LOAD FORECASTING

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Outline

• Introduction
• Motivation
• Types
• Factors Affecting Load
• Inputs
• Methods
• Forecast Algorithm
• Example
Load forecasting is way of estimating what future electric load will be for a given forecast horizon based on the available information about the state of the system.
CAISO Outlook

Supply and Demand
Graph displays current system demand plotted against forecast demand and available resources. See tutorial for more information on this graph.

Current System Demand:
(Actual Demand at this point in time)
32218 MW

Today’s Peak Demand:
(Highest point thus far today)
32218 MW

Today’s Forecast Peak Demand:
(Highest point expected today. Does not appear post-peak.)
32265 MW

Tomorrow’s Forecast Peak Demand:
(Not included on graph)
29892 MW

Information is current as of 21-May-2012 15:20. If browser does not support auto-refresh, select reload.

http://www.caiso.com/outlook/SystemStatus.html
Motivation

Operation and planning by ISOs and utility companies

- Trading in electricity market
- Load following
- Real time dispatch
- Operating Reserves
- Smart Grid-Automation and Control
<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>System</th>
</tr>
</thead>
<tbody>
<tr>
<td>Short Term Load Forecast (one hour - 1 week)</td>
<td>Independent System Operator e.g. ERCOT</td>
</tr>
<tr>
<td>Mid Term Load Forecast (a week - 1 month)</td>
<td>Utility e.g. SDG&amp;E</td>
</tr>
<tr>
<td>Long Term Load Forecast (month - years)</td>
<td>Organization e.g. UCSD</td>
</tr>
<tr>
<td></td>
<td>Building e.g. SDSC</td>
</tr>
</tbody>
</table>
An improved methodology to compute hour ahead forecasts for ancillary services, balancing and operation of the electric grid. There has been continuous research in improving this ensemble forecast are based solely upon Day-Ahead (DAM) is used as an input and hour ahead robustness of the methodology. The methodology used for producing CAISO HAM models is provided by California Independent System Operator and the associated error quality is presented. The same load forecast is for a week starting from Thursday to Wednesday of the year 2011, assuming perfect forecasts. Demand load profile for ERCOT region for the year 2011, assuming perfect forecasts.

Table representing time sensitive pricing for UCM campus. There has been 40% improvement in the forecast. The HAM forecasts have direct impact on the load demand from the grid, with estimated savings of $50,000/year at current prices.

UCM Campus: Moving the TES load closer to the off-peak hours, thus reducing high demand charges incurred due to peak time charges. This work was made possible with funding from a California Public Utilities Commission California Solar Initiative RD&D award (CPUC CSI RD&D III) and CEC RESCO. Funding for this project was provided in part by CEC RESCO and CITRIS grants. This research we present the  associated economic gains for such communities.

UCM Campus: Table representing time sensitive pricing for UCM campus. Applications

UCM Campus: Figure showing the load profile which is challenging to forecast at many temporal horizons of interest. Application of load forecasting for UCM campus with a 1 MWp solar and an effect on campus load profiles, but when the penetration increases to 15% or more, it adds proportional variability in shape as compared to UCSD load shape.

UCM Campus: Figure showing the load profile which is challenging to forecast at many temporal horizons of interest. Application of load forecasting for UCM campus with a 1 MWp solar and an effect on campus load profiles, but when the penetration increases to 15% or more, it adds proportional variability in shape as compared to UCSD load shape.

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Factors affecting Load

- Weather
- Time
- Economic
- Random


Inputs

- Meteorological forecast e.g. Temperature, Relative Humidity, Wind Speed, Dew Point, etc.

- Type of day e.g. Weekday, Holiday, Festival, etc.

- Time of the day


**Table I**

**INPUT CLASSIFICATION**

<table>
<thead>
<tr>
<th>Paper</th>
<th>Input variables to the forecasting system</th>
<th>Variable the classification is based on</th>
<th>No. of classes</th>
</tr>
</thead>
<tbody>
<tr>
<td>[14]</td>
<td>L, T</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[40]</td>
<td>L, T</td>
<td>C</td>
<td>11</td>
</tr>
<tr>
<td>[53]</td>
<td>L, T</td>
<td>...</td>
<td>1</td>
</tr>
<tr>
<td>[68]</td>
<td>L, T</td>
<td>C</td>
<td>2</td>
</tr>
<tr>
<td>[70]</td>
<td>L, T</td>
<td>C</td>
<td>5</td>
</tr>
<tr>
<td>[2]</td>
<td>L, T, H</td>
<td>C</td>
<td>5</td>
</tr>
<tr>
<td>[6]</td>
<td>L, T</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[15] [16]</td>
<td>L, T</td>
<td>C, C</td>
<td>8, 12</td>
</tr>
<tr>
<td>[17]</td>
<td>L, T, H, W</td>
<td>...</td>
<td>1</td>
</tr>
<tr>
<td>[28]</td>
<td>L, T</td>
<td>C</td>
<td>2</td>
</tr>
<tr>
<td>[49]</td>
<td>L, T, H</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[50]</td>
<td>L, T, H, W</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[51]</td>
<td>L, T, H</td>
<td>C, C</td>
<td>7, 3</td>
</tr>
<tr>
<td>[52]</td>
<td>L, T, f(T)</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[54]</td>
<td>L</td>
<td>L</td>
<td>15</td>
</tr>
<tr>
<td>[55]</td>
<td>L</td>
<td>C</td>
<td>6</td>
</tr>
<tr>
<td>[57]</td>
<td>L, T</td>
<td>C, C</td>
<td>7, 12</td>
</tr>
<tr>
<td>[63]</td>
<td>L, T</td>
<td>C, T</td>
<td>105 (?)</td>
</tr>
<tr>
<td>[66]</td>
<td>L, T, f(T)</td>
<td>C</td>
<td>7</td>
</tr>
<tr>
<td>[72]</td>
<td>L, T</td>
<td>T</td>
<td>2</td>
</tr>
<tr>
<td>[83]</td>
<td>L, T, H, W</td>
<td>C</td>
<td>3</td>
</tr>
<tr>
<td>[56]</td>
<td>L, LP</td>
<td>...</td>
<td>1</td>
</tr>
</tbody>
</table>

