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RESEARCH ARTICLE OPEN ACCESS

Development of Multilinear Regression Models for Online load price forecasting Estimation

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Abstract:
Forecasting is a function in management to assist decision making. It is also described as the process of estimation in unknown future situations. In a more general term it is commonly known as prediction which refers to estimation of time series or longitudinal type data.

Load forecasting is vitally important for the electric industry in the deregulated economy. It has many applications including energy purchasing and generation, load switching, contract evaluation, and infrastructure development. A large variety of mathematical methods have been developed for load forecasting. In this chapter we discuss various approaches to load forecasting. Due to the increase in demand in other parts of the world, it is necessary to develop a model that reflects the structure and pattern of gold market and forecast movement of gold price. The most appropriate approach to the understanding of load price forecasting is the Multiple Linear Regression (MLR) model..

Keywords:- Regression model; MATLAB; Short term forecasting

I. INTRODUCTION

Accurate models for electric power load forecasting are essential to the operation and planning of a utility company. Load forecasting helps an electric utility to make important decisions including decisions on pur-chasing and generating electric power, load switching, and infrastructure development. Load forecasts are extremely important for energy suppliers, ISOs, financial institutions, and other participants in electric energy generation, transmission, distribution, and markets. Load forecasts can be divided into three categories: short-term fore-casts which are usually from one hour to one week, medium forecasts which are usually from a week to a year, and long-term forecasts which are longer than a year. The forecasts for different time horizons are important for different operations within a utility company. The natures of these forecasts are different as well. For example, for a particular region, it is possible to predict the next day load with an accuracy of approximately 1-3%. However, it is impossible to predict the next year peak load with the similar accuracy since accurate long-term weather Forecasts are not available.

For the next year peak forecast, it is possible to provide the probability distribution of the load based on historical weather observations. It is also possible, according to the industry practice, to predict the so-called weather normalized load, which would take place for average annual peak weather conditions or worse than average peak weather conditions for a given area. Weather normalized load is the load calculated for the so-called normal weather conditions which are the average of the weather characteristics for the peak historical loads over a certain period of time. The duration of this period varies from one utility to another. Most companies take the last 25-30 years of data.

Load forecasting has always been important for planning and operational decision conducted by utility companies. However, with the deregulation of the energy industries, load forecasting is even more important.

With supply and demand fluctuating and the changes of weather conditions and energy prices increasing by a factor of ten or more during peak situations, load forecasting is vitally important for utilities. Short-term load forecasting can help to estimate load flows and to make decisions that can prevent overloading. Timely implementations of such decisions lead to the improvement of network reliability and to the reduced Occurrences of equipment failures and blackouts. Load forecasting is also important for contract evaluations and evaluations of various sophisticated financial products on energy pricing offered by the market.

In the deregulated economy, decisions on capital expenditures based on long-term forecasting are also more important than in a non-deregulated economy when rate increases could be justified by capital expenditure projects.

II. FORECASTING METHODS

Over the last few decades a number of forecasting methods have been developed. Two of the methods, so-called end-use and econometric approach are broadly used for medium- and long-term forecasting. A variety of methods, which include the so-called similar day approach, various regression models, time series, neural networks, expert systems, Fuzzy logic, and statistical learning algorithms, are used for short-term forecasting.

The development, improvements, and investigation of the appropriate mathematical tools will lead to the development of more accurate load forecasting techniques.

Statistical approaches usually require a mathematical model that represents load as function of different factors such as time, weather, and customer class. The two important categories of such mathematical models are: additive models and multiplicative models. They differ in whether the forecast load is the sum (additive) of a number of components or the product (multiplicative) of a number of factors.

$$L = L_n + L_w + L_s + L_r, \quad \text{.............(1)}$$

Where L is the total load, Ln represents the "normal" part of the load, which is a set of standardized load shapes for each "type" of day that has been identified as occurring throughout the year ,Lw represents the weather sensitive part of the load, Ls is a special event component that create a substantial deviation from the usual load pattern, and Lr is a completely random term, the noise.

III. PROCEDRUE

The load forecast influences a number of decisions including which generators to commit for a given period, and broadly affects the wholesale electricity market prices. Load forecasting algorithms typically also feature prominently in hybrid models for electricity prices, some of the most accurate class of approaches for modeling electricity markets. The electricity price forecast is used widely by market participants in many trading and risk management applications.

