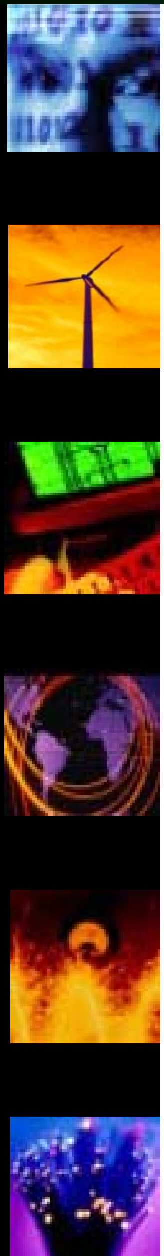

# Taking It Apart & Putting It Together:

## End-Use TOU Estimates Using Load Research, Billing, and Survey Data

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# With Thanks to

- Steve Bonanno, Lisa Shea, Cynthia DeRusso, NSTAR
- Ken Agnew, Cynthia Boyd, KEMA

# Overview

- Background
- Methods
- Results

# Project Background

- Multi-dimensional residential characterization study completed 2004
- Tasks include RASS, Focus Groups, fossil fuel savings potential study, and end-use TOU study

# End-Use TOU Study Goals

- Estimate end-use energy and demand by costing period
- Costing periods defined by ISO-NE
- Separate estimates by residential rate class

# Energy/Demand Estimates Developed

- **Energy (total kWh)**
  - **Summer June – Sept**
    - **On-Peak:** 6 am - 11 pm weekdays
    - **Off-Peak:** All other hours
  - **Winter Oct – May**
    - **On-Peak:** 6 am to 11 pm weekdays
    - **Off-Peak:** All other hours
- **Peak demand** (average kW)
  - **Summer:** Noon to 4 pm, July weekdays
  - **Winter:** 5 pm to 7 pm, January weekdays

# End Uses Estimated

- Heating
- Cooling
- Water heating
- Lighting
- All others

# Data Sources

- **2004 RASS**: 1,714 responses
- **Monthly Consumption (kWh)**: for the RASS respondents January 2003 to March 2004.
- **Load Research**:
  - Hourly data for all active LR sample points
  - Includes 74 cases with RASS responses
- **Weather**: Boston daily temperature data
- **Secondary Sources**

# Secondary Sources

- RECS: Energy Information Administration Residential Energy Consumption Survey
- DOE: Lighting technology & energy use study for DOE by KEMA (ADL subcontract)
- NEES: Long-term CFL usage study
- NSTAR: Lighting logger study for the impact evaluation of NSTAR's Residential High Use program

# Methods

# Summary of Approach

- Estimate annual consumption per customer for each end use.
- Allocate the annual energy into summer and winter seasons.
- Apply a load shape to separate the summer and winter totals into on- and off-peak components, and to estimate the average kW during the peak periods.

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# Annual kWh/customer by end use

- Heating and cooling: monthly consumption regression
- Water heating: conditional demand analysis applied to baseload from the heating-cooling decomposition
- Lighting: build-up from
  - hours of use by room type
  - room type & technology distributions by dwelling type
  - number of rooms
- All other uses are the remainder

