ANN Based Model for Prediction of Energy Requirement for Water-Energy Nexus Studies

Chandrasekaran Sivapragasam¹, Balakrishnan Baranitharan²*, Krishnasamy Rajesh³

¹Centre for Water Technology, Department of Civil Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, 626126, India.
²Department of Civil Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, 626126, India.
³Department of Electrical and Electronics Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamil Nadu, 626126, India.

*Corresponding author email address: jack.barans@gmail.com

Abstract. Water and energy are intricately connected. In order to have systematic planning of water resources to meet the future energy demands in a region, it is necessary to forecast the energy requirements appropriately. This work proposes development of an effective forecasting model. At the first level, forecasting of energy requirement is done with energy availability as the input information. At the second level, it is desired to forecast the energy requirement with weather parameters such as temperature and rainfall as the inputs. The variation in these parameters has a significant influence on the energy requirements. The proposed models are developed for 2 States in India with monthly data on energy requirement, energy availability and weather parameters for 11 years. Artificial Neural Network (ANN) is used as the forecasting tool because of its wide usage and acceptability by various researchers as an effective modelling tool and is implemented using MATLAB platform in this study. The results indicate that the propose ANN models are able to predict the energy requirements for two states with a CC of about 0.70, but fails to predict the peak, which needs further investigations. The importance of considering weather parameter changes as important source of information for planning water and energy related studies is found to be necessary.

1. Introduction

Energy and water requirement predictions are among the most complex and challenging tasks worldwide. Such predictions require large data. Over the last few decades, energy usage in all sectors have risen considerably. Based on the study report released by the United States Energy Information Administration (EIA), up to 2040 global energy consumption will rise by 28% [1]. How this is going to make impact in the energy conservation and the consequent energy policies will depend on the energy prediction as one of the parameter [2].

Many studies have already been reported on energy prediction. For instance, Ekici and Aksoy estimated the energy consumption of new constructed building property without environmental conditions. Specific possibilities are used in their analysis to forecast building heating energy...
requirements, including transparency ratio, insulation thickness and orientation [3]. Ahmad et al. predicted energy consumption by developing a Deep Neural Network and inserting weather conditions, including outdoor air temperature, dew point temperature, wind speed and relative humidity and energy consumption levels for buildings [4]. Rahat Hossaina et al. have introduced a novel hybrid system to predict the renewable energy from wind and solar radiation. The proposed hybrid (wind-solar) energy forecasting model has been tested for short-term (three-hour ahead) prediction based on Artificial Neural Network (ANN) algorithm [5]. Fermín Rodríguez et al, proposed an ANN to predict solar power generation from high standard photovoltaic generators with short term precision of 10 minutes [6].

Most of the works related to energy predictions have been focussed on predicting the energy consumption. However, the prediction of energy requirements seems to have received lesser attention. This study proposes ANN based modelling for prediction of energy requirements considering the influence of important weather parameters and in its absence. More specifically, the study considers weather parameters such as temperature and rainfall and investigates whether the energy requirements has any interconnection with these parameters for the States of Tamil Nadu and Kerala.

2. Study area

In this study Tamil Nadu and Kerala States of southern India is considered, involving specific geographical and climatic conditions. Moreover, the energy requirements in these two States are also expected to be different in terms of proportion of total energy required for various uses such as domestic, commercial, industrial, agricultural etc. Table 1 summarizes the geographic location, area, average temperature, average rainfall and average energy consumption for these two States. The rainfall and temperature data are collected from the database of the National Aeronautics and Space Administration (NASA) (https://power.larc.nasa.gov/data-access-viewer/) for the year 2008 to 2018. Likewise, the monthly energy availability and monthly energy requirement data are taken from the website of India's Central Electricity Authority (CEA) (http://cea.nic.in/reports). The sample data for both the states are shown in annexure 1.

| State/Parameter                | Units  | Tamil Nadu     | Kerala      |
|-------------------------------|--------|----------------|-------------|
| Geographical location         | degree | 11.1271N       | 10.8505 N   |
|                               |        | 78.6569 E      | 76.2711 E   |
| Area                          | km²    | 130058         | 38863       |
| Average temperature           | °C     | 33.33          | 28          |
| Average rainfall              | mm     | 998            | 3107        |
| Average energy consumption    | kW·h   | 1847           | 763         |

