Was it Conservation or Just the Weather: Tips for Weather Normalizing Electric Energy and Demands

Presented By

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CenterPoint Energy, Inc.

AEIC Annual Load Research Conference
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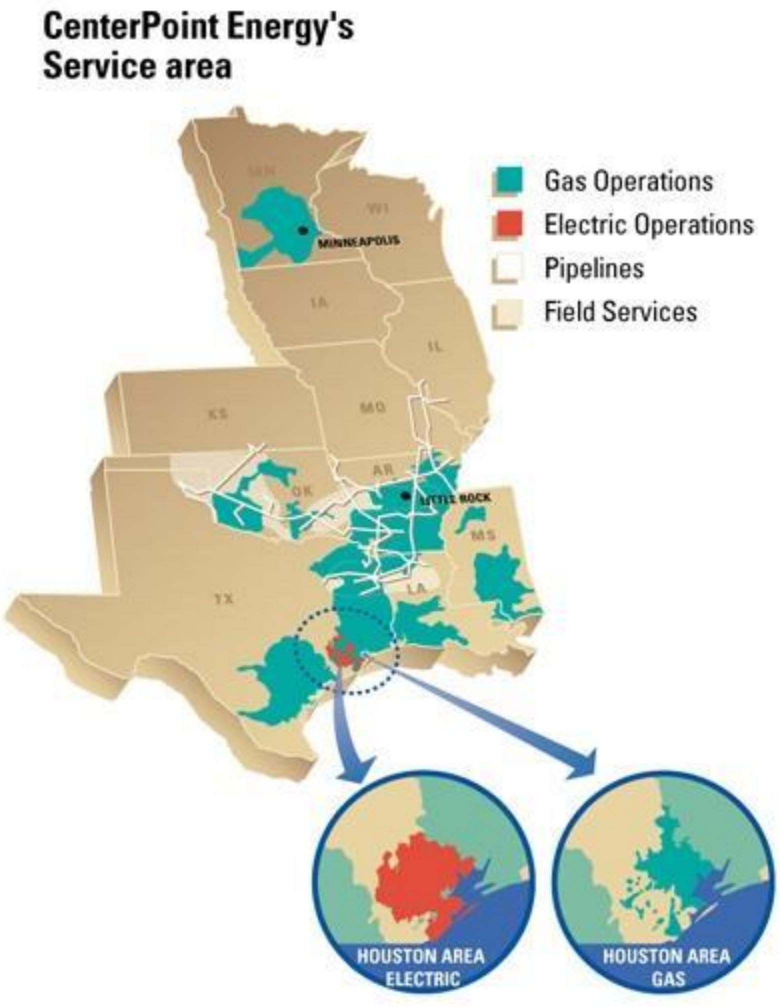
CNP Overview & Contact Information



CenterPoint Energy (CNP)

- Delivers electricity in the Houston area
- Buys, sells & delivers natural gas in six states (MN, OK, AR, MS, LA and TX) and
- owns & operates two major interstate pipelines

Contact Information

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Load Research at CenterPoint Energy

- What lies ahead?
  - ➢ Completed a technical assessment of the uses of interval data
  - ➢ Analytics Platform is forthcoming
  - ➢ AMI data will enable new processes & analysis
  - ➢ Management will be asking more questions about the loads we serve

This is an exciting time to be doing Load Research!
(as shown by the next slide)

Why Do Load Research?

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Load research gives insight into how and when electricity is being used which in turn supports internal & external analytics such as:

- Load and revenues forecasting
- Weather normalization of loads & revenues
- Cost allocation factors in rate case filings
- Distribution Planning
- Transmission Planning
- Rate Design
- Energy Efficiency Program Design, Measurement & Validation
- Plus several more

Definition of Terms

CONSERVATION

The term “conservation” as used in this presentation refers to net reductions in usage due to any of the following:

- Structural/Stock Changes associated with:
  - ✓ Appliance efficiencies and saturation rates
  - ✓ The thermal characteristics/tightness of structures
  - ✓ The size of homes & mix of home types

- Behavioral Changes associated with:
  - ✓ Price elasticities
  - ✓ Income elasticities
  - ✓ Actions motivated by concern for the environment

Was It Conservation?

- A consultant once told me:

"First, get the weather right."

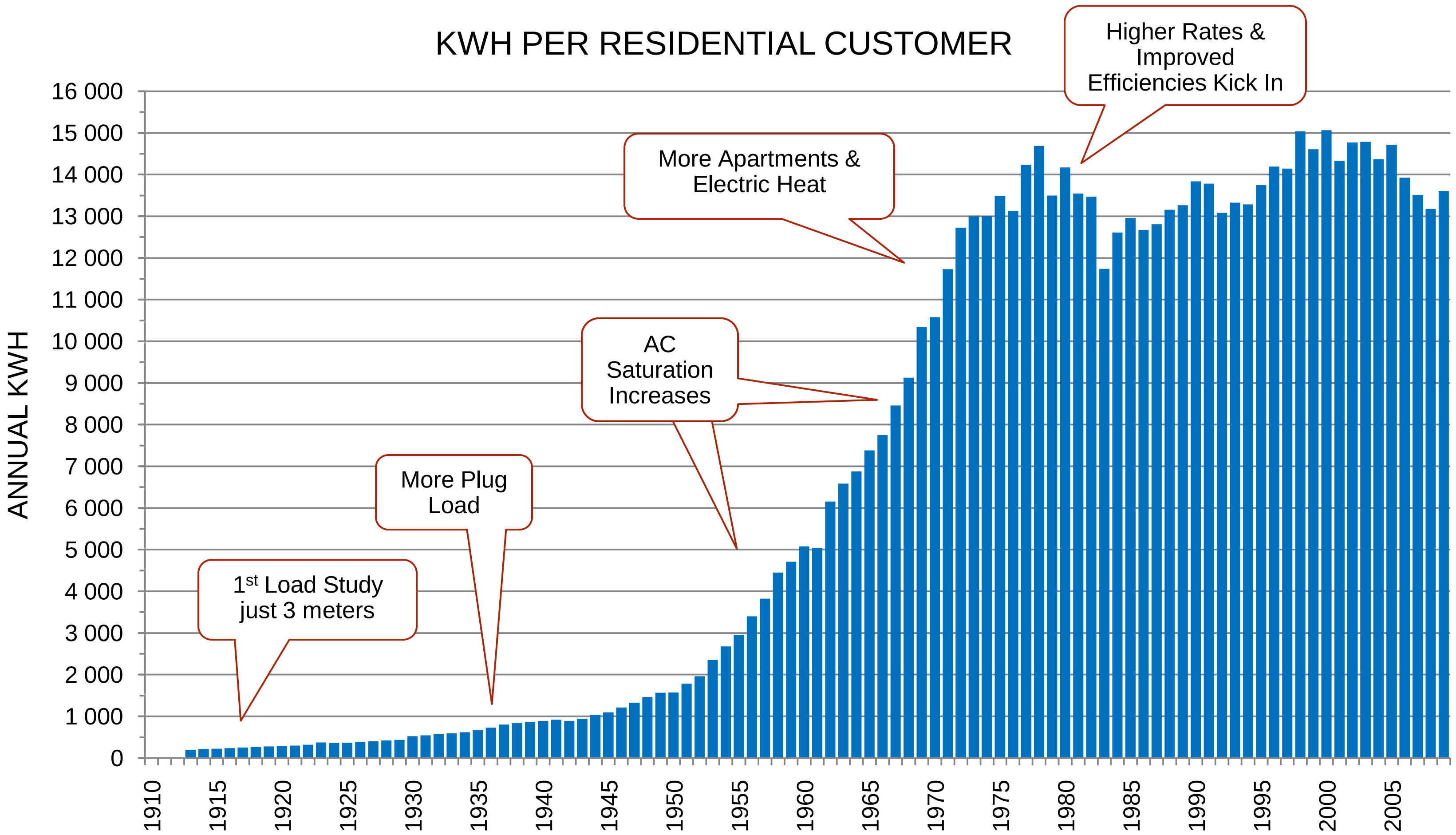
K.F.

Tip: Know your data

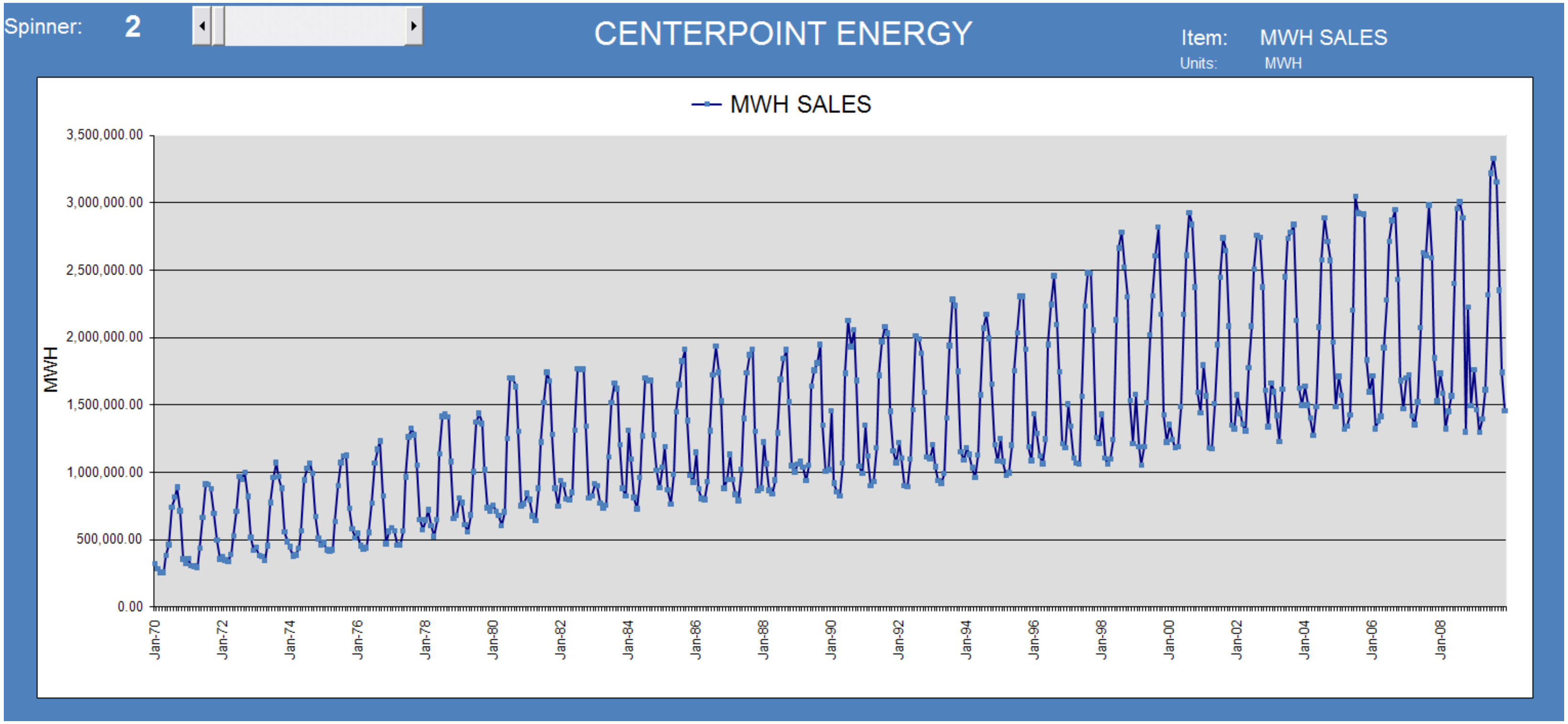
- Plots are a good place to start

- Recommended data:
  - ➢ Billing Month Data: KWH per Customer Per Billed Day
  - ➢ Load Study Data: Daily KWH per Customer

