JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ELECTRICAL SHORT TERM FORECASTING USING MULTIPLE REGRESSION CONSIDERING TIME REGENCY

Krishan Kumar, Er Gurpreet Kaur
M.Tech Student, Guru Kashi University, Talwandi Sabo
Assistant Professor, Guru Kashi University, Talwandi Sabo
krishankharar@gmail.com
ergurpreet88@ gmail.com

Abstract- Load forecasting is the basis for all planning and expansion solutions. The literature on forecasting is so wide and huge that it even exists before the existence of artificial intelligence. But the expansion and advancement of artificial intelligence have introduced forecasting to a whole new world. Electrical load forecasting is a very challenging task though. The behavior of customers is so diverse and vast that leads to vague results. However, even randomness also has some patterns. Therefore, electrical energy consumption also has some combination of patterns. Extracting those behavioral patterns is the key to successful load forecasting. The training methods of artificial intelligence have such capabilities that they can harness such a forecasting model with great accuracy. In this thesis, multiple linear regression has been used for forecasting the electrical load of a part of Spain using weather dependency and time lag factors.

Keywords:Loadestimate,LSTM.FuzzyLogic

INTRODUCTION

Load estimate helps an electric user to make necessary decisions including decisions on purchasing and arousing electric power, load switching, and restructure upgrade. Tiny-term load predetermining can help to foreshow load flows and to make a selection that can prevent overloading. Timely accomplishment of such selections lead to the upgrade of network trustability and the decrease in occurrences of equipment non-success and blackouts.

1.2 Forecasting Methods

Regression is the one of most huge used statistical techniques. For electric load guess regression methods are usually nearly new to model the connections of load consumer and other factors such as weather, day type, and customer class.

1.3 Regression Analysis

Regression inquiry is a widely nearly new technique for load conjecture. In the reverting analysis scaffolding, the load is usually handle as the dependent variable, while the weather and calendar changeable are treated as independent variables.

1.4 Test systems datasets

The most now load values may obtain one or many hours or every day later. Take the meter function, communication hazards, and equipment output, the rough load values may be further cleansed through the load decision procedure many weeks later.

Single Load predetermining Using (LSTM) Long short-term memory LSTM is one of the recurrent neural network (RNN) construction. Sequence learning is a forte of the LSTM model.

1.5 Classification of Forecasting Techniques

Several studies correlating demand forecasting method during founding. Demand forecasting (DF) techniques can be also categorized in terms of their degrees of mathematical analytical application in the predetermining model. The load predetermining method may be grouped broadly into three major groups:

1. Traditional Forecasting technique (TFT),
2. Modified Traditional Technique (MTT) and
3. Soft Computing Technique (SCT).

1.9 Factors Affecting Short Term Load prediction

1) Time Factor
2) Economic Factor
3) Weather Factor
4) Humidity
5) Random or Occasional Spikes:

1.10 Medium and Long-Term Load Forecasting

The end-uses modeling, macroeconomics modeling, and their combinations are the most regular used methods for medium and long-term load predetermining. Medium and long-term load prediction methods are:

- Trend Analytics (TA)
- End-Use Analytic (EUA)
- Econometric Analytic (EA)
- Neural Network Method (NNM)
- Multiple Linear Regressions (MLR)

1.11 Factors Affecting Medium and Long Term preselection

The end-use modeling, econometric modeling, and their mixture are the most regularly used methods techniques for medium and long-term load predetermining.

1) Descriptions of appliances used by consumers.
2) The sizes of the homes.
3) The age of apparatus.
4) Technology alters.
5) Consumer behavior.
6) Population flexibility are usually concluded in the statistical and simulation models based on the so-called end-use technique.
7) Economic factors like capita incomes.
8) Employment values, and
9) Electricity rates are concluded in econometric models.

II.PROBEM DEFINING

Load forecasting has been a conventional and important process in electric utilities since the early 20th century. As an outcome, the conventional business needs of load prediction, such as planning, operations, and maintenance, become huge important than before. Many of these techniques can be roughly grouped into two groups: statistical approaches, such as

- Regression analysis
- Time series analysis
- Artificial intelligence (AI),

Various combinations of these techniques have also been studied and applied to STLF problems. EED forecasting techniques can be grouped into three (3), such as

- Correlation,
- Extrapolation
- Combination of both.

A Fuzzy Logic (FL)-based forecasting model for the next-day electricity demand in Malaysia was presented in the literature. The time, the historical, and forecasting value of the temperature, and the previous day load (L) acts as independent variants of the next day's forecast. The results of the study revealed accurate predictions by the FL model. An adaptive neuron-fuzzy inference system (ANFIS) model for forecasting South African electricity needs. The authors concluded that increasing temperature as an input parameter to the suggested version did not improve prediction accuracy, as mainly anticipate.

