Modernization of Long Term Load Forecasting

An Integrated Approach Taking Advantage of Hourly Load and Weather Information

Tao Hong, PhD
SAS Energy Forecasting

Presentation at Electric Utility Forecasters Forum
Orlando, FL, Nov 8th, 2012

Outline

- Introduction
- Methodology
- Results
- Discussion
- Beyond this talk

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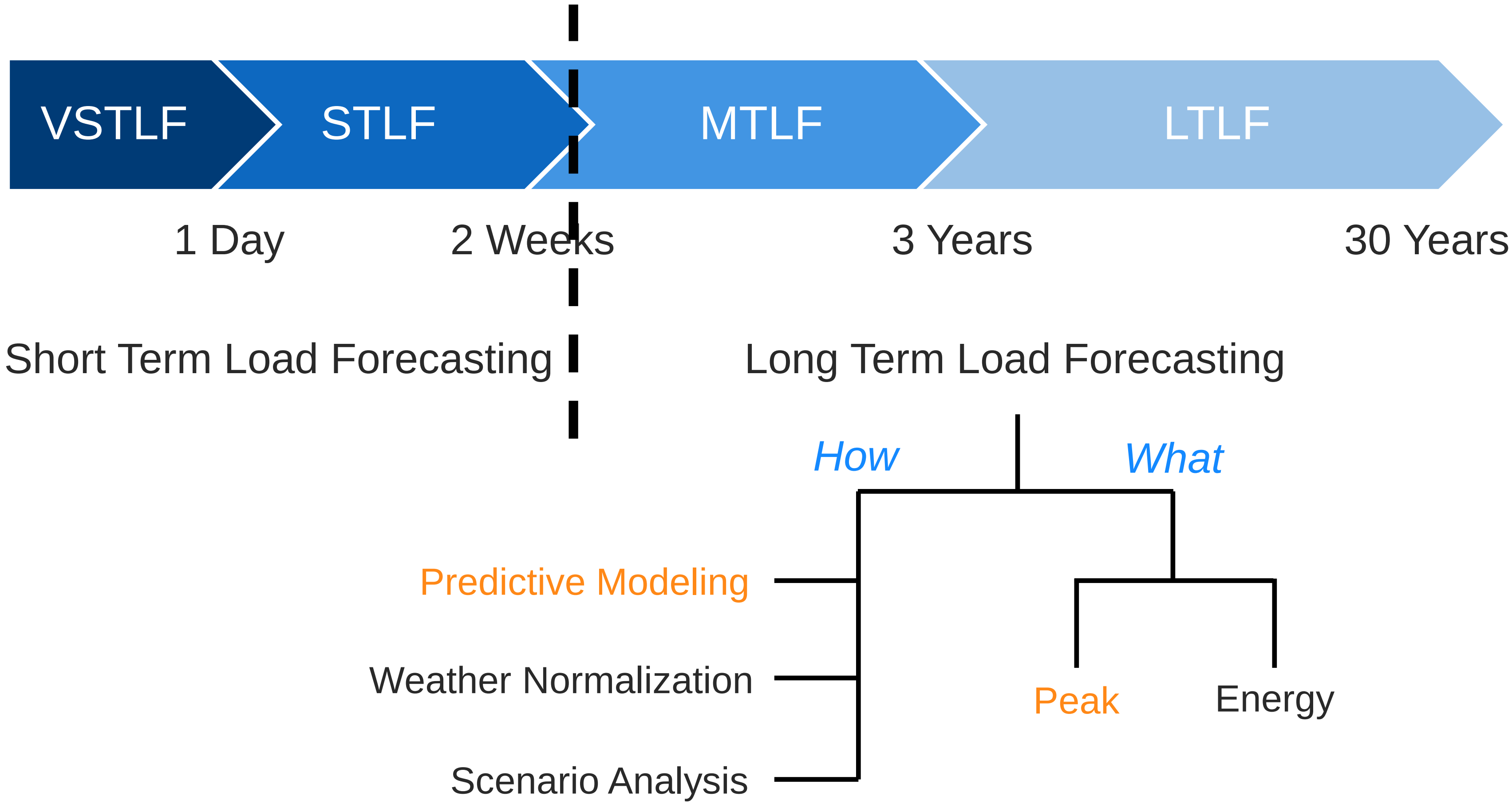
- **Introduction**
- Methodology
- Results
- Discussion
- Beyond this talk

- Terminology
- Business needs
- Two questions
- Modernization
- Integrated forecasting

Terminology



Terminology

- Data
  - Training: parameter estimation
  - Validation: variable/model selection
  - Test: predictive power assessment/confirmation
- Process
  - Ex ante: before the event, the only genuine forecasting accuracy for the future
  - Ex post: after the event

Ex Ante vs. Ex Post

Business Needs

- System planning
- Financial planning
- Rate case
- Energy trading

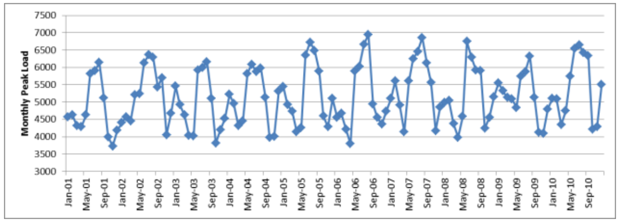
Two Questions

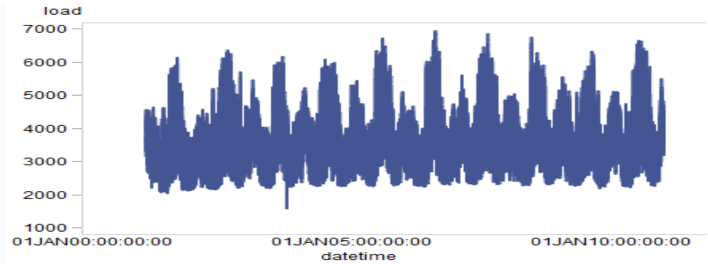
Did you consider this scenario?

Given this scenario,
is your forecast accurate?