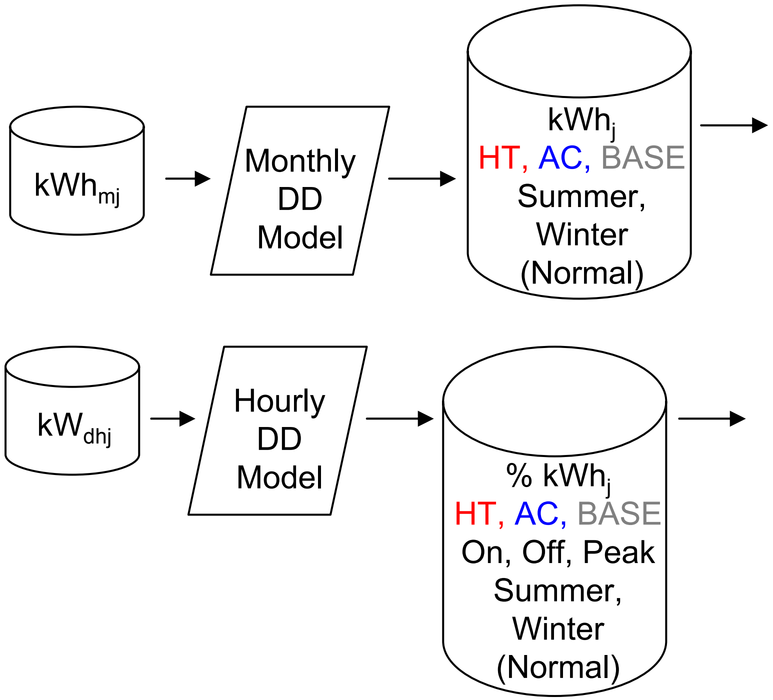
# Allocating Energy to Summer & Winter

- Heating and cooling: seasonal degree-days
- Lighting: monthly allocations from NEES report
- Water heating and other: assumed levels of variability over the year from secondary sources

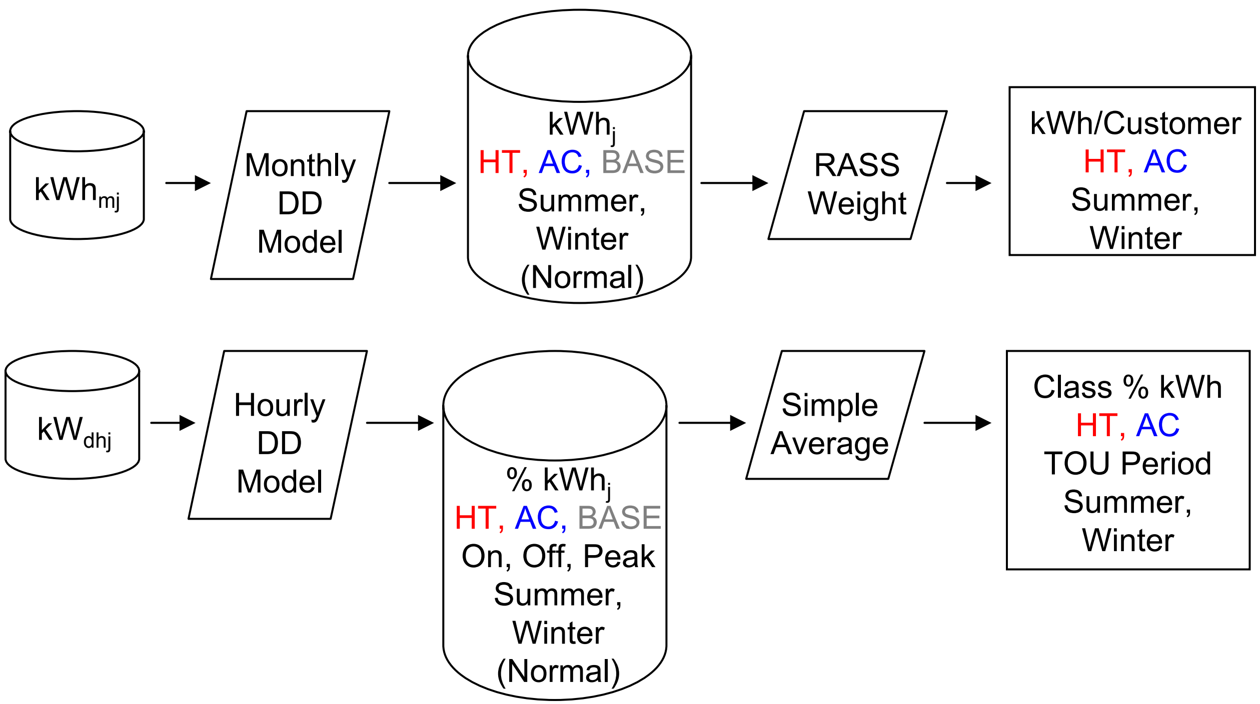
# Load shapes for TOU allocations

- Heating and cooling: hourly regression models similar to the monthly kWh models.
- Water heating: difference in baseload load shape between homes with and without water heating.
- Lighting: seasonal, weekday and weekend lighting shapes from the NEES report.
- "All other": baseload load shapes excluding water heating.

