LOAD FORECASTING WORKSHOP

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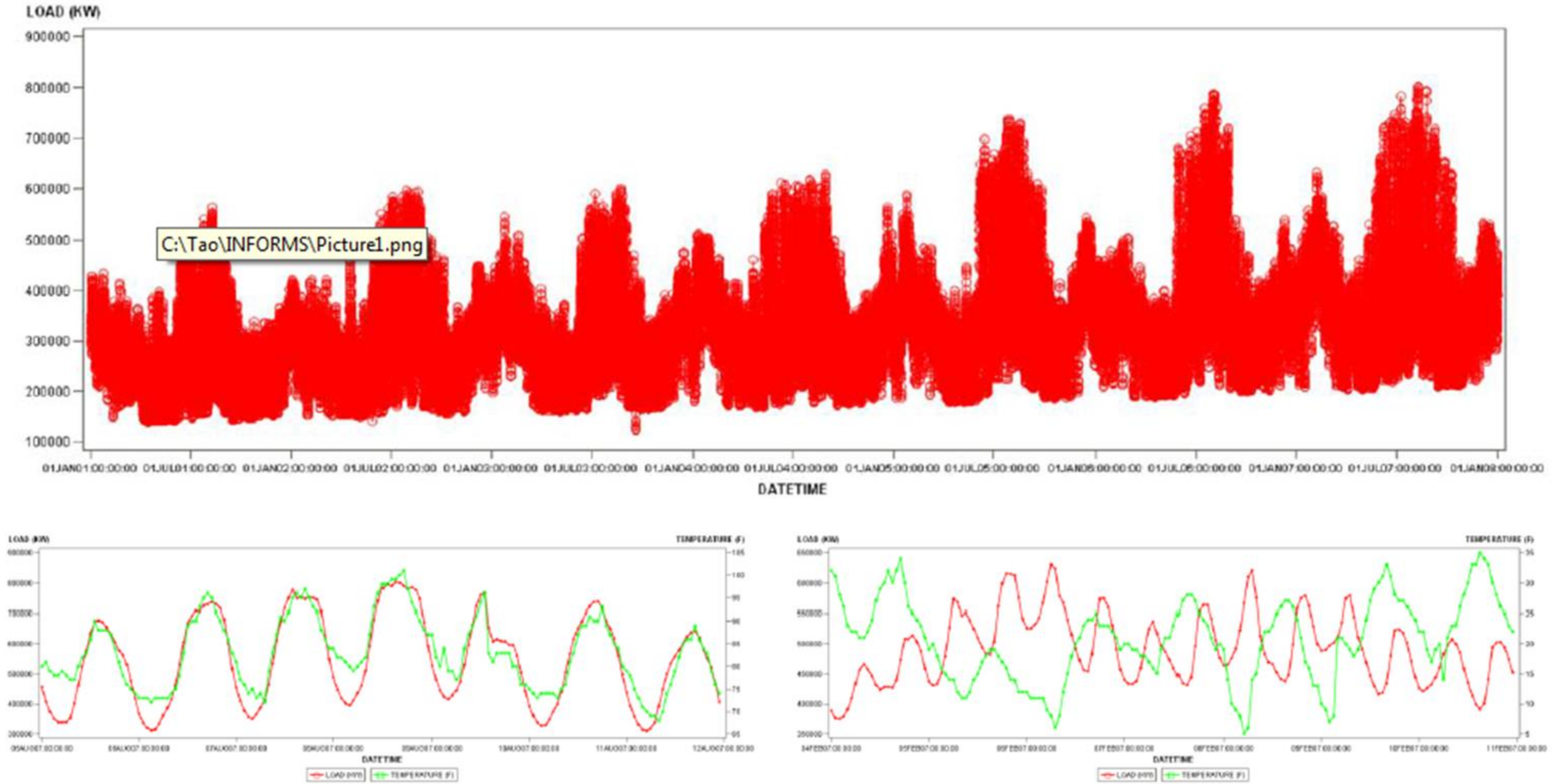
INTRODUCTION TO LOAD FORECASTING