In The Beginning

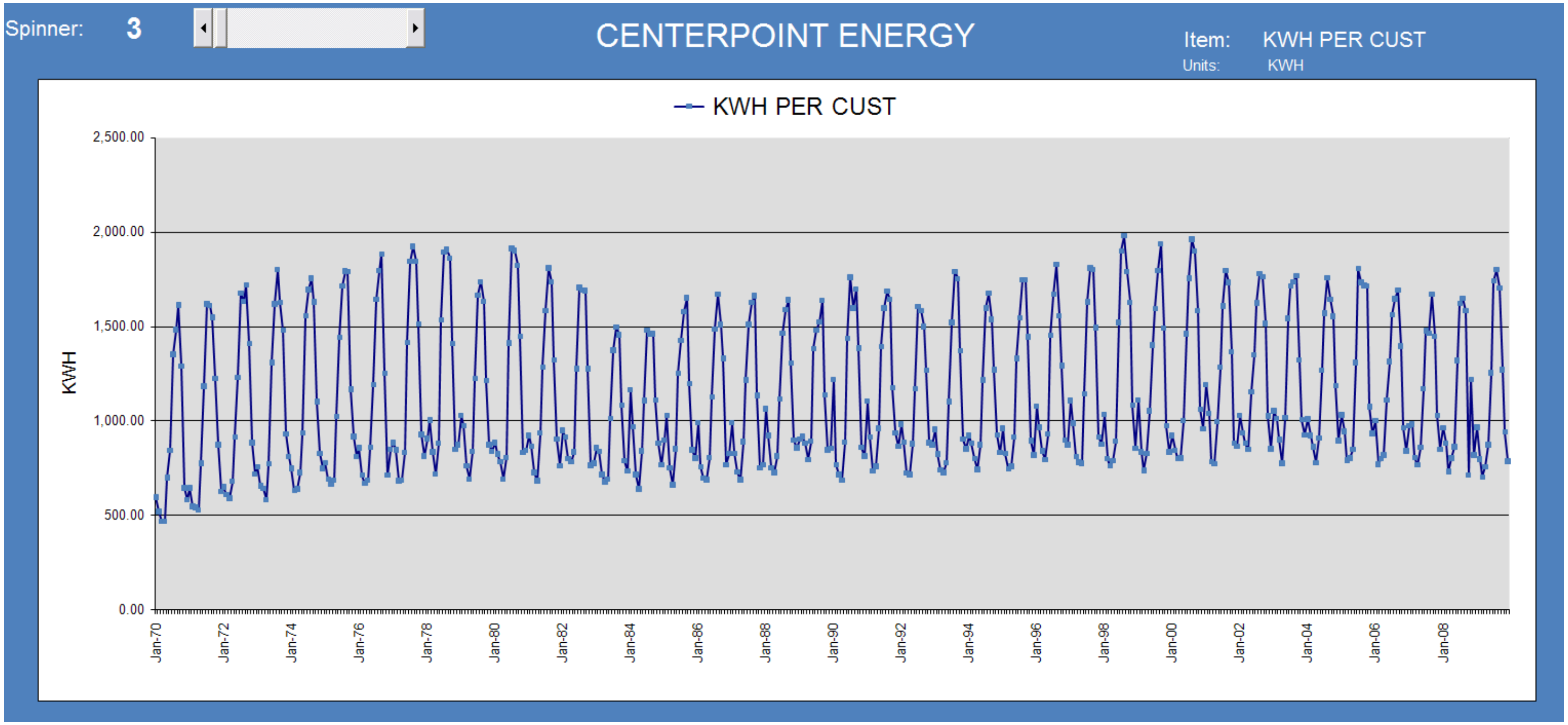


Plot Monthly Billing Data



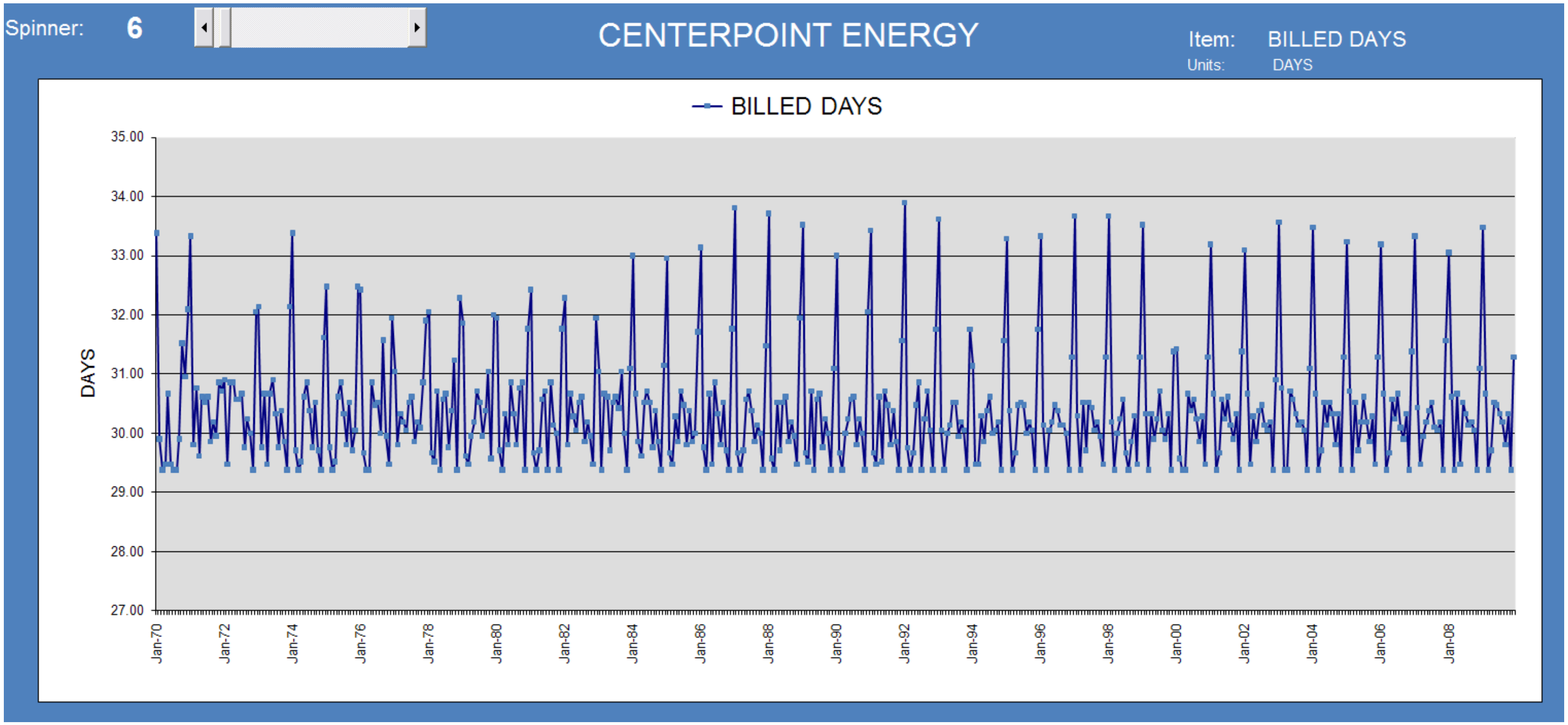
Plot Monthly Billing Data

"KWH PER CUSTOMER" is often closely watched.
However, since some billing months are much longer than typical,
we will go one step further.



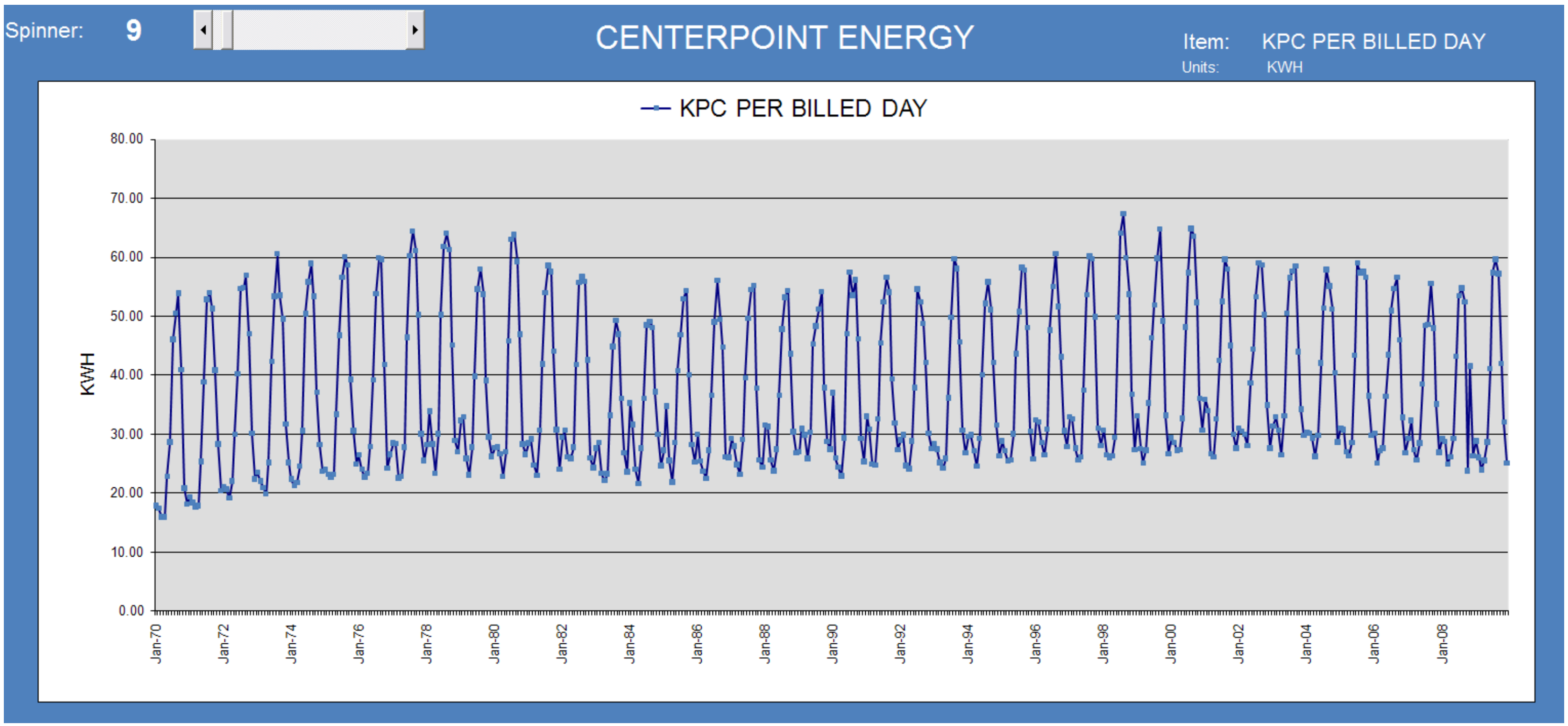
Plot Monthly Billing Data

Due to holidays, the billing months of December and January tend to be long.



