

Load Research from the User's Perspective: Fun with Load Research Data

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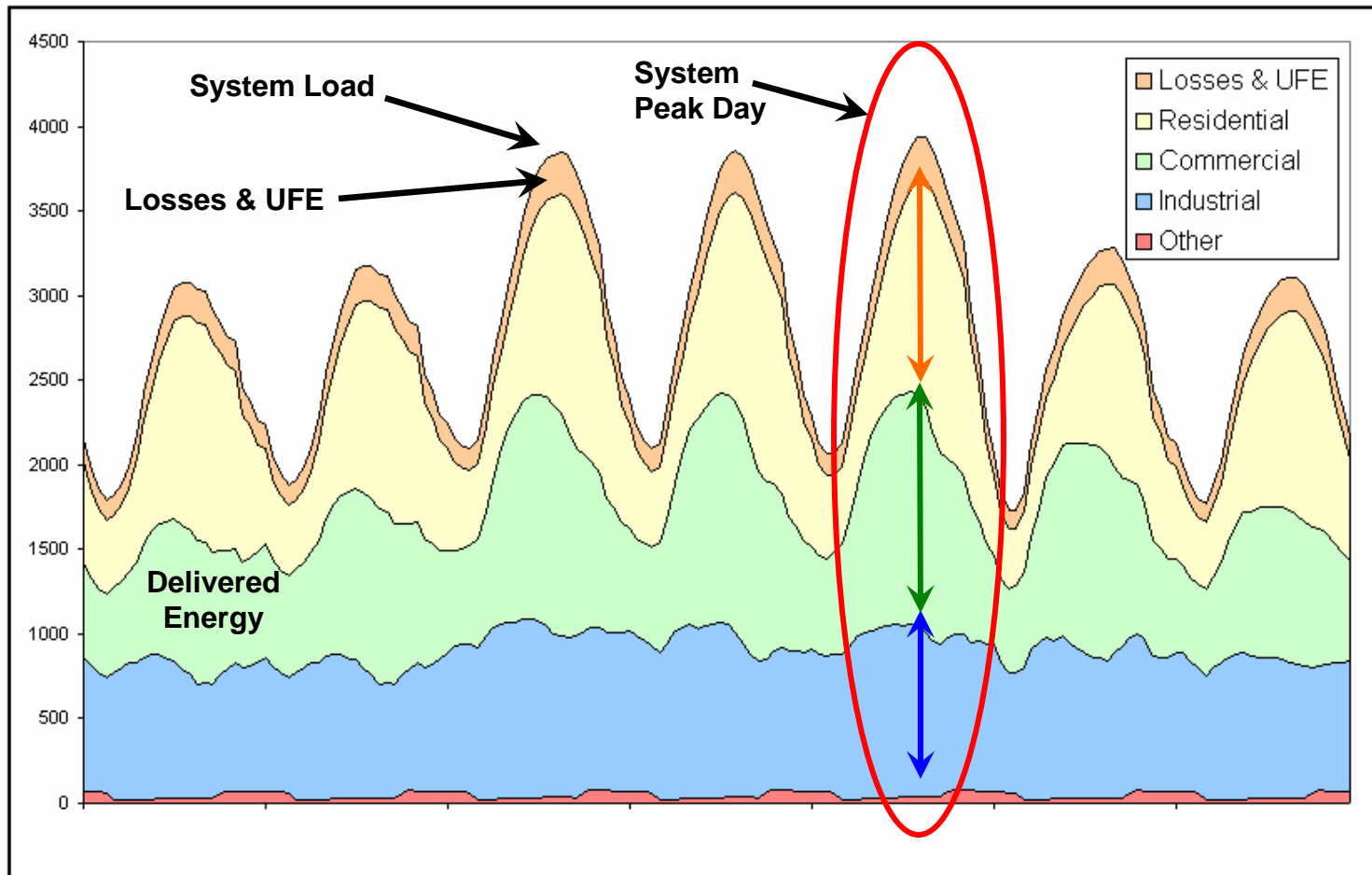


> Knowledge to Shape Your Future



From the Analyst's Perspective

Load research allows us to decompose system load by customer class, rate, and end-uses. System load data tells us how much energy was delivered in each hour (the total). Load research tells us where it went.

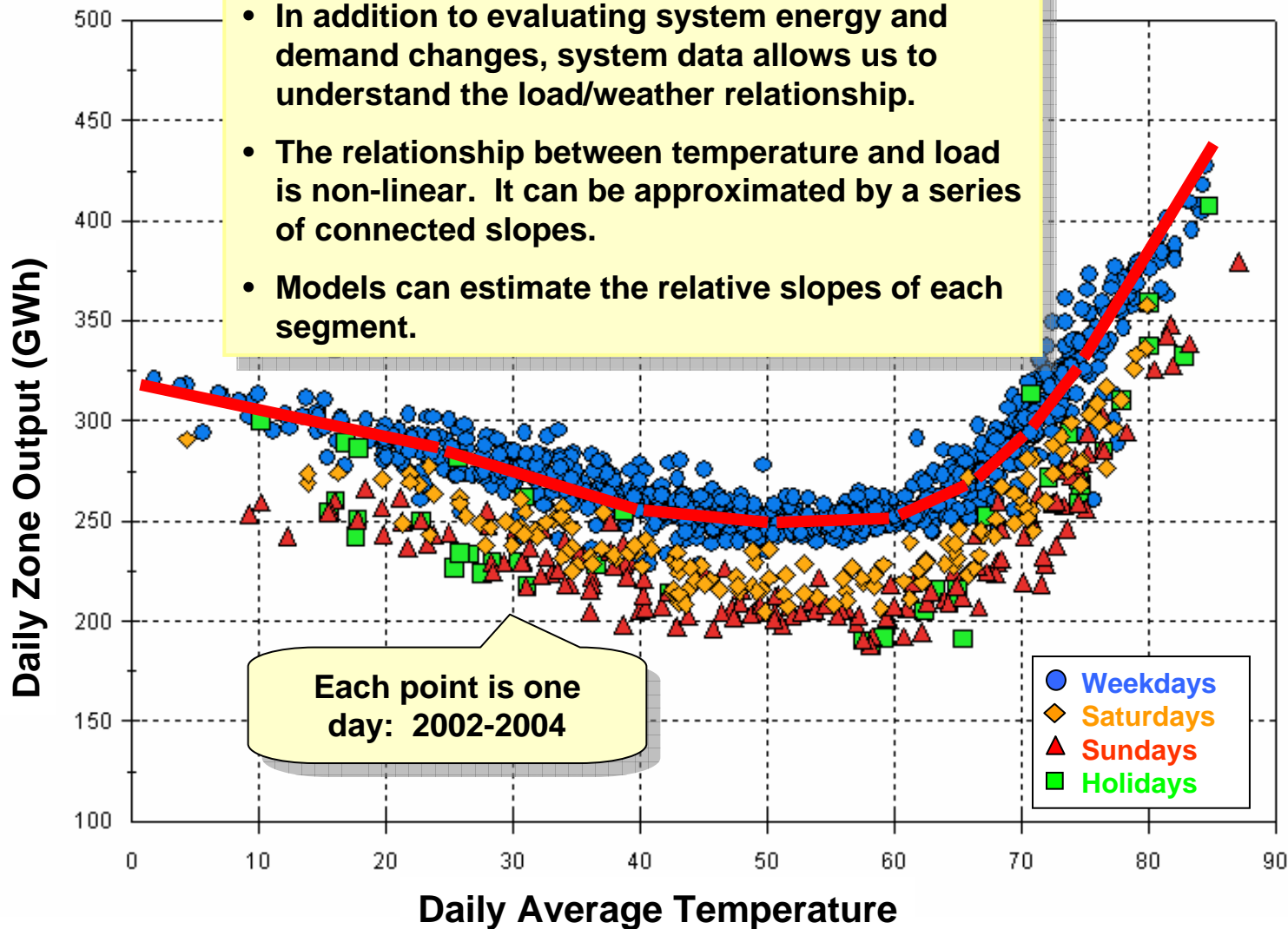


Load Research Data is Needed to Make Critical Business Decisions

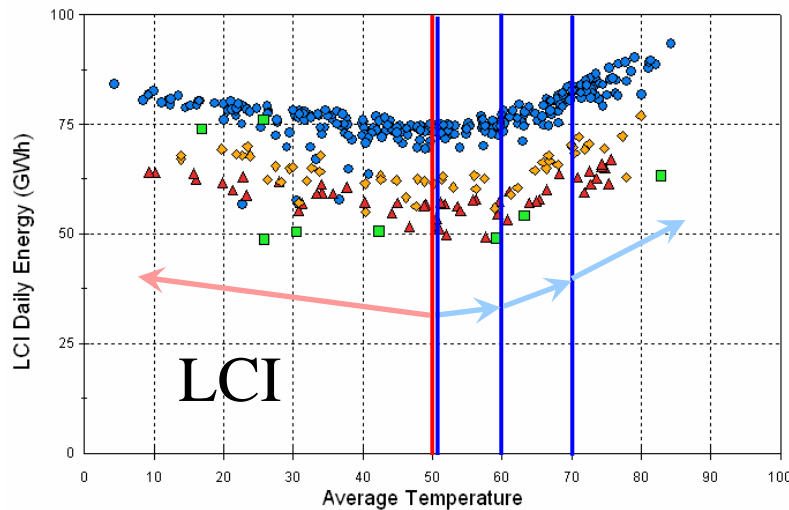
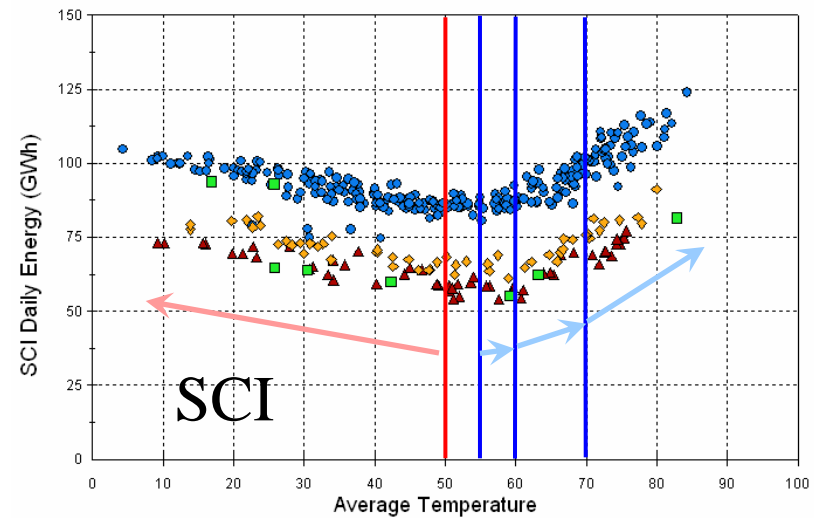
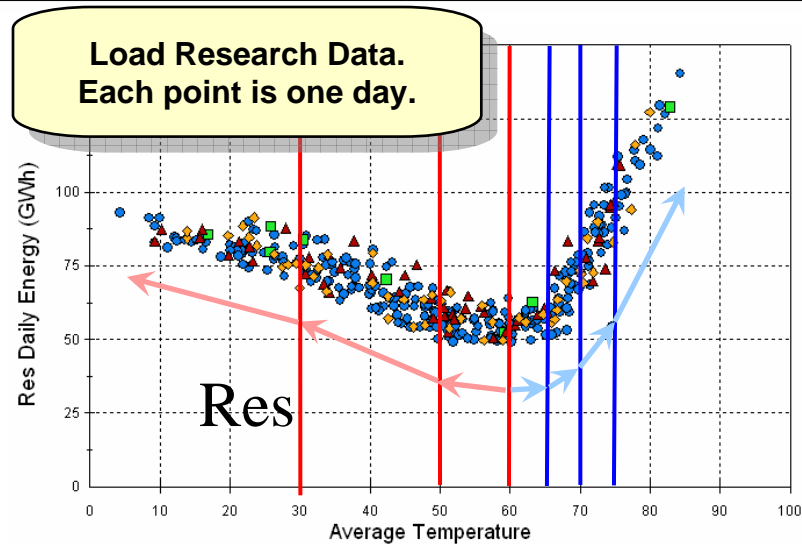
- Billed and unbilled sales estimation
 - Financial reporting
- Weather normalization
 - Sales variance reporting
 - Analyzing sales trends
- Profiling
 - Load settlement
 - Retail load costing
- Forecasting
 - Budget planning
 - Generation planning
- Cost of service and rate design
 - Class load characteristics
- DSM Assessment
 - Program demand impacts