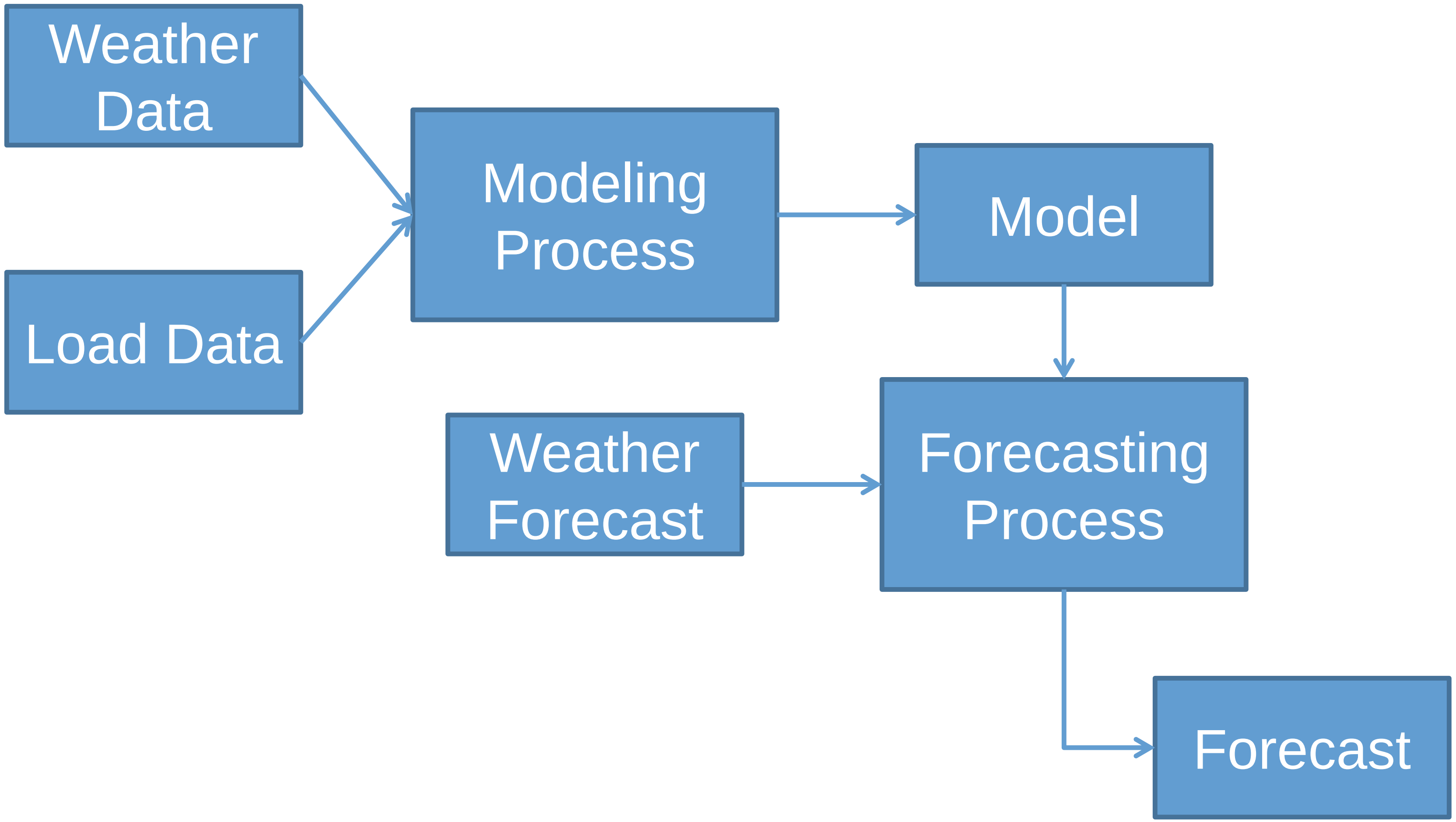
What is Electric Load Forecasting?



Why Electric Load Forecasting?

- National Grid USA is currently seeking an **Analyst in Electric Forecasting and Analysis**:
  - Use econometric and statistical modeling to develop and **analyze short and long term electric peak**, energy and supply forecasts;
  - Develop and **analyze statistical models to segment, profile and model consumers** across operating regions in order to support design solutions and enhance efficiency and operability;
  - Ability to **interact with external customers** including regulators, market operators and other market participants is critical. **Demonstrated experience in working on external teams and/or presenting the Company's position to regulators**, professional organizations and other market entities is preferred.

Load Forecasting Process

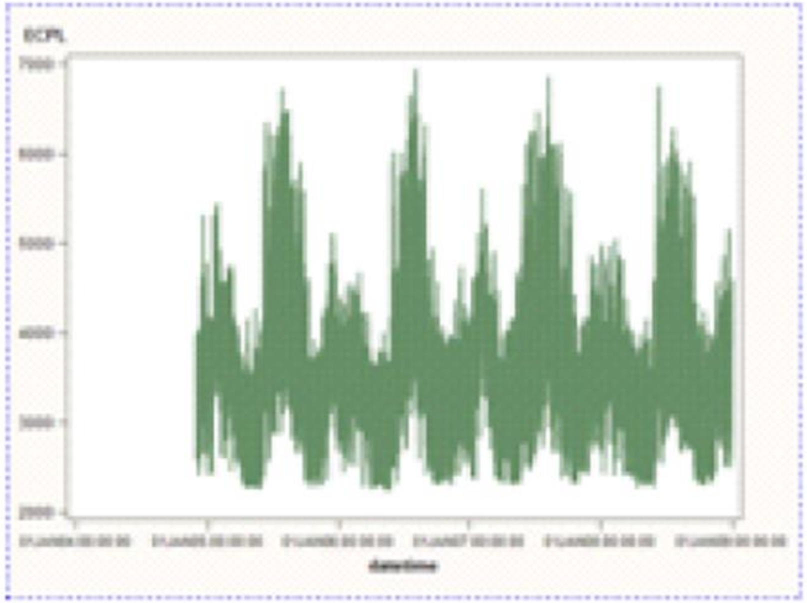


?