Plot Monthly Billing Data

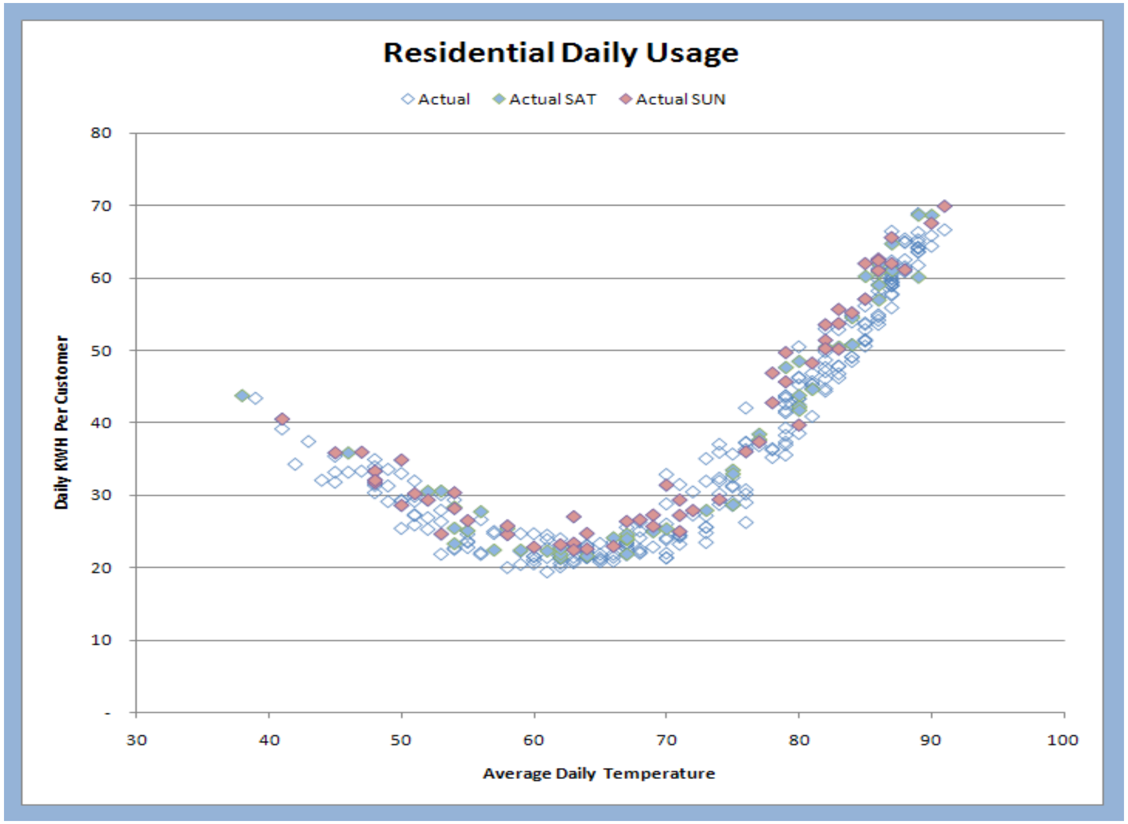
"KWH PER CUSTOMER PER BILLED DAY" is the preferred Billing Month Data Series



Lessons Learned

- **LESSON 1:** The relationship between loads and weather is likely to be non-linear (e.g. try using more slopes than just one heating slope & one cooling slope)
- **LESSON 2:** There likely are weather metrics that are better suited to model KWH sales than NOAA Heating & Cooling Degree Days (Base 65)
- **LESSON 3:** Heating & Cooling Slopes and Intercepts (representing non-weather sensitive loads – sometimes referred to as “base loads”) change over time for a combination of reasons. Some of which are:
  - Appliance efficiencies
  - Appliance saturation rates
  - Price & income effects
  - Better built homes
  - Larger single family homes and apartments
  - Proportionally more families living in single family homes

LESSON 1: Plot Daily Load Study Data



Daily data provides more resolution for understanding the relationship between KWH usage and weather than is available from MONTHLY BILLING data.

Observe that the data is U-Shaped with relatively little response to weather (i.e. “flat “) for temperatures in the range of 55-70 degrees.

TIP: There is nothing sacred about BASE 65. System and class loads can hit minimums at temperatures other than 65 degrees and not necessarily at the same temperature. Commercial rate classes may hit their minimum at a lower temperature than the residential class. Large buildings may have significant internal sources of heat from lighting, equipment and occupants.

LESSON 1: Choosing a Model - Energy

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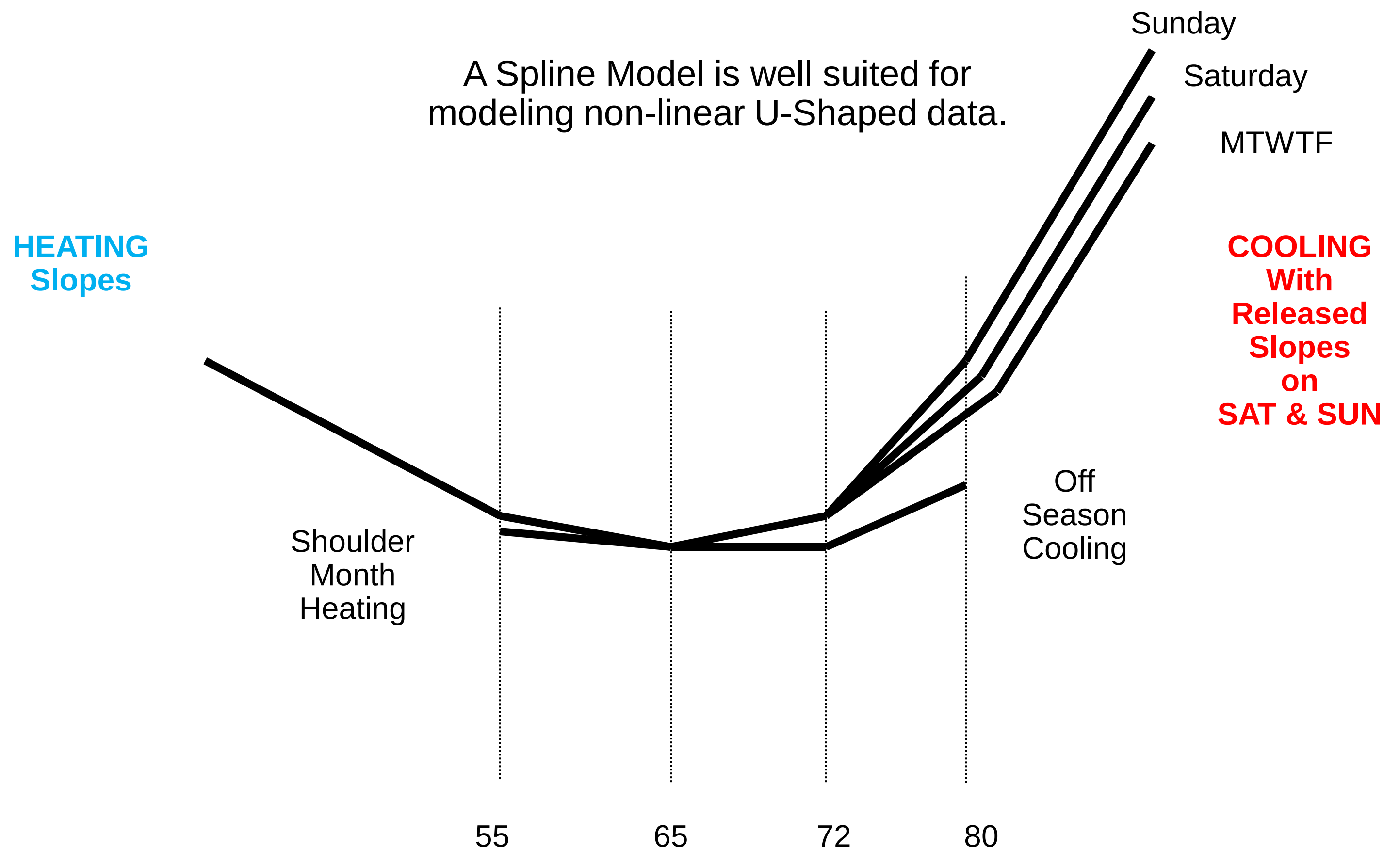
Residential
Daily KWH per Customer



NOTE: Depending on climate, it may be unnecessary to release the heating slopes if heating loads occur mostly at night when homes are usually occupied.

LESSON 2: Choosing Weather Metrics

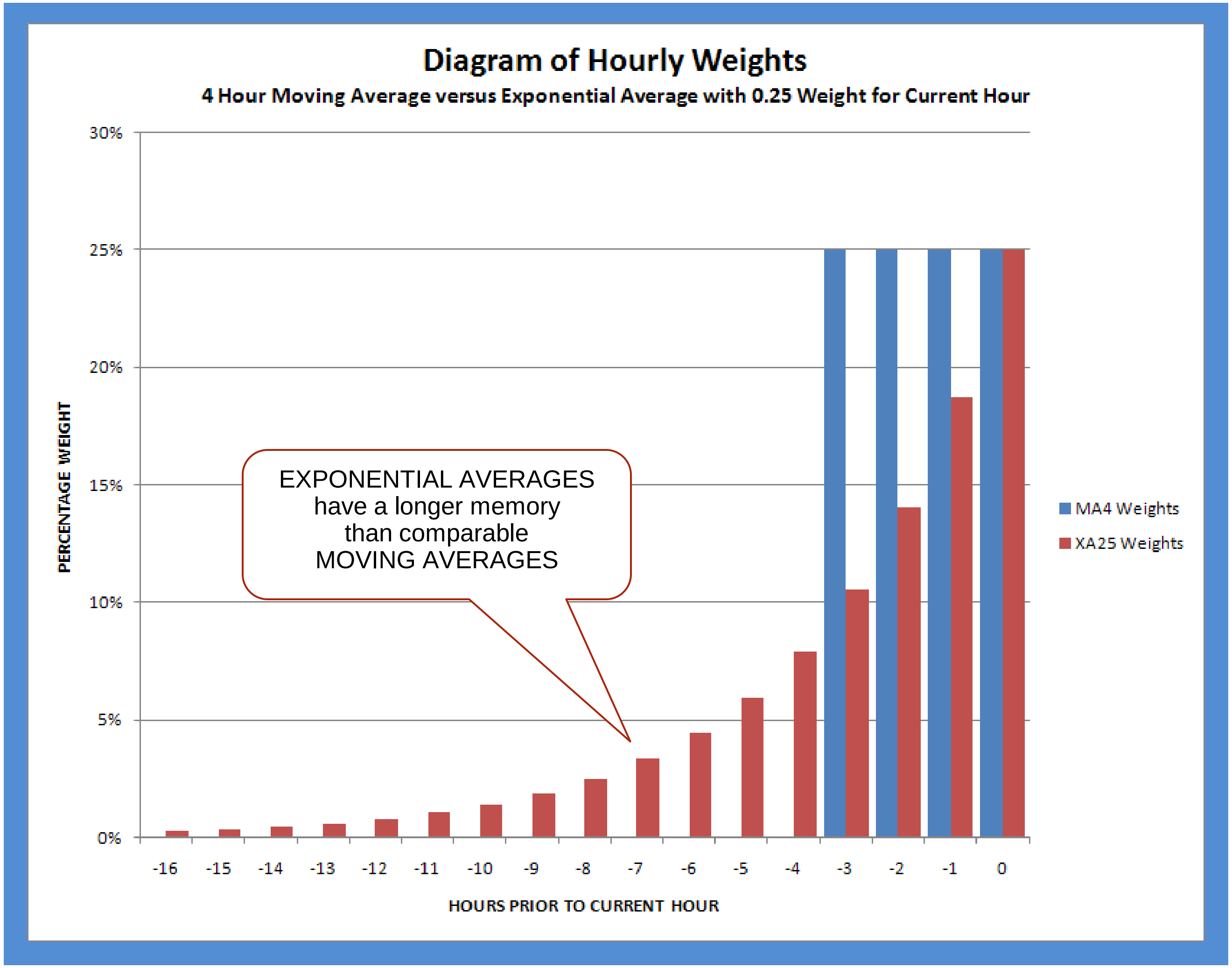
NOAA HDD65 & CDD65 are not the only weather metrics you should try.