Traditionally, utilities and marketers have used commercial software packages for performing load forecasts. The main disadvantage of these is that they are a black box, offering no transparency into how the load forecast is calculated. They also only typically offer 80-90% of the functionality needed by a utility. In many cases it is just not possible to meet all of the requirements through an off-the-shelf product, for instance taking into account regional loads, different weather patterns and so on.

1. Background

MathWorks tools provide the flexibility of building a completely customized load forecasting system that meets 100% of the requirements. And because of the built-in models, high-level language and ease of connecting to data, the time taken to develop such a system is also dramatically lower than building an equivalent system in a lower level programming language, as is demonstrated in this example.

2. Data

The data used for this example are historical hourly temperatures, system loads and day-ahead electricity prices from the New England Pool region.

3. Setup

The only setup that is required is adding the *Util* folder to the MATLAB path. This can be done through MATLAB preferences. The scripts *LoadScriptNN*, *LoadScriptTrees* and *PriceScriptNN* do this in the first section of the code.

4. Importing Data

The MAT files *Load\Data\ DBLoadData.mat* **and** *Price\Data\ DBPriceData.mat* contain data equivalent to that imported from the Access database in the webinar recording. This dataset is sufficient for all of the analyses in the example.

5. Building the Forecaster

The three steps to building the forecaster include creating a matrix of predictors from the historical data, selecting and calibrating the chosen model and then running the model live in the Excel interface. The Load Forecasting example demonstrates using both Neural Networks as well as Bagged Regression Trees to forecast load.

