Modernization of Long Term Load Forecasting

An Integrated Approach Taking Advantage of Hourly Load and Weather Information

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SAS Institute

Tao Hong

- Research
- Consulting
- Teaching

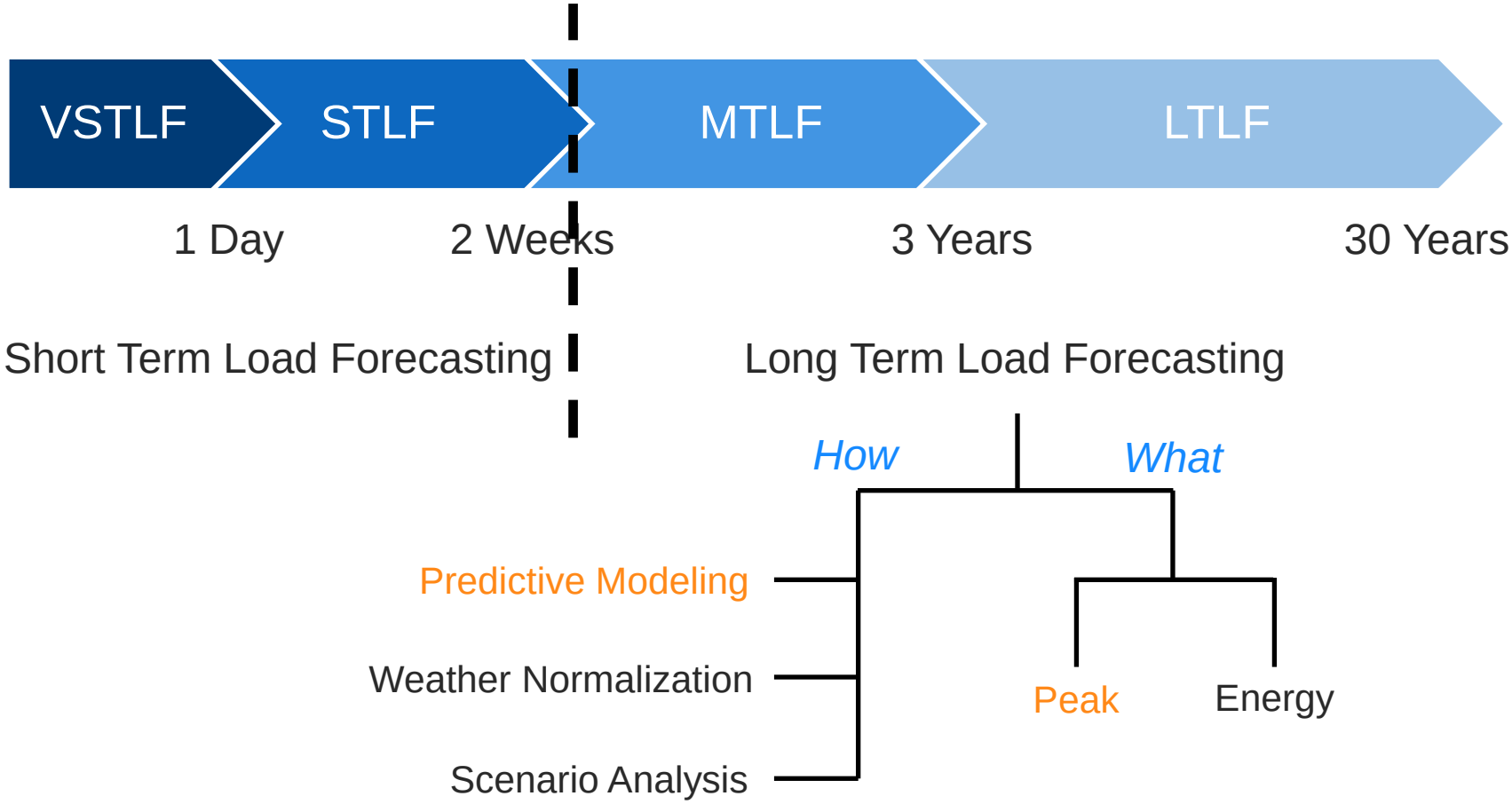
Outline

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

Outline

- **Introduction**
  - Terminology
  - Business needs
  - Modernization
  - Integrated forecasting
- Methodology
- Results
- Discussion
- Beyond this talk