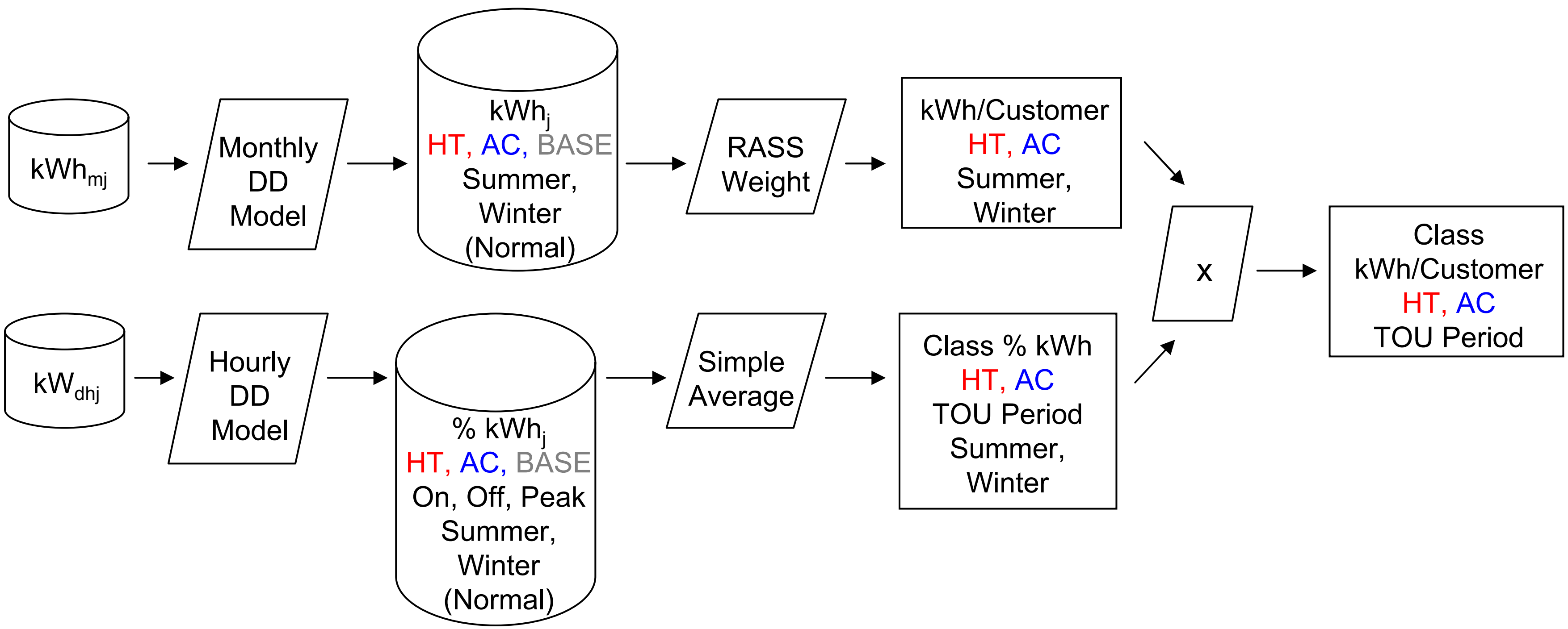
# Heating/Cooling Disaggregation



# Aggregating HT, AC Over Customers



# Shaping the HT, AC Energy



# Heating-Cooling Disaggregation

- Fit separately for each customer

$$E_m = \alpha + \beta H_m(\tau_H) + \gamma C_m(\tau_C) + \varepsilon_m$$

- $E_m$ = kWh/day, month $m$
- $H_m(\tau_H)$ = heating degree-days/day month $m$, base $\tau_h$
- $C_m(\tau_C)$ = cooling degree-days/day month $m$, base $\tau_h$
- $\varepsilon_m$ = random disturbance in month $m$
- $\alpha, \beta, \gamma, \tau_H, \tau_C$ = regression coefficients

# Seasonal End Use Estimates (example)

- Heating energy for a normal winter

$$E_{HW0} = \hat{\beta} H_{W0}(\hat{\tau}_H)$$

  - $H_{W0}$ = normal-year winter degree-days/day
- Determine for each RASS customer
- Take average by rate class using survey expansion weights

# Hourly Load Model

- Fit separately for each load research customer

$$L_{dh} = \alpha_h + \beta_h H_d(\tau_H) + \gamma_h C_d(\tau_C) + \varepsilon_{dh}$$