Objectives

Considering the above motivation, the following objectives have been proposed:

- To study and analyze the types of electrical load forecasting.
- To look at and examine quick-term load forecasting.
- To take a look at and analyze various factors that impact brief-term load forecasting.
- To develop short term load forecasting approach considering time regency.

III Research Methodology

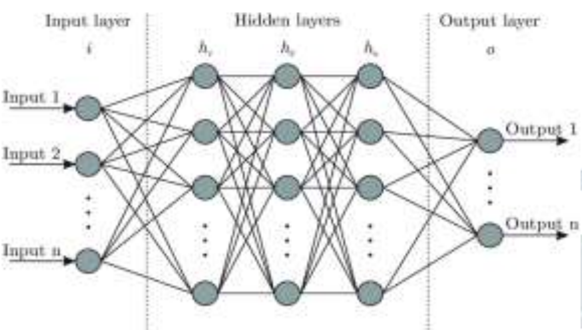
The literature for forecasting is very vast. A lot of these techniques are available in literature which can be roughly categorized into two groups: statistical approaches, such as

- Artificial intelligence (AI),

- Time series analysis
- Regression analysis

The most popular is an artificial neural network in AI techniques for short-term load forecasting. Neural networks are made up of basic pieces called neurons that operate together in a parallel manner. A neuron is a data processing component that is essential for a neural network's functionality. The neuron model is made up of three fundamental components.

Fig. 1. Multilayer model of Artificial Neural Network



An artificial neural network is made to perform an adjustment of a particular function by changing the weights of the variables of connection between the elements. The below shows the mathematical model for load forecasting. ANN is designed between a data collection of numeric inputs and a collection of numeric goals in fitting problems. A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons makes up the neural network matching tool. Given consistent input and enough neurons in its hidden layer, it can suit multi-dimensional mapping problems arbitrarily well. The Levenberg-Marquardt backpropagation method is used to train the neural network.

Designing the L-M method, the increase of weights Δw can be calculated as follows:

$$\Delta w = [J^T(w)J(w) + \mu I]^{-1} J^T(w)e$$

$J(w)$ is the jacobian matrix,

$J^T(w)J(w)$ is the Hessian matrix,

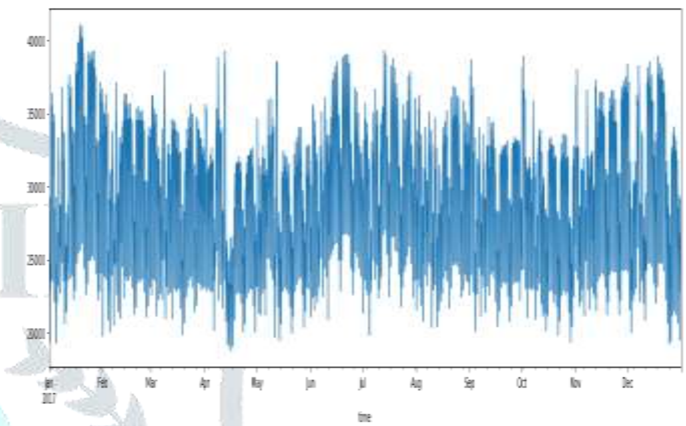
I is the identity matrix

μ is the update rate of learning, depends on the outcome

β is the decay rate (0 to 1)

The normal LM designing method can be described in the following steps:

1. Initialize the weightages and the value of μ.
2. Calculate the summation of the squared errors for all the inputs F (w).
3. Until the termination condition is met, Do
   a. Calculate (2) to get the increase of the weightages of Δw.
   b. Using w + Δw as the trial w. and judge IF trial F(w) < F(w) in step (2) THEN
      $w = w + \Delta w, \mu = \mu\beta$
      Go back to step (2)
      ELSE, $\mu = \mu / \beta$
      Go back to step (a)
      END IF



This is quite similar to the BP mechanism, the L-M mechanism is converged when the value of the slope is lesser than some predefined value. When, μ = 0 the mechanism becomes the Gauss-Newton algorithm. When, μ = 1 then the L-M mechanism works like the steepest descent algorithm.

y =
$$\alpha(L_{d-1}) + \beta(L_{d-7}) + \gamma(L_{d-365}) + \delta(T_d) + \epsilon(W_d) + \theta(H_d)$$

Where

$\alpha, \beta, \gamma, \delta, \varepsilon, \theta$ Are the coefficients whose values will be decided by training the model with the past data of a particular substation of Span.

(L_{d-1}), is the load of the previous day for same Time

(L_{d-7}) Is the load of the previous week for same time?

