that the forecasted Daily ET$_o$ estimates of the Boosted-NN Data model III were almost similar.
7. Conclusion
In practice, accurately computing Daily ET$_o$ is difficult because it is characterized by many climatic parameters. Therefore, models based on machine learning provide a new alternative to ET$_o$ forecasting problems. The potential of ensemble based modeling for forecasting Daily ET$_o$ upto365 days in advance was investigated in this paper. This work promotes a new forecasting model for time series prediction which combines ensemble of NN models. Bagging and Boosting were adopted to the problem of learning time series data for predicting future values of ET$_o$.

Back Propagation Neural Network (BPNN) was used as base learner in ensemble forecasting models. Results obtained show that the Boosting-NN algorithm actually improves the performance of model in forecasting ET$_o$ as compared to Bagged-NN and individual learners. Future work may include the alteration of the boosting algorithm for dealing with BPNN with parameter optimization.

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