- $L_{dh}$ = kW at hour h of day d
- $H_d(\tau_H)$ = heating-degree-days base $\tau_H$ day *d*
- $C_d(\tau_C)$ = cooling-degree-days base $\tau_C$ day *d*
- $\varepsilon_{hd}$ = random disturbance hour *h* day *d*
- $\alpha_h, \beta_h, \gamma_h, \tau_H, \tau_C$ = regression coefficients
  - Estimated separately for weekdays vs weekend/holiday

# Aggregate End-use Load Shapes—Challenges

- Holes in the load data
- Few LR customers with RASS data (74)
- Fewer with any one end use
- →no formal expansion of load shapes using sampling weights

# Aggregate Load Shapes—Approach

- For each customer
  - Hourly load model
    →heating, cooling, other for each hour of the year
  - →seasonal kWh by end use
  - →% of seasonal end-use kWh by costing period
- Simple average of seasonal end-use %s over customers with nonmissing end-use estimates

# Heating/cooling decomposition products

- Normal kWh/customer
  - heating, cooling, and baseload
  - Annual, summer, and winter
- Normal end-use hourly load shapes
  - heating, cooling, and baseload
  - percent of annual or seasonal
- Heating & cooling energy allocation factors
  - percent of annual energy in each TOU period
- Heating & cooling demand allocation factors
  - summer, winter peak kW /annual average kW