What Does System Data Tells Us?

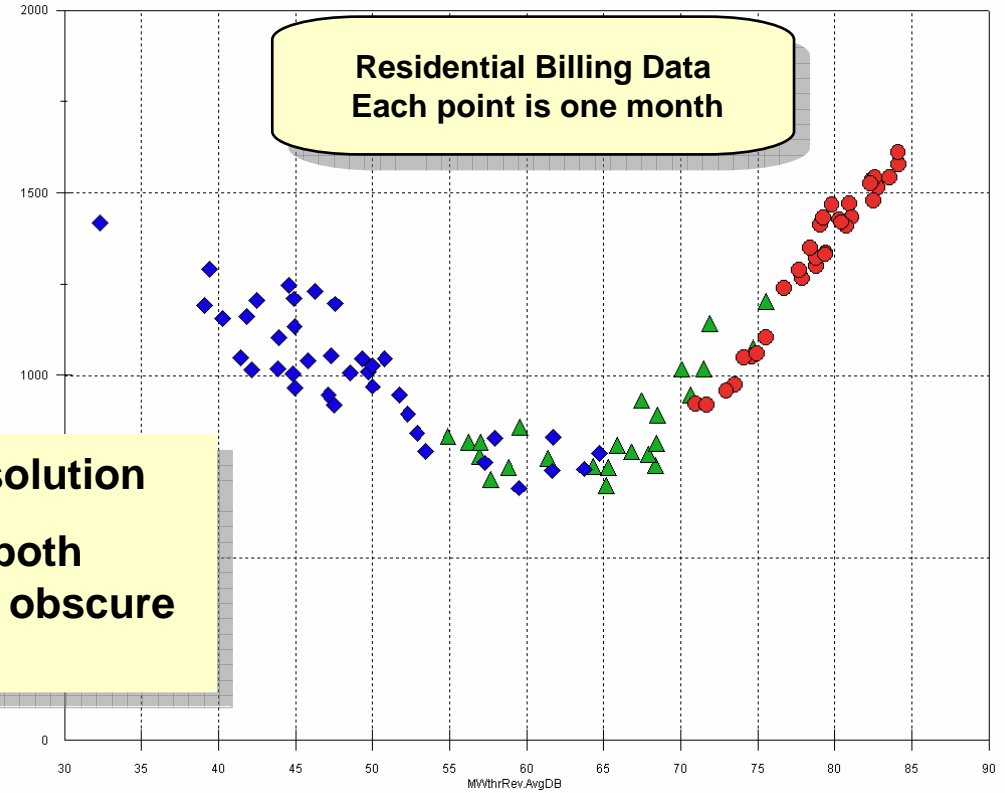
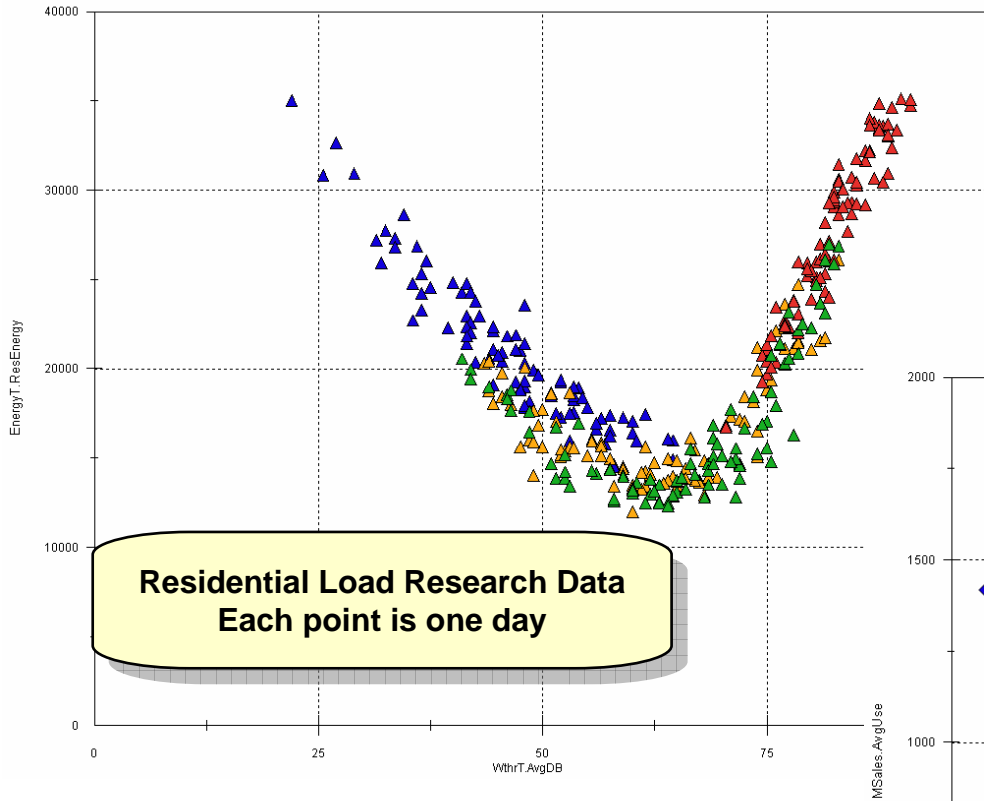


What Can We Learn from Load Research Data?



- Load Research data can help to clarify how weather-effects work at the revenue class level.
- These data suggest different HDD and CDD triggers for different classes.
- The relative power of degrees in each range can be estimated from these data and used in models of monthly sales.

Load Research Data vs. Billing Data

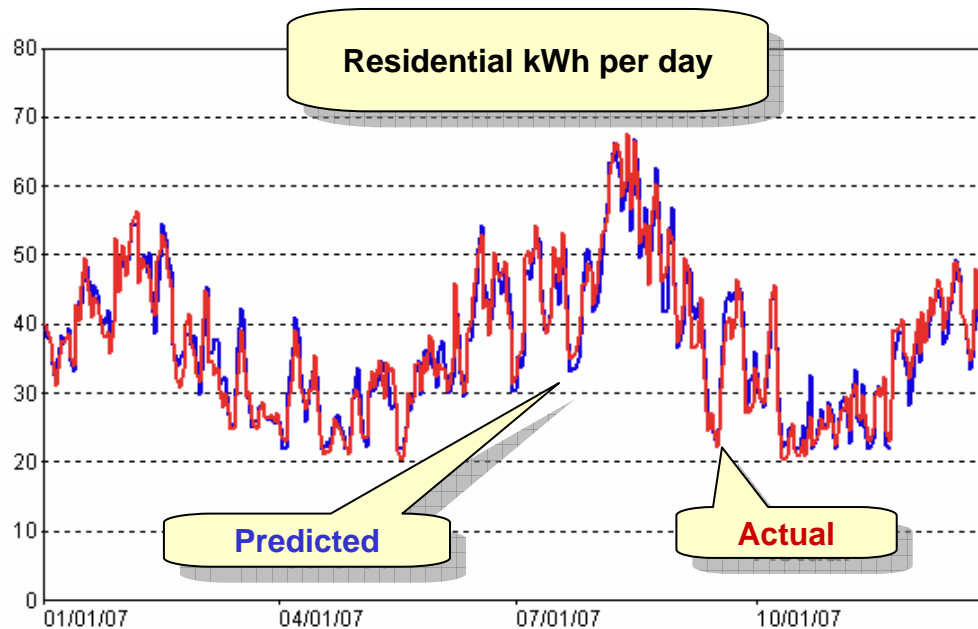


- Load research data provides higher resolution
- Monthly sales data includes days with both heating and cooling activity, which can obscure the load/weather relationship



Why is this Higher Resolution Important ?

- Load research data can help us construct stronger weather variables for use in monthly models, resulting in:
 - Better weather-normalization models
 - Better forecast models
- Load research data can be used directly to construct daily weather-response functions that can capture different weather impacts across day types (e.g., weekdays, weekends, holidays), months, and seasons.



Constructing Multi Part (Spline) Variables

The load research slope estimates can be used to construct monthly, multi-part heating and cooling weather variables.