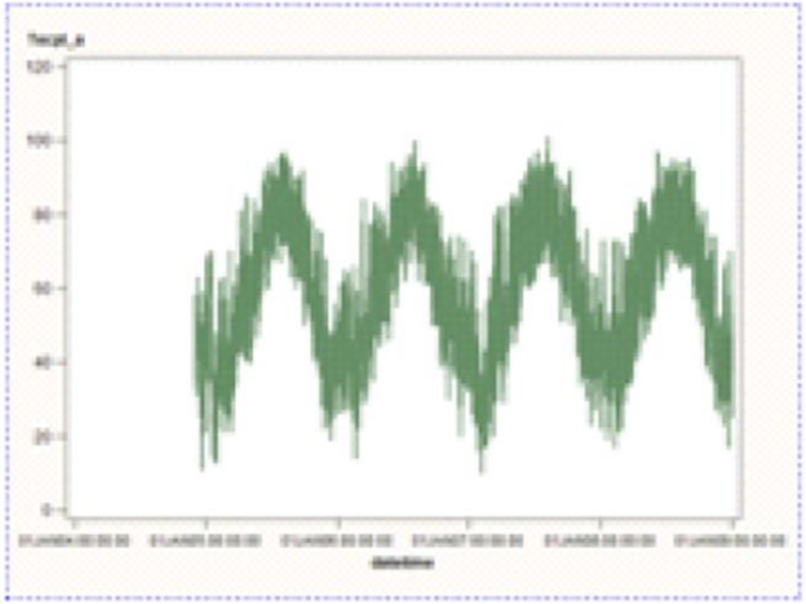
NAÏVE MODEL

Understanding Relationships

4 Years of Load

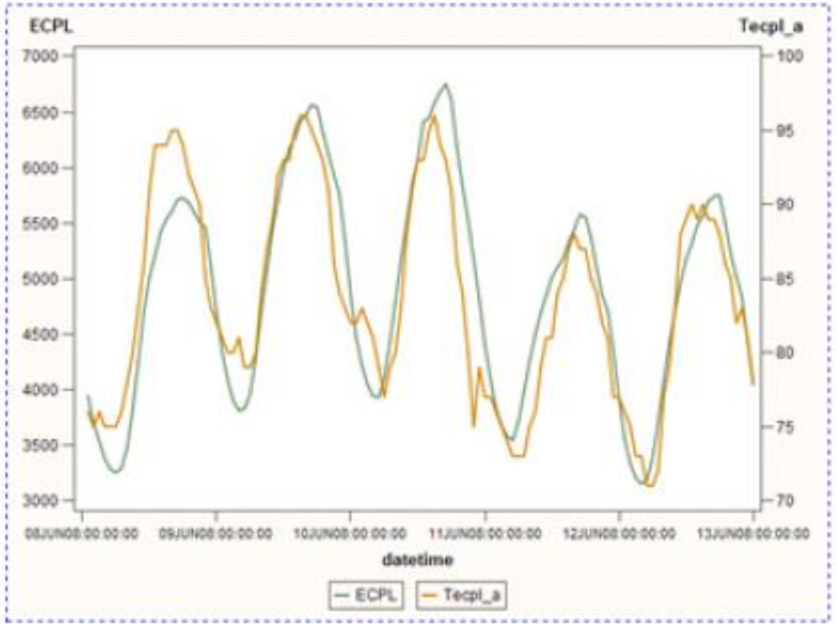


4 Years of Temperature

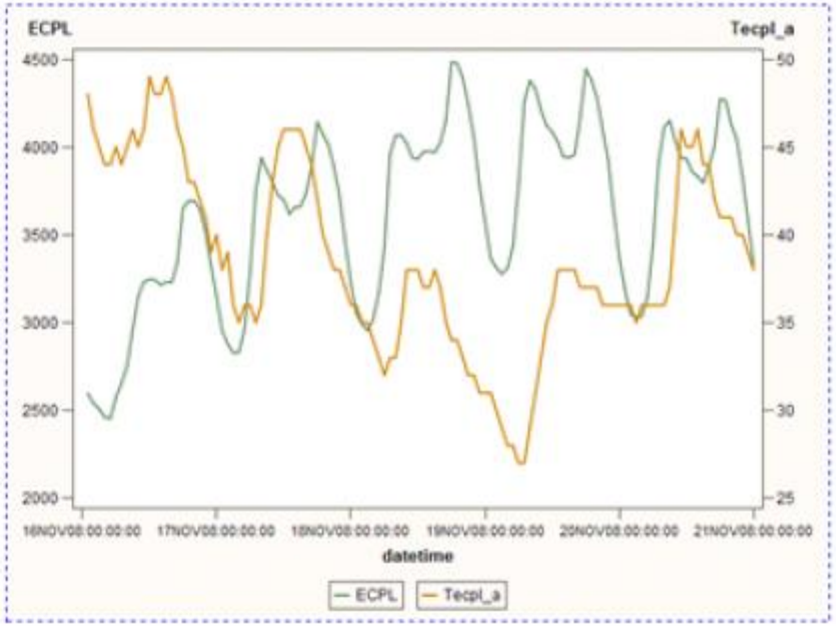


Understanding Relationships

July 8-12



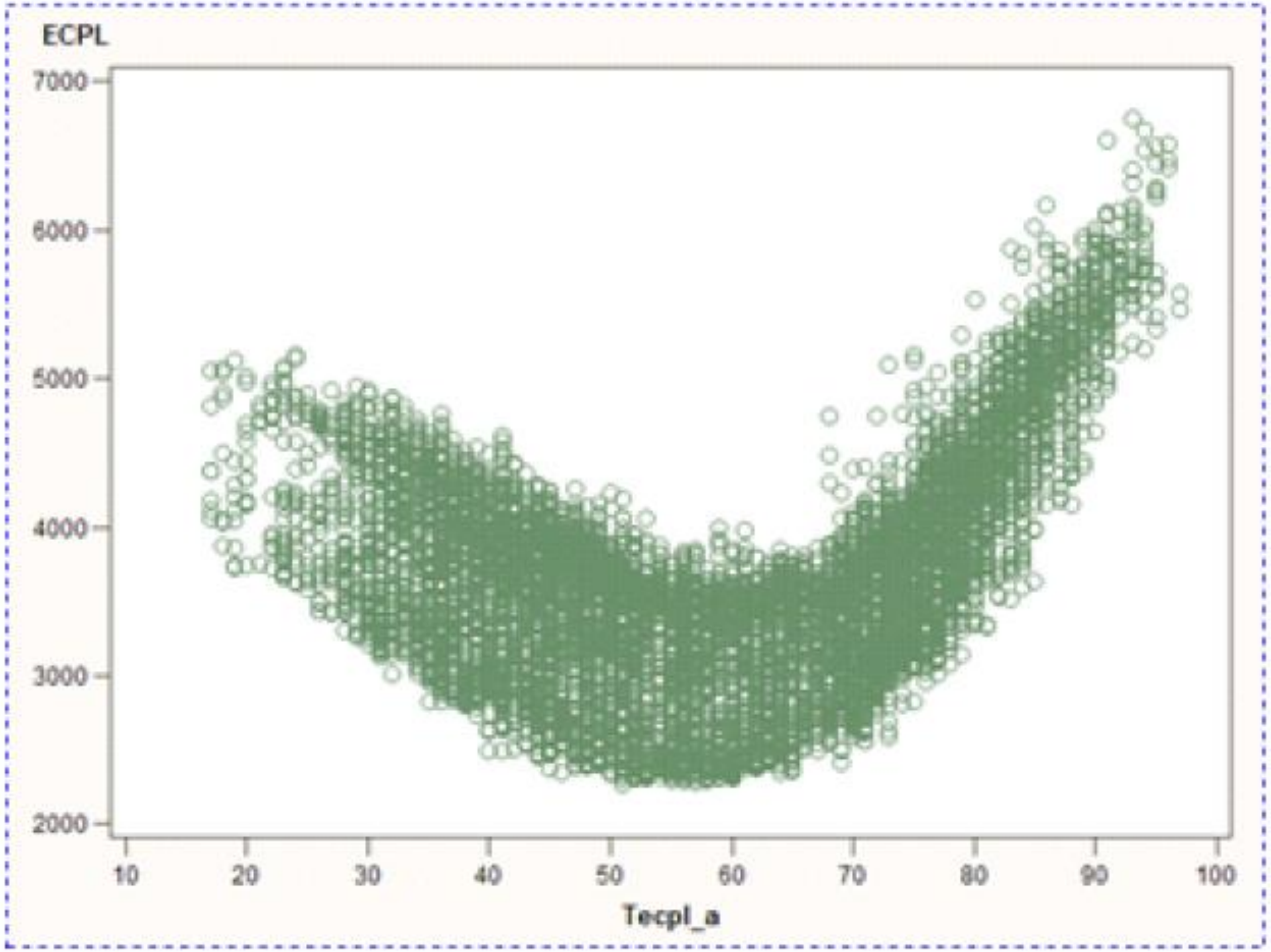