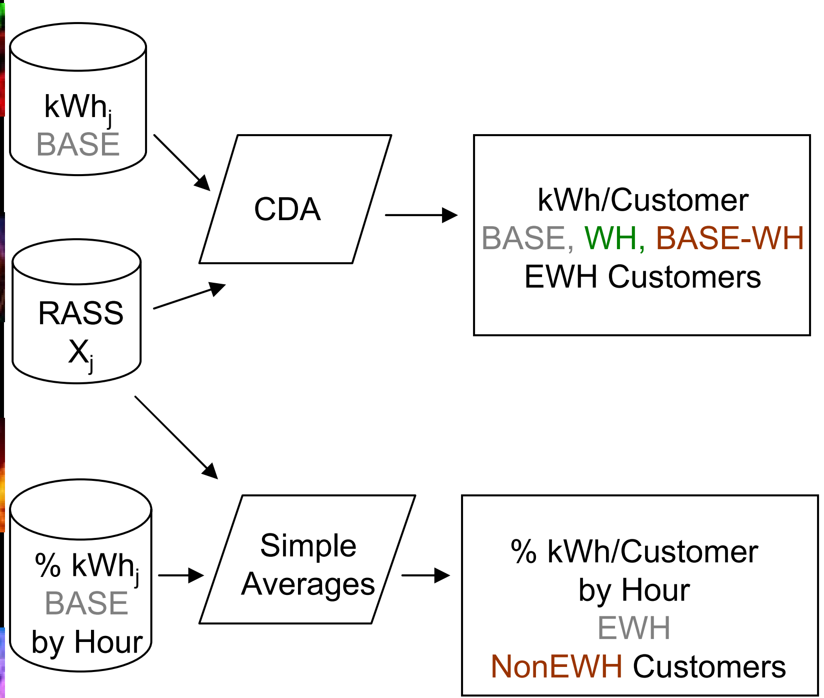
# Decomposing the Baseload

- Water heating
- Lighting
- Other

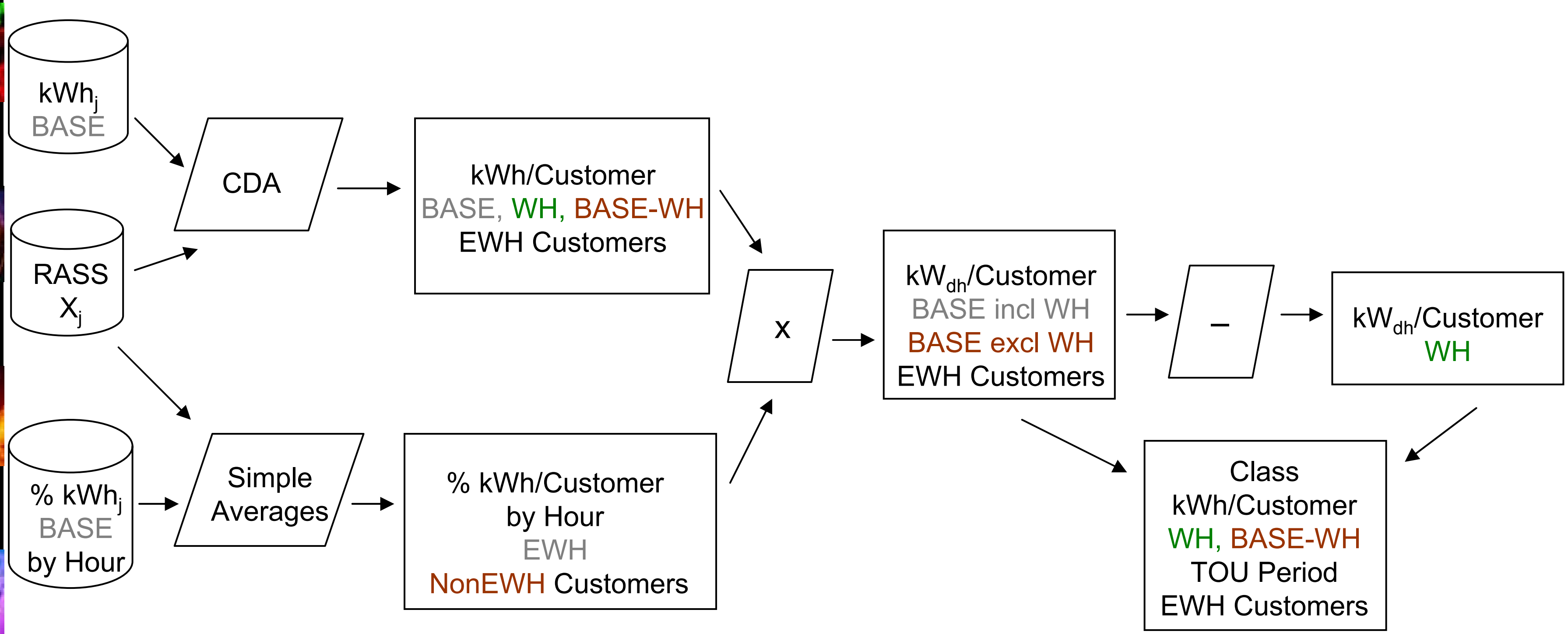
# Water Heating Energy

- Start with baseload estimate from heating-cooling kWh regression
- CDA analysis using RASS data to estimate water heating energy
- Adjust for "hidden nonheating" water heat in the aggregate kWh heating estimate

# Water Heat Energy and Shape



# Aggregate Water Heat and Other



# WH CDA Model Rationale

- WH kWh increases with sq ft regardless of # occupants—sq ft is related to tank size
- Consumption of many end uses increases with # occupants.
- Square root of sq ft & # occupants gives more linear relationship & stronger correlation
- Useful to include refrigerator and "other large use" terms to control for these effects
- Individual HW uses (# baths/week, laundry loads/week) don't help as much as # occupants

# CDA Results (y = baseload kWh/year)

| Variable | Parameter Estimate | P-value | Mean Value of Variable |
|---|---|---|---|
| Intercept | -3691 | <.00001 | |
| Count of Refrigerator and Freezers | 1383 | <.00001 | 1.5 |