Variable	Incremental Coef	Weight
HDD60	0.084	10.7%
HDD55	0.563	71.8%
HDD50	0.137	17.5%
HDD30	-0.167	-21.3%
Tot (excl 30)	0.784	100.0%

HDD Spline

$$0.107 * W_{thr.HDD60} + 0.718 * W_{thr.HDD55} + 0.175 * W_{thr.HDD50} - 0.213 * W_{thr.HDD30}$$

Variable	Incremental Coef	Weight
CDD60	0.298	6.1%
CDD65	3.303	67.5%
CDD70	0.283	5.8%
CDD75	1.008	20.6%
Total	4.892	100.0%

CDD Spline

$$0.061 * W_{thr.CDD60} + 0.675 * W_{thr.CDD65} + 0.058 * W_{thr.CDD70} + 0.206 * W_{thr.CDD75}$$

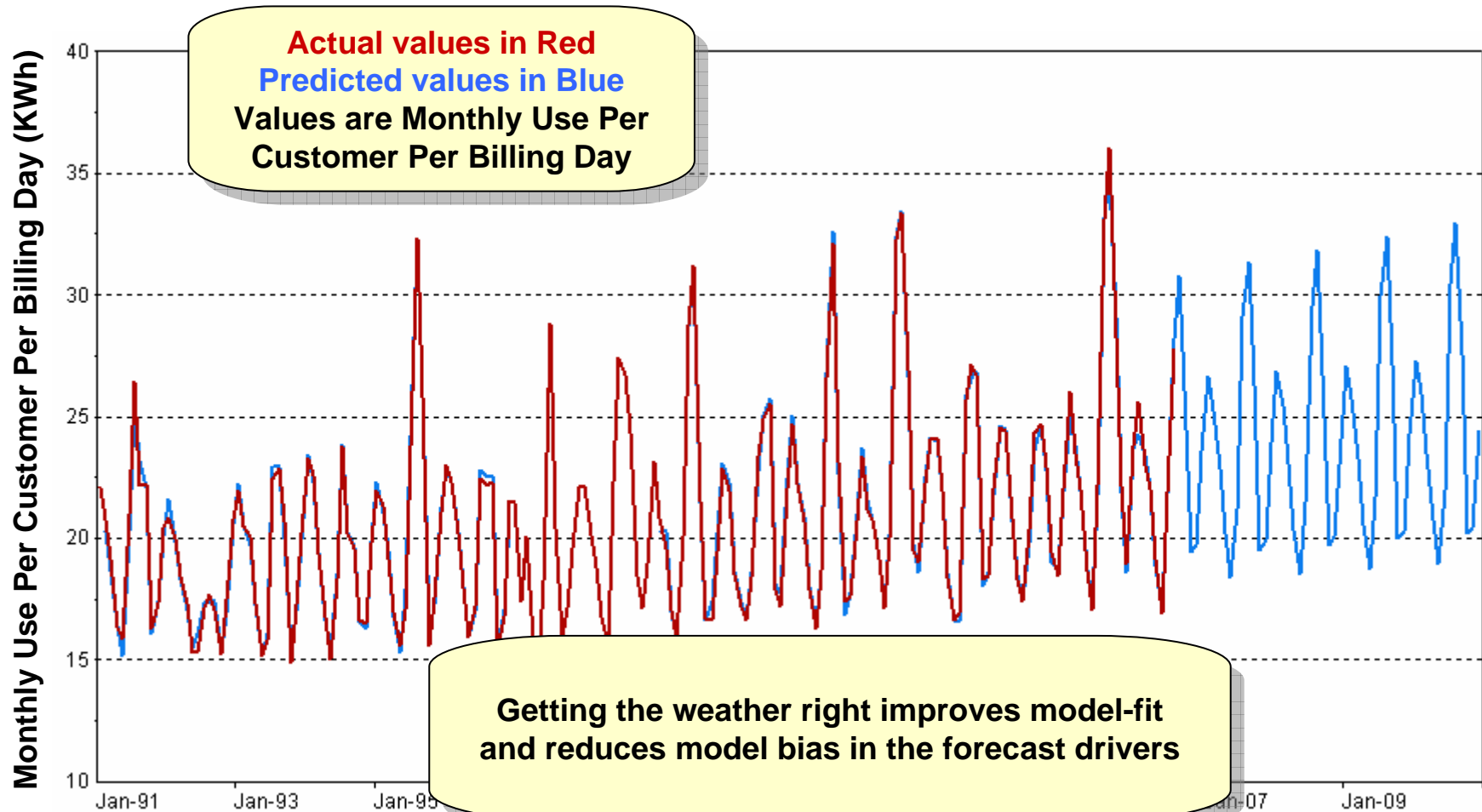
Monthly Model with Constructed Weather Splines

Dependent variable is monthly use per customer per billing day
(i.e., Sales/Customers/Billing Days).

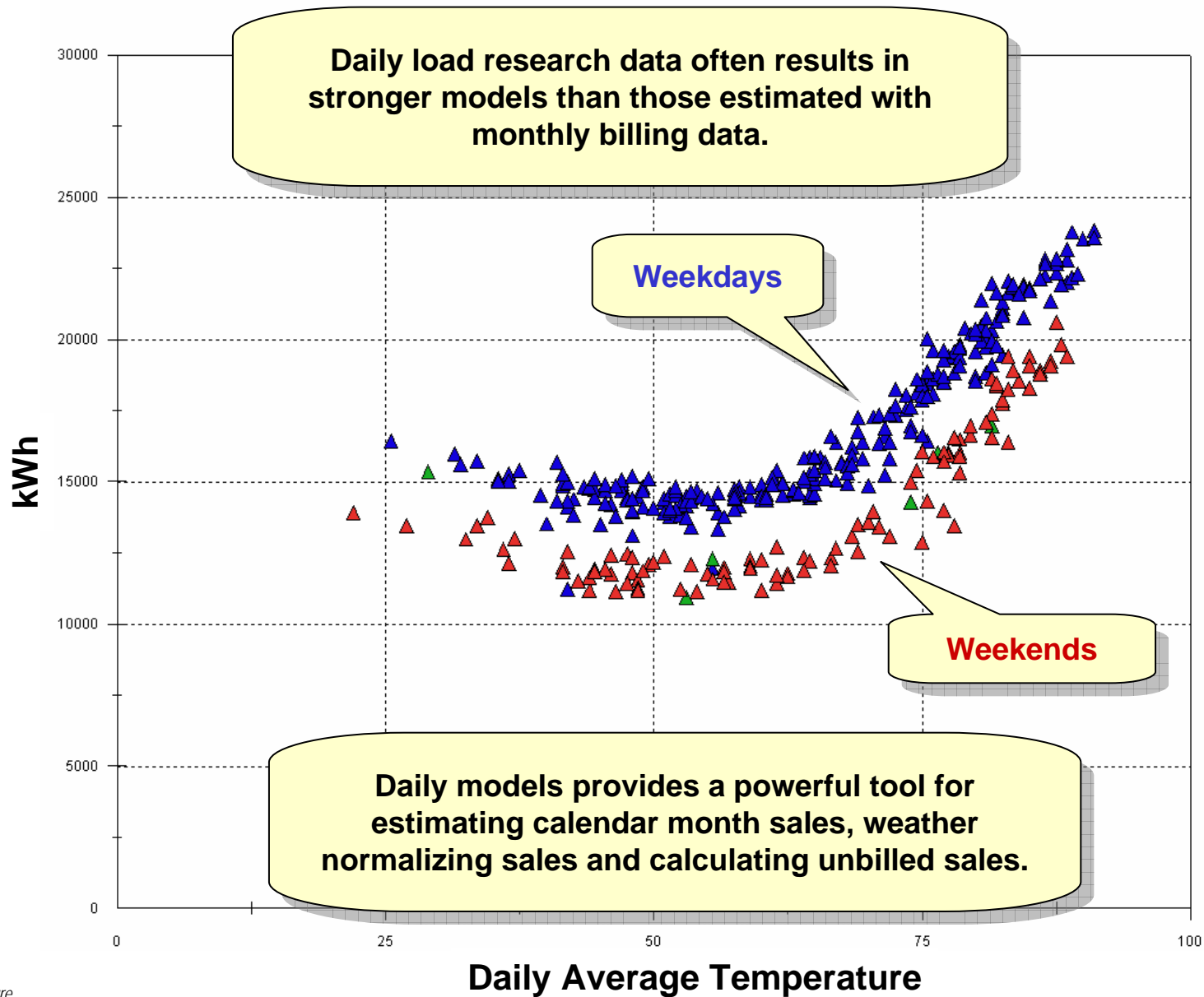
Stat	Value
R Square	0.953
MAD	0.660
MAPE	3.13%
DW	0.607

Variable	Coef	StdErr	T-Stat
Jan	1.789	1.241	1.441
Feb	0.438	1.242	0.353
Mar	0.007	1.111	0.006
Apr	-0.532	0.947	-0.562
May	-1.387	0.860	-1.613
Jun	-1.766	0.856	-2.063
Jul	-1.713	0.948	-1.807
Aug	-1.340	0.959	-1.397
Sep	-1.148	0.899	-1.277
Oct	-0.566	0.849	-0.667
Nov	0.112	0.907	0.124
Dec	1.317	1.080	1.220
Income Per HH	0.199	0.010	19.428
HDD Spline	0.219	0.028	7.730
CDD Spline	1.948	0.076	25.723