DEGREE DAYS		DEGREE HOURS
NOAA HDD65 & CDD65		HDH65 & CDH65
CME HDD65 & CDD65		
HDD55 & CDD72		HDH55 & CDH72
		HDH55XA25, HDH65XA25, CDH65XA25, CDH72XA25, CDH80XA25
Spline Weighted HDD & CDD		Spline Weighted HDH & CDH

Notes:

1. The suffix "XA25 " refers to use of temperatures that are exponentially smoothed (with the current temperature receiving a 0.25 weight) prior to calculating HDH or CDH. Observe that thermometers recording dry bulb temperatures are located outside while thermostats controlling HVAC are located inside. Insulation will dampen and lag the impacts of changes in outside temperatures on inside heating and cooling requirements.
2. SPLINE WEIGHTED DEGREE DAYS refers to degrees days that have been calculated by using the various slopes from a spline model to weight degree days for each of the various ranges of temperature in the spline model by their relative impact of KWH usage. SPLINE WEIGHTED DEGREE HOURS would be calculated similarly using the slopes from a degree hour spline model.
3. CME refers to the Chicago Mercantile Exchange which does not round the average of the daily high and low temperatures prior to calculating degree days.

Smoothed Temperatures (MA4 vs XA25)

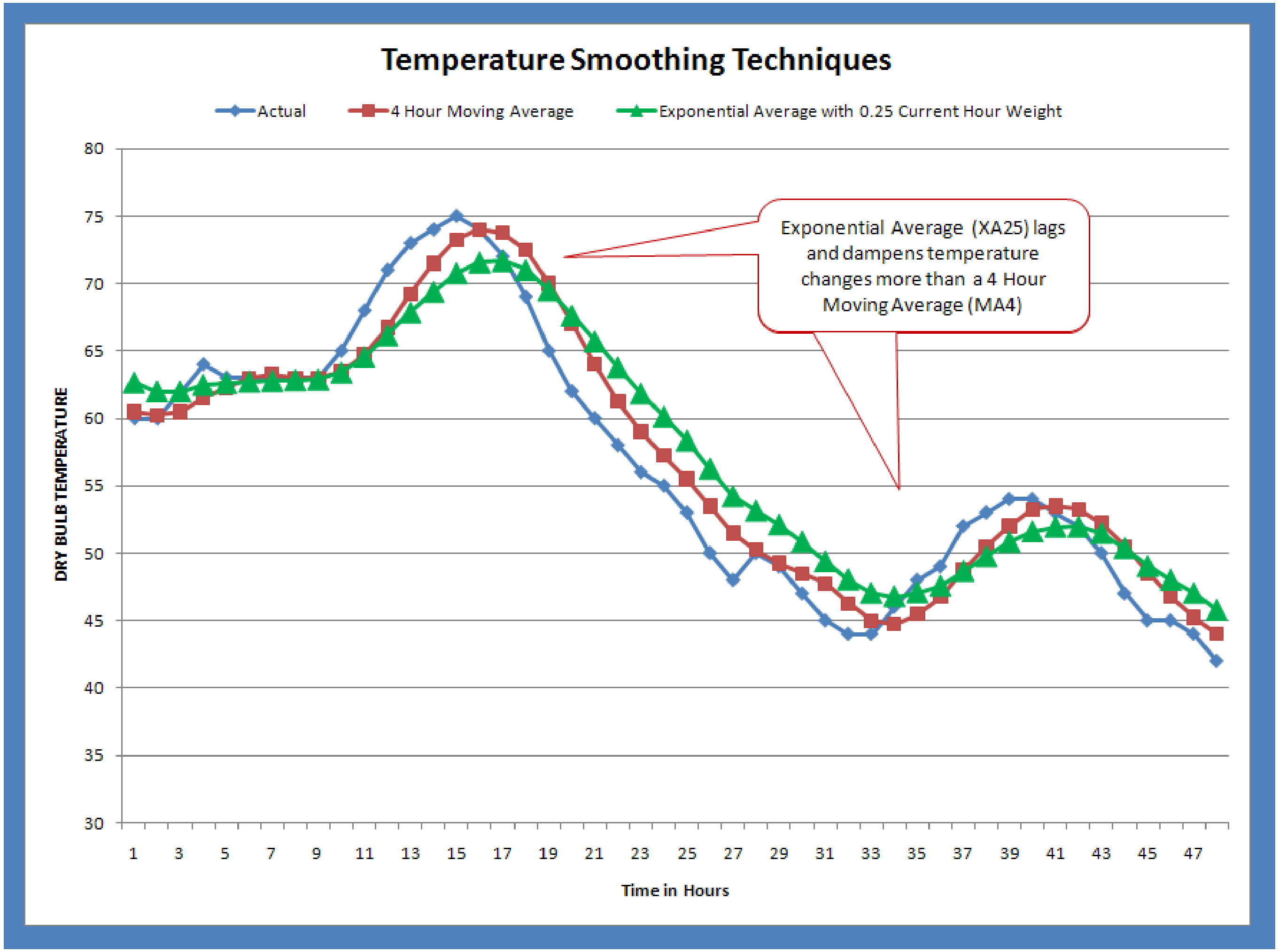


Smoothed Temperatures (Illustration)

Consider smoothing temperatures prior to calculating degree hours.

Note that thermometers measure outside temperatures while the thermostats controlling HVAC equipment are responding to inside temperatures.

Since the impact that changes in outside temperatures have on the heating and cooling requirements of homes is dampened and lagged by the insulation in walls and attics, the use of smoothed temperatures may improve your model of HVAC loads.



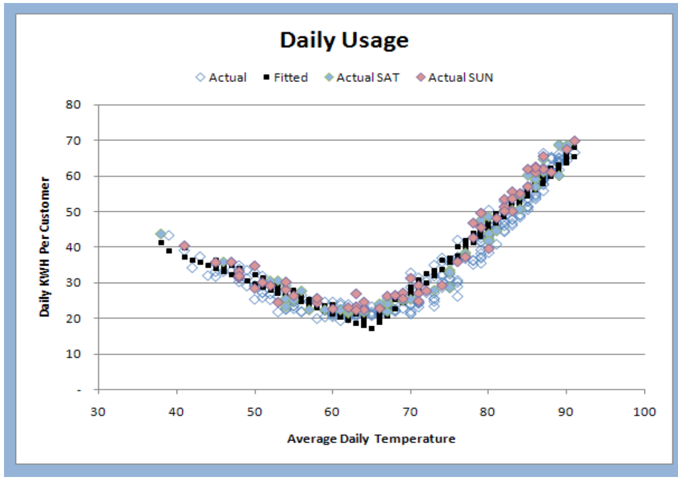
Comparing Models - Daily Residential kWh

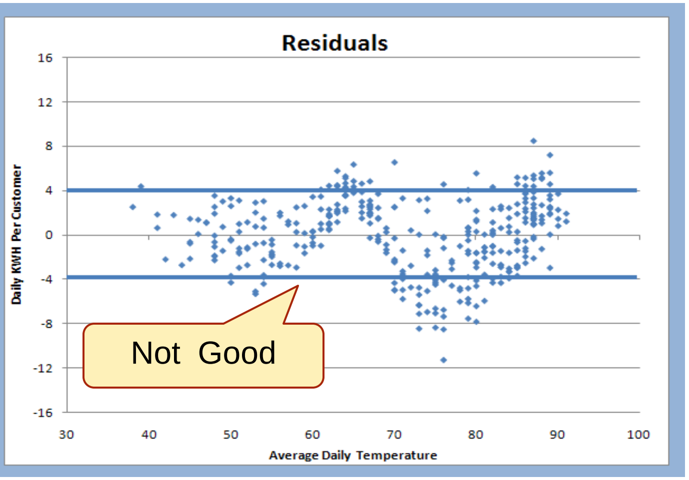
MODEL 1

V Shaped
Degree Day
Model

MAPE 7.1%

Can Do Better





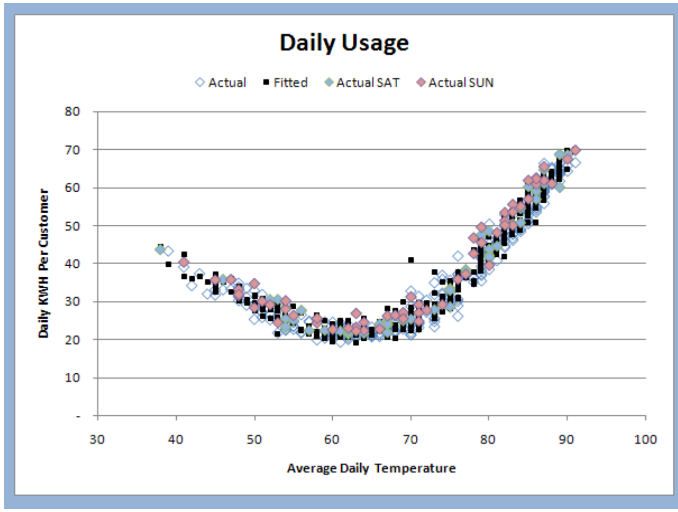
MODEL 2

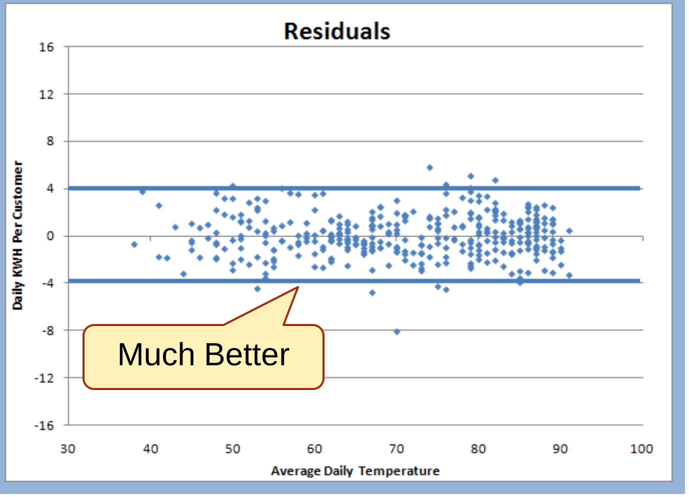
U Shaped
Degree Hour
Spline
Model

MAPE 3.8%

Much Better

See Next Slide for an even better model with released slopes





Incrementally Improving a Model

MAPE: Mean Absolute Percent Error

Model 1 shown on prior slide.

MAPE	Model
7.1%	•HDD65 & CDD65 V-Shaped Model •Daily Max & Min Temperatures
5.5%	•HDD55 & CDD72 Model •Daily Max & Min Temperatures
5.1%	•HDH65 & CDH65 V-Shaped Model •Actual Hourly Temperature
4.9%	•HDH55 & CDH72 Model •Actual Hourly Temperatures
4.8%	•HDH65 & CDH65 V-Shaped Model •Exponentially Smoothed Hourly Temperatures
4.2%	•HDH55 & CDH72 Model •Exponentially Smoothed Hourly Temperatures
3.8%	•HDH & CDH Spline Model •Exponentially Smoothed Hourly Temperatures
3.5%	•HDH & CDH Spline Model with Released Slopes •4 Hour Moving Average of Hourly Temperatures
3.1%	•HDH & CDH Spline Model with Released Slopes •Exponentially Smoothed Hourly Temperatures

A degree day model with a perfectly flat response for temperatures from 55 to 72 is better than Model 1, but there is much room for improvement.

Still V shaped (i.e. no flat segment) but much better than the V shaped HDD65 & CDD65 model.