| Square Root of Square Feet | 81 | <.00001 | 41.1 |
| Square Root of Count of Residents | 2023 | <.00001 | 1.5 |
| Sq. Rt of Res. Cts by Large Miscellaneous Binary | 923 | <.00001 | 0.2 |
| Electric Hot Water Binary[1] by Sq. Rt. of Sq. Ft. | 49 | <.00001 | 5.6 |

[1]Large Miscellaneous binary indicates Pool Heater, Pond, Well or Pool Pump or Waterbed

- Implies
  - 500 sq ft home with 1 refrigerator, 1 person uses 1522 kWh/year
  - WH kWh/year for average size home around 4000 kWh/year

# Using the CDA Results

- Apply the model to each RASS customer
  - → WH kWh
- Aggregate with RASS weights to get average WH kWh by rate class
  - Conditional on having WH end use
  - Unconditional, accounting for fuel share
- Adjust aggregate result for hidden nonheating

# WH Load Shape

- CDA on LR data unsuccessful
  - Too few cases
- Customers with LR data, good heating/cooling load decomposition, & RASS data
  - → average baseload shape
  - Separately by those with electric WH (EWH) & those without (0WH)
- Scale each baseload shape
- Subtract without-WH shape from with-WH shape to get WH-only shape
  - separately for Summer, Winter kWh