Monthly Residential Sales Forecast Model

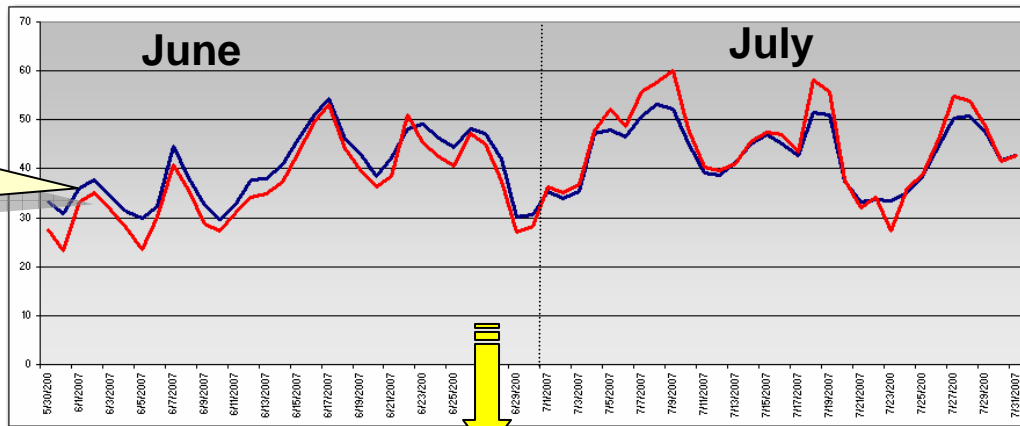


Estimating Daily Weather Response Functions

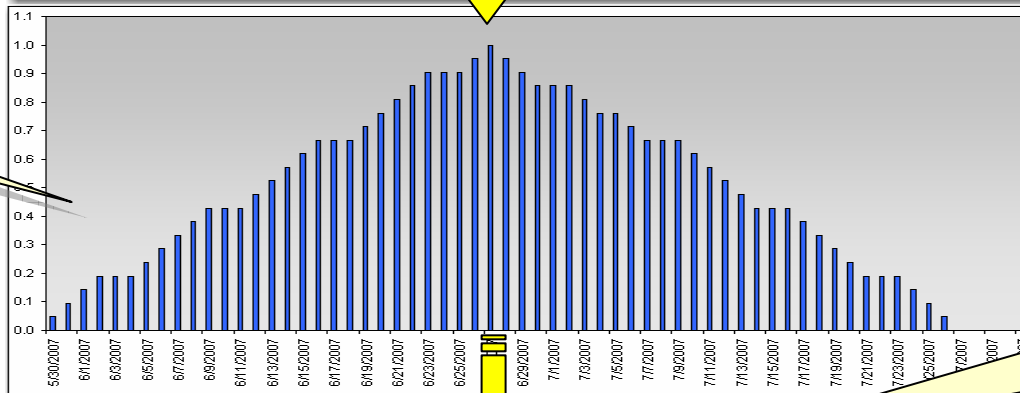


Model Estimated Average Use For The July Billing Period

Daily predicted values with **normal** and **actual** weather

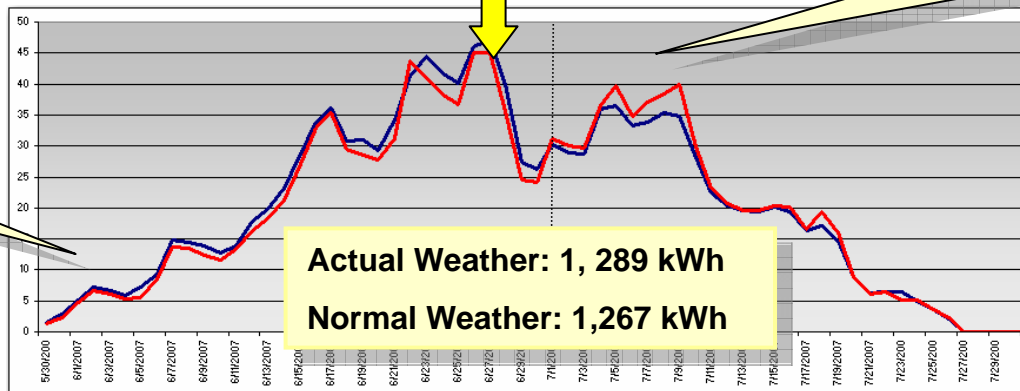


Cycle-weights



Each day is weighted according to the meter-read schedule

Cycle-weighted predicted values with **normal** and **actual** weather

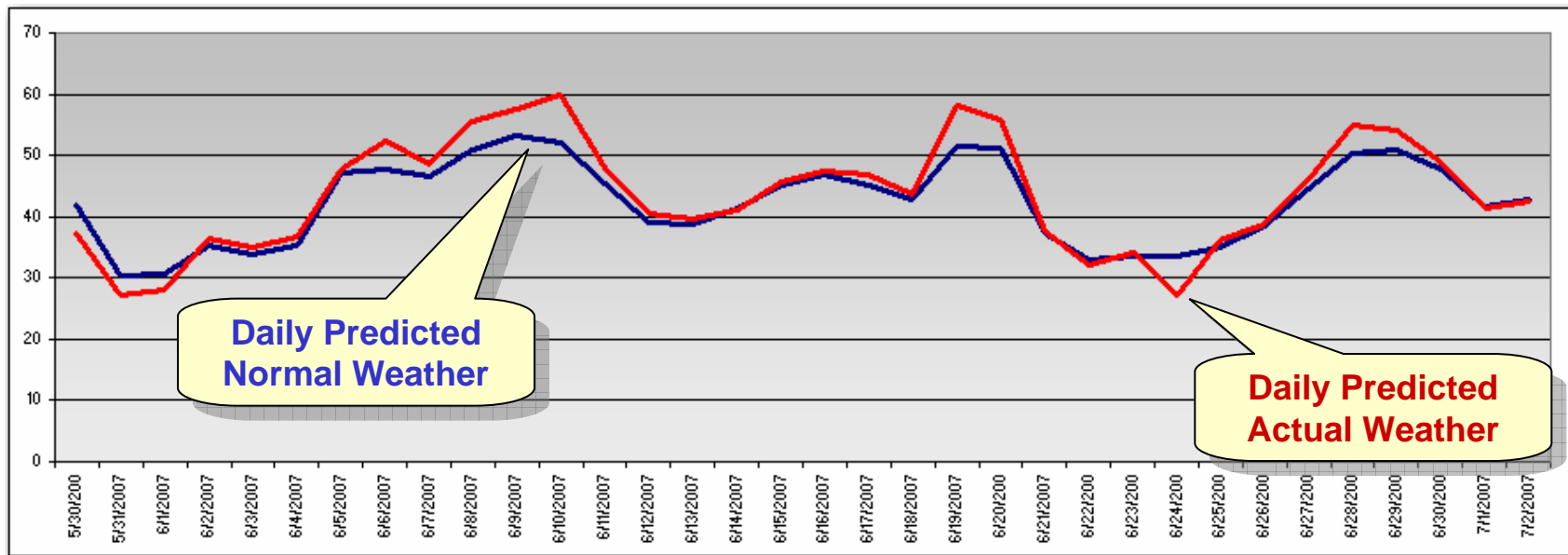


Actual Weather: 1,289 kWh
Normal Weather: 1,267 kWh



Model Estimated Average Use For The July Calendar Period

July 2007



Actual Weather: 1,339 kWh

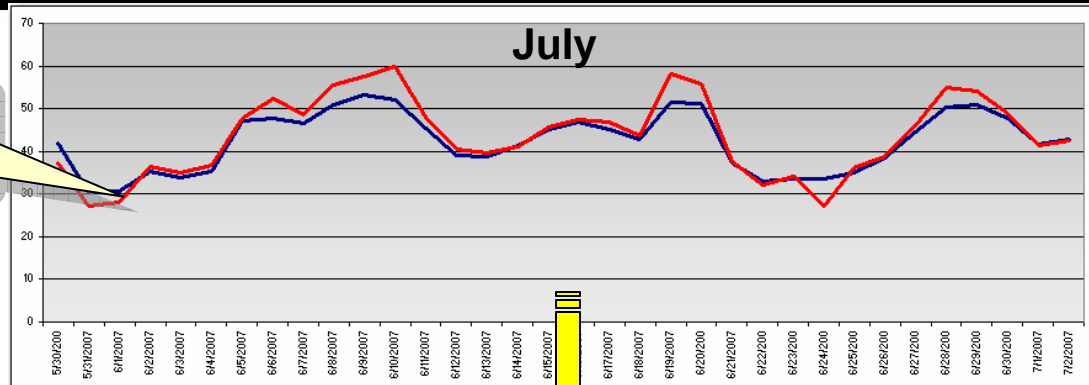
Normal Weather: 1,391 kWh



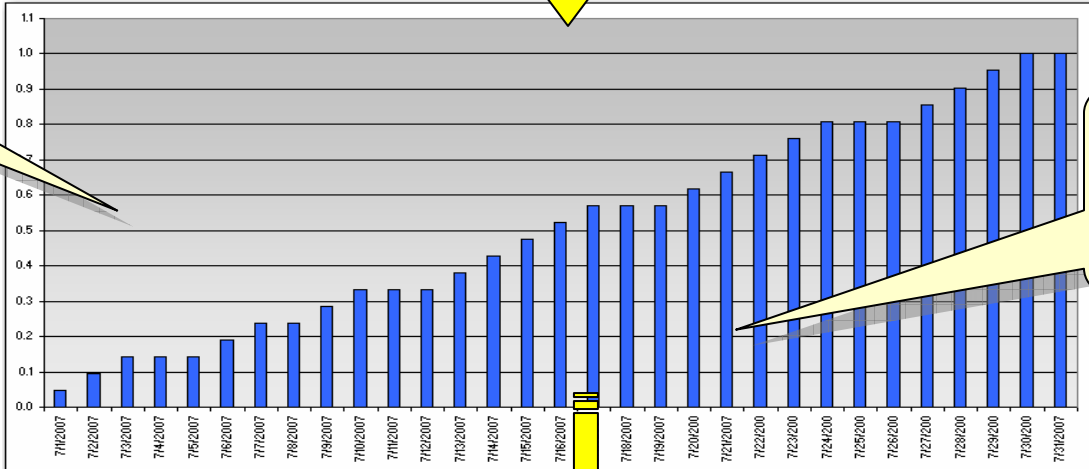
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Model Estimated Average Use for the July Unbilled Period

Predicted values with **normal** and **actual** weather

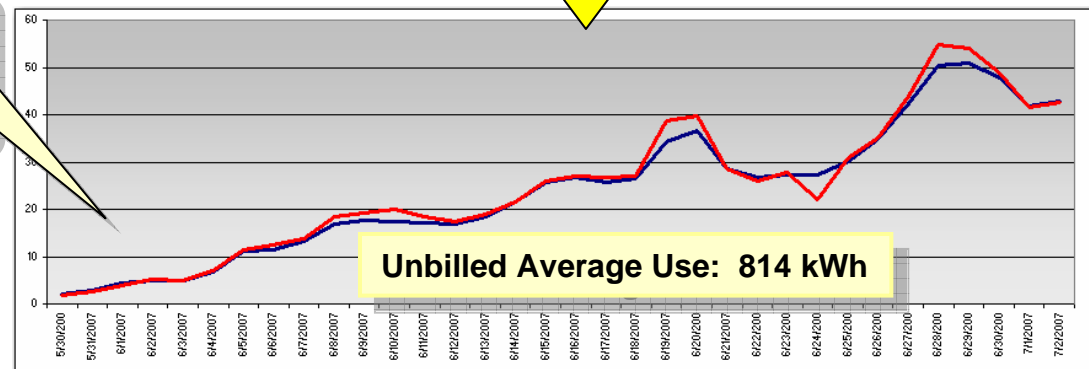


Unbilled Cycle-weights



Days at the end of the billing month are given more weight for the estimation of unbilled.