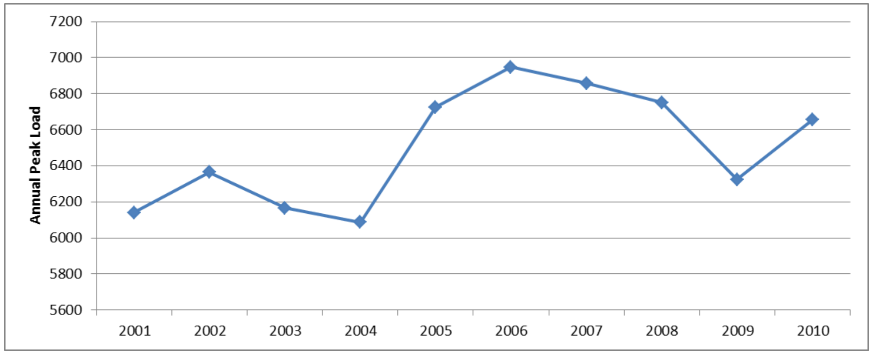
Modernization

Traditional Approach





Modern Approach

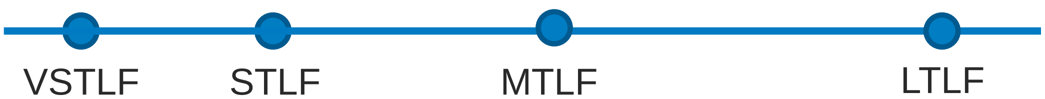


Integrated Forecasting

VSTLF STLF MTLF LTLF

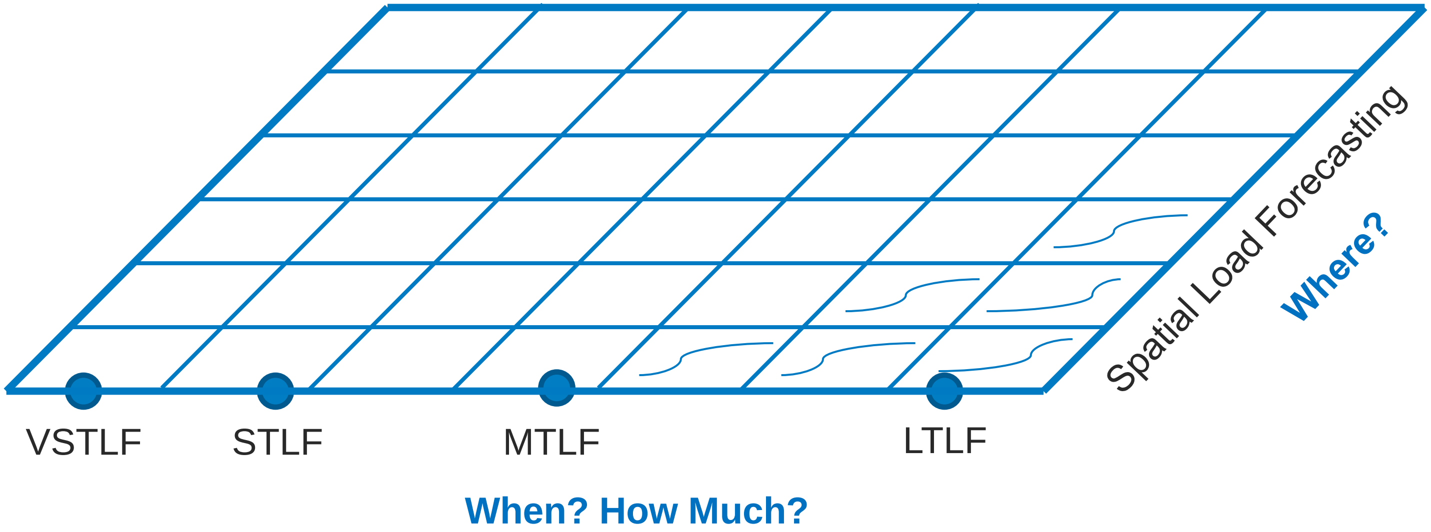
When? How Much?

Integrated Forecasting

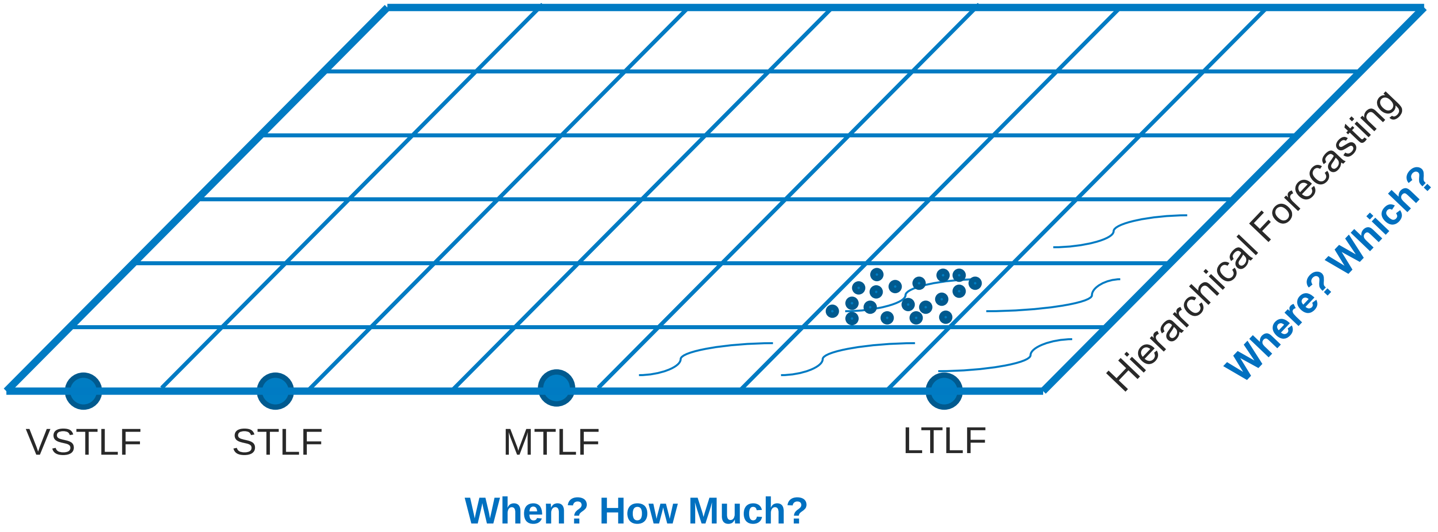


When? How Much?