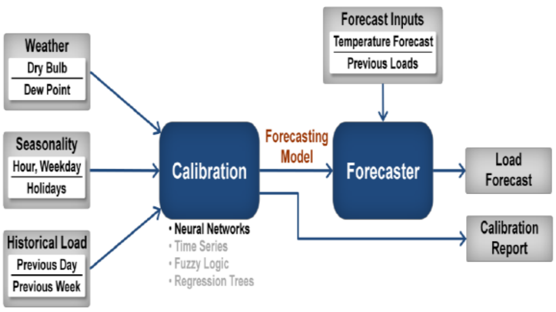

Fig 1. Load forecaster Block Diagram

IV. M-FILE PROGRAMMING

```
%% Electricity Load Forecasting using Neural Networks
% This demonstrates building and validating a short term
% electricity load forecasting model with MATLAB. The models take into
% account multiple sources of information including temperatures and
% holidays in constructing a day-ahead load forecaster. This script uses
% Neural Networks. A similar script "LoadScriptTrees" uses Bagged
% Regression Trees.

%% Import Weather & Load Data
% The data set used is a table of historical hourly loads and temperature
load Data\DBLoadData.mat
addpath ..\Util
 %% Import list of holidays
% A list of holidays that span the historical date range is
% imported from an Excel spreadsheet
 [num, text] = xlsread('..\Data\Holidays.xls');
holidays = text(2:end,1);
 %% Generate Predictor Matrix
% The function *genPredictors* generates the predictor variables used as
% inputs for the model. For short-term forecasting these include
%
% * Dry bulb temperature
% * Dew point
% * Hour of day
% * Day of the week
% * A flag indicating if it is a holiday/weekend
% * Previous day's average load
% * Load from the same hour the previous day
% * Load from the same hour and same day from the previous week
%
% If the goal is medium-term or long-term load forecasting, only the inputs
% hour of day, day of week, time of year and holidays can be used
% deterministically. The weather/load information would need to be
% specified as an average or a distribution

% Select forecast horizon
term = 'short';

[X, dates, labels] = genPredictors(data, term, holidays);

%% Split the dataset to create a Training and Test set
% The dataset is divided into two sets, a _training_ set which includes
% data from 2004 to 2007 and a _test_ set with data from 2008. The training
% set is used for building the model (estimating its parameters). The test
% set is used only for forecasting to test the performance of the model on
% out-of-sample data.

% Create training set
trainInd = data.NumDate < datenum('2008-01-01');
trainX = X(trainInd,:);
trainY = data.SYSLoad(trainInd);

% Create test set and save for later
testInd = data.NumDate >= datenum('2008-01-01');
testX = X(testInd,:);
testY = data.SYSLoad(testInd);
testDates = dates(testInd);

save Data\testSet testDates testX testY
clear X data trainInd testInd term holidays dates ans num text

%% Build the Load Forecasting Model
% The next few cells builds a Neural Network regression model for day-ahead
% load forecasting given the training data. This model is then used on the
% test data to validate its accuracy.

%% Initialize and Train Network
% Initialize a default network of two layers with 20 neurons. Use the "mean
% absolute error" (MAE) performance metric. Then, train the network with
% the default Levenburg-Marquardt algorithm. For efficiency a pre-trained
% network is loaded unless a retrain is specifically enforced.

reTrain = false;
if reTrain || ~exist('Models\NNModel.mat', 'file')
   net = newfit(trainX', trainY', 20);
   net.performFcn = 'mae';
   net = train(net, trainX', trainY');
   save Models\NNModel.mat net
else
   load Models\NNModel.mat
end

%% Forecast using Neural Network Model
% Once the model is built, perform a forecast on the independent test set.
 load Data\testSet
forecastLoad = sim(net, testX')';
```

```
%% Compare Forecast Load and Actual Load
% Create a plot to compare the actual load and the
predicted load as well
% as compute the forecast error. In addition to the
visualization, quantify
% the performance of the forecaster using metrics
such as mean absolute
% error (MAE), mean absolute percent error (MAPE)
and daily peak forecast
% error.

err = testY-forecastLoad;
fitPlot(testDates, [testY forecastLoad], err);

errpct = abs(err)./testY*100;

fL = reshape(forecastLoad, 24,
length(forecastLoad)/24)';
tY = reshape(testY, 24, length(testY)/24)';
peakerrpct = abs(max(tY,[],2) -
max(fL,[],2))./max(tY,[],2) * 100;

MAE = mean(abs(err));
MAPE = mean(errpct(~isinf(errpct)));

fprintf('Mean Absolute Percent Error (MAPE):
%0.2f%% \nMean Absolute Error (MAE): %0.2f
MWh\nDaily Peak MAPE: %0.2f%%\n',...
   MAPE, MAE, mean(peakerrpct))


%% Examine Distribution of Errors
% In addition to reporting scalar error metrics such as
MAE and MAPE, the
% plot of the distribution of the error and absolute
error can help build
% intuition around the performance of the forecaster

figure;
subplot(3,1,1); hist(err,100); title('Error distribution');
subplot(3,1,2); hist(abs(err),100); title('Absolute error
distribution');
line([MAE MAE], ylim); legend('Errors', 'MAE');
subplot(3,1,3); hist(errpct,100); title('Absolute
percent error distribution');
line([MAPE MAPE], ylim); legend('Errors', 'MAPE');

%% Group Analysis of Errors
% To get further insight into the performance of the
forecaster, we can
% visualize the percent forecast errors by hour of day,
day of week and
% month of the year

[yr, mo, da, hr] = datevec(testDates);
% By Hour
clf;
boxplot(errpct, hr+1);
xlabel('Hour'); ylabel('Percent Error Statistics');
title('Breakdown of forecast error statistics by hour');

% By Weekday
figure
boxplot(errpct, weekday(floor(testDates)), 'labels',
{'Sun','Mon','Tue','Wed','Thu','Fri','Sat'});
ylabel('Percent Error Statistics');
title('Breakdown of forecast error statistics by
weekday');

% By Month
figure
boxplot(errpct, datestr(testDates,'mmm'));
ylabel('Percent Error Statistics');
title('Breakdown of forecast error statistics by
month');

%% Generate Weekly Charts
% Create a comparison of forecast and actual load for
every week in the
% test set.
generateCharts = true;
if generateCharts
   step = 168*2;
   for i = 0:step:length(testDates)-step
       clf;
       fitPlot(testDates(i+1:i+step), [testY(i+1:i+step)
forecastLoad(i+1:i+step)], err(i+1:i+step));
       title(sprintf('MAPE: %0.2f%%',
mean(errpct(i+1:i+step))));
       snapnow

   end
end
%#ok<*ASGLU>
%#ok<*CTCH>
```

Day-ahead System Load Forecaster

Hour	Temperature Forecast		Load Forecast	
	Dry Bulb	Dew Point	Neural Net	Tree Model
1	38	31	11229	10942
2	36	30	10928	10796
3	36	30	10567	10711
4	36	30	10424	10725
5	35	30	10835	10897
6	34	29	12101	12143
7	35	30	13891	14069
8	35	31	15147	15407
9	36	32	15690	15495
10	38	32	15846	15584
11	40	32	15854	15702
12	41	32	15841	15550
13	42	32	15796	15442
14	43	32	15731	15280
15	44	32	15633	15146
16	44	32	15620	15040
17	44	34	15837	15220
18	43	35	16300	15650
19	42	36	16767	15821
20	41	37	17050	16200
21	40	38	16486	15913
22	40	38	15216	14977
23	40	38	13723	13617
24	40	38	12315	12201