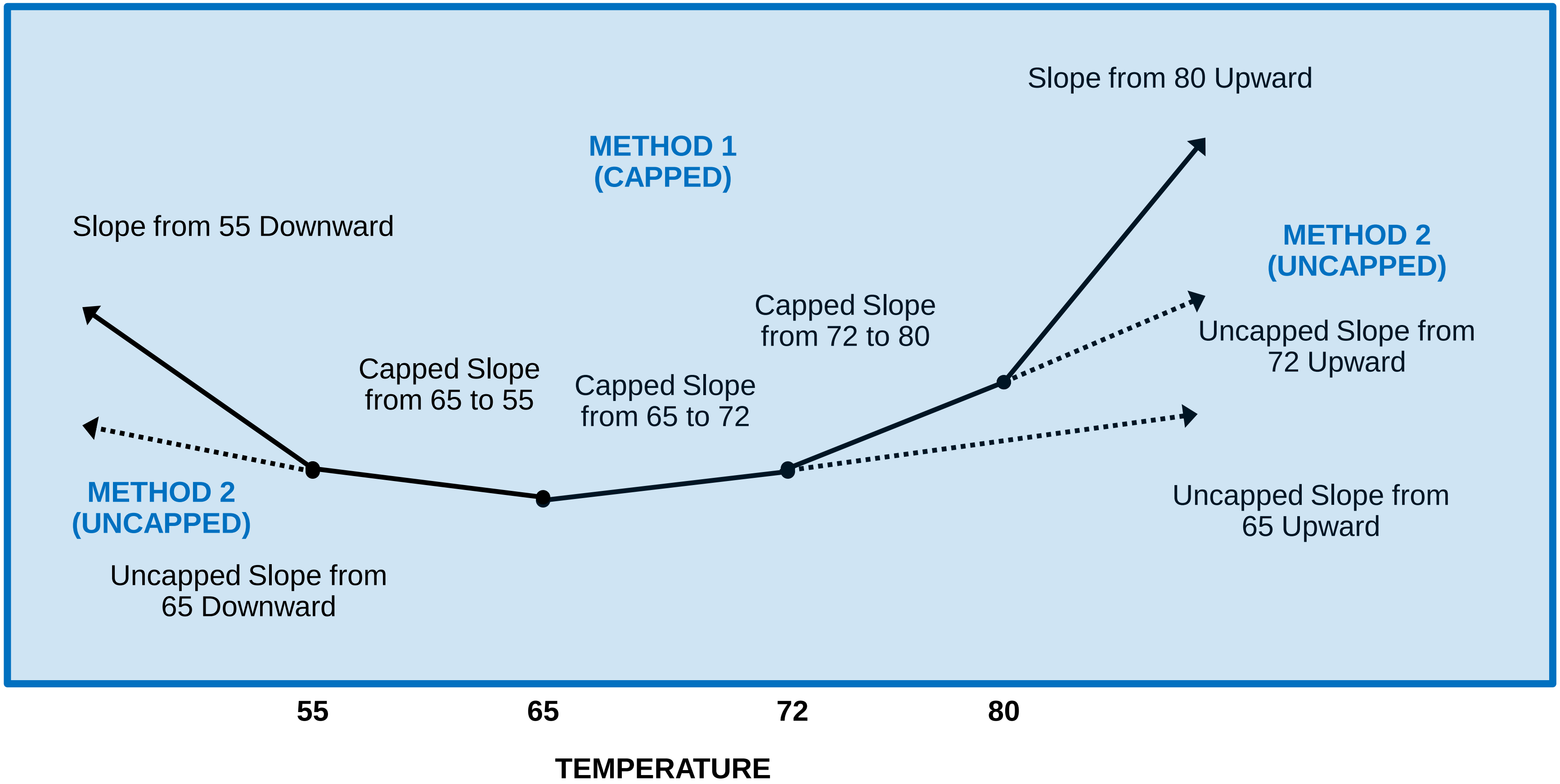
Model 2 shown on prior slide.

A spline model using a 4 hour moving average of temperatures to calculate HDH & CDH is good, but not as good as the same model using exponentially smoothed temperatures.

Like Model 2 but with released slopes.

More on SPLINE MODELS

- ➢Equivalent Spline models can be estimated using “CAPPED” or “UNCAPPED” versions of temperature variables.
- ➢ The type of model is determined by how the regression dataset is setup.



"Capped" & "Uncapped" Regression Datasets

"CAPPED" Dataset

Date	Type of Day	Daily kWh per Customer	Intercept	HEAT2 HDH	HEAT1 HDH	COOL1 CDH	COOL2 CDH	COOL3 CDH
FEB 3	COLD	41.5	1	260	220	0	0	0
APR 9	MILD	29.3	1	0	12	15	3	0
AUG 5	HOT	56.2	1	0	0	165	180	100

"UNCAPPED" Dataset

Date	Type of Day	Daily kWh per Customer	Intercept	HEAT2 HDH	HEAT1 HDH	COOL1 CDH	COOL2 CDH	COOL3 CDH
FEB 3	COLD	41.5	1	260	480	0	0	0
APR 9	MILD	29.3	1	0	12	18	3	0
AUG 5	HOT	56.2	1	0	0	445	280	100

Note: This data is for illustration purposes only. It is not actual data nor are the slopes on the following 3 slides.

Understanding “Capped” & “Uncapped” Slopes

(HINT: There are two ways to get to the same answer.)

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Cold Day Example

Model Type	Term	Metric	Degree Hours	Regression Slopes	Predicted KWH for Heating
CAPPED	HEAT2	=HDHXA25 Base 55	260	0.055	14.3 kWh
	HEAT1	=HDHXA25 Base 65 – HDHXA25 Base 55	220	0.010	2.2 kWh
	COOL1	=CDHXA25 Base 65 – CDHXA25 Base 72	0	0.040	
	COOL2	=CDHXA25 Base 72 – CDHXA25 Base 80	0	0.070	
	COOL3	=CDHXA25 Base 80	0	0.120	
	TOTAL				16.5 kWh
UNCAPPED	HEAT2	=HDHXA25 Base 55	260	0.045	11.7 kWh
	HEAT1	=HDHXA25 Base 65	480	0.010	4.8 kWh
	COOL1	=CDHXA25 Base 65	0	0.040	
	COOL2	=CDHXA25 Base 72	0	0.030	
	COOL3	=CDHXA25 Base 80	0	0.050	
	TOTAL				16.5 kWh

Coefficients sum to 0.055

Coefficients sum to 0.12

Understanding "Capped" & "Uncapped" Slopes

(HINT: There are two ways to get to the same answer.)

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Hot Day Example

Model Type	Term	Metric	Degree Hours	Regression Slopes	Predicted KWH for Cooling
CAPPED	HEAT2	=HDHXA25 Base 55	0	0.055	
	HEAT1	=HDHXA25 Base 65 – HDHXA25 Base 55	0	0.010	
	COOL1	=CDHXA25 Base 65 – CDHXA25 Base 72	165	0.040	6.6 kWh
	COOL2	=CDHXA25 Base 72 – CDHXA25 Base 80	180	0.070	12.6 kWh
	COOL3	=CDHXA25 Base 80	100	0.120	12.0 kWh
	TOTAL				31.2 kWh
UNCAPPED	HEAT2	=HDHXA25 Base 55	0	0.045	
	HEAT1	=HDHXA25 Base 65	0	0.010	
	COOL1	=CDHXA25 Base 65	445	0.040	17.8 kWh
	COOL2	=CDHXA25 Base 72	280	0.030	8.4 kWh
	COOL3	=CDHXA25 Base 80	100	0.050	5.0 kWh
	TOTAL				31.2 kWh

Coefficients sum to 0.055

Coefficients sum to 0.12

What are SPLINE WEIGHTED Degree Hours?

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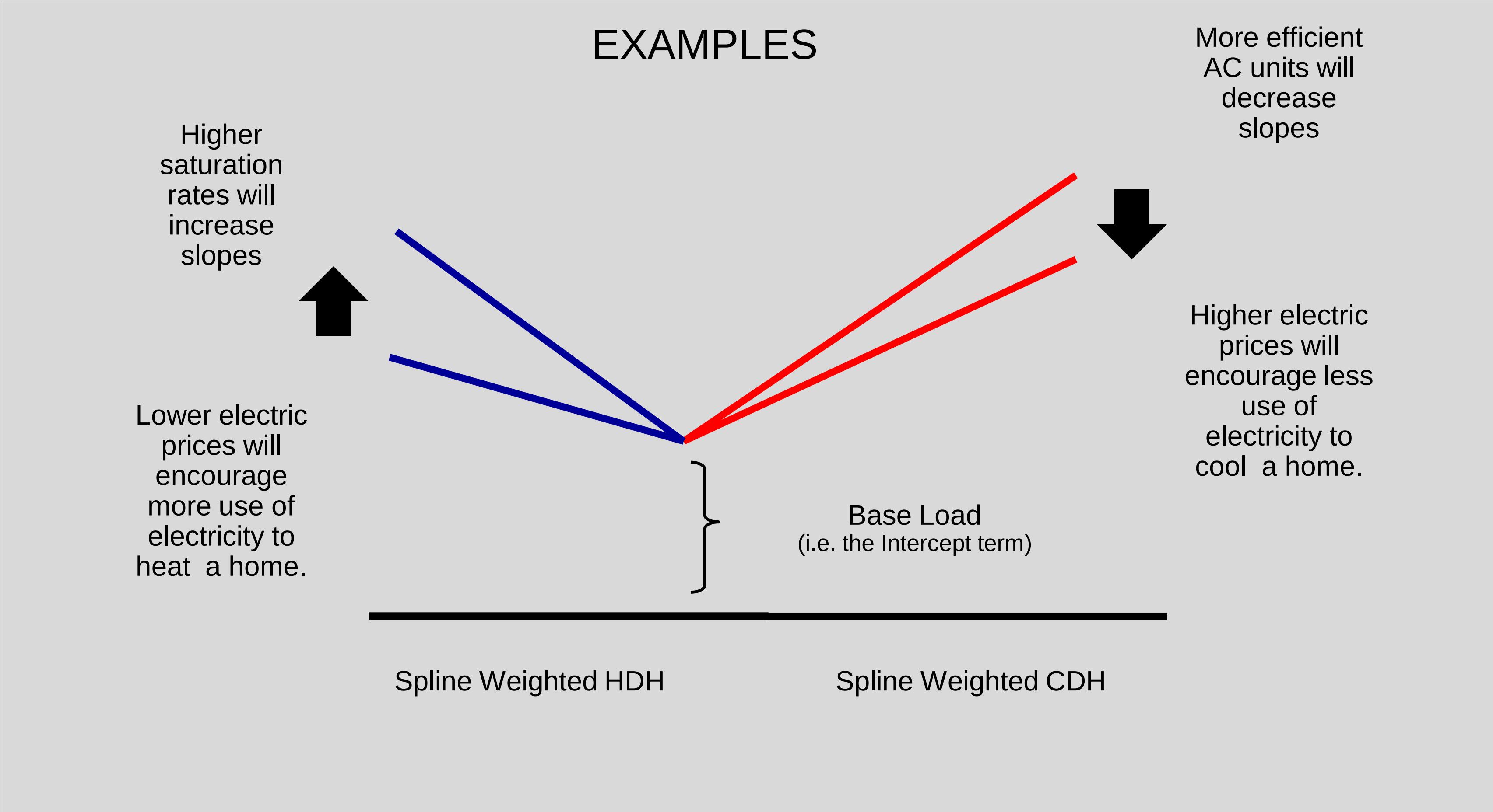
Illustrated Using "CAPPED" Slopes

Temperature Range	Name of Slope	Slope Coefficient	Spline Weight	COLD DAY Degree Hours	COLD DAY Spline Weighted Degree Hours	HOT DAY Degree Hours	HOT DAY Spline Weighted Degree Hours	MILD DAY Degree Hours	MILD DAY Spline Weighted Degree Hours
Below 55	HEAT 2	.055	.055 / .055 =1.00	260	260.0	0	0	0	0
65 to 55	HEAT 1	.01	.01 / .055 = .182	220	40.0	0	0	0	0
TOTAL HDH				480	300.0	0	0	0	0
65 to 72	COOL 1	.04	.04 / .12 = .333	0	0	165	54.9	20	5 (#1)
72 to 80	COOL 2	.07	.07 / .12 = .583	0	0	180	104.4	0	0
Above 80	COOL 3	.12	.12 / .12 = 1.00	0	0	100	100.0	0	0
TOTAL CDH				0	0	445	259.3	20	5

Interpretation: The 480 HDH on the cold day is estimated to have an impact on home heating requirements comparable to 300 HDH Base 55. Similarly, the 445 CDH on the hot day have a cooling requirement that is comparable to 259.3 CDH Base 80.

