LOAD FORECASTING

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Coimbra Group
Solar Forecasting

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.

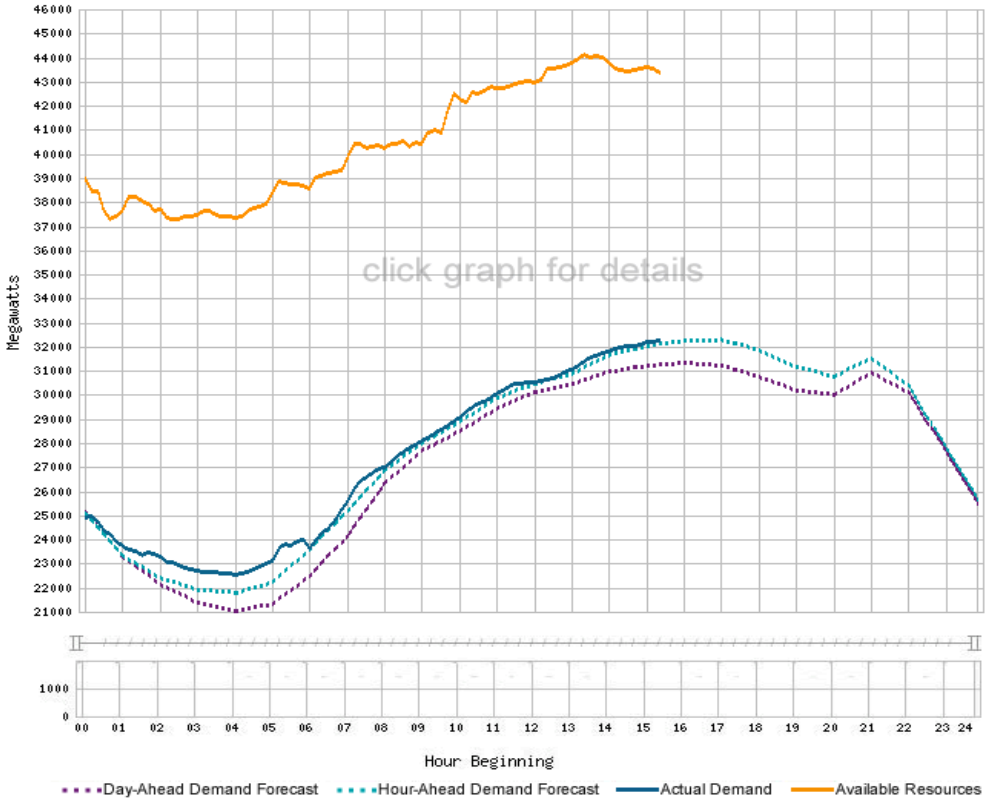
Current System Demand:
(Actual Demand at this point in time)
32218 MW