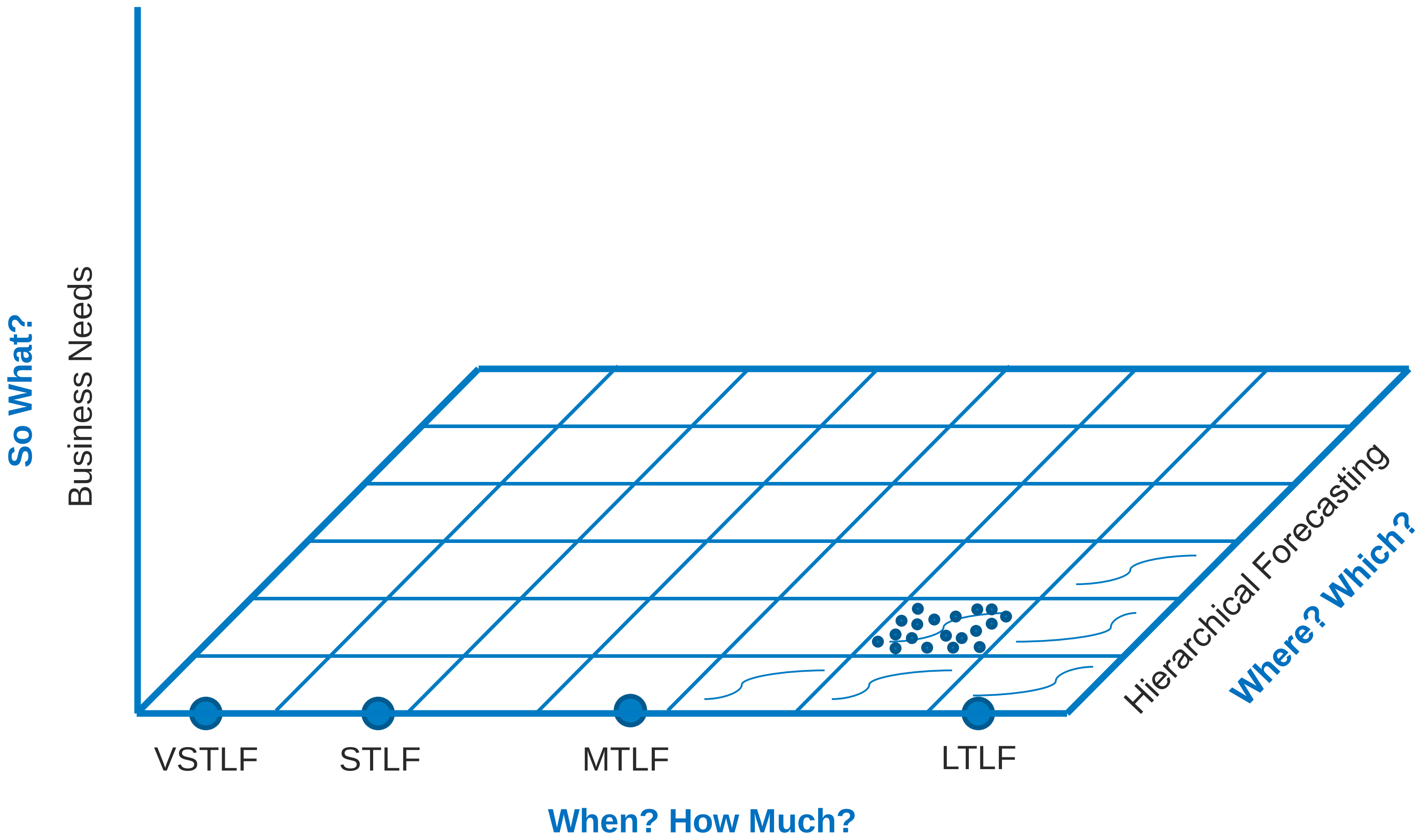
Integrated Forecasting



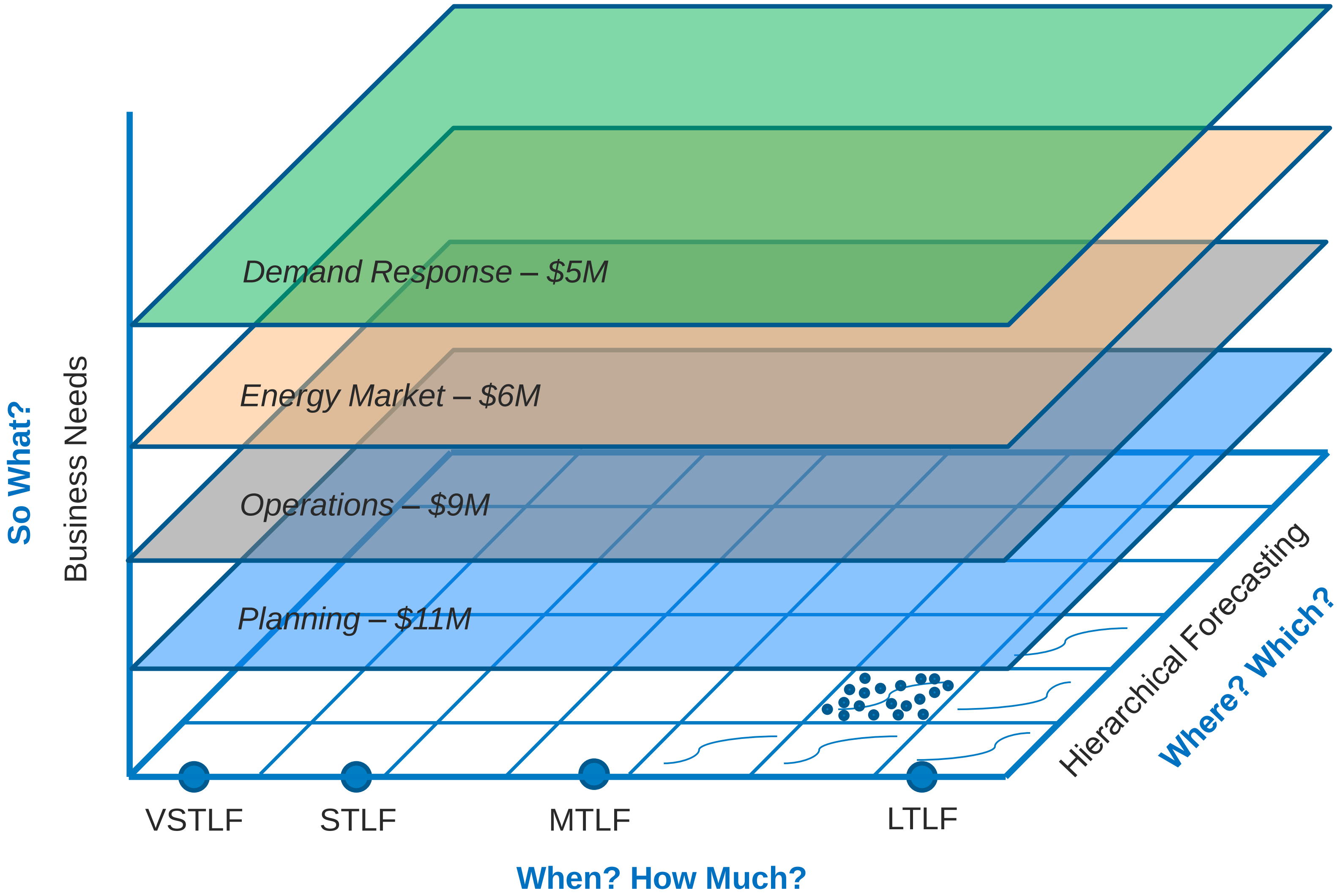
Integrated Forecasting



Integrated Forecasting



Integrated Forecasting



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- Build a STLF model
- Add macroeconomic indicator(s)
- Create weather scenarios
- Create economy scenarios

Build a STLF Model

- Naïve MLR Benchmarking Model

$E(Load) = \beta_0 + \beta_1*Trend + \beta_2*Day*Hour + \beta_3*Month + \beta_4*Month*T + \beta_5*Month*T^2 + \beta_6*Month*T^3 + \beta_7*Hour*T + \beta_8*Hour*T^2 + \beta_9*Hour*T^3$

- Recency effect

$E(Load) = \beta_0 + \beta_1*Trend + \beta_2*Day*Hour + \beta_3*Month + \beta_4*Month*T + \beta_5*Month*T^2 + \beta_6*Month*T^3 + \beta_7*Hour*T + \beta_8*Hour*T^2 + \beta_9*Hour*T^3 + \beta_{10}*Month*T(-1) + \beta_{11}*Month*T(-1)^2 + \beta_{12}*Month*T(-1)^3 + \beta_{13}*Hour*T(-1) + \beta_{14}*Hour*T(-1)^2 + \beta_{15}*Hour*T(-1)^3 + \ldots$

- Weekend effect
- Holiday effect
- …

Tao Hong, *Electric Load Forecasting: Fundamentals and Best Practices*
Course information webpage: https://support.sas.com/edu/schedules.html?id=1326

Add Macroeconomic Indicators

- Replace *Trend* by *GXP*
- Divide *Load* by *GXP*
- Interact *GXP* with other terms

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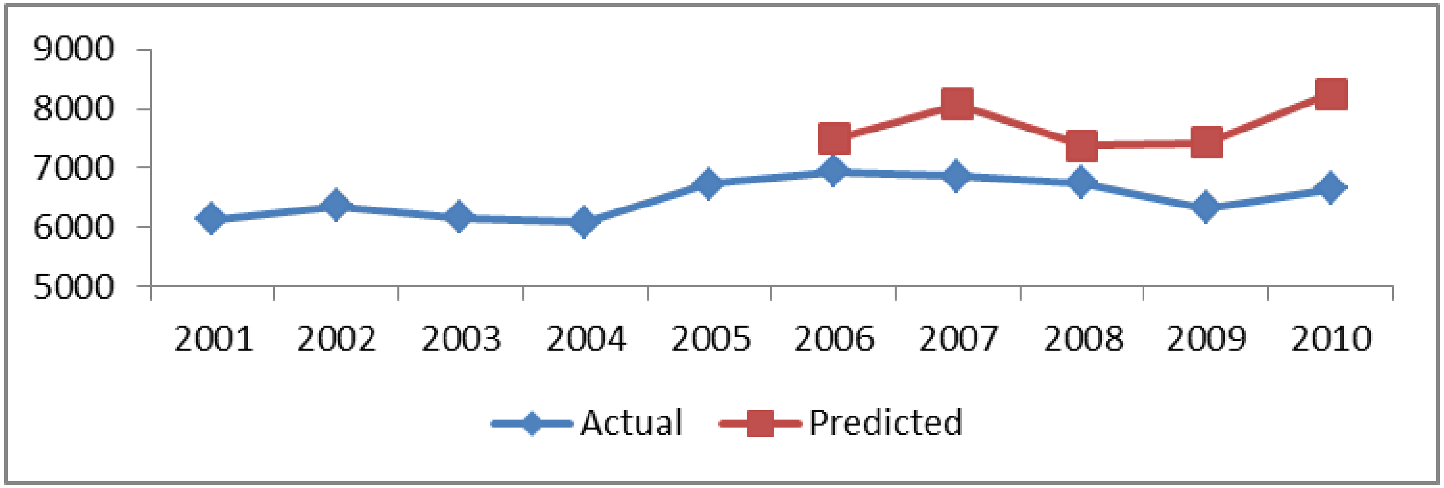
- Traditional approach
- Naïve MLR model
- Recency effect model
- Summary