From Table 1, it is observed that, the average annual temperature in Tamil Nadu is high when compared to Kerala. Of course, temperature varies throughout the year with summer seasons witnessing very high temperature. Similarly, the average annual rainfall in Kerala is very high when compared to Tamil Nadu. The average annual energy consumption is found to be the higher in Tamil Nadu probably because of more industry requirements as well as domestic requirements (owing to larger population).
3. Artificial Neural Network

ANN has been developed to model complex non-linear classification and regression problems. These models operate according to the biological neurons theory of the human brain for processing of the data. For the regression analysis, optimal ANN structure has to be designed to map the dependent variable to the independent variable(s). Generally, a three layered ANN is found to be suitable for most of the engineering problems which consists of an input layer, a hidden layer and an output layer. The optimal structure of the ANN depends on the problem being investigated. Consequently, a trial-and-error approach is followed for to arrive at the number of hidden neurons. The data set is divided into training, testing and validation, out of which the training of the ANN is carried out using the training and the testing data. The developed model performance is checked in the validation data before converging to the optimal structure. Of the many algorithms that are used for training ANN model, the back propagation algorithm has been very commonly used and the same has been adopted in this study. A typical three layered ANN structure is shown in Figure 1. In this study, ANN is implemented using MATLAB Ver. 2020a.

![Figure 1 Structure of 3-layered ANN](image)

4. Methodology

In this study two different models was attempted for predicting the future energy requirement viz., (a) using antecedent monthly energy requirement values and (b) using monthly rainfall and temperature values. These two models are functionally represented as:

\[
E(t) = f[E(t-1)] \\
E(t) = f[E(t-1), R(t), T(t)]
\]

Where \(t\) represents time; \(E(t)\), the energy requirement with respect to time; \(E(t-1)\) represents the one time period antecedent energy requirement; \(T(t)\) denotes temperature with respect to time; and \(R(t)\) represents rainfall with respect to time.
A total of 132 data have been collected for the two States. Out of 132 data, 60% of data is used for training, 30% of data is used for testing and 10% of data is used for validation.

Lara-Fanego et al. investigated the prediction of solar irradiance model for southern Spain. The assessment was separately performed with various prediction horizons (1, 2 and 3 days ahead), the various seasons of the year and three different weather types such as clear, cloudy and dark. Forecasted performance was evaluated in terms of the Root Mean Square Error (RMSE) [7]. Amit Kumar Yadav, and S.S. Chandel established the solar potential of the western Himalayan Indian State of Himachal Pradesh using ANN-based Global Solar Radiation (GSR) modelling approach. In this study various aspects are found namely radiation, clearness index, latitude, longitude, highest temperature, lowest value, altitude and sunlight hours [8].

For this study, the error measures are chosen as Root Mean Square Error (RMSE) and Correlation Coefficient (CC) as adopted by many of the previously reported study which are described as below [9-10].

Root Mean Square Error
The Root Mean Square Error (RMSE) is an indication of the variations between the value expected by an estimator or model and the real observed values which is estimated as the square root of differences between expected values and observed values. The RMSE calculates the magnitude of the defects. This is an indicator of accuracy that is used for comparative forecasting errors for a single variable from different estimators, but not within variables, since this metric is scale-dependent. RMSE is determined by

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2}
\]  

(3)

Where \(n\) represents number of data, \(Y_i\) is the actual value, and \(\hat{Y}_i\) is the predicted value.

Correlation Coefficient (CC)
The Correlation Coefficient provides the proportion of the variance of the variables that is observable from the other variables as determined in equation (4). The CC ranges between -1 to 1, with a value of 1 indicating perfect positive correlation while -1 indicates the perfect negative correlation. A CC of zero indicates no correlation [11]. The Correlation Coefficient (CC) is estimated using:

\[
CC = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}
\]  

(4)

where Cov\((x, y)\) represents the covariance of \(x\) and \(y\), \(\sigma_x\) is the standard deviation of \(x\), \(\sigma_y\) is the standard deviation of \(y\), \(\bar{x} = \frac{\sum x_i}{n}\), \(\bar{y} = \frac{\sum y_i}{n}\), \(x_i\) is the average magnitude of any one of the aforementioned variables, \(i =\) month, \(n =\) number of data, \(x_i\) is the average magnitude of any one of the aforementioned variables, \(x_i \neq y_i\).
5. Results and Discussion