Cycle-weighted predicted values with **normal** and **actual** weather



Estimation of Calendar Month, Weather Normal, and Unbilled Sales

July 2007

Calendar Sales = Billed Sales * (Predicted Calendar Mo kWh / Predicted Billing Month)

1,475 GWh = 1,420 GWh * (1,339 kWh / 1,289 kWh)

WN Billed Sales = Billed Sales * (Predicted Billed Normal Weather / Predicted Billed Actual Weather)

1,396 GWh = 1,420 GWh * (1,267 kWh / 1,289 kWh)

WN Calendar Sales = Billed Sales * (Predicted Calendar Normal Weather / Predicted Billed Actual Weather)

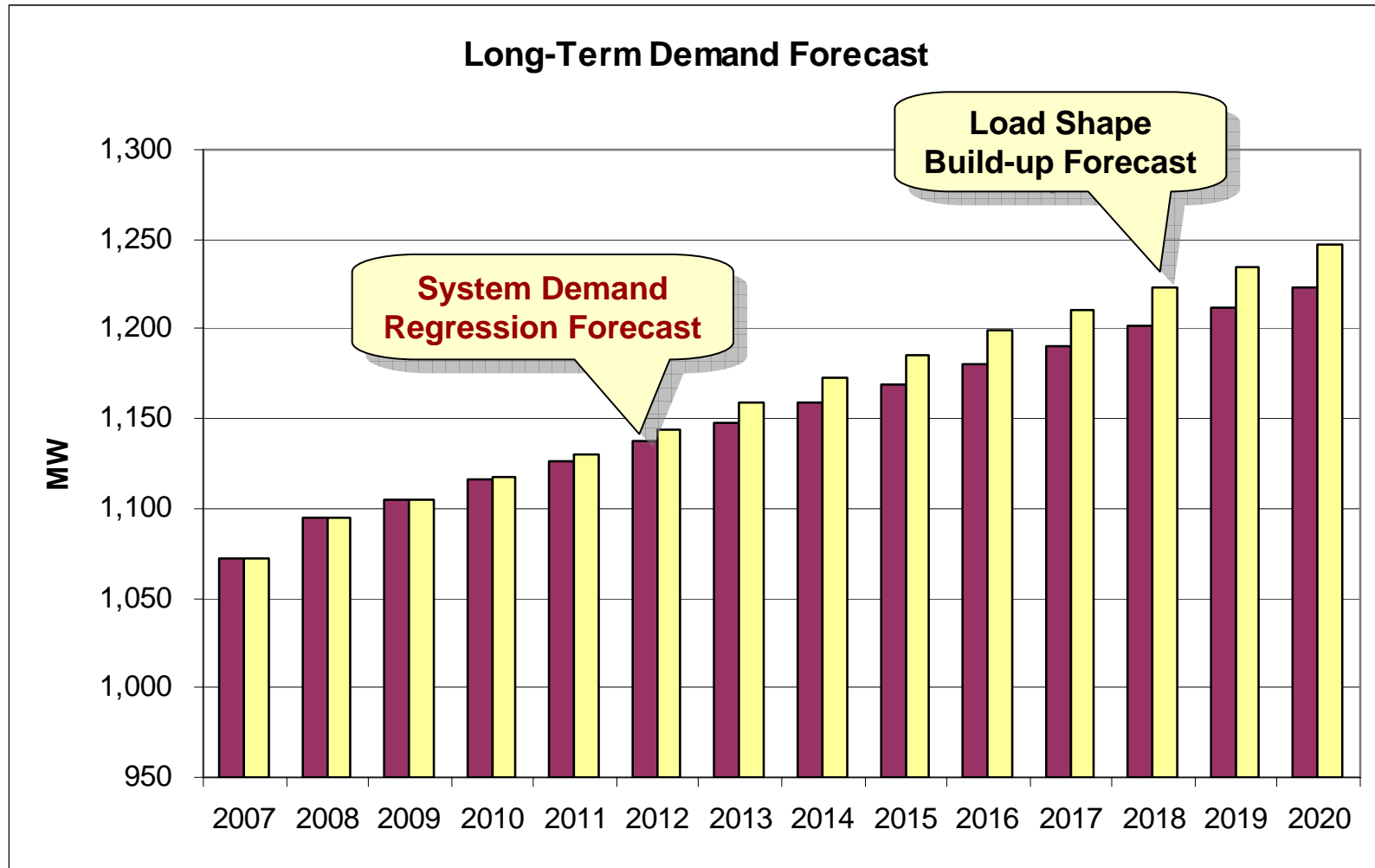
1,532 GWh = 1,420 GWh * (1,391 kWh / 1,289 kWh)

Unbilled Sales = Billed Sales * (Predicted Unbilled Period / Predicted Billing Month)

897 GWh = 1,420 GWh * (814 kWh / 1,289 kWh)



Peak Demand Modeling

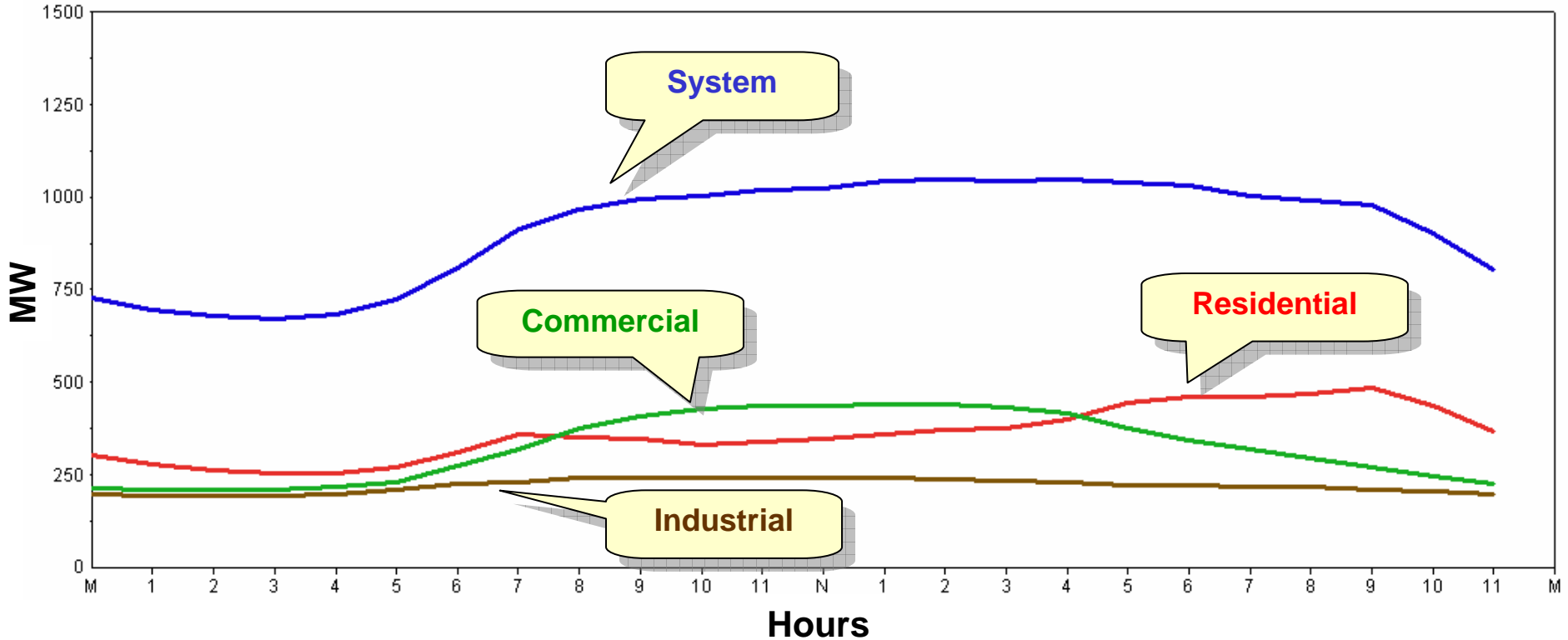


Build-up models using load research data allow us to identify the impact of changes in customer class and end-use energy demand on system peak.



Peak-Day System Hourly Load Profile (MW)

Friday, July 18, 2008



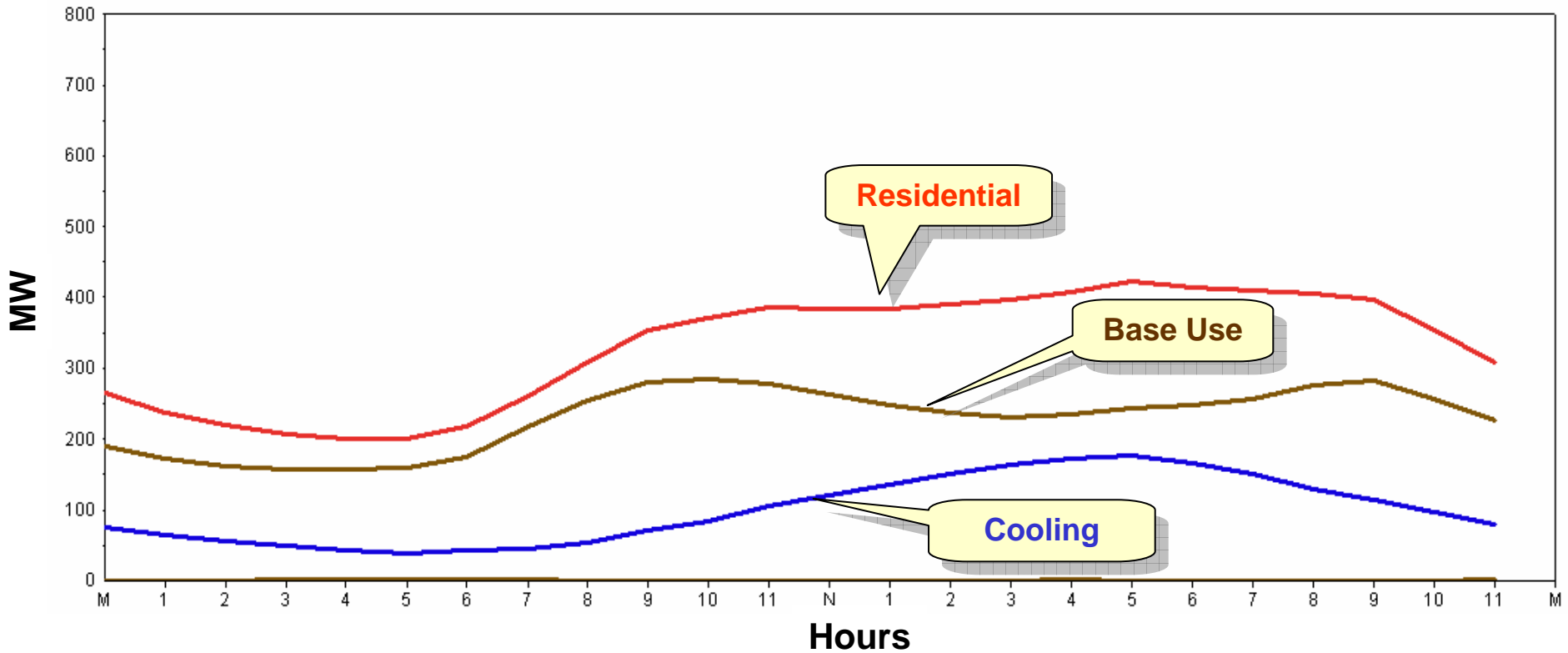
Small differences in customer class load growth can have a significant impact on the peak and its timing.