Traditional Approach – Monthly

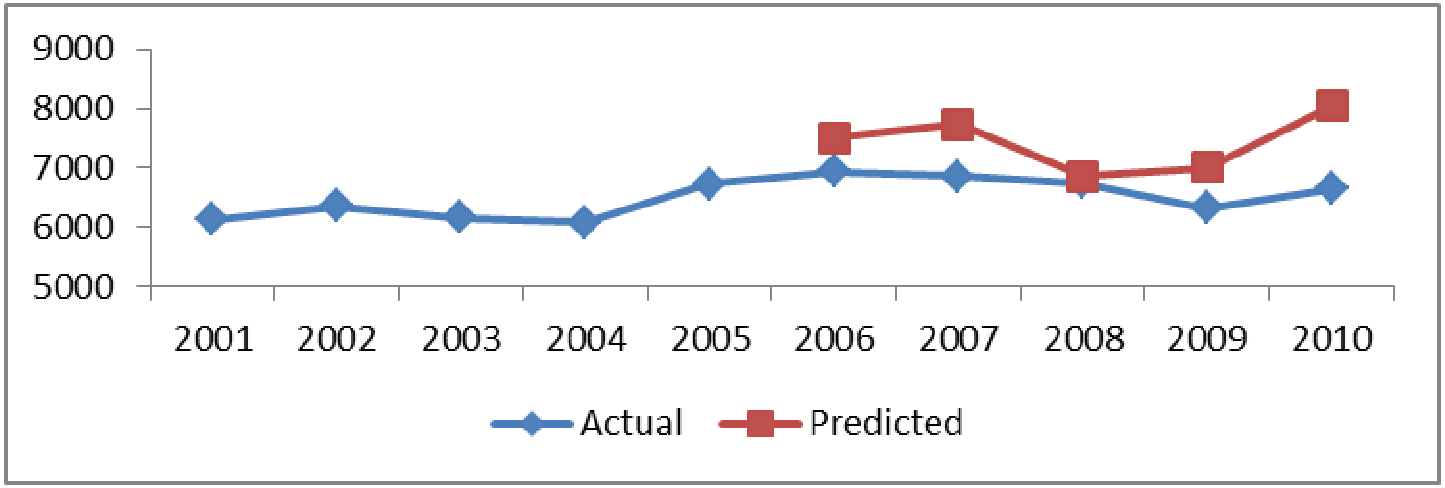
$$E(Load) = \beta_0 + \beta_1*GSP + \beta_2*HDD + \beta_3*CDD + \beta_4*T + \beta_5*T^2 + \beta_6*T^3 + \beta_7*Month$$



	2006	2007	2008	2009	2010	Average
APE (%)	7.91	17.65	9.35	17.44	24.06	**15.28**

Traditional Approach – Daily

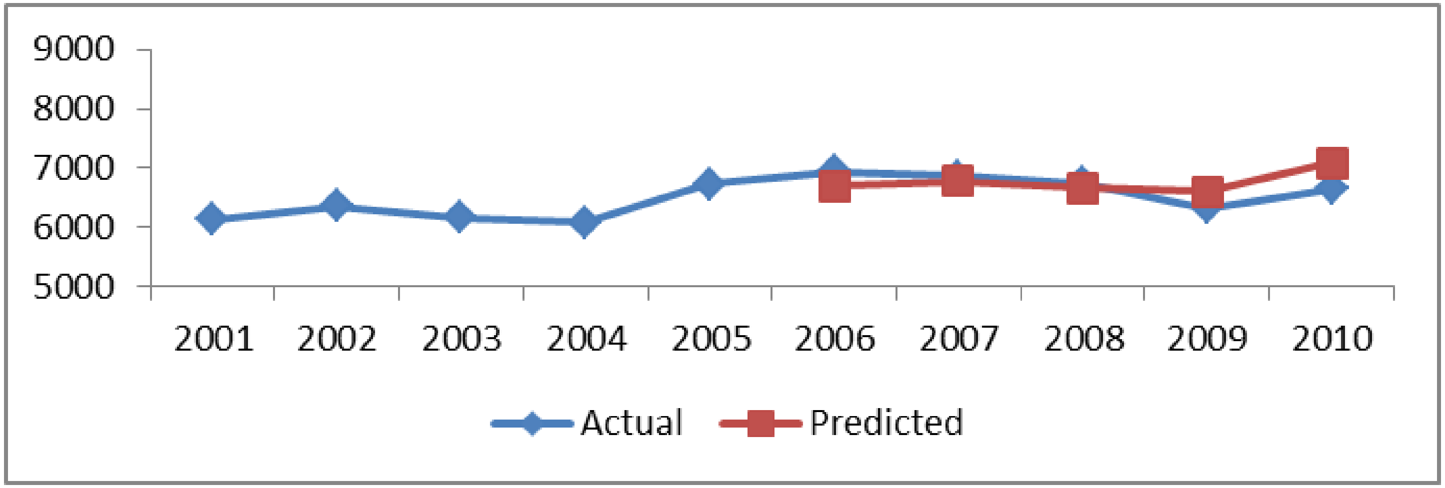
$$E(Load) = \beta_0 + \beta_1{*}GSP + \beta_2{*}HDD + \beta_3{*}CDD + \beta_4{*}T + \beta_5{*}T^2 + \beta_6{*}T^3 + \beta_7{*}Month + \beta_8{*}Day$$