November 16-21



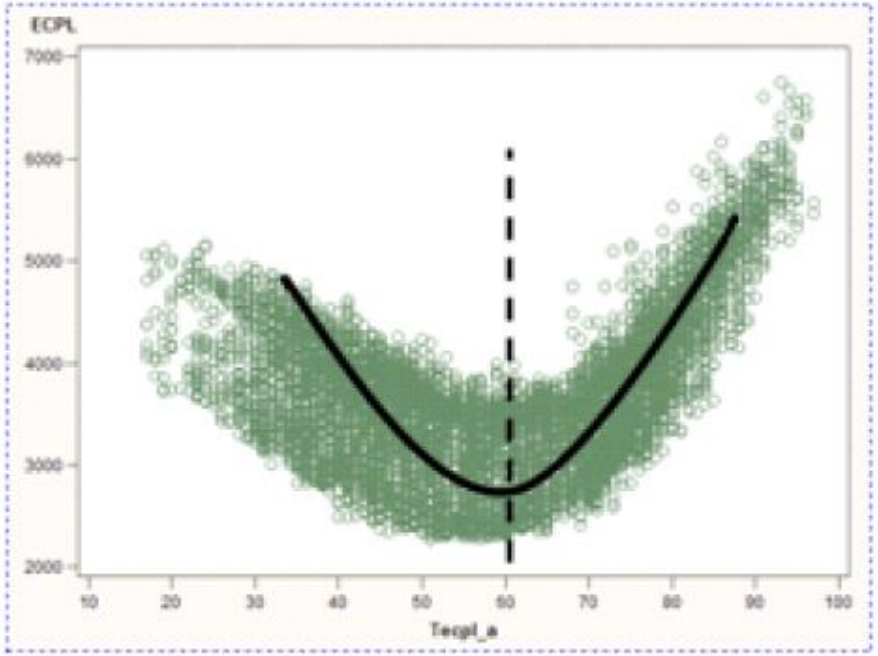
Understanding Relationships

- Typically this data exhibits the following:
  - Trend – energy usage increases / decreases over time
  - Seasonality
    - Year to Year?
    - Day to Day
    - Week to Week!