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

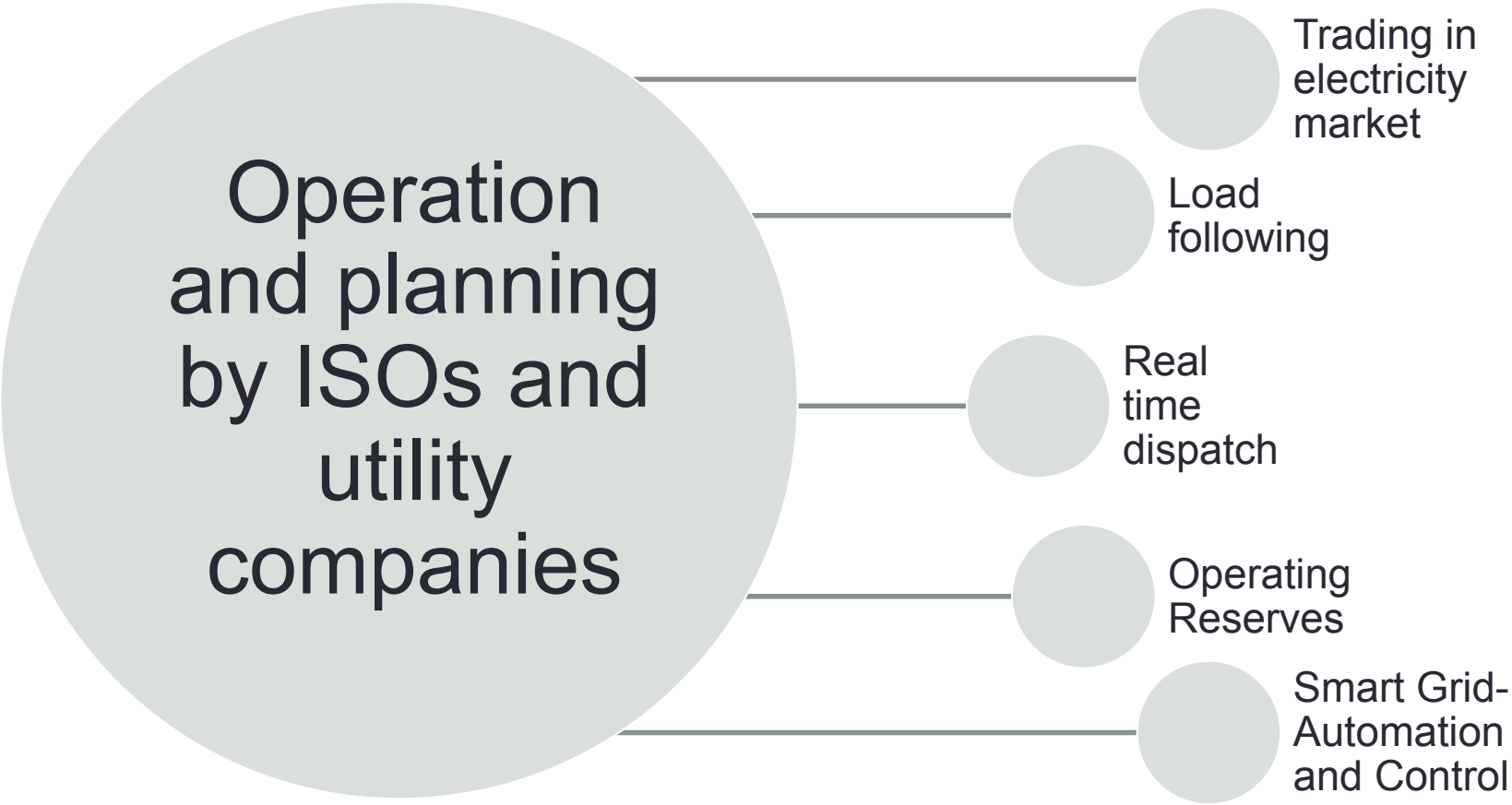
Tomorrow's Forecast Peak Demand:
(Not included on graph)
29892 MW

Information is current as of 21-May-2013 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

Types

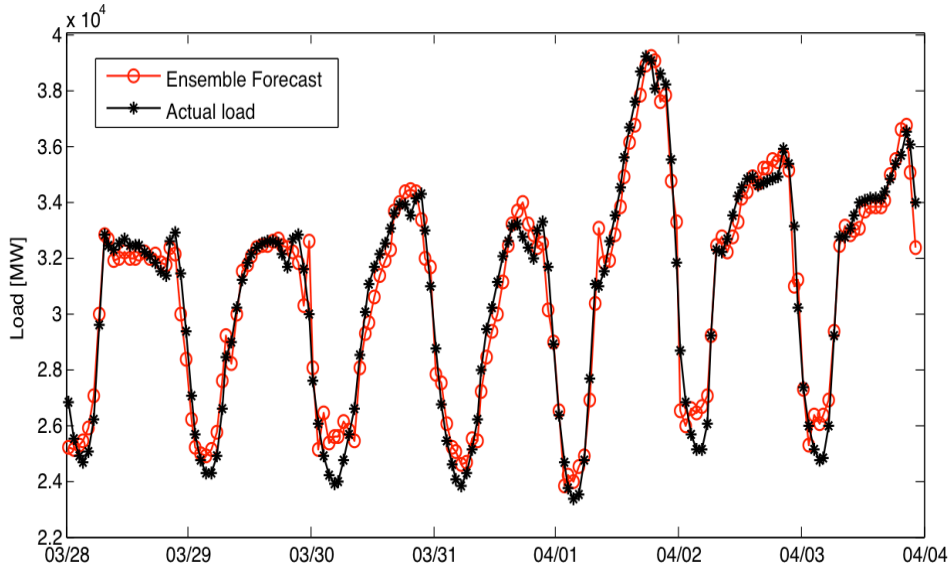
Forecast Horizon

Short Term Load Forecast (one hour -1 week)
Mid Term Load Forecast (a week - 1 month)
Long Term Load Forecast (month - years)