	2006	2007	2008	2009	2010	Average
APE (%)	8.00	12.70	1.74	10.86	20.82	**10.82**

Naïve MLR Model

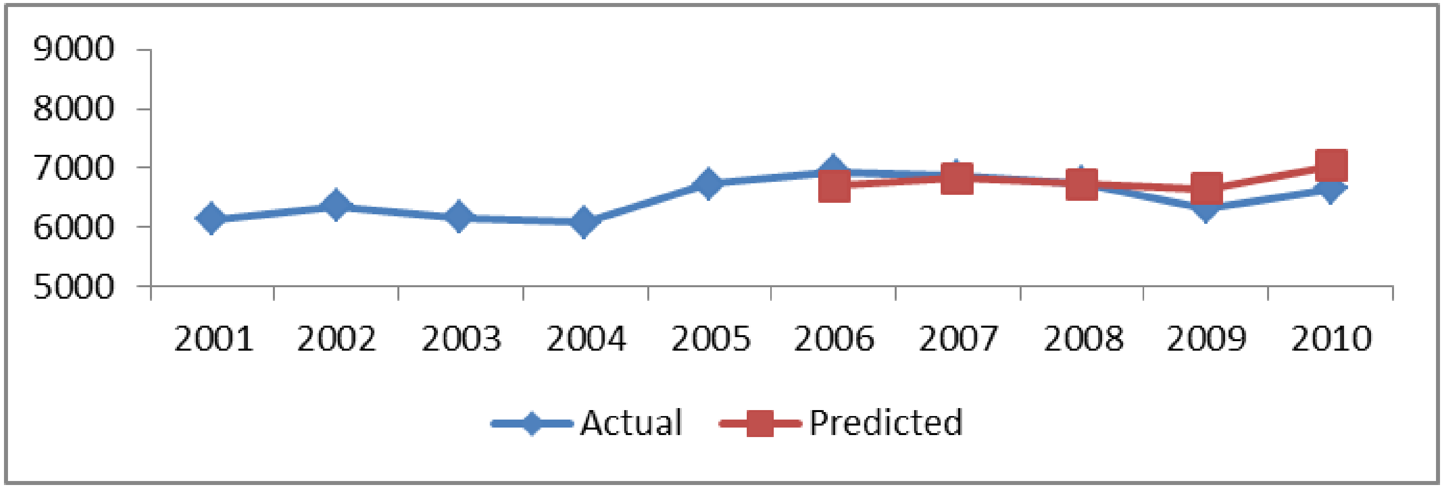
$E(Load) = \beta_0 + \beta_1 * GSP + \beta_2 * Day * Hour + \beta_3 * Month + \beta_4 * Month * T + \beta_5 * Month * T^2 + \beta_6 * Month * T^3 + \beta_7 * Hour * T + \beta_8 * Hour * T^2 + \beta_9 * Hour * T^3$



	2006	2007	2008	2009	2010	Average
APE (%)	3.58	1.12	1.29	4.35	6.64	**3.40**

Recency Effect Model

$$E(Load) = \beta_0 + \beta_1 * GSP + \beta_2 * Day * Hour + \beta_3 * Month + \beta_4 * Month * T + \beta_5 * Month * T^2 + \beta_6 * Month * T^3 + \beta_7 * Hour * T + \beta_8 * Hour * T^2 + \beta_9 * Hour * T^3 + \beta_{10} * Month * T(-1) + \beta_{11} * Month * T(-1)^2 + \beta_{12} * Month * T(-1)^3 + \beta_{13} * Hour * T(-1) + \beta_{14} * Hour * T(-1)^2 + \beta_{15} * Hour * T(-1)^3$$