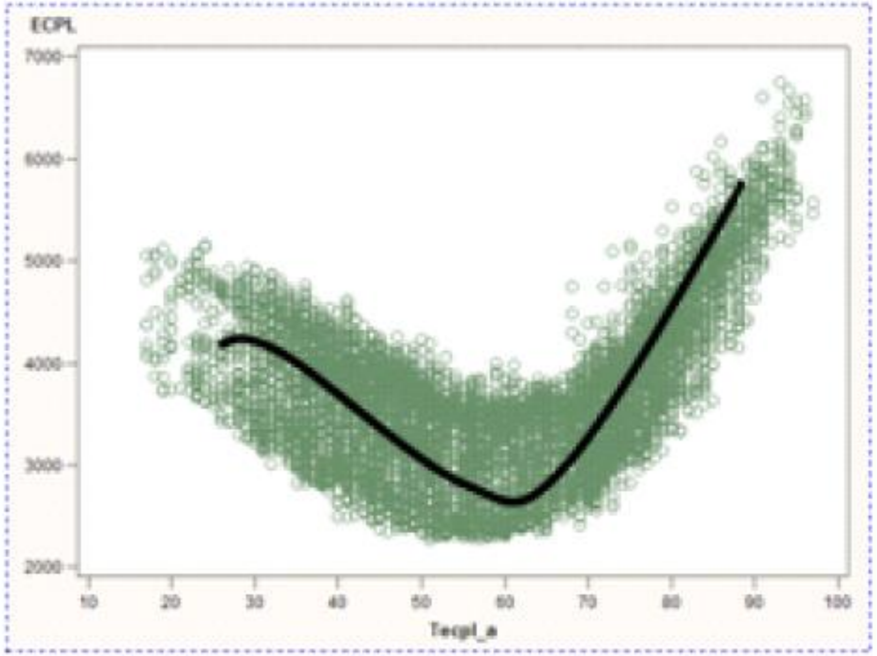
Load-Temperature Relationship



Load-Temperature Relationship

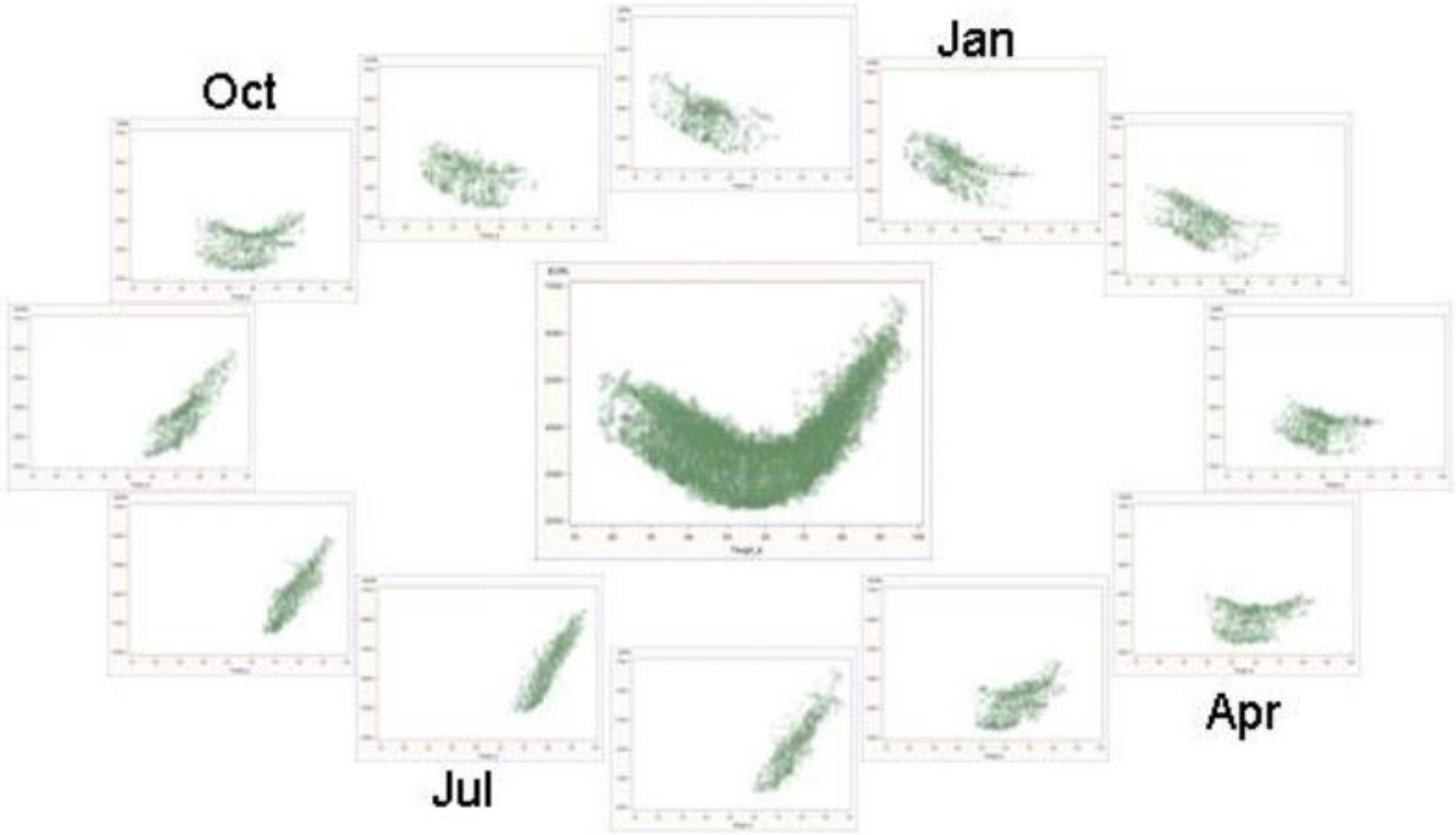


2nd order – symmetric

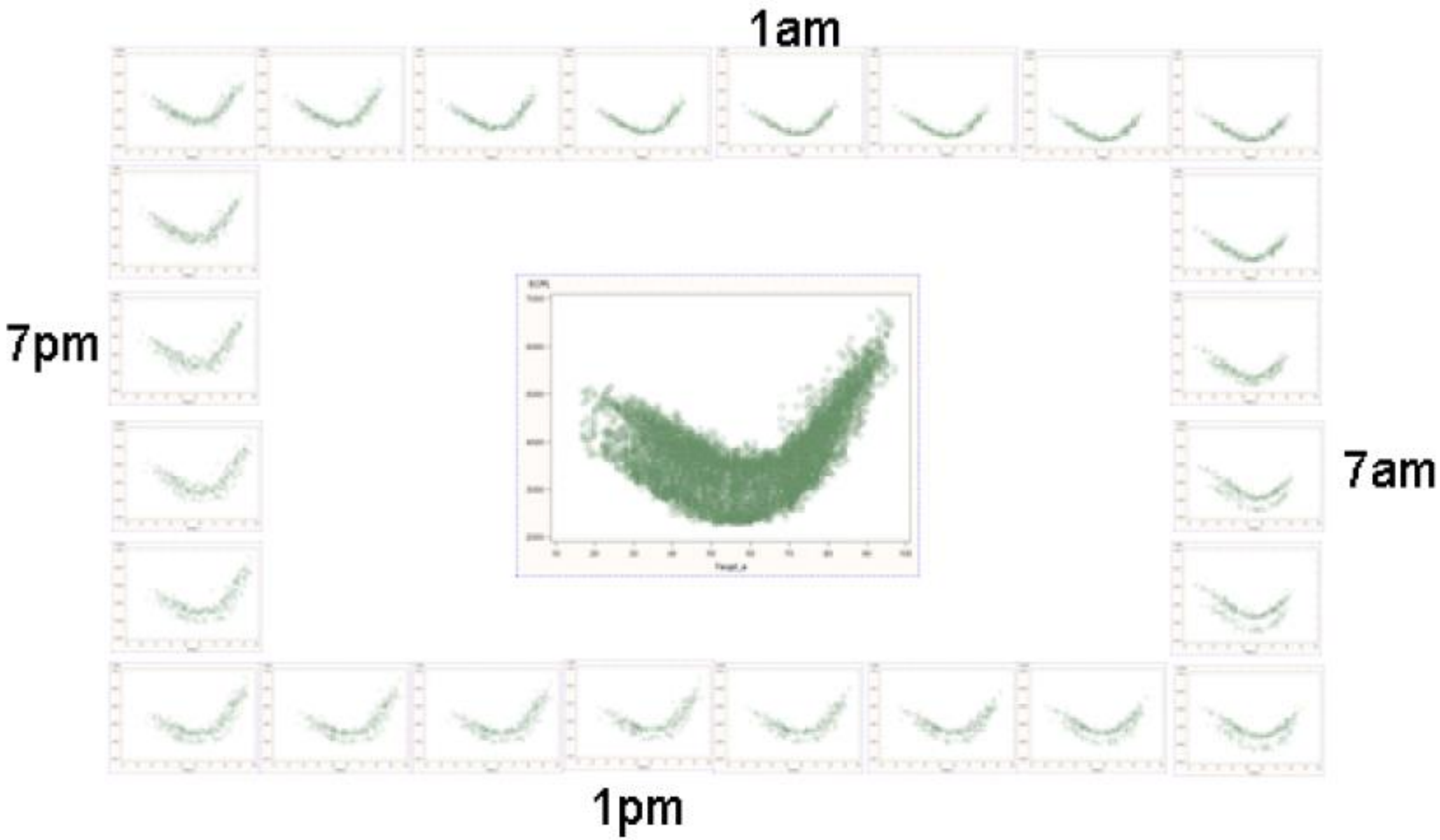


3rd order – asymmetric

Load-Temperature Relationship



Load-Temperature Relationship



Naïve Load Model

- The following variables would be in the naïve load forecasting model:
  - Interaction of Day & Hour
  - Month
  - Trend
  - “Temperature”: T, T^2, T^3
  - Interaction of “Temperature” and Hour
  - Interaction of “Temperature” and Month

Naïve Load 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 MODEL

Recency Effect

- The phenomenon that when people are asked to recall in any order the items on a list, those that come at the end of the list are more likely to be recalled than the others.