Terminology



Terminology

- Data
  - Training: parameter estimation
  - Validation: variable/model selection
  - Test: predictive power assessment/confirmation

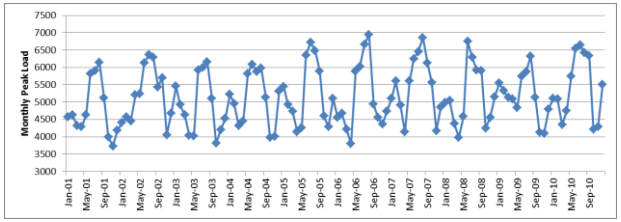
- Process
  - Ex ante: before the event, genuine forecasting accuracy
  - Ex post: after the event, answers “given the scenario, how accurate is my forecast”

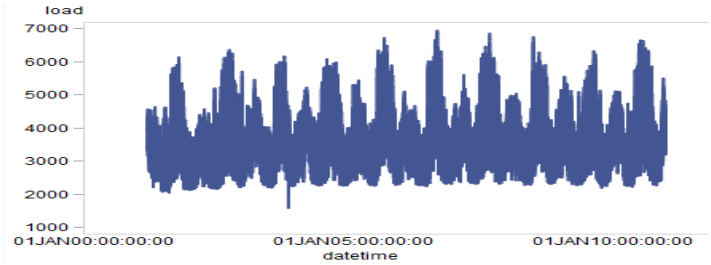
Business Needs

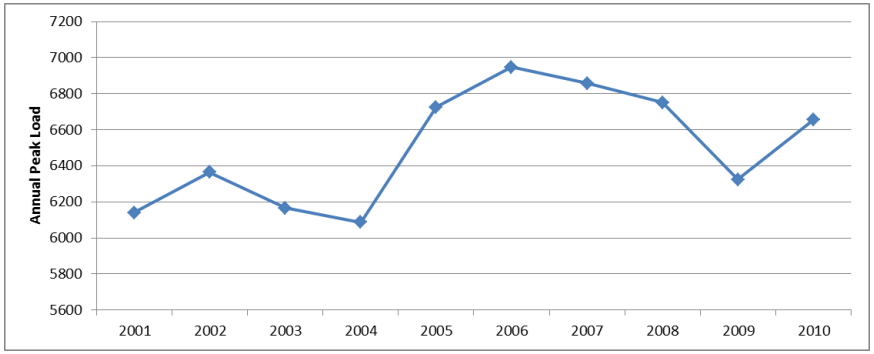
- System planning
- Financial planning
- Rate case
- Energy trading