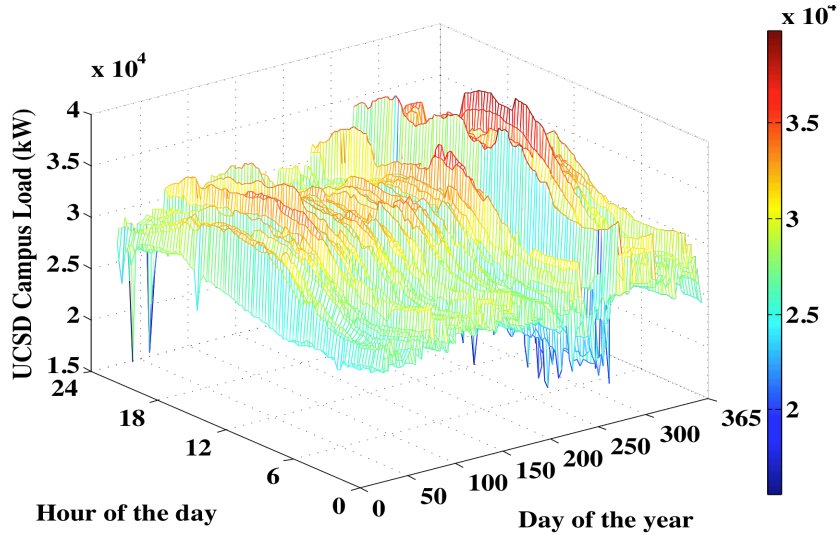
System

Independent System Operator e.g. ERCOT
Utility e.g. SDG&E
Organization e.g. UCSD
Building e.g. SDSC