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Peak-Day Residential Load Profile (MW)

Tuesday, July 15, 2008

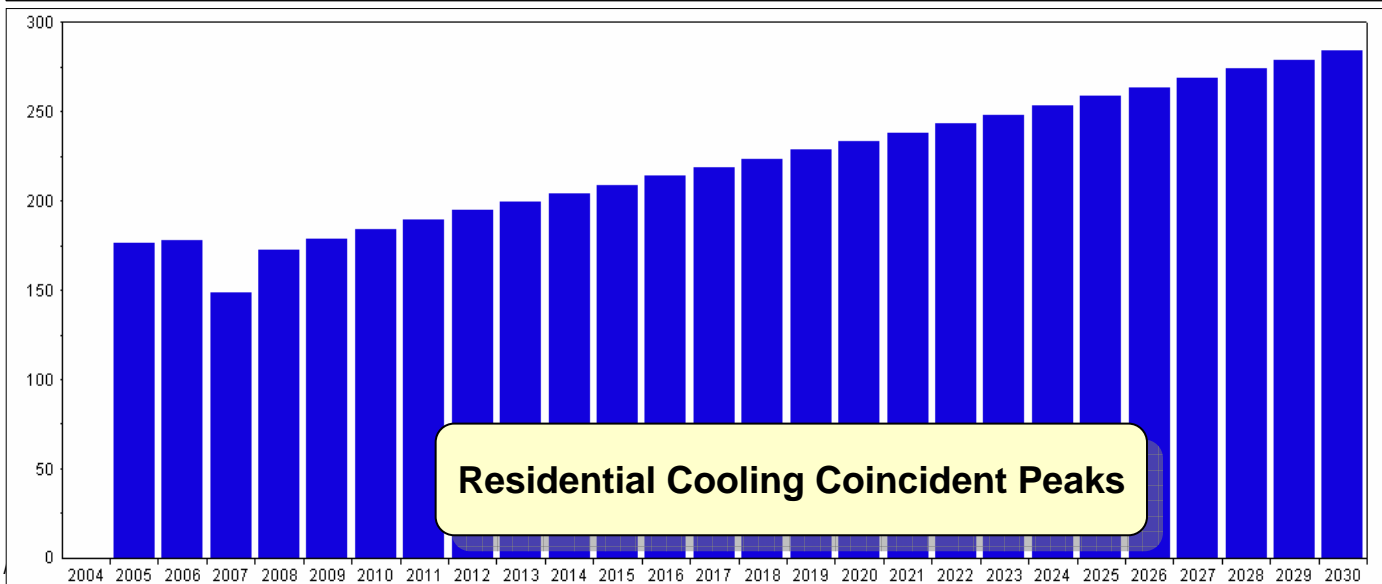
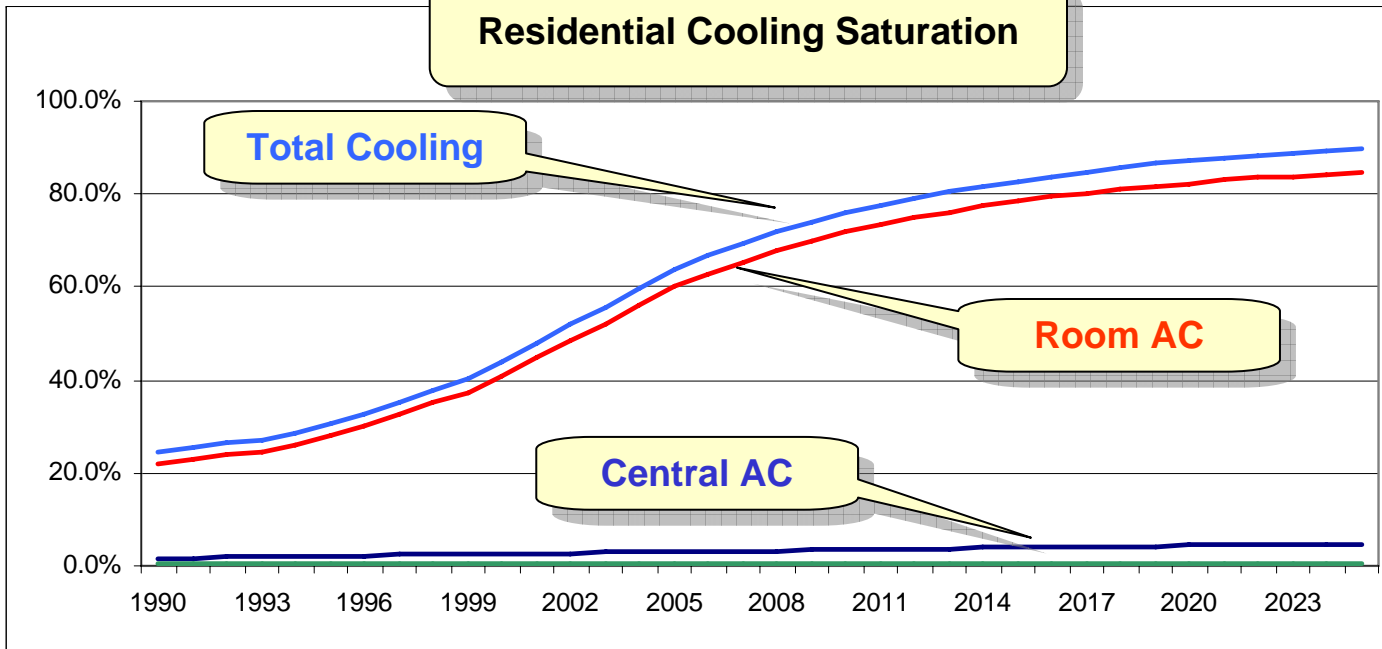


Changes in end-use sales
growth in turn impact
customer class hourly load.