Modernization

Traditional Approach

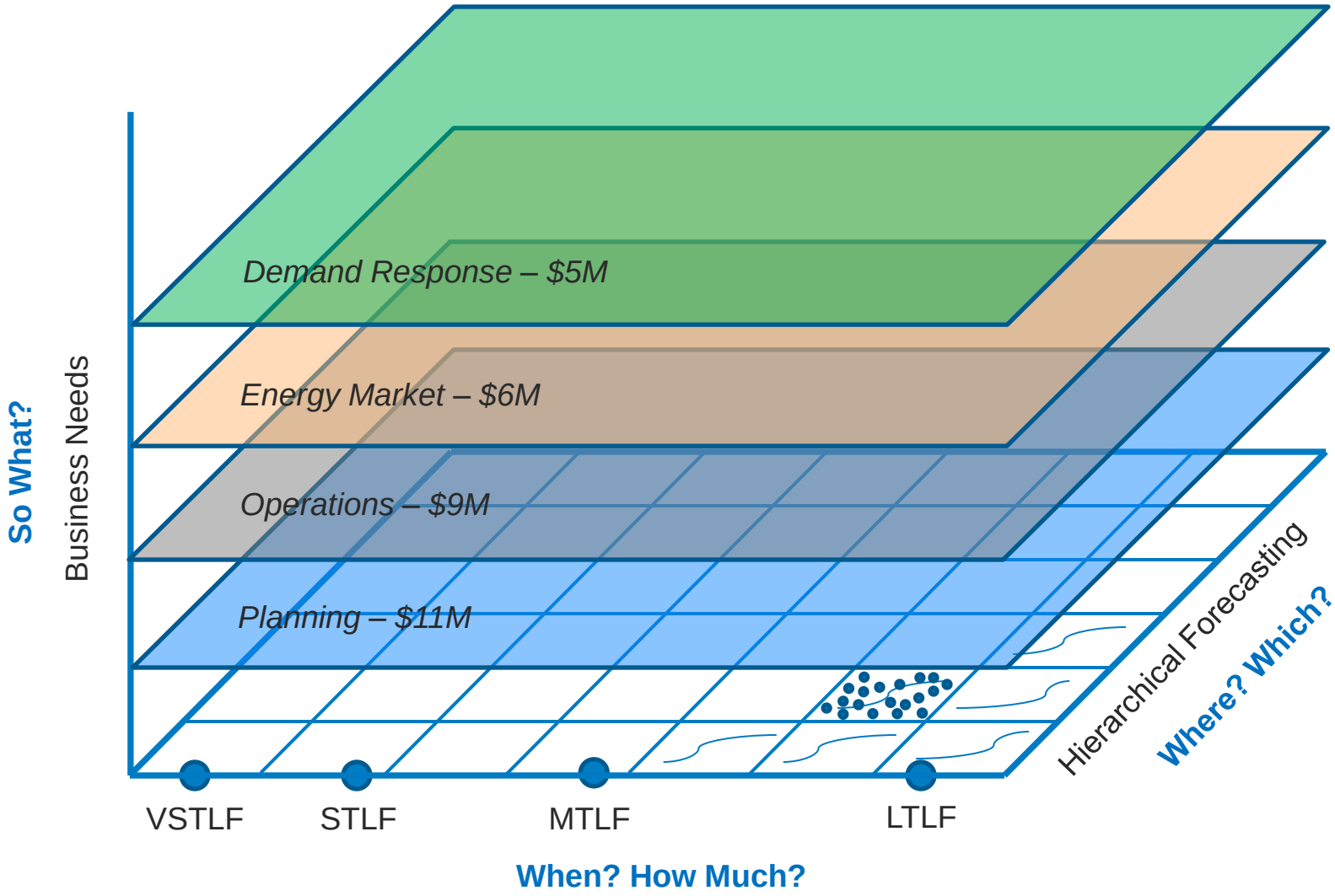






Modern Approach

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

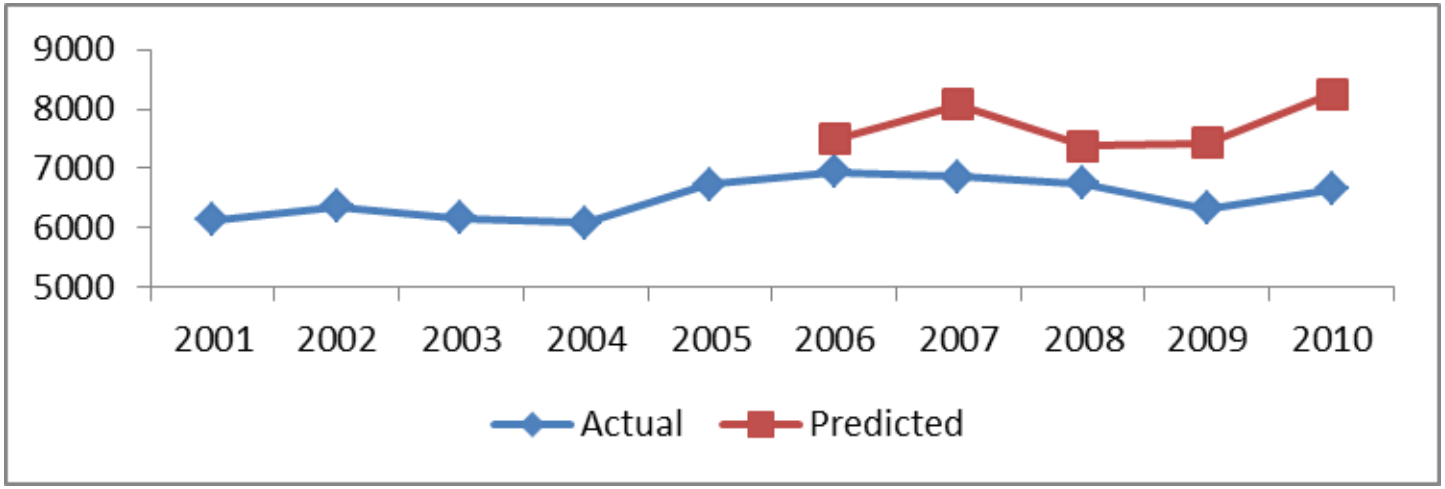
- Replace *Trend* by *GXP*
- Divide *Load* by *GXP*
- Interact *GXP* with other terms