Note: #1 The assumed coefficient for OFF SEASON air conditioning is 0.03 resulting in a "discount factor" of 0.03 / 0.12 = 0.25.

LESSON 3: Slopes & Base Loads Change



Not shown: “Base Loads” will change as appliance saturation rates and efficiencies change.

LESSON 3: “Snap-Shot” & “Movie” Models

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SNAP-SHOT MODELS	MOVIE MODELS
These models describe slopes & the intercept at a point in time. Snap-shots based upon load study data provide the best resolution (“most pixels”), but a lot can be learned from monthly billing data when load study data is not available.	These models impute a “cause & effect” relationship between explanatory variables and usage. The goal is to be able to predict the next several frames in the movie from the previous frames.
Examples:	Examples:
Spline models fitted to test-year load study data (see previous slides)	Y = b0 + b1 Price + b2 Income + b3 HDH + b4 CDH
Descriptive models can also be fitted to monthly billing data such as:	Y = b0 + b1 Income + b2 HDH + b3 CDH + b4 CDH * PRICE
Y_m = b0_1970-1974 + b1_1970-1974 * Spline Weighted HDH_m + b2_1970-1974 * Spline Weighted CDH_m + …. for each 5 year cluster of data for clusters from 1970-1974 through 2005-2009 and “m” indicates data from month 1 to the final month	Y = b0 + b1 Income + b2 Spline Weighted HDH + b3 Spline Weighted CDH + b4 Spline Weighted CDH * “Unitless Combined PRICE & TREND Variable” with user specified weights for PRICE and TREND
This will provide “Snap-shots” across time for all of the years in the billing history (as shown by the next 2 slides)	Statistically Adjusted End-Use (SAE) Models (yet to be discussed)

BETTER

What can a Snap-Shot Model tell us?

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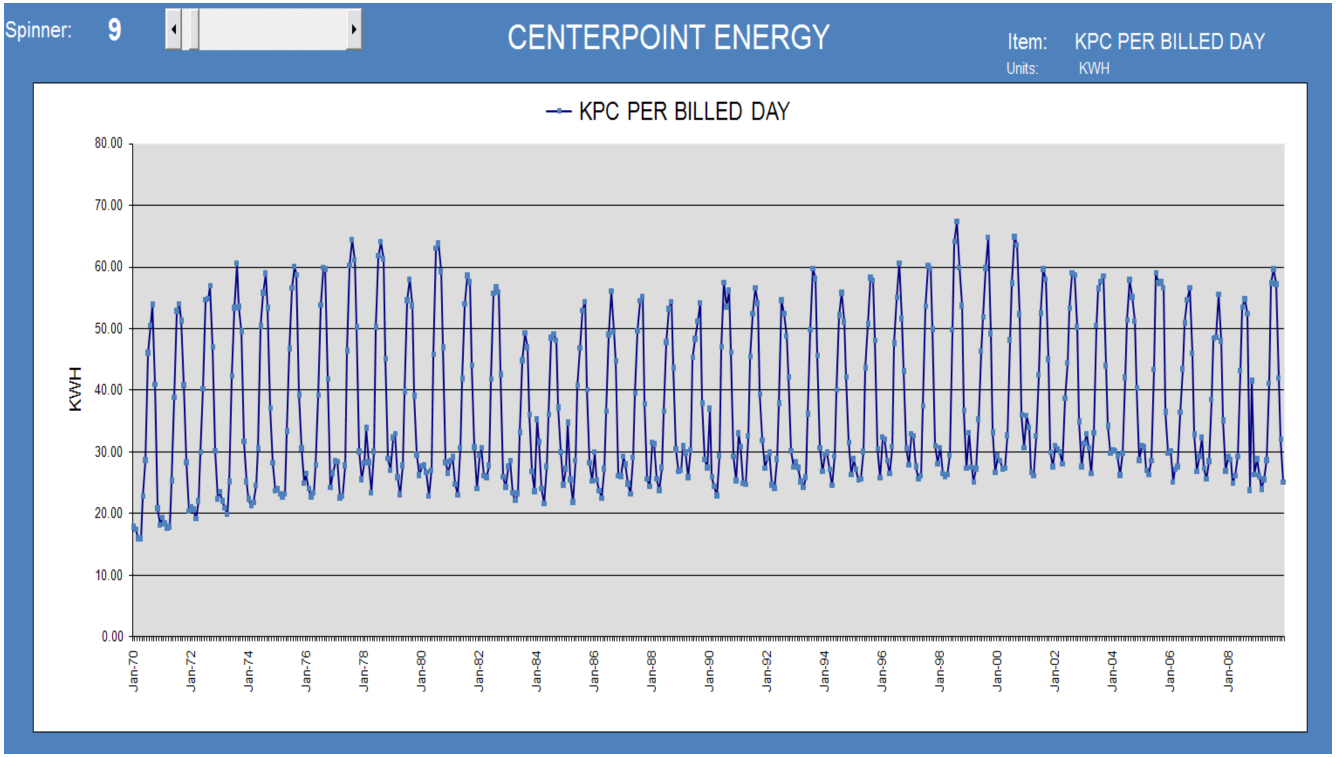
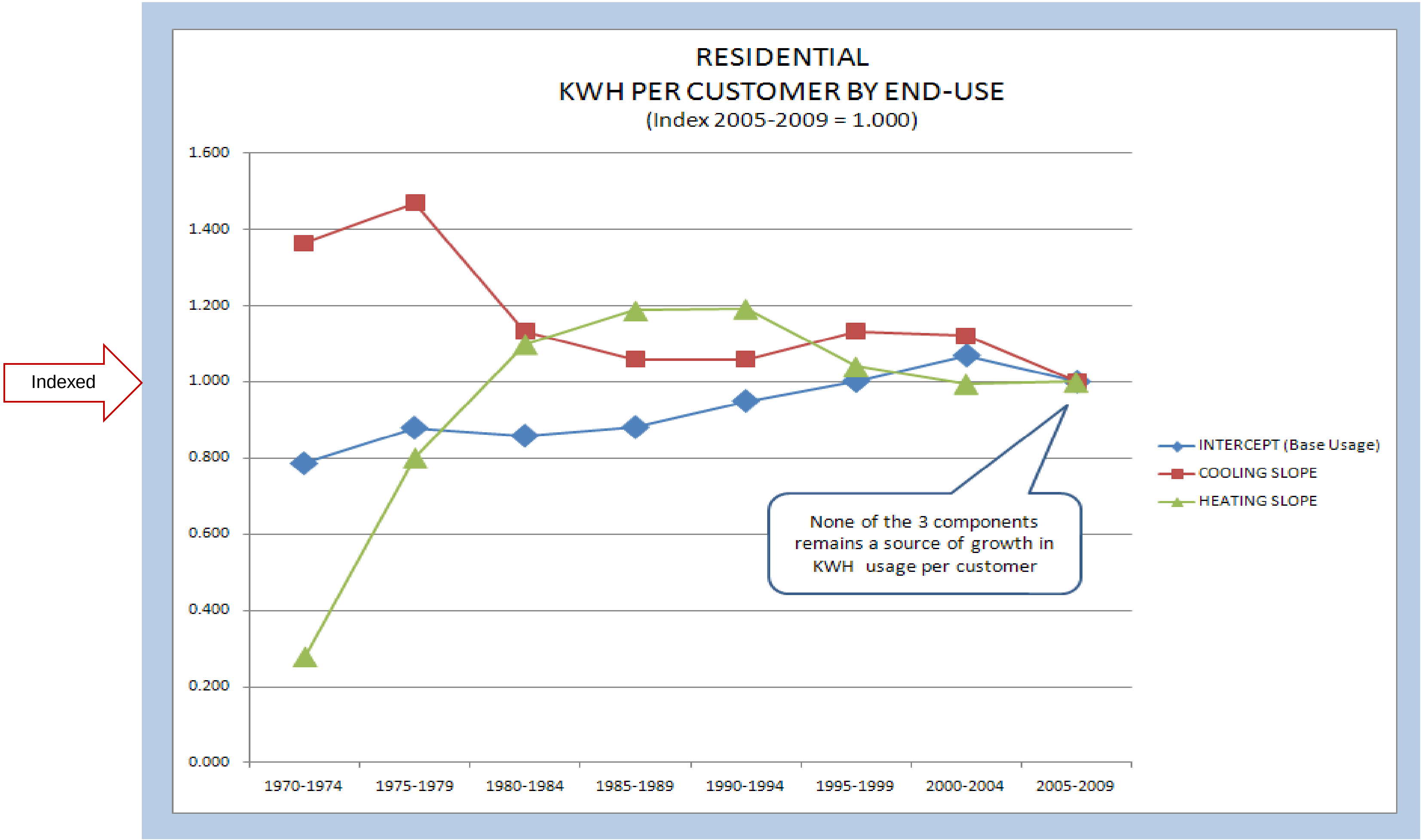
It can help tell us how much slopes and base loads have changed over time which is a good thing – but stops short of telling us what is driving the changes.

With careful inspection several trends can be visually identified in this data, but a Snap-Shot model is needed to quantify those trends.

The next slide quantifies the relative changes in heating slopes, cooling slopes and base loads from 1970 through 2009.



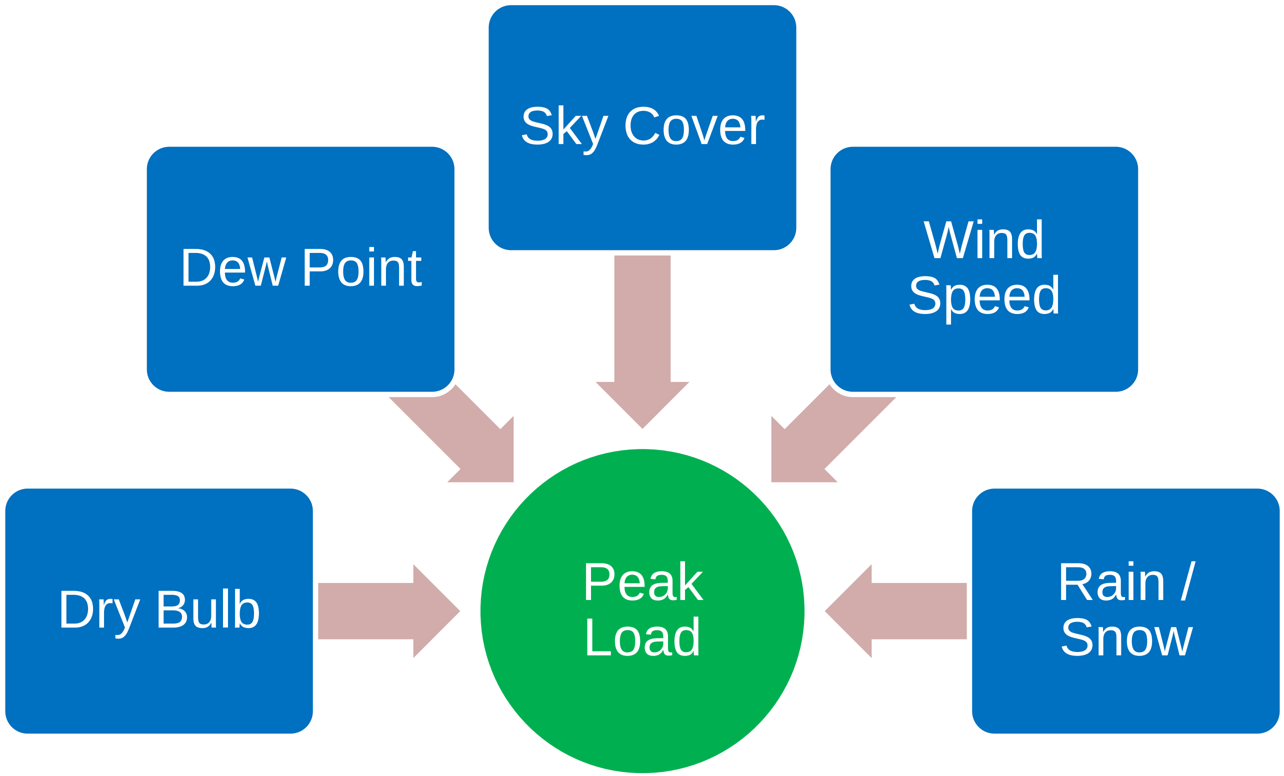
What can a Snap-Shot Model tell us?