(L_{d-365}) Is the load of the previous year for same time?

(L_{d-1}), (L_{d-7}), (L_{d-365}) are the factors which account for the time lag factor

(T_d) is the temp. of that day

W_d is the wind speed of that day

H_d is the humidity of that day

The above-mentioned factors account for the weather dependency. The above model is trained with the 3 year data of a particular sub-station of Spain. The values of the coefficients of the models is calculated from the training. And the 20% data is kept from the dataset just for testing

V Result &Discussion

The three-year dataset of electrical consumption has been taken for load forecasting. Figure 1 shows the electrical load data of the datasets and the model has been trained with electrical load data and weather data. The equation and the coefficients are shown below.

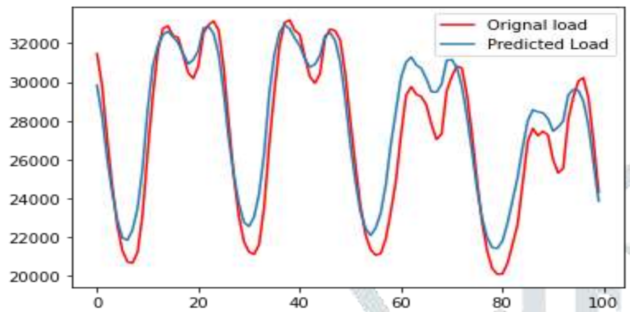


Figure 2. The electrical load data of the datasets

As the coefficients presented in table 1 define the models. As, it can be noted that with the help of coefficients it is clear that time lag has a positive correlation and in weather temperature has a positive but wind speed and humidity has a negative correlation.

Table 1. Coefficients of the model

Coeff.	**Value**	**Coeff.**	**Value**	**Coeff.**	**Value**
A	0.333124	γ	0.245195	ε	- 12.922
β	0.311407	δ	5.63372	θ	- 13.141

The results of forecasting are shown in Figures 2 and 3. The data which was kept for testing has been used for that training and testing data should be separate. Figure 2 shows the scatter plot between the actual test data and forecasted data. And figure 3 shows the line plot between predicted and actual data.

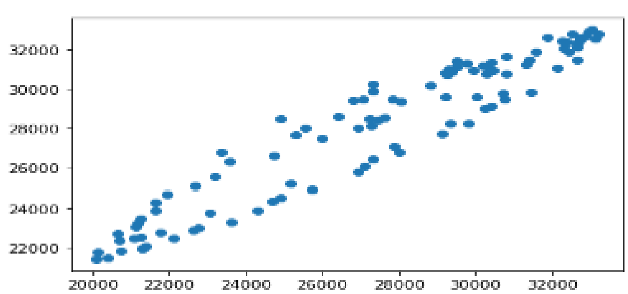


Figure 3 Scatter plot between actual and predicted data

No of Days	Original Load	Predict Load
5	2255.70	2473.65
20	2185.38	2185.38
40	2102.28	2140.63
60	2524.20	2306.84
80	3201.82	2939.72
90	2498.63	2415.52

Table 2 : Original Load and Predicted Load

VI.Conclusion & Future Scope

A multiple regression model has been developed using the three-year data of a particular place in Spain. In this model, the time lag and weather dependency have been considered. For time lag, the previous day, week, and year's load of that particular time were considered. For the weather dependency temperature, wind speed, and humidity were considered. According to the values of the coefficients, it is clear that time lag has a positive correlation and in weather temperature has positive but wind speed and humidity has a negative correlation. The data set was divided into the ratio of 80:20. The 20% percent of data was kept for testing purposes so to avoid missing train and testing data. As seen from the graphs of results, the prediction was quite efficient. The mean absolute percentage error was calculated and found to be 5.34%. The MAPE shows that load forecasting is reliable.

Future Scope

For future work, this model can be extended to other factors like likelihood estimation for particular customers and the probabilistic techniques combined with artificial intelligence should be studied.

Figure 4: Line plot between orignal load and predicted load

The above figure shows the error between forecasted and actual data is very less i.e. the mean absolute percentage error of 5.34% is there.

REFERENCES

[1] M. M. Iqbal, "Optimal Scheduling of Residential Home Appliances," 2019.

[2] S. Amin, "Solution to optimal reactive power dispatch in transmission system," 2020.

[3] Z. Yahia, "Multi-objective optimization of household appliance scheduling problem," 2020.

[4] G. hafeez, "Electric load forecasting based on deep learning and optimized," 2020.

[5] Z. Y. Dong, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," 2019.

[6] W. Kong, "Short-Term Residential Load Forecasting Based on LSTM Recurrent Neural Network," 2019.