Outline

- Introduction
- Methodology
- **Results**
  - Traditional approach
  - Naïve MLR model
  - Recency effect model
  - Summary
- Discussion
- Beyond this talk

Traditional Approach

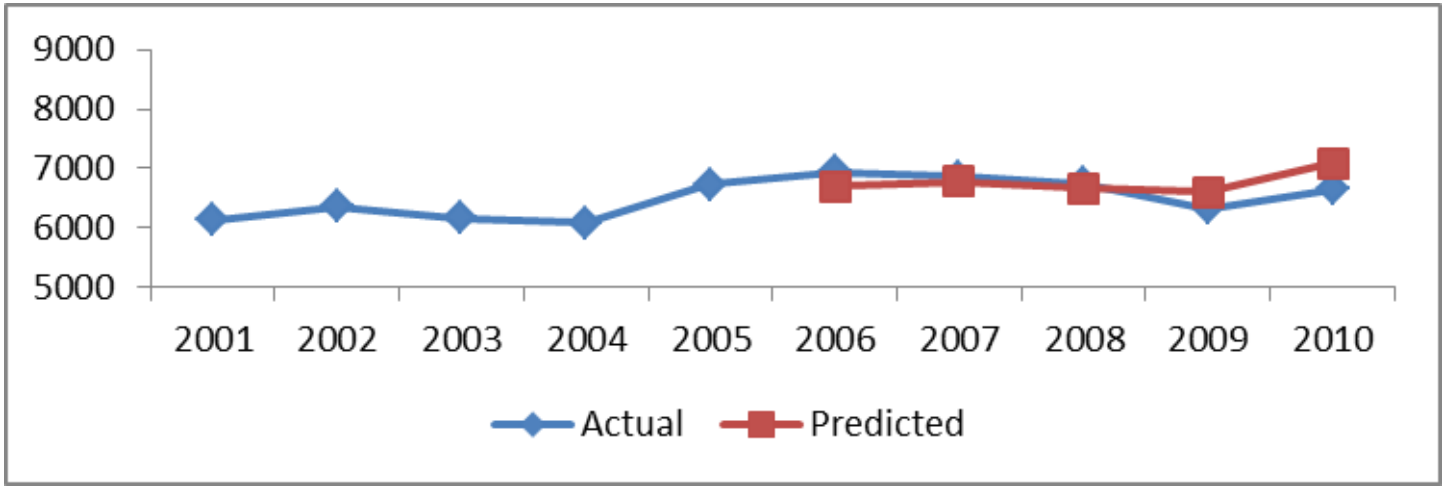
$$E(Load) = \beta_0 + \beta_1*GSP + \beta_2*HDD + \beta_3*CDD + \beta_4*T + \beta_5*T^2 + \beta_6*T^3 + \beta_7*Month$$