(2) and (3)-C: the day’s position in the calendar (weekday/weekend/holiday, month, or season), L: load, T: temperature, H: humidity, W: weather variables (other than T and H), f(T): nonlinear functions of T, LP: load parameters. (4) There are as many sets of classes as classification criteria. Cells marked with “...”: values were not reported in the paper.
Methods

Regression
Stochastic Time Series
Fuzzy Logic
Artificial Intelligence/ Machine Learning
Hybrid

Stochastic Time Series

- AutoRegressive Model (AR)
  - AutoRegressive Model with eXogenous Input (ARX)
  - Non-Linear ARX
- AutoRegressive Moving Average (ARMA)
  - ARMAX
- ARIMA (Seasonal Modeling)

State Space Models e.g. Kalman Filter

Fuzzy Logic

- It is many valued logic that approximates the expected values
- Disadvantage: Rules for fuzzy logic are determined experimentally with hit and trial
- Proposed Solution: Using optimization techniques like Simulated Annealing, GA and ANN model functions.


Artificial Intelligence

Artificial Neural Network

- Advantage: Ability to learn
- Disadvantage: Over fitting and over parameterizing

k Nearest Neighbor

- Advantage: Good for forecasting load profile for a whole day or longer period of time
- Disadvantage: Requires historical data to create a database.

Expert & Hybrid Models

• Support Vector Regression (SVR)
• Self Organizing Map (SOM)
• Meta Learning
• Hybrid Model: Combination of various forecasting models

Using various optimization techniques like particle swarm, ant colony, GAs, etc. are introduced to optimize the model parameters, input selection and model selection !!

• Bo-Juen Chen; Ming-Wei Chang; Chih-Jen Lin, "Load forecasting using support vector Machines: a study on EUNITE competition 2001," Power Systems, IEEE Transactions on , vol.19, no.4, pp.1821,1830, Nov. 2004
Load Forecast Algorithm

1. Data Preprocessing
2. Model formulation or selection
3. Identification or updating model parameters
4. Testing the model performance and updating the forecast
   - If performance is unsatisfactory return to Step 1 or Step 2, else return to Step 3
Example: HAM CAISO Forecast using Ensemble Method

**Forecast Model**

The forecast model is a combination of various forecasts computed using machine learning methods. Each forecast is computed by the Least Square (LS) optimization on various models. The forecasts are combined using weights for each model. The forecast of the Hour-Ahead Market (HAM) load forecast using Hourly Ensemble Forecast is produced.

![Block diagram of the forecast model. Day-Ahead Market (DAM) is shown as an input to the Least Square (LS) optimization, which then computes the forecast for each model. The forecasts are combined using weights for each model.](http://coimbra.ucsd.edu/forecasting_plots/CAISO_HAM.php?z=4)

**Mathematical Formulation**

The forecast model can be represented mathematically as follows:

\[
\begin{bmatrix}
    f_{1,1} & f_{1,2} & \cdots & f_{1,n}
    \\
    f_{2,1} & f_{2,2} & \cdots & f_{2,n}
    \\
    \vdots & \vdots & \ddots & \vdots
    \\
    f_{m,1} & f_{m,2} & \cdots & f_{m,n}
\end{bmatrix}
\begin{bmatrix}
    w_1 \\
    w_2 \\
    \vdots \\
    w_n
\end{bmatrix}
= \begin{bmatrix}
    \hat{F}_1 \\
    \hat{F}_2 \\
    \vdots \\
    \hat{F}_n
\end{bmatrix}
\]

**Examples and Results**

- **Load [MW]**
  - DAM forecasts are available in real-time for CAISO and the work is in progress.
  - The HAM forecasts have been substantially improved over the existing HAM forecast.
  - Hour-ahead forecasts show robustness of the methodology.

- **Reliability**
  - MAPE for this period: Ensemble Hrly: 1.11, CAISO: 1.85
  - MAPE since 03-16-13: Ensemble Hrly: 0.91, CAISO: 1.69

**Conclusion**

An improved methodology to compute hour-ahead forecasts for the California Independent System Operator (CAISO) has been developed. This methodology is based on the ensemble forecast method and uses machine learning techniques. The forecasts are produced by combining the results of various models through Least Square optimization. The approach has shown substantial improvement over the existing HAM forecast. Hour-ahead forecasts have been found to be robust and reliable.
Error Analysis

[Graph showing sample autocorrelation and partial autocorrelation plots for CAISO, LS-Hourly, LS-Weekly, LS-Models, and ANN-Models. Each plot has two subplots: one for sample autocorrelation and one for sample partial autocorrelation. The x-axis represents lag, and the y-axis represents the correlation value.]
QUESTIONS ?

Thanks !