- We can apply this thinking to modeling as well:
  - Previous values of **temperature** might effect the current value of **load**.
  - T(t-1) refers to the temperature at lag one, T(t-2) refers to the temperature at lag two, …

Recency Effect Load Model

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

Recency Effect Load Model

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$$\boxed{\begin{aligned}&+ \beta_{10} * Month * T(t-1) + \beta_{11} * Month * T(t-1)^2 + \beta_{12} * Month * T(t-1)^3\\&+ \beta_{13} * Hour * T(t-1) + \beta_{14} * Hour * T(t-1)^2 + \beta_{15} * Hour * T(t-1)^3\end{aligned}}$$

DYNAMIC TIME SERIES MODEL

Dynamic Time Series Load Model

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

+ TIME SERIES RESIDUALS

Dynamic Time Series Load Model

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\begin{aligned}
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 \\
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\end{aligned}
$$

+ TIME SERIES RESIDUALS

ARIMA / ESM / Neural Network

ESM Example

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

Exponential Smoothing Model

ESM Example

$$
\begin{aligned}
E(\text{Load}) = {} & \beta_0 + \beta_1 * \text{Trend} + \beta_2 * \text{Day} * \text{Hour} + \beta_3 * \text{Month} \\
& + \beta_4 * \text{Month} * T + \beta_5 * \text{Month} * T^2 + \beta_6 * \text{Month} * T^3 \\
& + \beta_7 * \text{Hour} * T + \beta_8 * \text{Hour} * T^2 + \beta_9 * \text{Hour} * T^3 \\
& + \beta_{10} * \text{Month} * T(t\text{-}1) + \beta_{11} * \text{Month} * T(t\text{-}1)^2 + \beta_{12} * \text{Month} * T(t\text{-}1)^3 \\
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& + Z_t
\end{aligned}
$$

$$\hat{Z}_{t+k} = L_t + kT_t + S_{t-p+k}$$

$$L_t = \theta\left(Z_t - S_{t-p}\right) + (1-\theta)(L_{t-1} + T_{t-1})$$

$$T_t = \gamma(L_t - L_{t-1}) + (1-\gamma)T_{t-1}$$

$$S_t = \delta(Z_t - L_t) + (1-\delta)S_{t-p}$$

ARIMA Example

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$$+ Z_t$$

$$\hat{Z}_t = \omega + \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \cdots + \theta_q \varepsilon_{t-q}$$

NN Example – k Hidden Nodes

$$
\begin{aligned}
E(\text{Load}) = {} & \beta_0 + \beta_1 * \text{Trend} + \beta_2 * \text{Day} * \text{Hour} + \beta_3 * \text{Month} \\
& + \beta_4 * \text{Month} * T + \beta_5 * \text{Month} * T^2 + \beta_6 * \text{Month} * T^3 \\
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& + Z_t
\end{aligned}
$$

$$
\begin{aligned}
\hat{Z}_t = {} & \omega_0 + \omega_1 f\left(\omega_{1,1} Z_{t-1} + \cdots + \omega_{1,p} Z_{t-p}\right) \\
& + \omega_2 f\left(\omega_{2,1} Z_{t-1} + \cdots + \omega_{2,p} Z_{t-p}\right) \\
& + \cdots + \omega_k f\left(\omega_{k,1} Z_{t-1} + \cdots + \omega_{k,p} Z_{t-p}\right)
\end{aligned}
$$

OTHER APPROACHES & NUANCES

How Much Data to Use?

- Only recent data for the forecasting period
  - Advantages – No Need for Complicated Interaction Model, Easier Hypothesis Test α Levels
  - Disadvantages – Not Generalizable, Proxies for Holidays / Other Interventions Not in Data

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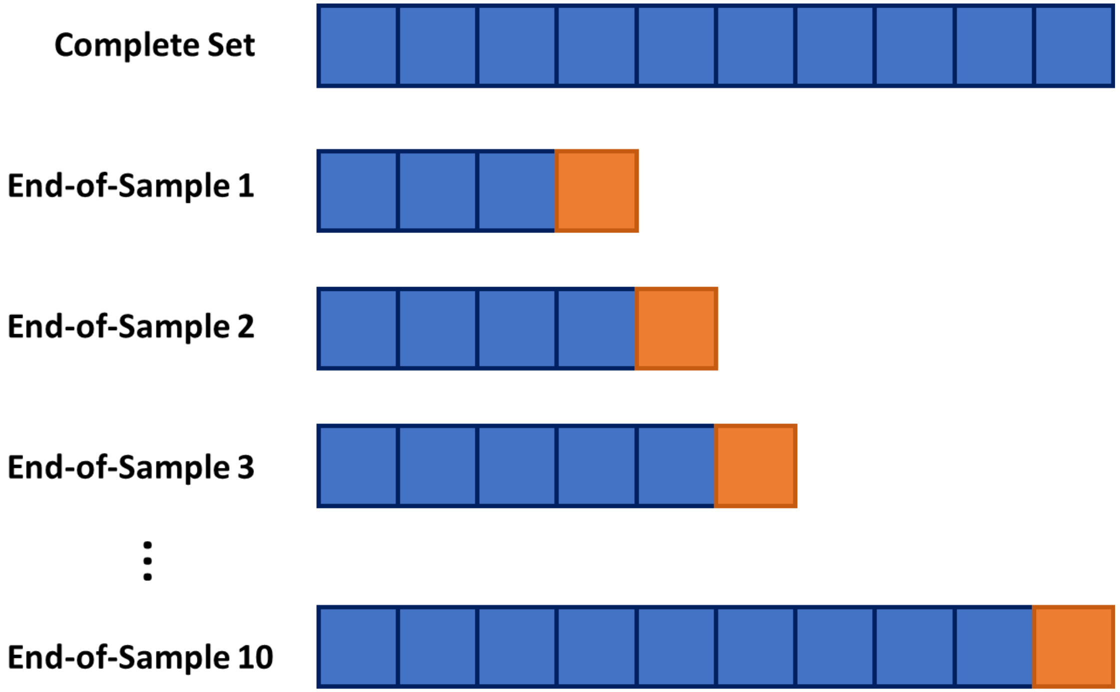
- Use long history
  - Advantages – Generalizable Model, Model has Seen Many Different Interventions Previously
  - Disadvantages – Complicated Interactions, Hypothesis Test α Levels Difficult