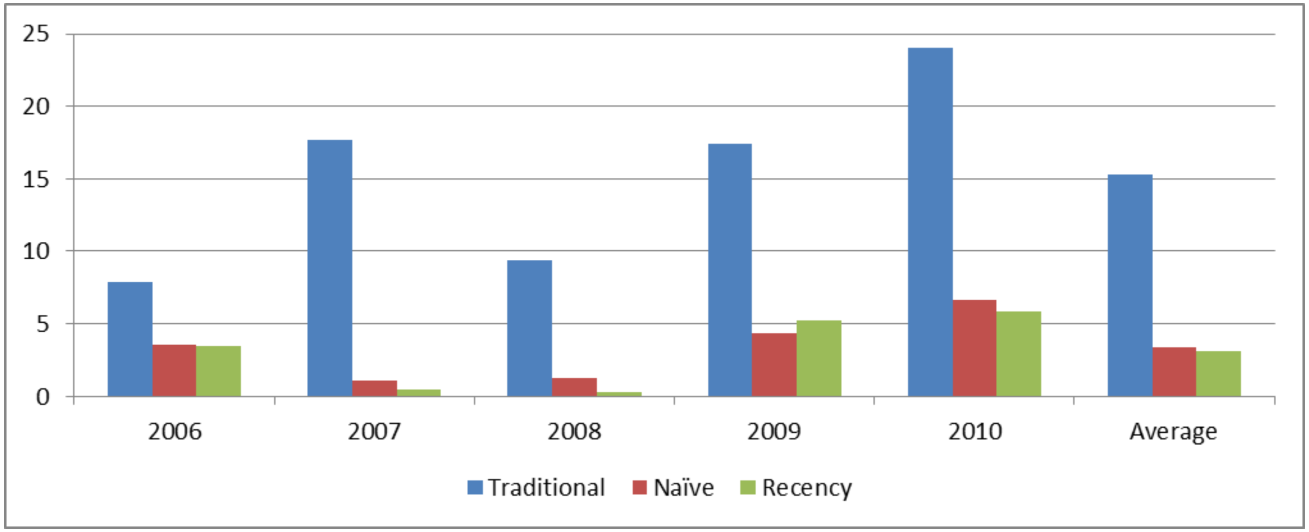


	2006	2007	2008	2009	2010	Average
APE (%)	3.48	0.49	0.30	5.27	5.84	**3.08**

Summary

Using 5-year history to forecast the next 5 years

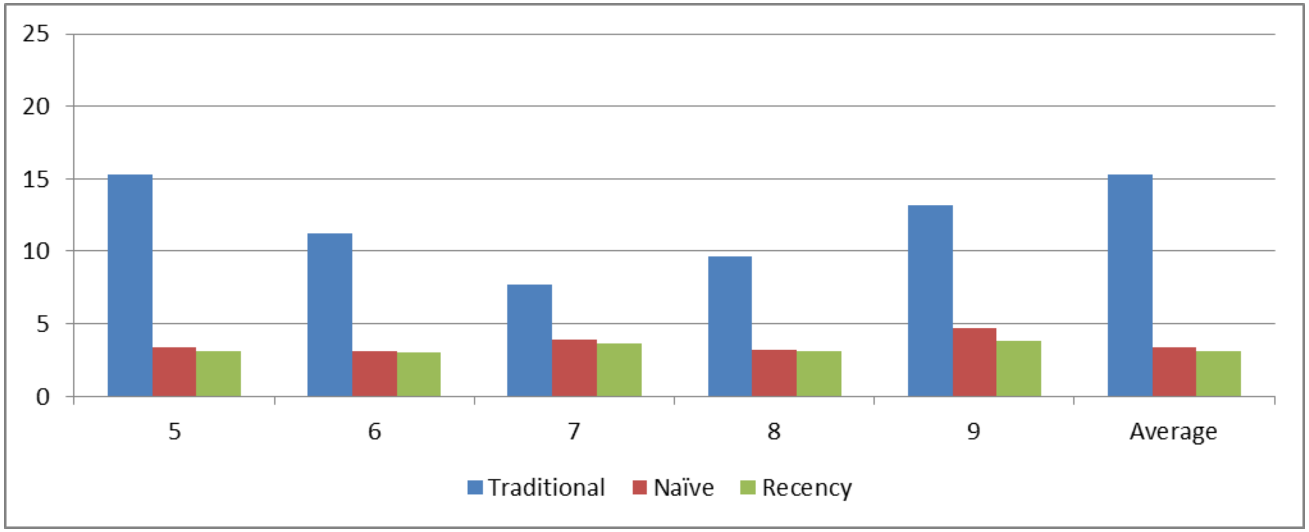
	2006	2007	2008	2009	2010	Average
Traditional	7.91	17.65	9.35	17.44	24.06	**15.28**
Naïve	3.58	1.12	1.29	4.35	6.64	**3.40**
Recency	3.48	0.49	0.30	5.27	5.84	**3.08**



Summary

Altering the length of history

	5 years	6 years	7 years	8 years	9 years	Average
Traditional	15.28	11.27	7.71	9.67	13.15	**10.29**
Naïve	3.40	3.15	3.89	3.24	4.67	**3.67**
Recency	3.08	3.00	3.62	3.13	3.79	**3.32**



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  - Complexity
  - R-square
  - HDD and CDD
  - Improvement
- Beyond this talk

Complexity

Traditional Approach

12 observations/year × 10 years = 120 observations

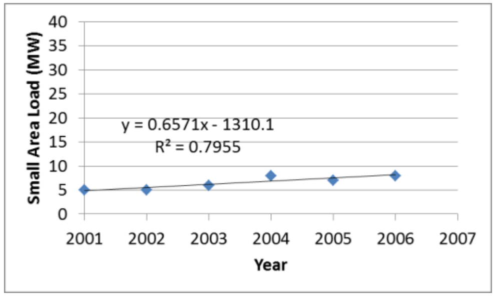
120 observations / 20 parameters = ***6*** observations/parameter