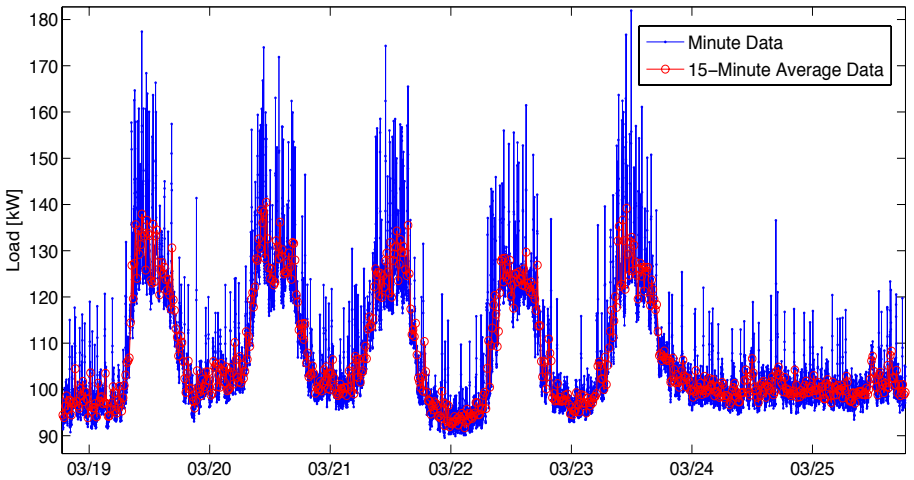
ERCOT



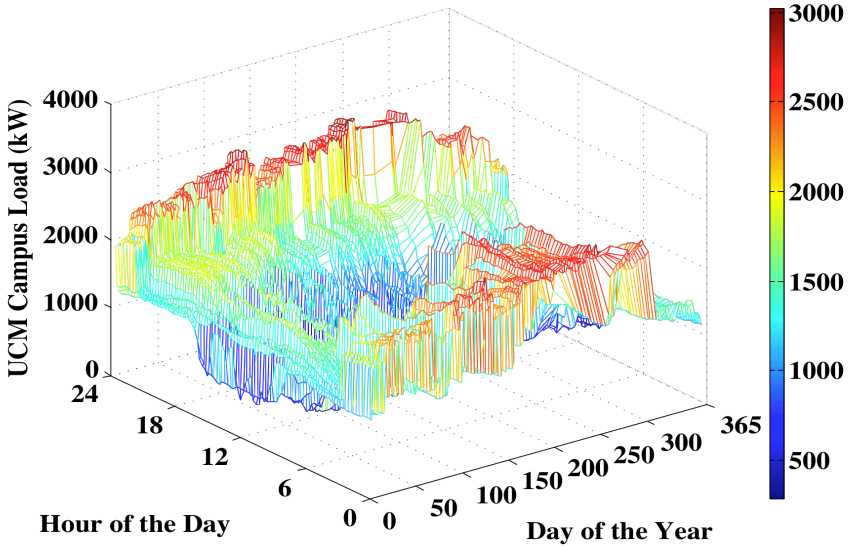
UCSD



SDSC

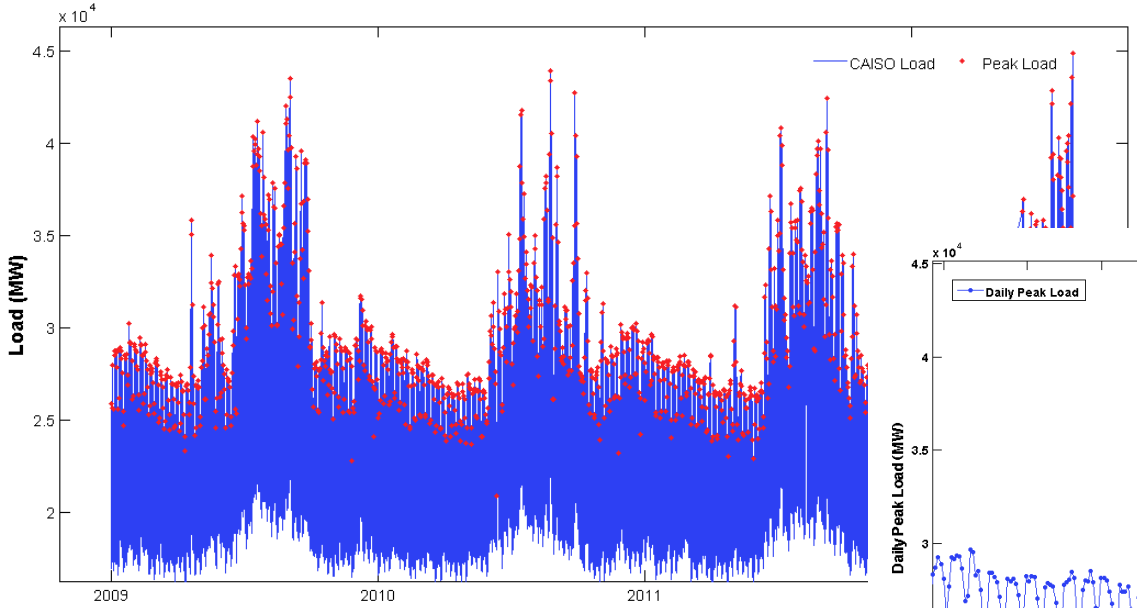


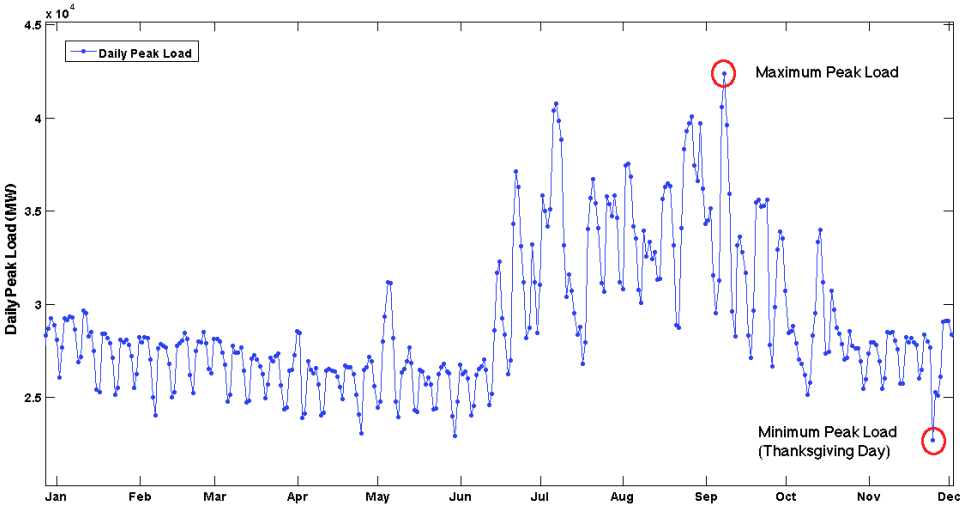
UCM



Factors affecting Load

- Weather
- Time
- Economic
- Random





Time series of CAISO hourly (2009 – 2012) and daily peak load (2012).

- **Heinemann, G. T.; Nordmian, D. A.; Plant, E. C., "The Relationship Between Summer Weather and Summer Loads - A Regression Analysis," *Power Apparatus and Systems, IEEE Transactions on* , vol.PAS-85, no.11, pp. 1144,1154, Nov. 1966**
- Gross, G.; Galiana, F.D., "Short-term load forecasting," *Proceedings of the IEEE* , vol.75, no.12, pp.1558,1573, Dec. 1987

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

Paper (1)	Input variables to the forecasting system (2)	Variable the classification is based on (3)	No. of classes (4)
[14]	L, T	C	7
[40]	L, T	C	11
[53]	L, T	…	1
[68]	L, T	C	2
[70]	L, T	C	5
[2]	L,T, H	C	5
[6]	L,T	C	7
[15] [16]	L, T	C, C	8, 12
[17]	L, T, H, W	…	1
[28]	L, T	C	2
[49]	L, T, H	C	7
[50]	L, T, H, W	C	7
[51]	L, T, H	C, C	7, 3