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

Naïve MLR Model

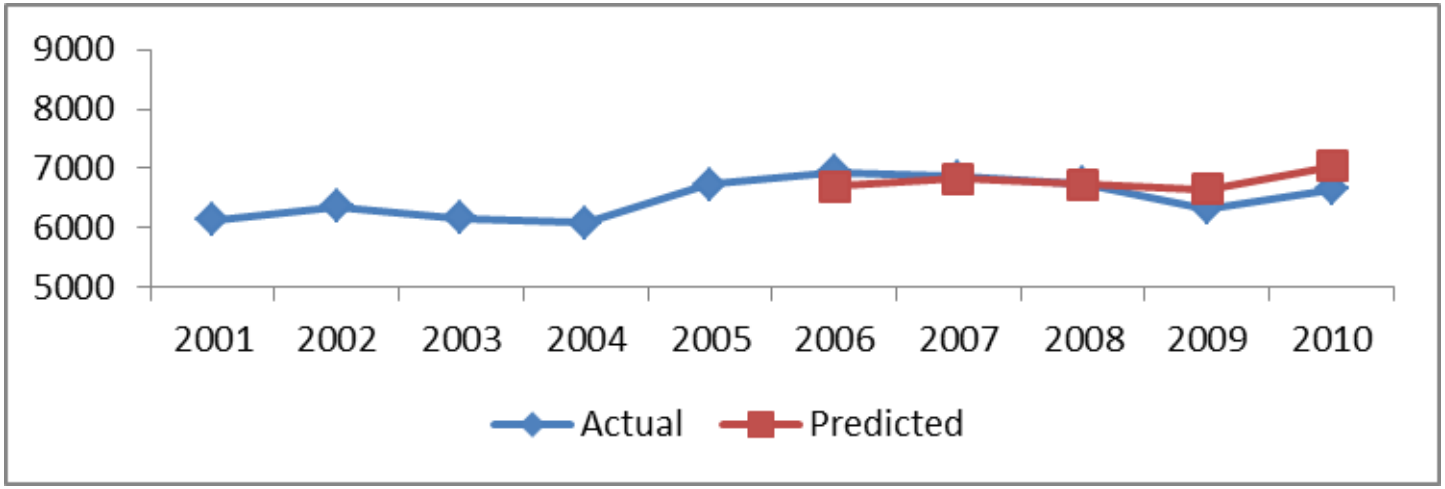
$$E(Load) = \beta_0 + \beta_1*GSP + \beta_2*Day*Hour + \beta_3*Month + \beta_4*Month*T + \beta_5*Month*T^2 + \beta_6*Month*T^3 + \beta_7*Hour*T + \beta_8*Hour*T^2 + \beta_9*Hour*T^3$$