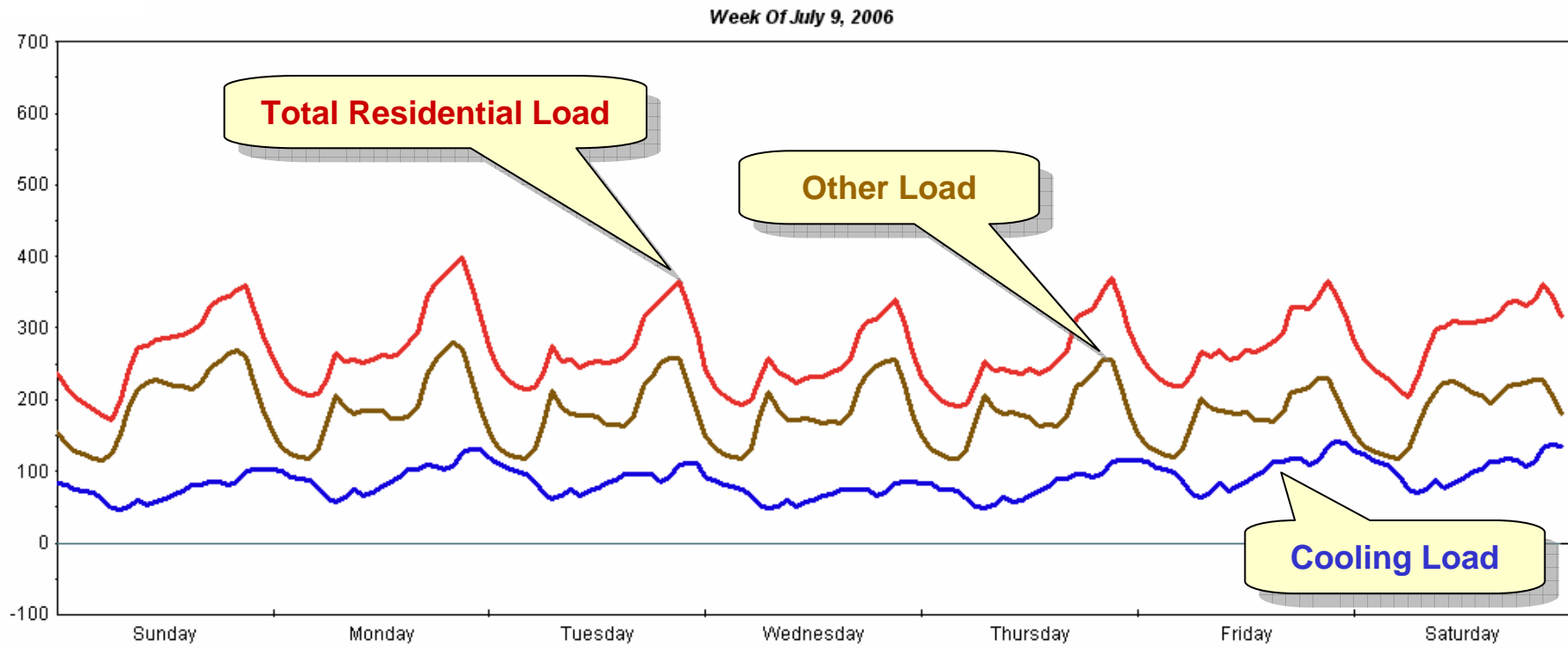
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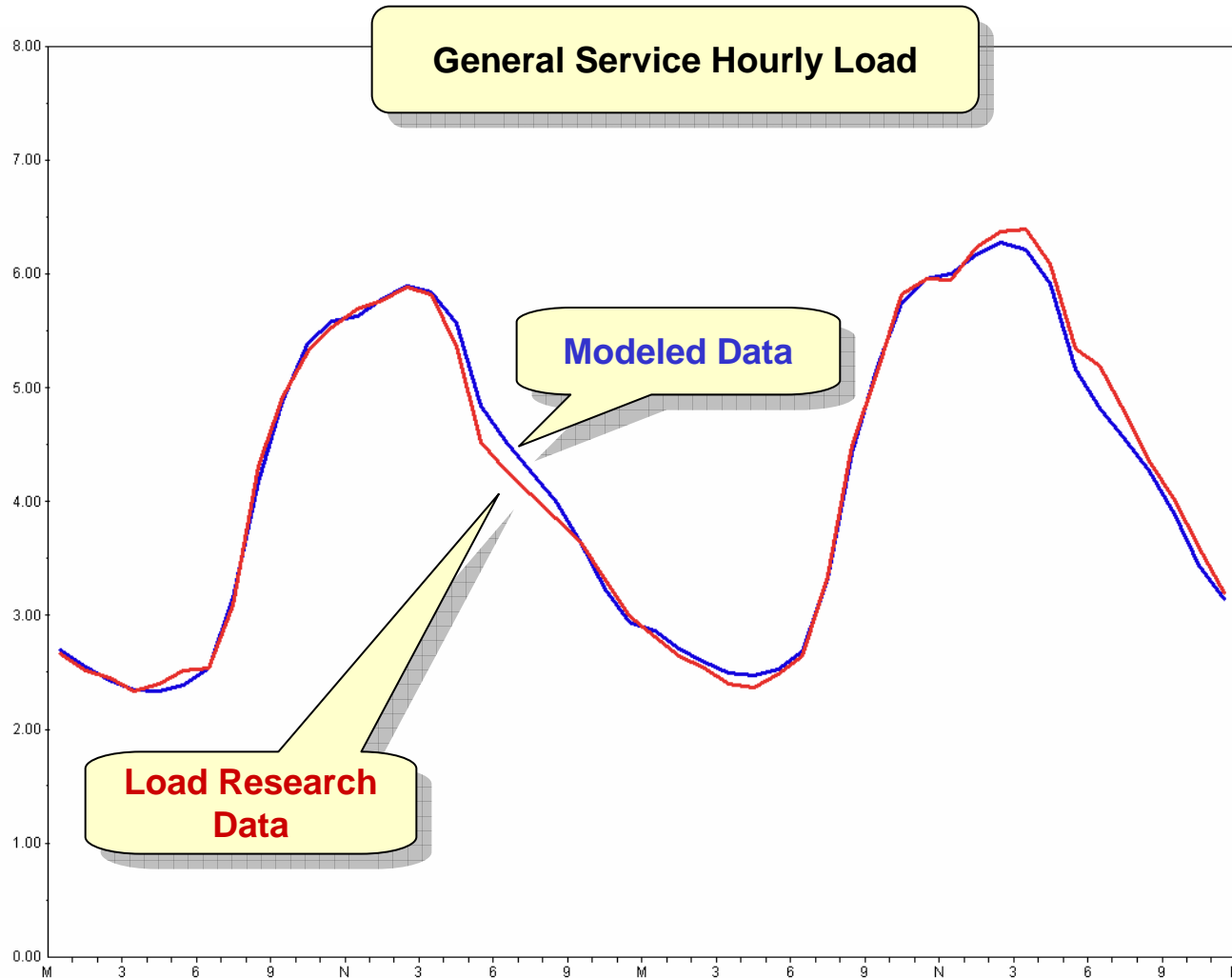
Residential Cooling Driving System Demand



Load Research Data Is Needed to Estimate Class and End-Use Profiles

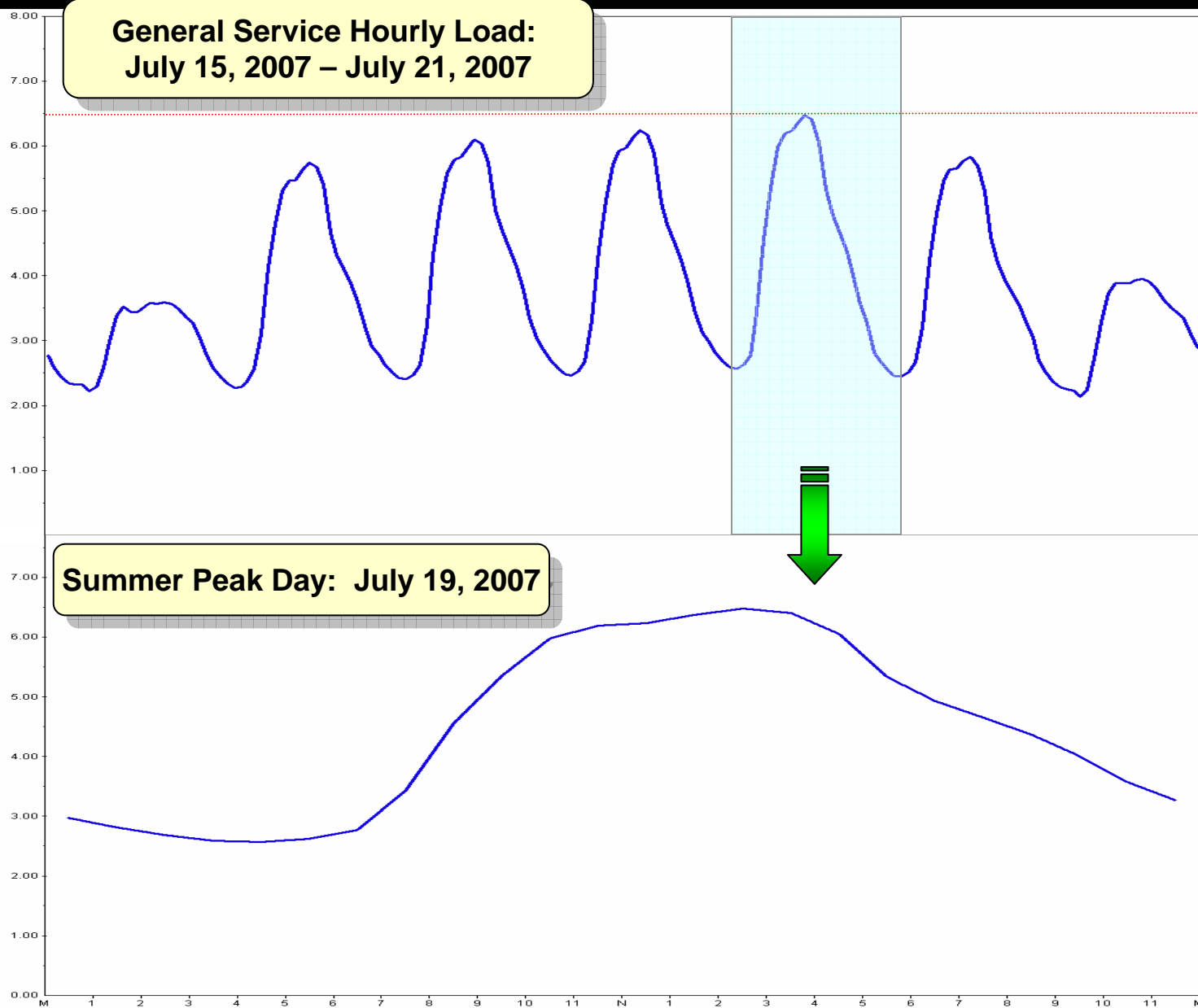


It Works Both Ways: Models Can Improve Load Research

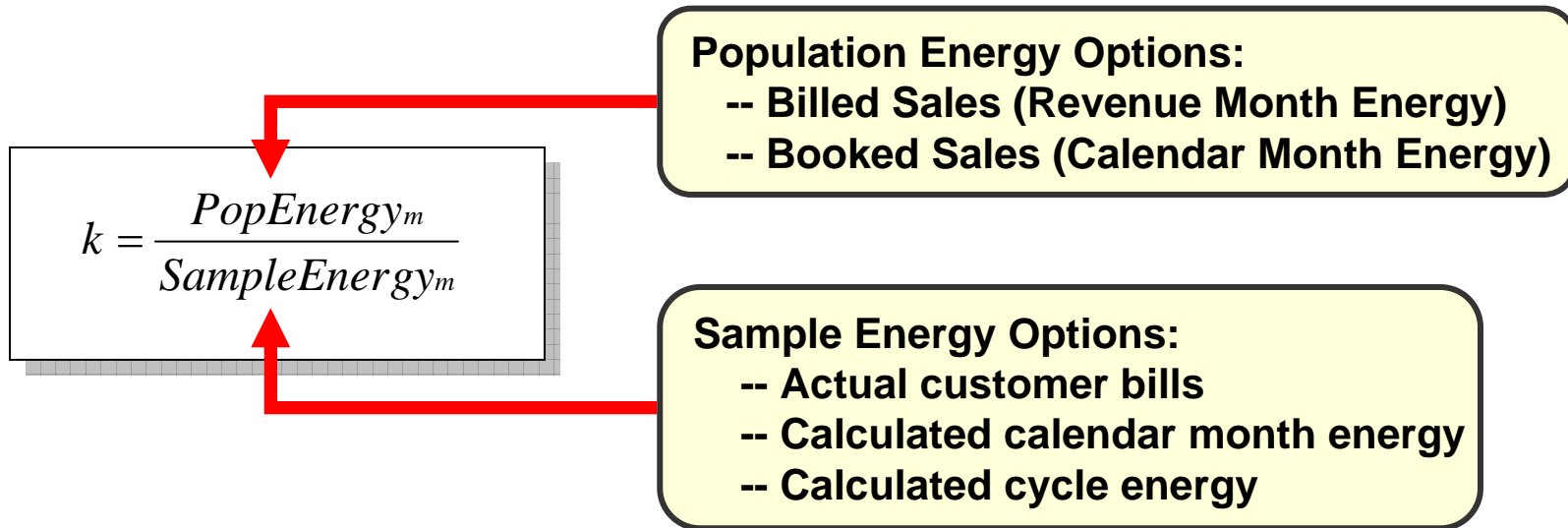


Models are often better than the data, since the models smooths through the data.