[52]	L, T, f(T)	C	7
[54]	L	L	15
[55]	L	C	6
[57]	L, T	C, C	7, 12
[63]	L, T	C, T	105 (?)
[66]	L, T, f(T)	C	7
[72]	L, T	T	2
[83]	L, T, H, W	C	3
[56]	L, LP	…	1

(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.

Hippert, H.S.; Pedreira, C.E.; Souza, R.C., "Neural networks for short-term load forecasting: a review and evaluation," *Power Systems, IEEE Transactions on* , vol. 16, no.1, pp.44,55, Feb 2001

Methods

Regression

Stochastic Time Series

Fuzzy Logic

Artificial Intelligence/ Machine Learning

Hybrid

- H. K. Alfares and M. Nazeeruddin, “Electric load forecasting: literature survey and classification of methods,” International Journal of System Science, vol. 33, no. 1, pp. 23–34, 2002.
- L. Suganthi and A. A. Samuel, “Energy models for demand forecasting review,” Renewable and Sustainable Energy Reviews, vol. 16, no. 2, pp. 1223 – 1240, 2012.

Stochastic Time Series

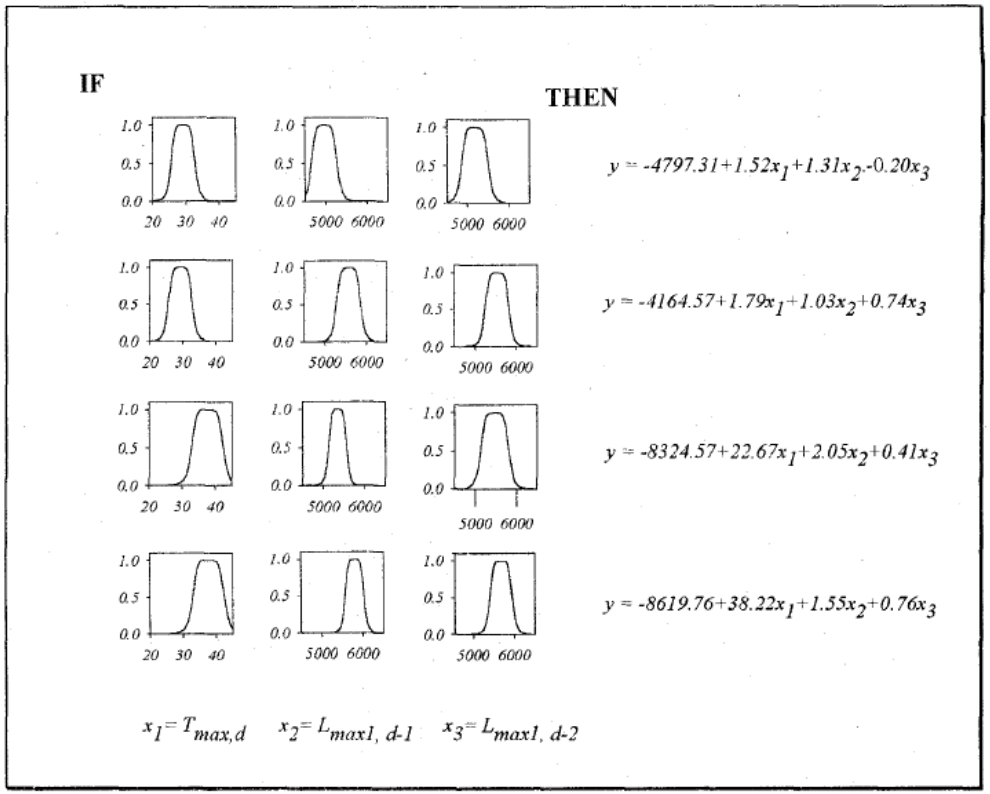
- AutoRegressive Model (AR)
  - AutoRegressive Model with eXogenous Input (ARX)
  - Non-Linear ARX
- AutoRegressive Moving Average (ARMA)
  - ARMAX
- ARIMA (Seasonal Modeling)