Note: Spline weighted CDH & HDH were used to develop the cooling and heating slopes presented above.

Demand Models: Choosing Weather Metrics

How do these weather metrics impact winter and summer system peak load?



Note: Can use a Temperature Humidity Index (THI) to combine dry bulb & dew point temperatures into a single metric to model air conditioning.

Tips for Modeling Class & System Peak Demands

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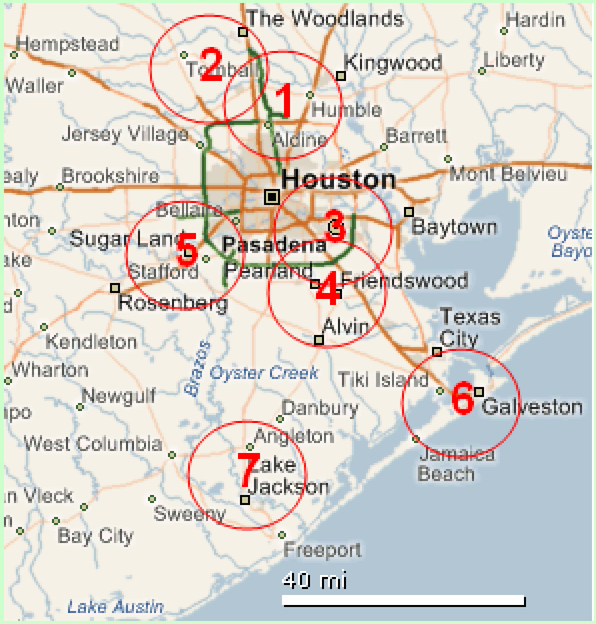
Be sure to consider metrics other than dry bulb temperature when modeling peak loads

Metric	Winter Peak	Summer Peak
Dry Bulb Temperature	Colder more load	Hotter more load
Dew Point Temperature		More moisture more load
Sunny / Sky Cover	More sunshine less load	More sunshine more load
Wind	More wind more load	Mixed impacts
Rain		Reduces load but good luck trying to model it

Tip: Consider leaving Saturdays, Sundays, holidays and rainy days (in summer months) out of your regression dataset.

Weather can be diverse during a single hour

AUTOMATED SURFACE OBSERVATION SYSTEM (ASOS)



STATIONS IN HOUSTON AREA

#	Call Sign	Name	ASOS Data Available Since
1	IAH	Bush Airport	JUN 96
2	DWH	Hooks Memorial Airport	DEC 97
3	HOU	Hobby Airport	AUG 98
4	LVJ	Clover Field	APR 97
5	SGR	Sugar Land Memorial	DEC 00
6	GLS	Scholes Field	DEC 96
7	LBX	Brazoria County Airport	MAY 98

- To reduce measurement errors on weather variables consider using observations from more than one weather station to represent weather across the service area.
- This is especially important when weather normalizing system peaks since a small amount of measurement error may materially impact the estimated change in the year-over-year normalized peak.

Asymptotic K Function

(one more tool for your toolbox)

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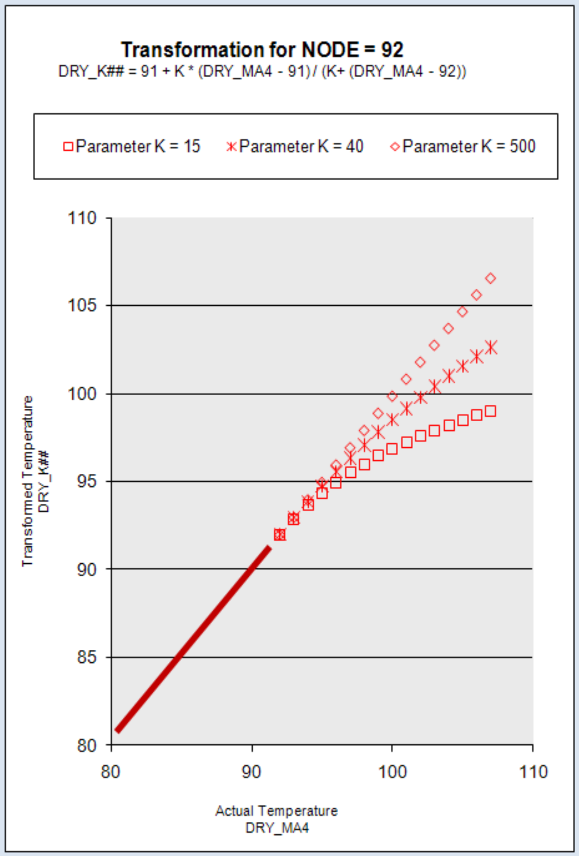
If hourly loads flatten out at extreme temperatures, what model options are available?



Actual Dry Bulb Temperature MA4		K = 15		K = 40		K = 500	
	Node =	92		92		92	
	Node -1 =	91		91		91	
	K =	15		40		500	
	K - 1 =	14		39		499	
		Transformed Values	Incremental Change per Actual Degree	Transformed Values	Incremental Change per Actual Degree	Transformed Values	Incremental Change per Actual Degree
92		92.0	1.00	92.0	1.00	92.0	1.00
93		92.9	0.88	93.0	0.95	93.0	1.00
94		93.6	0.77	93.9	0.91	94.0	0.99
95		94.3	0.69	94.7	0.86	95.0	0.99
96		94.9	0.61	95.5	0.82	96.0	0.98
97	NORMAL	95.5	0.55	96.3	0.79	96.9	0.98
98		96.0	0.50	97.1	0.75	97.9	0.98
99		96.5	0.45	97.8	0.72	98.9	0.97
100		96.9	0.42	98.5	0.69	99.9	0.97
101		97.3	0.38	99.2	0.66	100.8	0.96
102		97.6	0.35	99.8	0.64	101.8	0.96
103		97.9	0.32	100.4	0.61	102.7	0.96
104		98.2	0.30	101.0	0.59	103.7	0.95
105	EXTREME	98.5	0.28	101.6	0.57	104.6	0.95
106		98.8	0.26	102.1	0.55	105.6	0.95
107		99.0	0.24	102.6	0.53	106.5	0.94
110		99.6	0.21	104.1	0.49	109.3	0.94
120		101.1	0.15	108.1	0.40	118.5	0.91
999,999	Asymptote:	106.0	0.00	131.0	0.00	590.8	0.00

SAMPLE REGRESSION DATASET USING A SPLINE MODEL:

OBS	Y	INTERCEPT	X1	X2	X3	X4	DRY BULB TEMPERATURE ACTUAL	DRY BULB TEMPERATURE TRANSFORMED
	Hour 17 MW		DRY MA4	DRY K40	DEW MA4	10th SKY MA4	DRY MA4	DRY K = 40
1	14,000	1	82.0	0.0	66.50	3.50	82	
2	14,250	1	87.5	0.0	68.00	2.25	87	
3	14,700	1	0.0	92.0	67.50	4.50	92	92
4	15,000	1	0.0	95.5	72.00	1.00	96	95.5
5	15,900	1	0.0	99.8	66.75	0.00	102	99.8
ETC.								

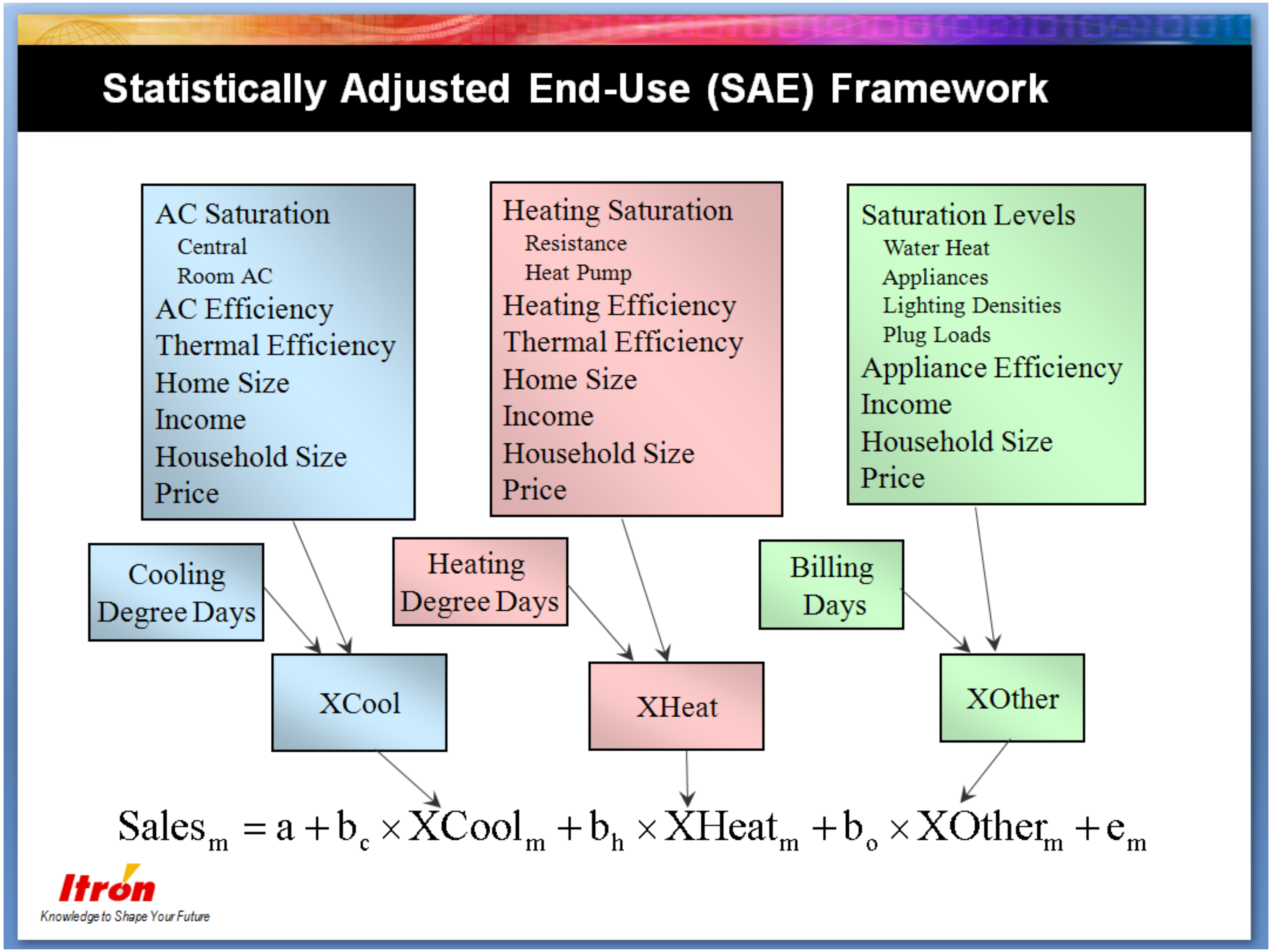
(HYPOTHETICAL DATA)

Tip: Compared to polynomial models, the Asymptotic K Function will likely better predict loads at extreme temperatures.