Users Want Typical Hourly Load Profiles



Getting the Ratio Estimator Right

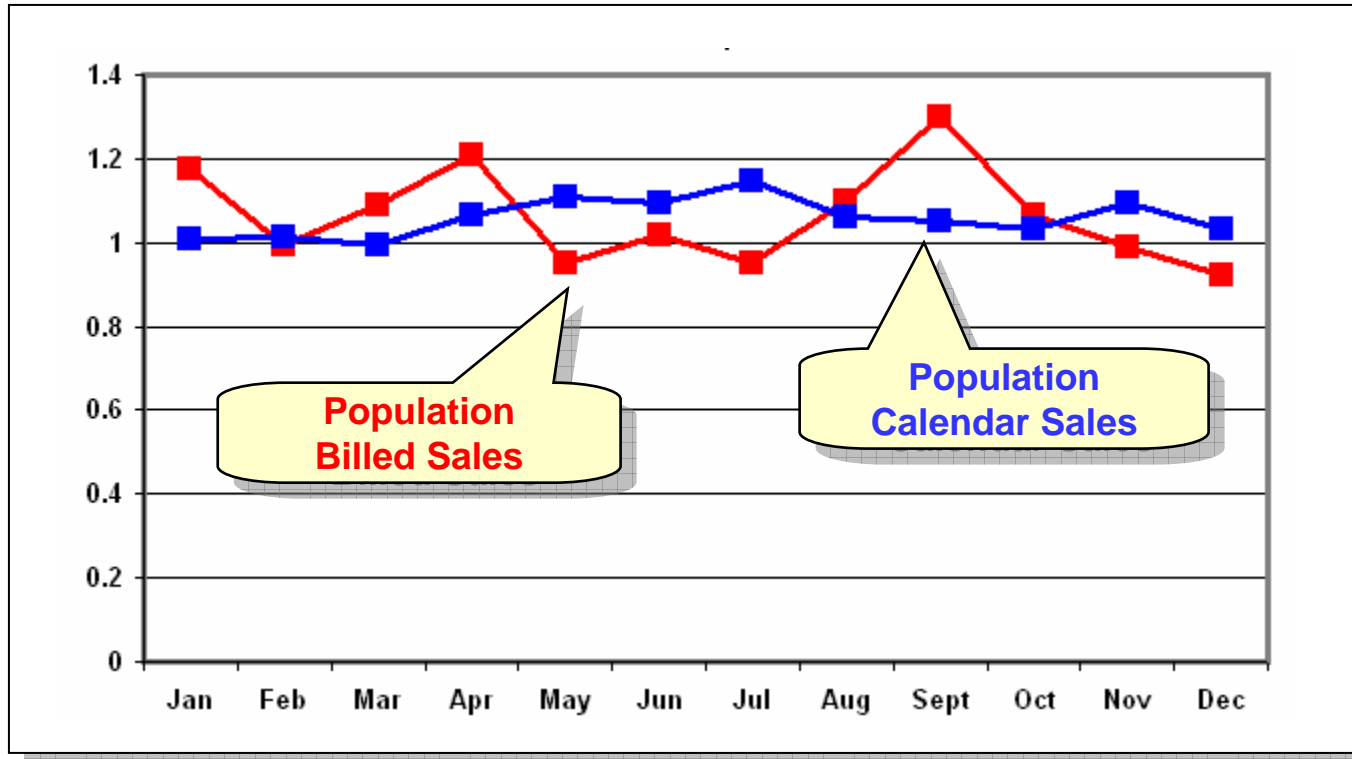


If a ratio method is used, it is important to use an apples-to-apples ratio.

Using calendar month population sales estimates for sample expansion has the added advantage that the profile values for the calendar month will add to calendar month sales.

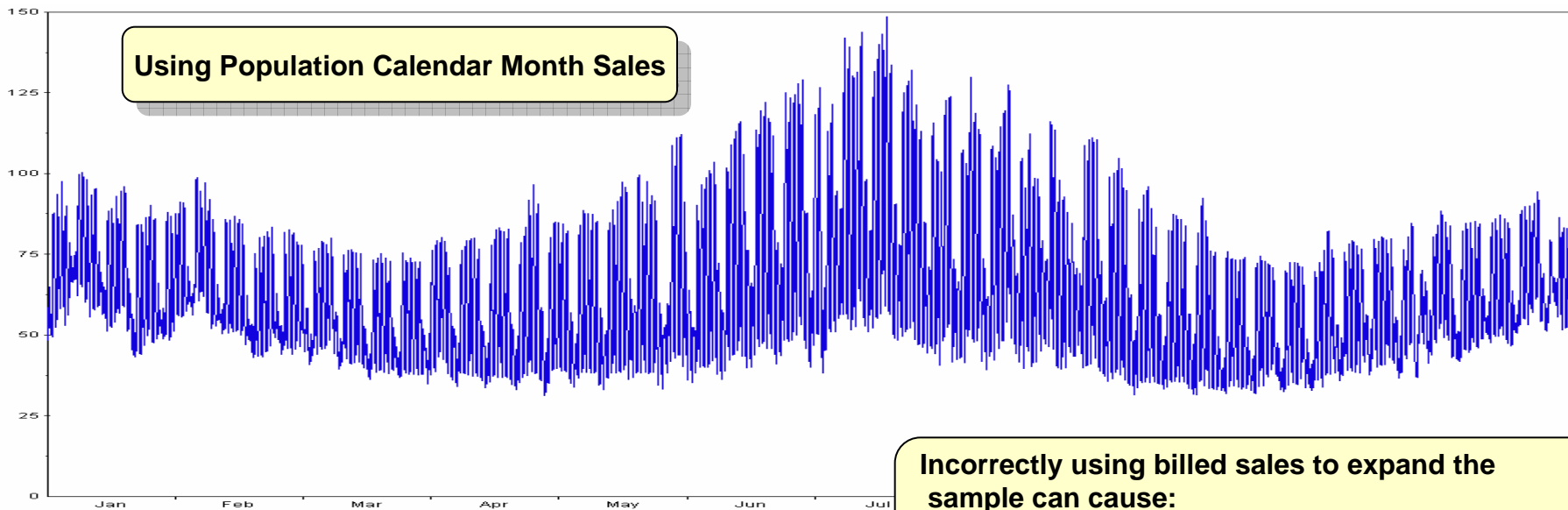
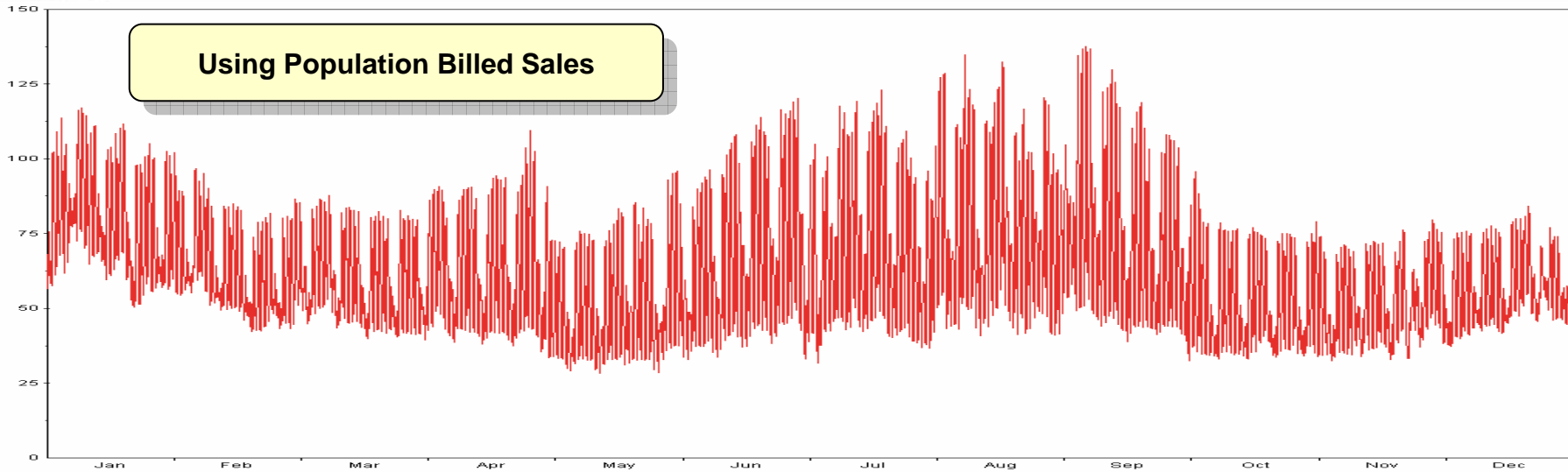
Population calendar month sales can be estimated using models.

K Factor Comparison



$$\text{K Factor} = \text{Population Average Use}_m / \text{Sample Average Use}_m$$

Sample Expansion Comparison: General Service



Incorrectly using billed sales to expand the sample can cause:

- Peaks to occur in the wrong month
- Discontinuities in the shape

Making Good Business Decisions Requires Good Load Research Information

- Surprisingly, load research data is difficult to come by
 - Limited data, old samples, poor sample expansion, difficult to access, no program...
- Load research data provides a powerful source of information about the load/weather relationship
 - Can help in constructing stronger monthly weather variables for forecasting
 - Can be used directly in constructing weather-response functions for estimating calendar, unbilled, and weather-normal sales
- Load research allows us to disaggregate system load into classes and end-uses
 - Allows us to evaluate the impact of changing end-use saturation and efficiency trends, new standards, and DSM programs on load and peak



Modeling Can Play an Important Role in Improving Information Provided by Load Research

- Models of load research data are often better than the data
 - Analysts want typical load profiles to support analysis – not load research data
 - Profiles for evaluating cost of serving specific customer loads
 - Weather-normal profiles for cost of service, rate design, and DSM program design
- Model-generated calendar month population sales estimates can result in improved sample expansion
 - Process calibrates profiles to calendar month energy estimates