State Space Models e.g. Kalman Filter

- Gross, G.; Galiana, F.D., "Short-term load forecasting," *Proceedings of the IEEE* , vol.75, no.12, pp.1558,1573, Dec. 1987
- Taylor, J.W.; McSharry, P.E., "Short-Term Load Forecasting Methods: An Evaluation Based on European Data," *Power Systems, IEEE Transactions on* , vol.22, no.4, pp.2213,2219, Nov. 2007
- Carter C.K. and Kohn R., On Gibbs sampling for state space models *Biometrika (1994) 81(3): 541-553 doi:10.1093/biomet/81.3.541*

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.



. The fuzzy rule base for the model $F_{\max 1,d}$ ($L_{\max 1,d}$ forecasting of Summer Thursdays).

- Papadakis, S.E.; Theocharis, J.B.; Kiartzis, S. J.; Bakirtzis, A.G., "A novel approach to short-term load forecasting using fuzzy neural networks," *Power Systems, IEEE Transactions on* , vol.13, no.2, pp.480,492, May 1998
- Mori, H.; Kobayashi, H., "Optimal fuzzy inference for short-term load forecasting," *Power Industry Computer Application Conference, 1995. Conference Proceedings., 1995 IEEE* , vol., no., pp.312,318, 7-12 May 1995

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.

- Hippert, H.S.; Pedreira, C.E.; Souza, R.C., "Neural networks for short-term load forecasting: a review and evaluation," *Power Systems, IEEE Transactions on* , vol.16, no.1, pp.44,55, Feb 2001
- Lora A.C., Riquelme J.C., Ramos J.L.M., Santos J.M.R. , Exposito A.G., Influence of kNN-Based Load Forecasting Errors on Optimal Energy Production*, Progress in Artificial Intelligence, Lecture Notes in Computer Science,* Volume 2902, 2003, pp 189-203

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
- Shu Fan; Luonan Chen, "Short-term load forecasting based on an adaptive hybrid method," *Power Systems, IEEE Transactions on* , vol.21, no.1, pp.392,401, Feb. 2006
- Marin Matijaš, Johan A.K. Suykens, Slavko Krajcar, Load forecasting using a multivariate meta-learning system, Expert Systems with Applications, Volume 40, Issue 11, 1 September 2013, Pages 4427-4437, ISSN 0957-4174.