Tip: If you subtract 80 (or 90) from the temperatures in columns X1 & X2, the coefficient for the intercept term will be the estimated MW demand at that temperature. Otherwise it will be the a negative value representing load at a temperature of "zero" which is a meaningless extrapolation of the model to temperatures outside of the range of the data.

Looking Ahead - Forecasting

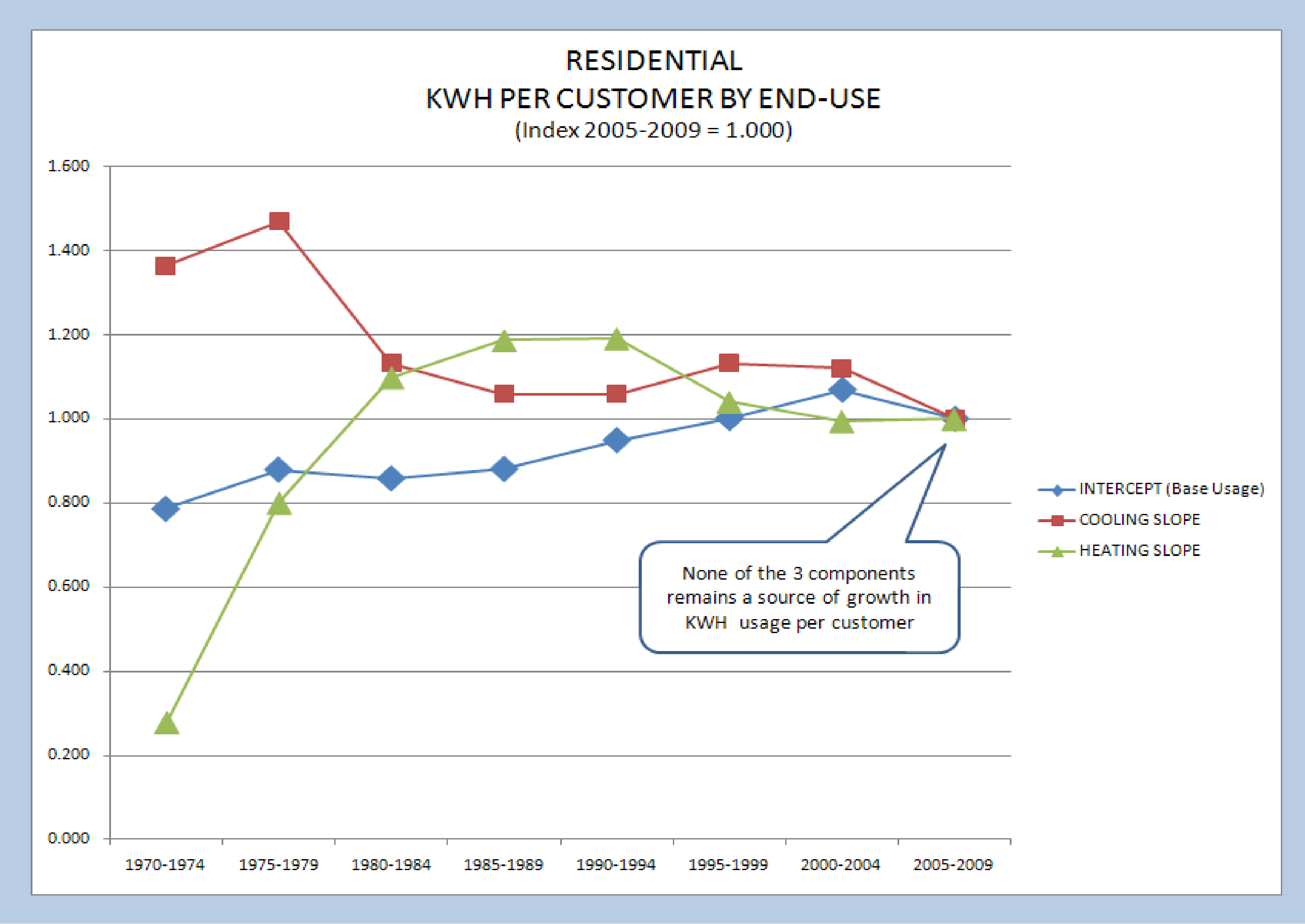
Looking Ahead – Choosing a Model



ITRON's SAE model provides a solid framework for forecasting future kWh sales.

Also it is not an overwhelming task to get one setup.

These indices are close cousins to XOTHER, XHEAT and XCOOL and can help calibrate your model.



Choosing a Model

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End-Use Variable - Cooling

$$\boxed{XCool_{y,m} = CoolIndex_{y} \times CoolUse_{y,m}}$$

$$CoolIndex_{y} = StructuralIndex_{y} \times \sum_{Type} Weight_{y}^{Type} \times \frac{\left(Sat_{y}^{Type} / Eff_{y}^{Type} \right)}{\left(Sat_{05}^{Type} / Eff_{05}^{Type} \right)}$$

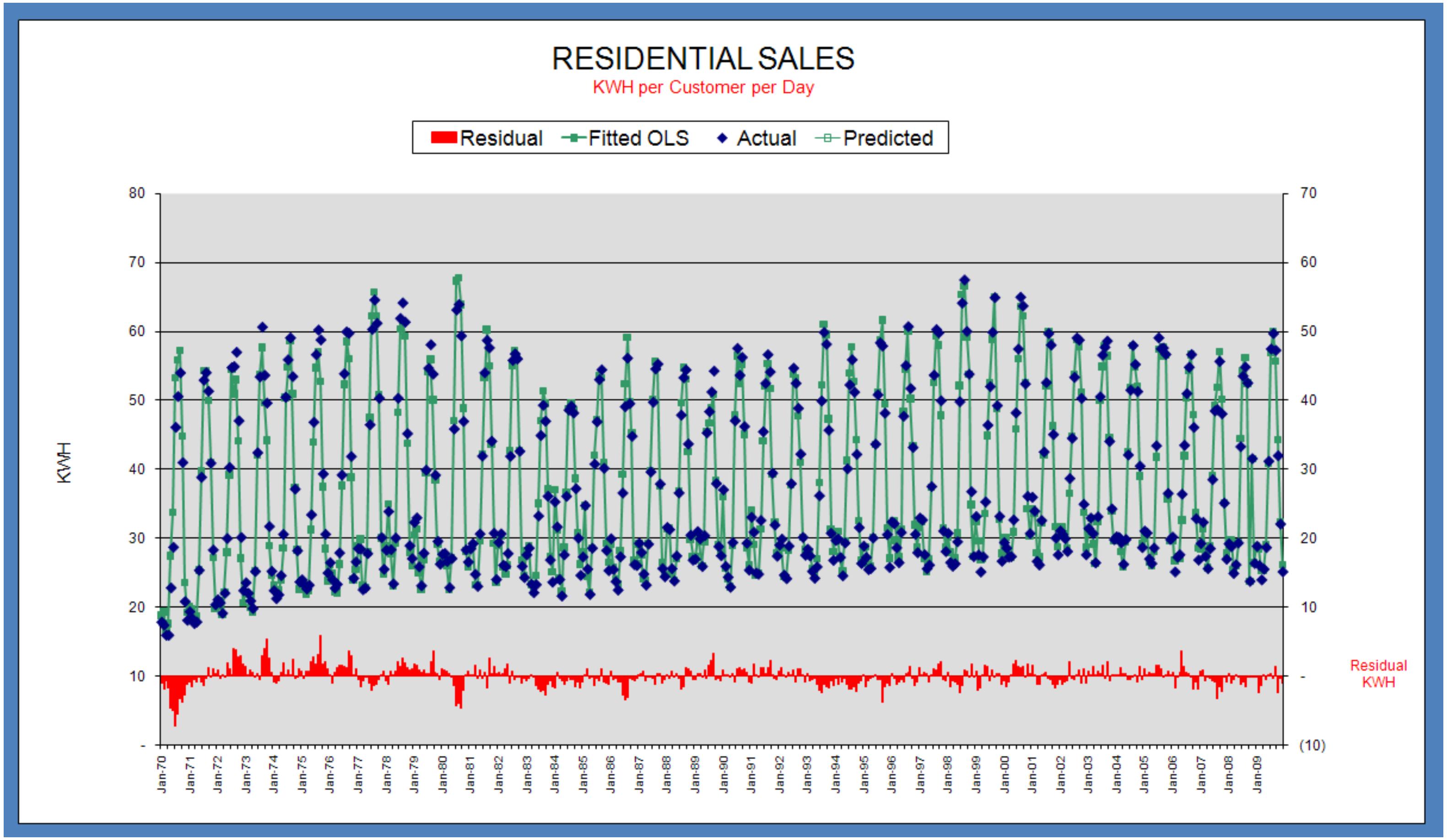
$$CoolUse_{y,m} = \left(\frac{CDD_{y,m}}{CDD_{05}} \right) \times \left(\frac{HHSize_{y,m}}{HHSize_{05}} \right)^{0.20} \times \left(\frac{Income_{y,m}}{Income_{05}} \right)^{0.20} \times \left(\frac{Price_{y,m}}{Price_{05}} \right)^{-0.15}$$

Itron
Knowledge to Shape Your Future

DOE2 models can help calibrate the "base year" in your forecast and give insight into likely future values required by the End Use Variables.

This model is straight forward and unlike REEPS forecasts monthly kWh.

Fitting an SAE Model



Fitted SAE Model

CenterPoint® Energy

This is CNP's first cut at an SAE model.

For a well calibrated model, the coefficients for XOTHER, XCOOL & XHEAT will be close to 1.0

Regression Model

Ordinary Least Squares

ANOVA		Sum of Squares	Root Mean Square Error			
	Model	78,232			SSY	747637
	Error	977	1.43		Ybar	37.1
	Total	79,209			N Obs	486
	R Square	0.98767			DF	477
	Adjusted R Square	0.98746			Parameters	9

Dependent Variable: **KPC PER BILLED DAY**

Modeled Class: **RESIDENTIAL**

Independent Variables:		Coefficients	Std of Coef	T Value		
1	INTERCEPT	(1.902230)	0.7278	-2.61	RMSE	1.43
2	XOTHER	1.090362	0.0341	31.96	Ybar	37.1
3	XCOOL	1.005778	0.0066	151.80	RMSE / Ybar	3.86%
4	XHEAT	0.959614	0.0278	34.51	MAPE	2.8%
5	DUMMY IKE OCT08	(19.698523)	1.4413	-13.67		
6	DUMMY IKE NOV08	10.875439	1.4422	7.54	AVG DEVIATION	1.02
7	DUMMY CALIB 2009	0.090570	0.3458	0.26	(Abolute Values)	
8	DUMMY SPRING	(1.169502)	0.1971	-5.93		
9	DUMMY FALL	1.551810	0.1923	8.07		
10						DATA
11					START OBS:	1
12					END OBS:	486
13						
14						
15						

MAPE is low.

Can calibrate your model to fit the last year of actual data and add seasonal variables as well.

A Quick Recap

- Lessons Learned
  - Be alert to non-linear responses of load to temperature
  - Try weather metrics other than NOAA HDD & CDD (base 65)
  - Be alert to changes in heating and cooling slopes and non-weather sensitive loads
  - Try an SAE forecasting model (possibly assisted by a DOE 2 model to help calibrate your expectations for future conservation due to appliance efficiencies and thermal characteristics/tightness of structures, etc.)

This is an exciting time to be doing Load Research!
I will close with the next slide.