# Scaling

- EWH customers differ from 0WH customers apart from WH
  - →have to estimate non-water-heating base for customers with electric water heating
- Scale
  - EWH baseload shape x EWH baseload kWh
  - →total baseload by hour for EWH customers
  - 0WH baseload shape x (EWH baseload kWh minus WH kWh) for customers with elec WH
  - →baseload excl WH by hour for EWH customers

# Products of the WH Analysis

- Water-heating energy use per customer
  - Annual, summer, and winter
- Non-heating, non-cooling energy use per electric water-heating customer
  - Annual, summer, and winter
- Energy allocation factors for water heating
- Demand allocation factors for water heating

# Lighting kWh

- Annual runtime hours by room type from the NSTAR logger study
- Distribution of room type by dwelling type from the American Housing Survey
- Number of lamps per room and average wattage from the Tacoma lighting study
- Number of rooms by dwelling type from the RASS

# Lighting Load Shape

- Annual kWh allocated to months based on NEES lighting logger study
- Load shapes applied to each monthly energy—weekday, weekend load shapes from the NEES study

# Products of the Lighting Analysis

- Annual, monthly, and seasonal lighting kWh
- Lighting energy allocation factors
- Lighting demand allocation factors

# Results

# Conditional UECs (kWh/year for homes with the end use)

| | Source | | | | | | |
|---|---|---|---|---|---|---|---|
| | This Study | | RECS | | | | DOE (ADL/ KEMA) |
| | RASS Saturation | Conditional UEC | RECS Saturation | Conditional UEC | RECS Year | Area Covered | |
| **Heating** | 25% | 2,145 | 24% | 2,995 | 2001 | Northeast Census Region | |
| **Cooling** | 70% | 772 | 59% | 805 | 2001 | New England Census Division | |
| **Water Heat** | 14% | 2,136 | 26% | 2,149 | 2001 | New England Census Division | |
| **Lighting** | 100% | 2,390 | 100% | 940 | 1993 | U.S. | 1946 |

# Energy Allocation Factor
# (% annual kWh in each TOU period)

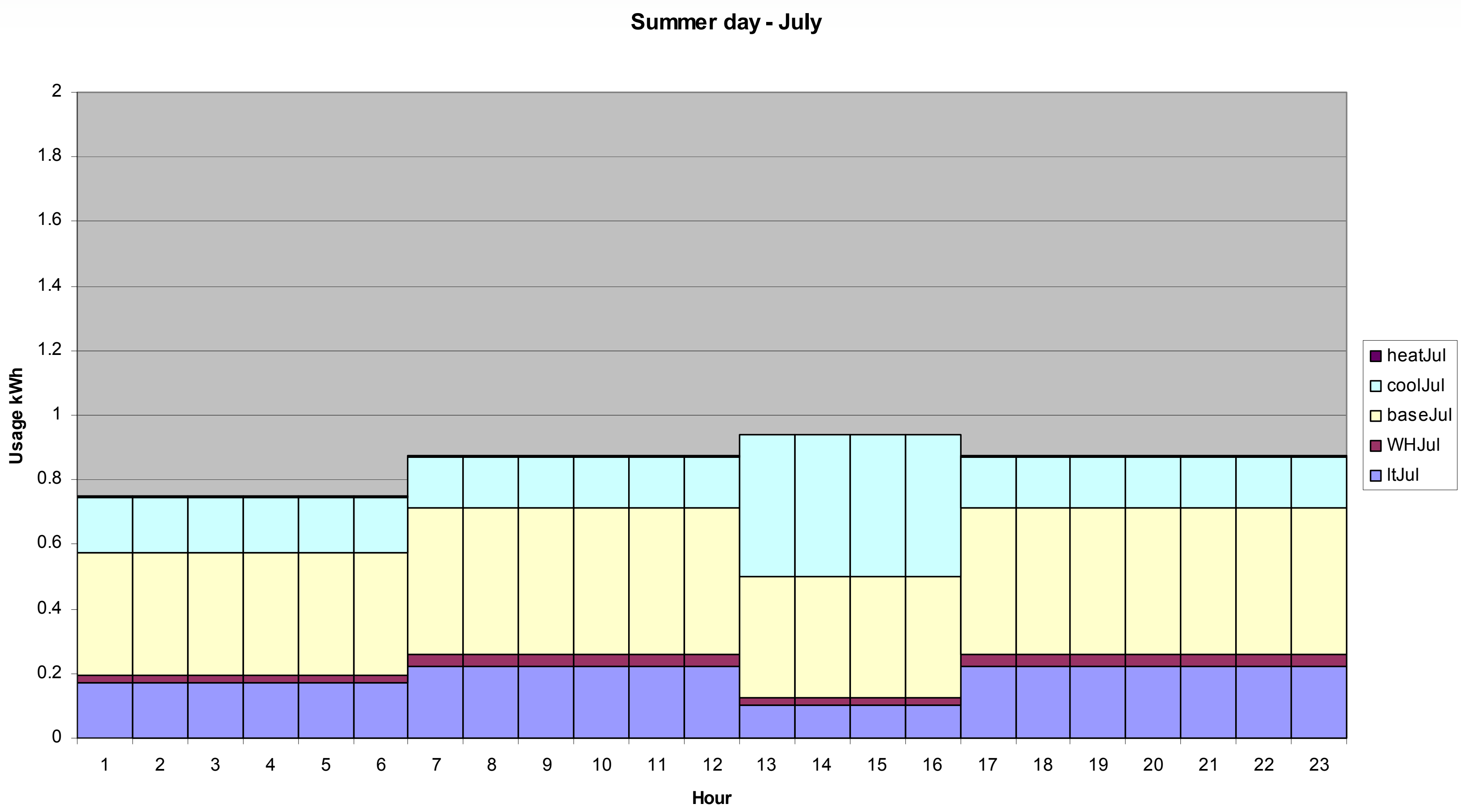
| | Summer June–September | | | Winter October–May | | |
|---|---|---|---|---|---|---|
| | Onpeak 6:00–23:00 weekdays | Offpeak all others | Peak 12:00–16:00 July weekday | Onpeak 6:00–23:00 weekdays | Offpeak all others | Peak 17:00–19:00 January weekday |
| **Heating** | 1% | 1% | 0% | 53% | 45% | 3% |
| **Cooling** | 48% | 47% | 7% | 3% | 3% | 0% |
| **Water Heat** | 17% | 12% | 1% | 43% | 28% | 1% |
| **Lighting** | 13% | 10% | 0% | 42% | 34% | 1% |
| **All Others** | 22% | 18% | 1% | 33% | 27% | 1% |