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

Recency Effect Model

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

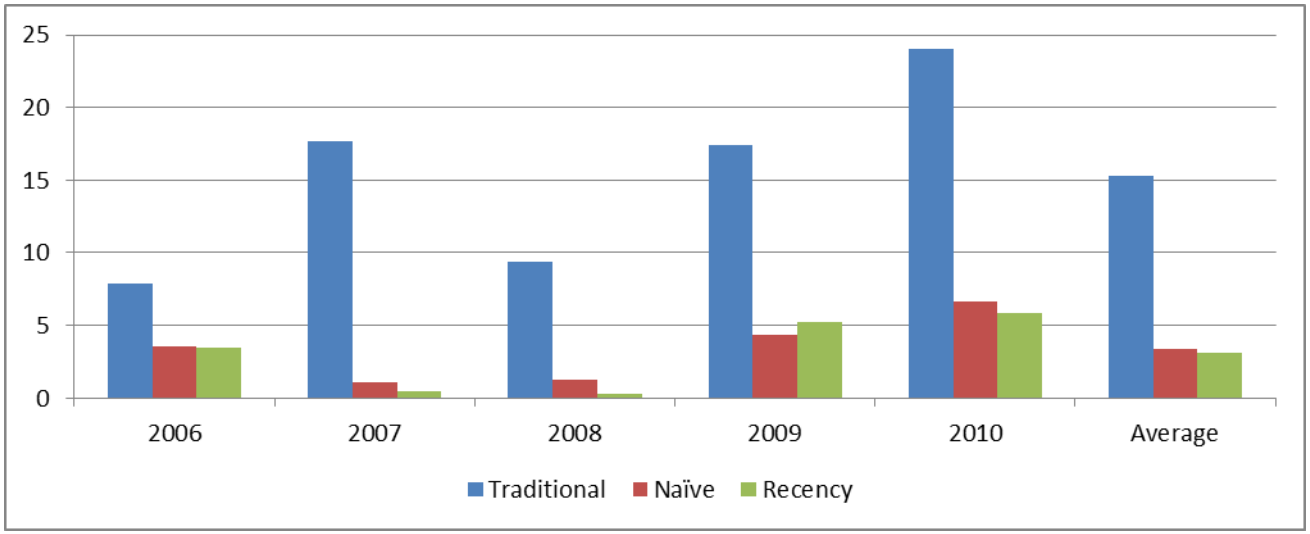


	2006	2007	2008	2009	2010	Average
APE (%)	3.48	0.49	0.30	5.27	5.84	**3.08**

Summary

Using 5-year history to forecast the next 5 years

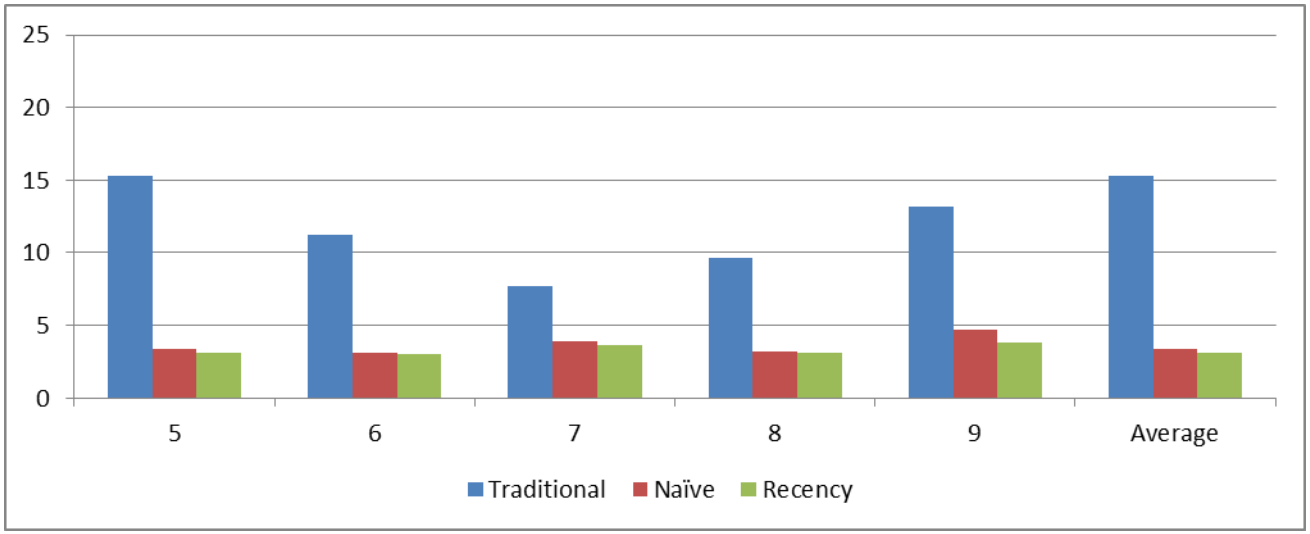
	2006	2007	2008	2009	2010	Average
Traditional	7.91	17.65	9.35	17.44	24.06	**15.28**
Naïve	3.58	1.12	1.29	4.35	6.64	**3.40**
Recency	3.48	0.49	0.30	5.27	5.84	**3.08**



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
  - Improvement
- Beyond this talk