Load Forecast Algorithm

Data Preprocessing

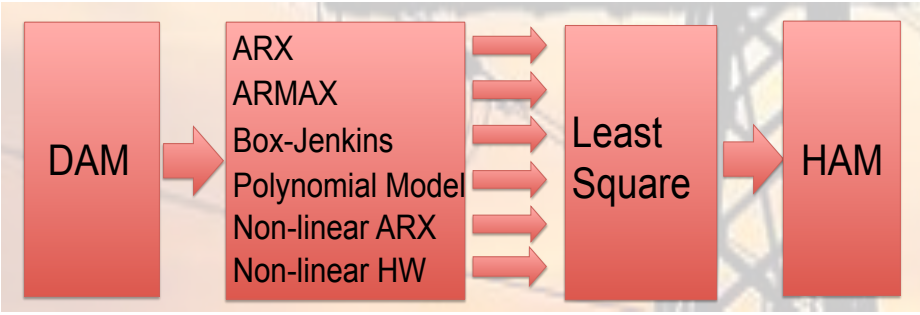
Model formulation or selection

Identification or updating model parameters

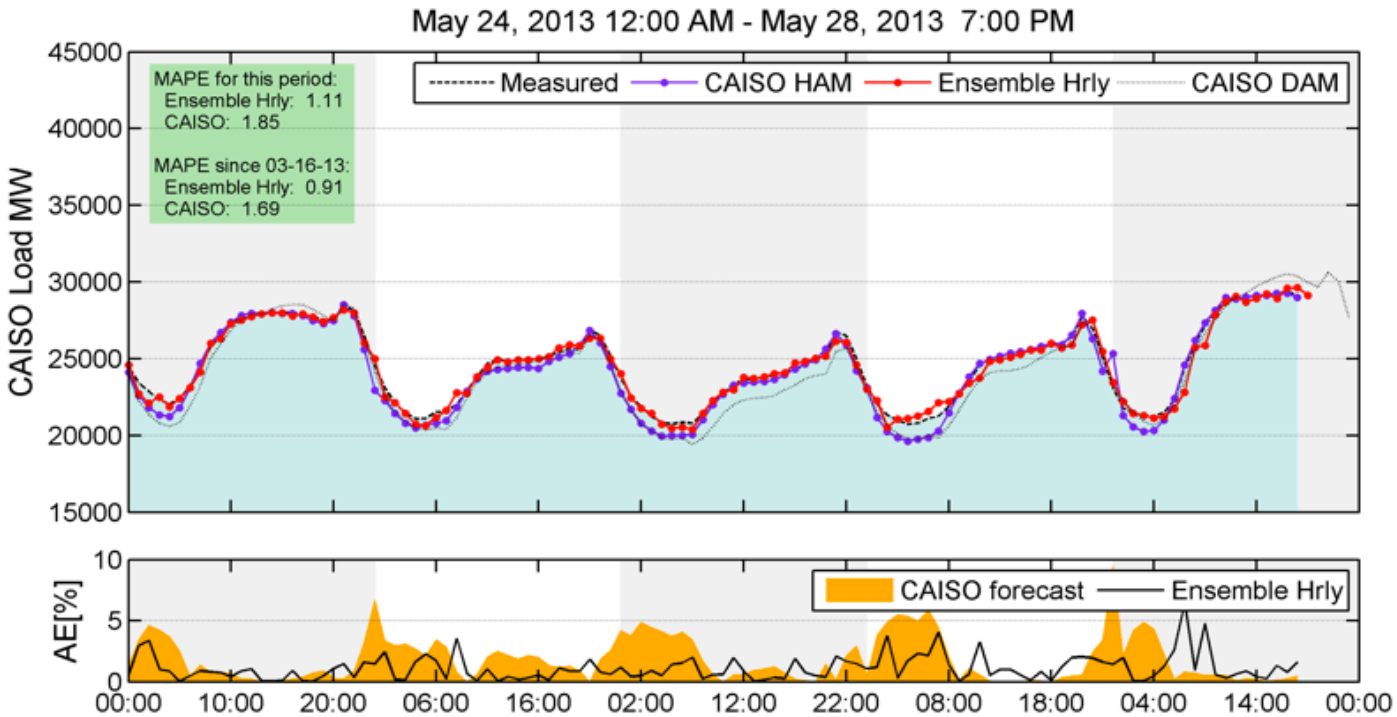
Testing the model performance and updating the forecast