End-of-Data Hold Out Sample

- Cannot randomly sample from different points in time.
- Sample isolated to end of data set.

Rolling Hold-out Samples

- Comparable to k-fold cross-validation.
- Rolling windows of same length to predict.
- Can be as small as one observation.



Seasonal ARIMA Models

- Only use stochastic differences to account for the seasonality in the model.
  - Advantages – Temperature (and its forecast) is NOT needed.
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- Use deterministic methods to account for the seasonality in the model.
  - Advantages – More Accurate Long Term
  - Disadvantages – Need Accurate Forecasts of Temperature

Temperature Forecasting

- One problem with using temperatures is that you need accurate forecasts of temperatures for accurate forecasts of load.
  - Weather data typically available.
  - Could forecast own temperatures.

Temperature Forecasting

- What temperature data did you use when you calculated MAPE in your validation data set?

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  - What might be the problem here?

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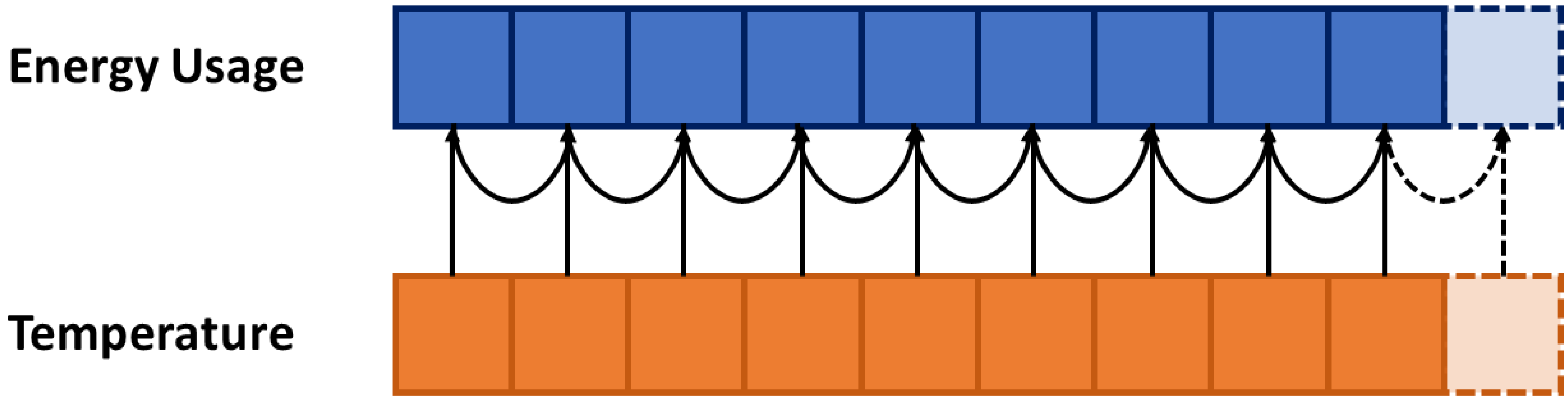
- What temperature data did you use in your actual forecasts?

Look Ahead Bias

- Temporal structure of data can lead to inherent biases.
- **Look ahead bias** – using unknown information in prediction of model.



Temperature Forecasting

- What temperature data did you use when you calculated MAPE in your validation data set?
  - Actual?
  - What might be the problem here?

- What temperature data did you use in your actual forecasts?
  - LOOK AHEAD BIAS! → MAPE's ARE TOO LOW!!

Intervention Analysis

- Weekends
  - Saturday and Sunday are inherently different than the rest of the week.

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  - Does your model depend on what happened 24 hours ago?

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  - Lags of 24 hours throw off the models around weekends because of the severe drop.
  - Lags of 168 hours would correct this problem.

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  - Lags of 168 hours would correct this problem.

Typically think of bigger seasons into smaller Seasons.

Intervention Analysis

- Holidays
  - If Monday is holiday, do we treat Tuesday as a typical Monday?
  - If Friday is a holiday, do we treat Saturday differently?
  - Are all Friday holidays actually holidays in the sense of load?
  - What to do with data sets without holidays?
    - Are weekends like holidays?

Intervention Analysis

- Severe Weather Outages
  - Hurricanes
  - Snow Storms
  - Polar Vortex
    - Are we in normal November weather?
    - Should our model be treated like another month of year?
- Outliers