# Demand Allocation Factors

# (TOU period Avg kW)/(Annual Avg kW)

| | Summer June–September | | | Winter October–May | | |
|---|---|---|---|---|---|---|
| | Onpeak 6:00–23:00 weekdays | Offpeak all others | Peak 12:00–16:00 July weekday | Onpeak 6:00–23:00 weekdays | Offpeak all others | Peak 17:00–19:00 January weekday |
| **Heating** | 0.09 | 0.07 | 0.00 | 1.50 | 1.35 | 5.50 |
| **Cooling** | 2.54 | 2.82 | 7.18 | 0.09 | 0.09 | 0.00 |
| **Water Heat** | 1.06 | 0.70 | 0.68 | 1.27 | 0.85 | 1.16 |
| **Lighting** | 0.82 | 0.63 | 0.37 | 1.23 | 1.03 | 2.86 |
| **All Others** | 1.34 | 1.11 | 1.10 | 0.96 | 0.81 | 1.10 |

# July Weekday



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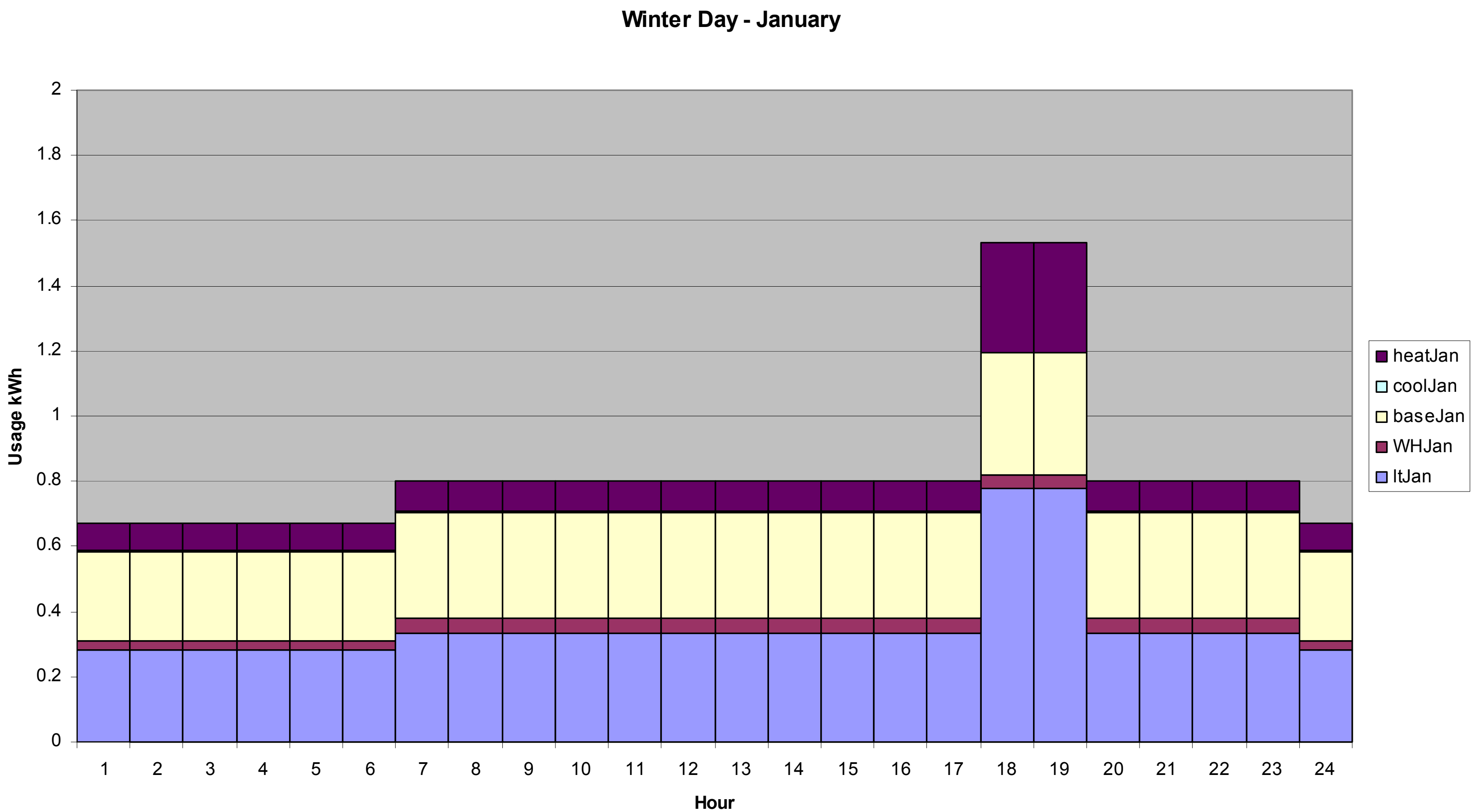
# January Weekday



# Hidden Nonheating

# Adjusting for “Hidden Nonheating”

- Non-heating non-cooling uses have seasonal variation, picked up in DD terms
- Fels & Rachlin (Energy & Buildings 1986) estimate how much of heating coefficient is seasonal variation in other end uses
- Use to adjust heating & nonheating estimates from regressions

# Hidden Nonheating

- Nonheating seasonality is approximately a sine curve
- Heating degree-days are a truncated sine curve
- →Correlation and interference can be estimated from simple information

# Hidden Nonheating Components

- $F_0$ = fraction of days in normal year with temperature < mean htg ref temp.
- $r_u$ = relative variability for end use u
  - $r_u$ = [(max monthly use) – (min monthly use)]/(2 x avg monthly use).
- $E_{u0}$ = uncorrected end-use energy from heating/cooling decomposition.

# Correcting WH & OTHER kWH

- Corrected kWh from decomposition

$$E_u = E_{u0}(1 + r_u \sin(\frac{\pi}{2} F_0))$$

- Overstatement in initial heating estimate

$$d_u = E_u - E_{u0} = E_{u0}(r_u \sin(\frac{\pi}{2} F_0))$$

# Correcting Lighting in Heating Estimate

- Lighting use in the regression baseload

$$E_{u0} = \frac{E_u}{1 + r_u \sin\left(\frac{\pi}{2} F_0\right)}$$

- Lighting use in the initial heating estimate

$$d_u = E_u - E_{u0} = E_u \left( 1 - \frac{1}{1 + r_u \sin\left(\frac{\pi}{2} F_0\right)} \right)$$