If performance is unsatisfactory return to Step1 or Step2, else return to Step 3

Example: HAM CAISO Forecast using Ensemble Method

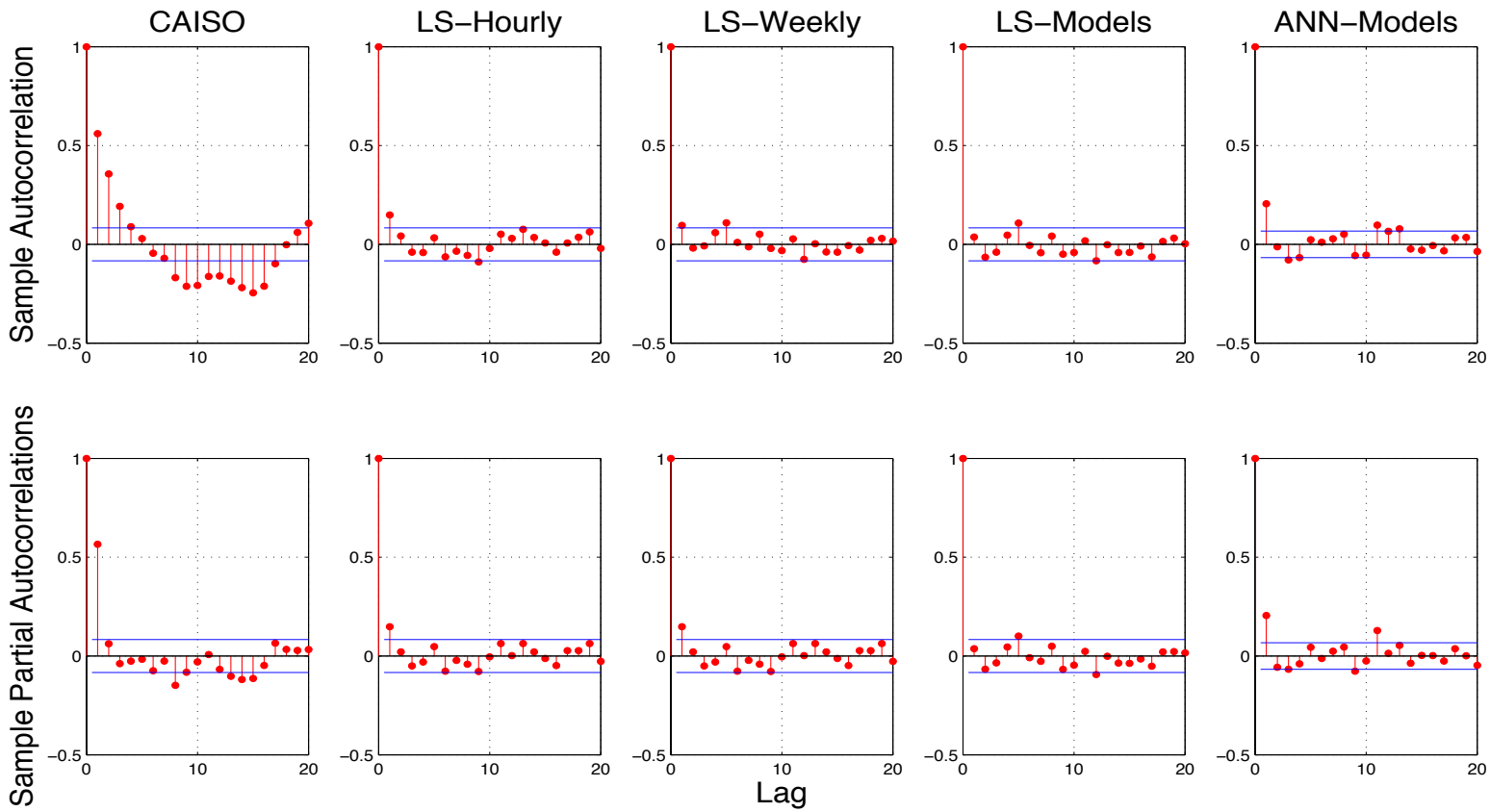


$$\begin{pmatrix} f_{1,1} & f_{1,2} & \cdots & f_{1,n} \\ f_{2,1} & f_{2,2} & \cdots & f_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m,1} & f_{m,2} & \cdots & f_{m,n} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = \begin{pmatrix} \widehat{F}_1 \\ \widehat{F}_2 \\ \vdots \\ \widehat{F}_n \end{pmatrix}$$



http://coimbra.ucsd.edu/forecasting_plots/CAISO_HAM.php?z=4

Error Analysis



QUESTIONS ?

Thanks !