Complexity

Traditional Approach

12 observations/year × 10 years = 120 observations

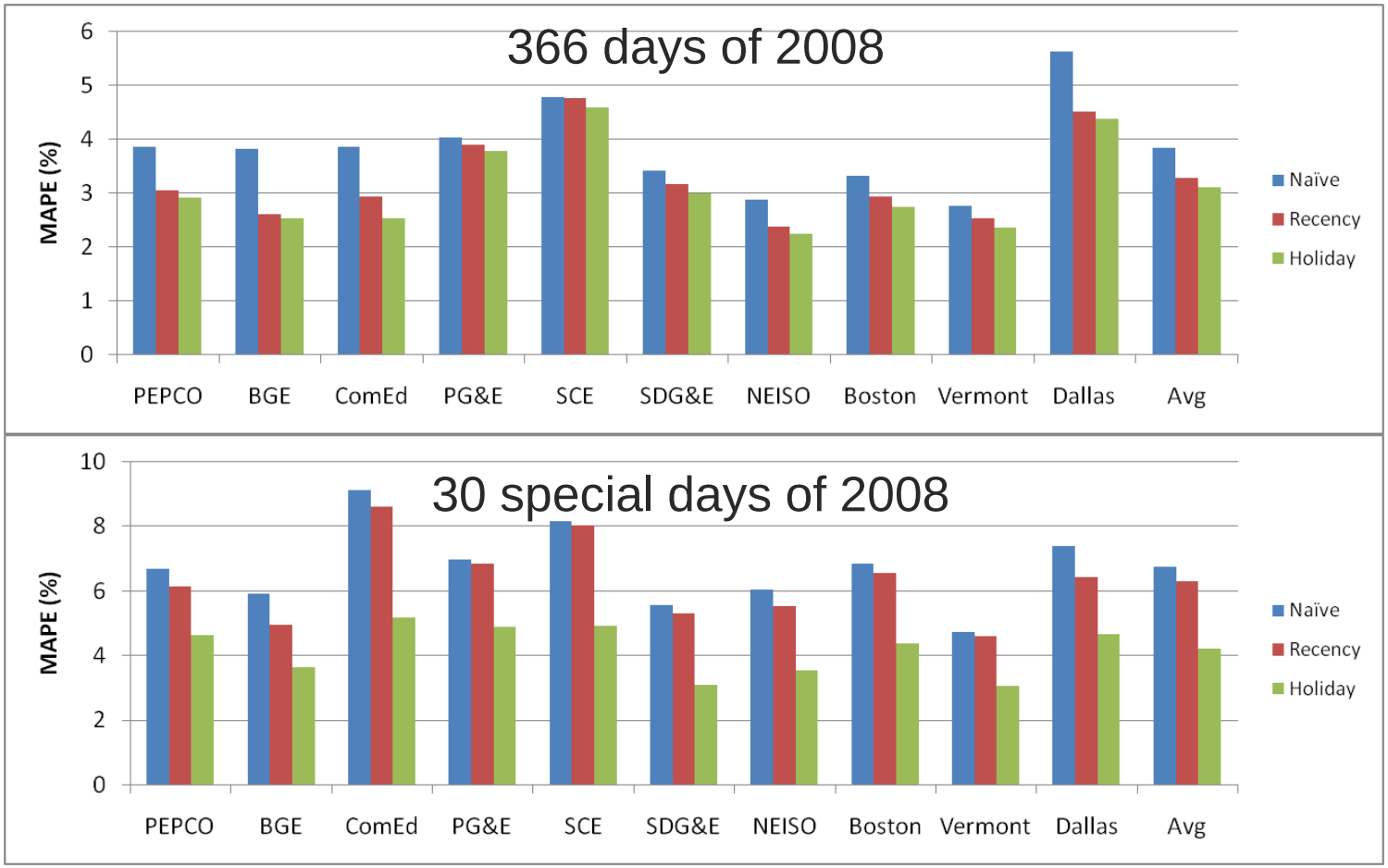
120 observations / 20 parameters = ***6*** observations/parameter

Modern Approach

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

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

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

SAS BKS Course

Electric Load Forecasting: Fundamentals and Best Practices

- Introduction to Electric Load Forecasting
- Salient Features of Electric Load Series
- Mulitiple 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

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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/

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