Table 1. Load forecaster data

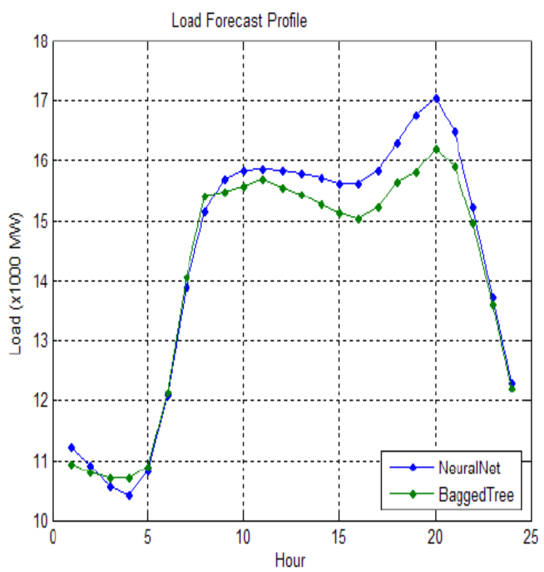

Fig.2. Load forecaster profile

V. Conclusions

Accurate load forecasting is very important for electric utilities in a competitive environment created by the electric industry deregulation. In this paper we review some statistical and artificial intelligence techniques that are used for electric load forecasting. We also discussed factors that affect the accuracy of the forecasts such as weather data, time factors, customer classes, as well as economic and end use factors. Load forecasting methods use advanced mathematical modeling. Additional progress in load forecasting and its use in industrial applications can be achieved by providing short-term load forecasts in the form of probability distributions rather than the forecasted numbers; for example the so-called ensemble approach can be used. We believe that the progress in load forecasting will be achieved in two directions: (i) basic research in statistics and artificial intelligence and (ii) better understanding of the load dynamics and its statistical properties to implement appropriate models.

REFERENCES

[1] A.G. Bakirtzis, V. Petridis, S.J. Kiartzis, M.C. Alexiadis, and A.H. Maissis. A Neural Network Short-Term Load Forecasting Model for the Greek Power System. IEEE Transactions on Power Systems , 11:858–863, 1996.
[2] B.J. Chen, M.W. Chang, and C.J. Lin. Load Forecasting using Support Vector Machines: A Study on EUNITE Competition 2001. Technical report, Department of Computer Science and Information Engineering, National Taiwan University, 2002.
[3] W. Charytoniuk, M.S. Chen, and P. Van Olinda. Nonparametric Regression Based Short-Term Load Forecasting. IEEE Transactions on Power Systems , 13:725–730, 1998.
[4] H. Chen, C.A. Canizares, and A. Singh. ANN-Based Short-Term Load Forecasting in Electricity Markets. Proceedings of the IEEE Power Engineering Society Transmission and Distribution Conference , 2:411–415, 2001.
[5] M.Y. Cho, J.C. Hwang, and C.S. Chen. Customer Short-Term Load Forecasting by using ARIMA Transfer Function Model.Proceedingsof the International Conference on Energy Management and Power Delivery, 1:317–322, 1995.
[6] N. Christiani and J.S. Taylor.An Introduction to Support Vector Machines and Other Kernel-Based Learning Methods.Cambridge University Press, Cambridge, 2000.

[7] T.W.S. Chow and C.T. Leung. Nonlinear Autoregressive Integrated Neural Network Model for Short-Term Load Forecasting.IEE Proceedings on Generation, Transmission and Distribution, 143:500–506, 1996.
[8] J. Dudhia and J.F. Bresch. A Global Version of the PSU-NCARMesoscale Model. Monthly Weather Review, 130:2989–3007, 2002.
[9] R.F. Engle, C. Mustafa, and J. Rice. Modeling Peak ElectricityDemand.Journal of Forecasting, 11:241–251, 1992.
[10] J.Y. Fan and J.D. McDonald. A Real-Time Implementation of Short-Term Load Forecasting for Distribution Power Systems.IEEE Transactions on Power Systems, 9:988–994, 1994.