The result of energy requirement for Kerala:
The results of the two models with antecedent energy requirements (model M1) and with weather parameters (model M2) as input parameters are applied for the State of Kerala. The RMSE and CC values for these two models are shown in Table 2.

| S.no | Model | No of hidden neurons | Function | CC   | RMSE  |
|------|-------|----------------------|----------|------|-------|
| 1    | M1    | 10                   | Tansig   | 0.5562 | 149.13 |
| 2    | M2    | 10                   | logsig   | 0.6972 | 126.81 |

It is seen from the Table 2 that the model M2 gives a better prediction when compared to model M1. This implies that the changes in weather conditions affect the energy requirements. The prediction accuracy is moderate as reflected by a CC value of around 0.70. For this model, the logistic activation function with 10 hidden neurons is found to be the optimal using the trial-and-error approach. The comparison between actual energy requirement and predicted energy requirement using models M1 and M2 is shown in Figure 2. As seen from the model, both M1 and M2 do not perform well in predicting the peak. However, model M2 predicts the lower range of energy requirements better. The peak energy requirement corresponds to the months of March, April and May with lower rainfalls and relatively higher temperature. Failure of both the models in capturing the peak indicates possibilities other than weather effect such as export of energy to other States etc.

![Figure 2 Comparison of actual energy and predicted energy for Kerala](image_url)
The result of energy requirement for Tamil Nadu:
Similar to the studies carried out for Tamil Nadu, the results of the two models with antecedent energy requirements (model M1) and with weather parameters (model M2) as input parameters are applied for the State of Tamil Nadu. The RMSE and CC values for these two models are shown in Table 3.

| S.no | Model | No of hidden neurons | Function | CC     | RMSE  |
|------|-------|----------------------|----------|--------|-------|
| 1    | M1    | 10                   | Tansig   | 0.5829 | 275   |
| 2    | M2    | 10                   | logsig   | 0.7297 | 130.71|

The comparison between actual energy requirement and predicted energy requirement using models M1 and M2 is shown in Figure 3. The performance of model M2 is found to be good, very similar to that for Kerala. In this case also, the peak is not predicted properly. Hence, it is recommended that for such modeling, more information such as the possibility of export of energy to other States should be considered.

![Figure 3 Comparison of actual energy and predicted energy for Tamil Nadu](image-url)
6. Conclusions
In this study, we have investigated the prediction of energy requirement with two different models using ANN for Tamil Nadu and Kerala States and the following conclusions are made:

a) For both Kerala and Tamil Nadu, two models with antecedent energy requirement and with rainfall & temperature as weather parameters are used for predicting energy requirement.
b) For both the States, the model with weather parameters as inputs gives a good prediction for lower ranges of energy requirement. However, both the models fail to predict the peak.
c) It is recommended that modelling should be carried out considering export of energy to other States or any other parameter which might contribute to the modelling of the peak.

7. References
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Annexure 1
Sample data for energy requirement:

| S.No | Year | Month | Energy Requirement (MU) for Tamil Nadu | Energy Requirement (MU) for Kerala |
|------|------|-------|----------------------------------------|-----------------------------------|
| 1    | 2018 | Jan   | 8,421                                  | 2,098                             |
| 2    | 2018 | Feb   | 8,508                                  | 2,125                             |
| 3    | 2018 | Mar   | 10,222                                 | 2,544                             |
| 4    | 2018 | Apr   | 9,840                                  | 2,376                             |
| 5    | 2018 | May   | 9,905                                  | 2,264                             |
| 6    | 2018 | Jun   | 9,270                                  | 1,949                             |
| 7    | 2018 | Jul   | 9,590                                  | 2,024                             |
| 8    | 2018 | Aug   | 9,225                                  | 2,081                             |
| 9    | 2018 | Sep   | 8,810                                  | 2,027                             |
| 10   | 2018 | Oct   | 9,030                                  | 2,135                             |
| 11   | 2018 | Nov   | 8,650                                  | 2,064                             |
| 12   | 2018 | Dec   | 8,475                                  | 2,115                             |