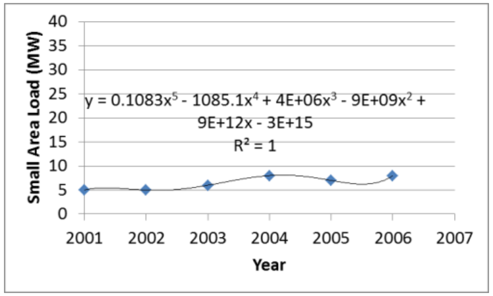
Modern Approach

8760 observations/year × 10 years = 87,600 observations

87,600 observations / 400 parameters = ***219*** observations/parameter

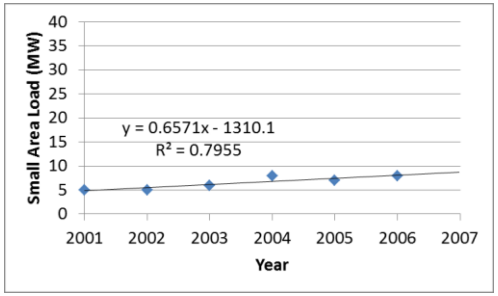
R-Square

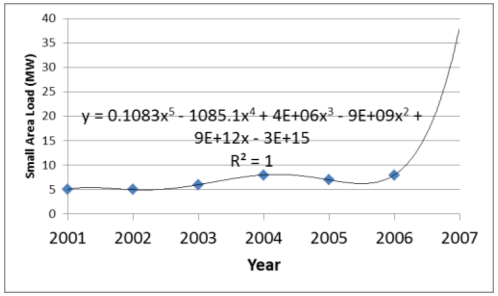




Goodness of Fit

Predictive Power



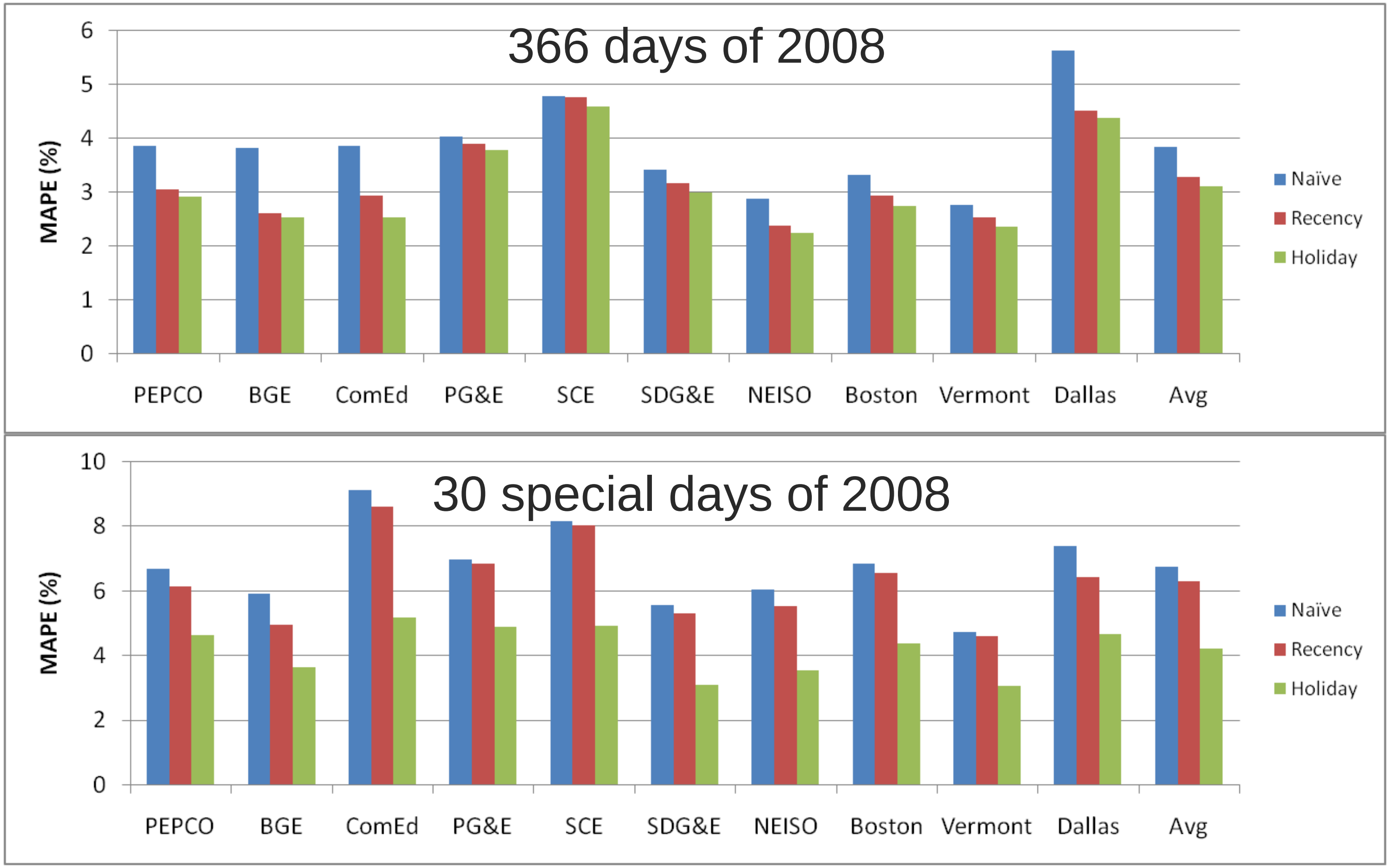


Tao Hong, *How Accurate is My Forecast?* SAS Utilities Users Group Meeting, May 18, 2012

HDD and CDD

- They don't tell you which hour of the day and which day of the week the high/low temperatures fall into.
- They don't tell you the variation of the temperatures through out a day or a month.
- They don't tell the temperature profile so they are not helpful for modeling recency effect.
- They require you to specify the threshold, which may not be very defensible.

Improvement



Note: Results are for educational purposes only, not representing the best accuracy obtained for each utility.

Tao Hong, *Electric Load Forecasting with Holiday Effect,* AEIC Workshop 2012, Orlando, FL, Mar 19-20, 2012

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- SAS BKS course
  - *Electric Load Forecasting*
- IEEE Working Group on Energy Forecasting
- Global Energy Forecasting Competition (GEFCom2012)

SAS BKS Course

Electric Load Forecasting: Fundamentals and Best Practices

- Introduction to Electric Load Forecasting
- Salient Features of Electric Load Series
- Multiple Linear Regression
- A Naive Benchmark for Short-term Load Forecasting
- Customizing the Benchmarking Model
- Very Short-Term Load Forecasting
- Medium/Long-Term Load Forecasting
- Variables, Methods, Techniques, and Further Readings
- Frequently Made Mistakes

Course information webpage: https://support.sas.com/edu/schedules.html?id=1326

SAS BKS Course
Electric Load Forecasting: Fundamentals and Best Practices

- 6 offerings in the first 6 months
  - About 60 participants, average rating > 4.8/5
  - Organizations: consulting firm, Trans/Dis/Gen company, Co-op, IOU, muni, ISO, REP, vendor, regulatory commission, university
  - Titles: analyst, forecaster, lead, manager, director, VP, consultant
  - Industry experience: 0 to 35+ years
  - SAS experience: zero to expert
  - Statistics background: no background to Ph.D.

Offerings in 2013

April 8-9, Rockville, MD
April 25-26, Irvine, CA
June 3-4, Chicago, IL

Course information webpage: https://support.sas.com/edu/schedules.html?id=1326

IEEE WG on Energy Forecasting

- Activities in PESGM 2011, Detroit, MI
  - Practical aspects of electric load forecasting
- Activities in PESGM 2012, San Diego, CA
  - Demand response: analytics, practice, and challenges in smart grid environment
  - Load forecasting and its applications in operations and planning
- Ongoing projects
  - Global Energy Forecasting Competition 2012
  - Benchmarking STLF accuracy
  - Review of literature and practice of load forecasting
  - IEEE Transactions on Smart Grid – Special Issue on Analytics for Energy Forecasting with Applications to Smart Grid

http://sites.ieee.org/pes-pspic/about-pspi/subcommittees/energy-forecasting/

GEFCom2012

✓ Hierarchical Load Forecasting

- $7,500
- 651 unique users
- 107 teams
- 160 participants
- 1010 entries
- 27 teams got better scores than Tao's Vanilla Benchmark

✓ Wind Power Forecasting

- $7,500
- 583 unique users
- 134 teams
- 198 participants
- 1397 entries
- 126 teams got better scores than the benchmark

GEFCom2012
Load Forecasting

GEFCom2012
Wind Forecasting

WWW.GEFCOM.ORG

Tao Hong, PhD

Tao.Hong@sas.com
SAS Energy Forecasting

www.sas.com