Measurement, Modeling, Analysis and Reporting Protocols for Short-term M&V Of Whole Building Energy Performance

ASHRAE RP-1404

Principal Investigator:

Bass Abushakra, Ph.D., Associate Professor

Civil and Architectural Engineering and Construction Management Department

Milwaukee School of Engineering

Milwaukee, WI

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ASHRAE Chicago Chapter

Executive Summary

Developing analysis methodologies by which the time period for field monitoring of energy use in buildings can be reduced to less than a whole year while satisfying preset accuracy levels of annual energy performance verification.

Cost effective alternative for ESCO's, and energy professionals.

Application areas of the methodology are: Detailed Audits, Green Building Performance Verification, and Verification of Post-Retrofit Claims using Pre-Post Monitored Data.

Executive Summary

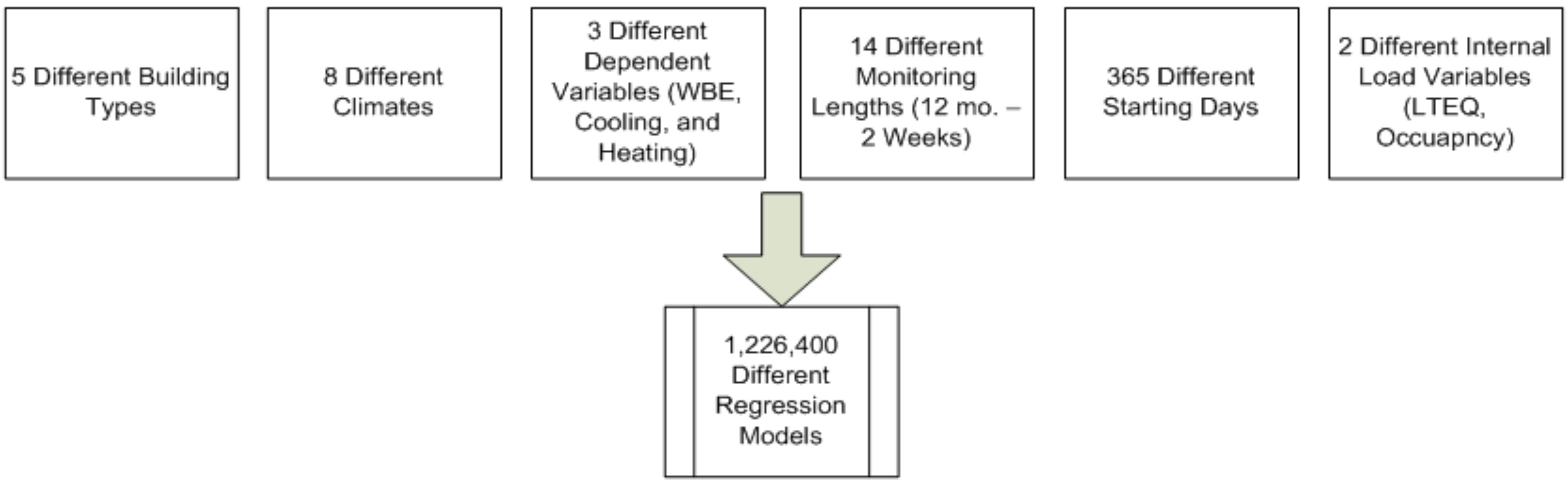
The research revealed the following:

1- Two weeks of hourly monitored data can be adequate for producing accurate long-term whole building energy predictions, provided the monitoring is taken at a correct time.

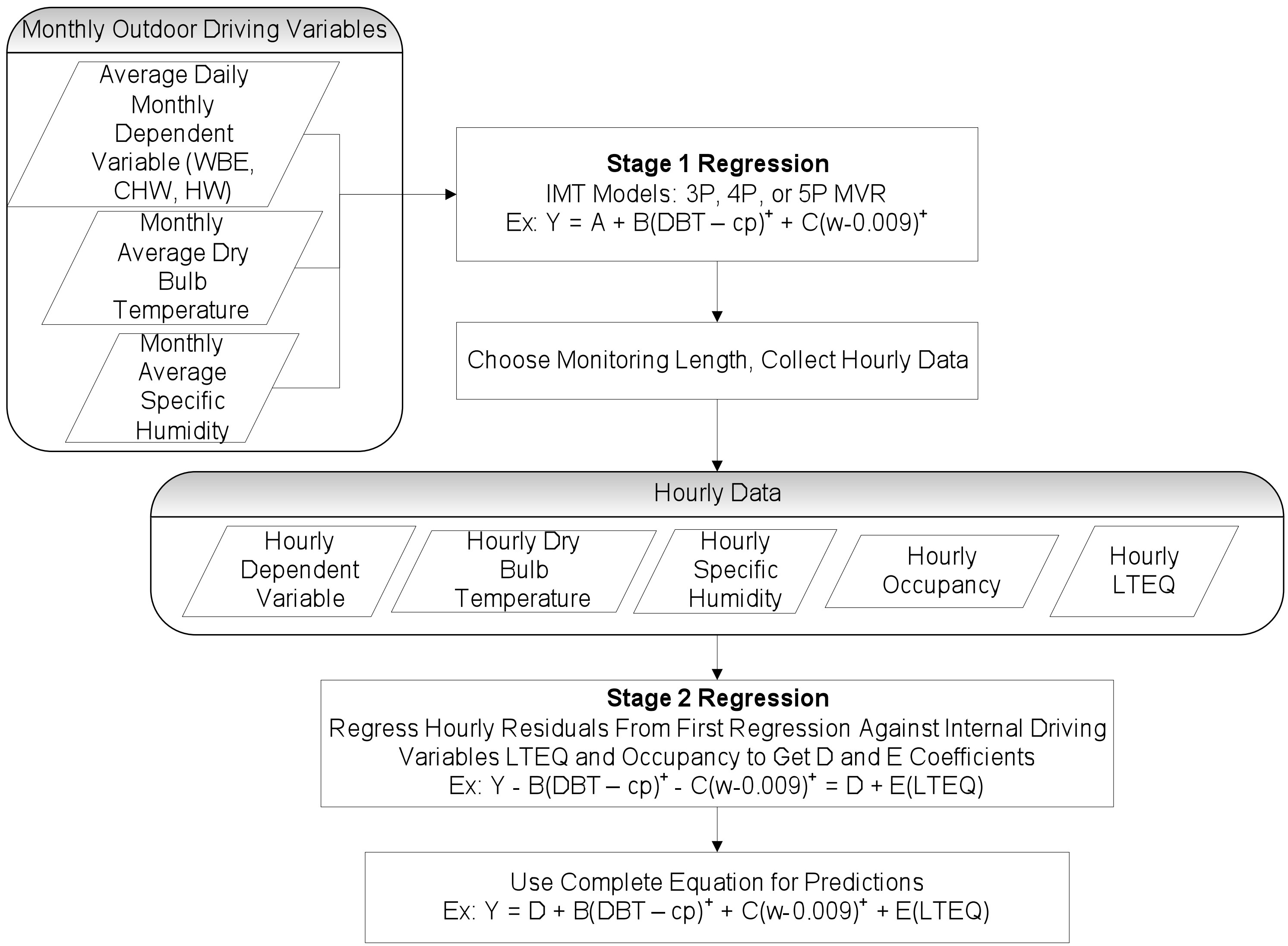
2- Adding more data to the regression model (extending the length of the short-term monitoring period) can, contrary to intuition, make the predictive model much poorer.

3-The proper monitoring period is highly dependent on the time at which the data is taken, with the best time to collect data being during the swing seasons.

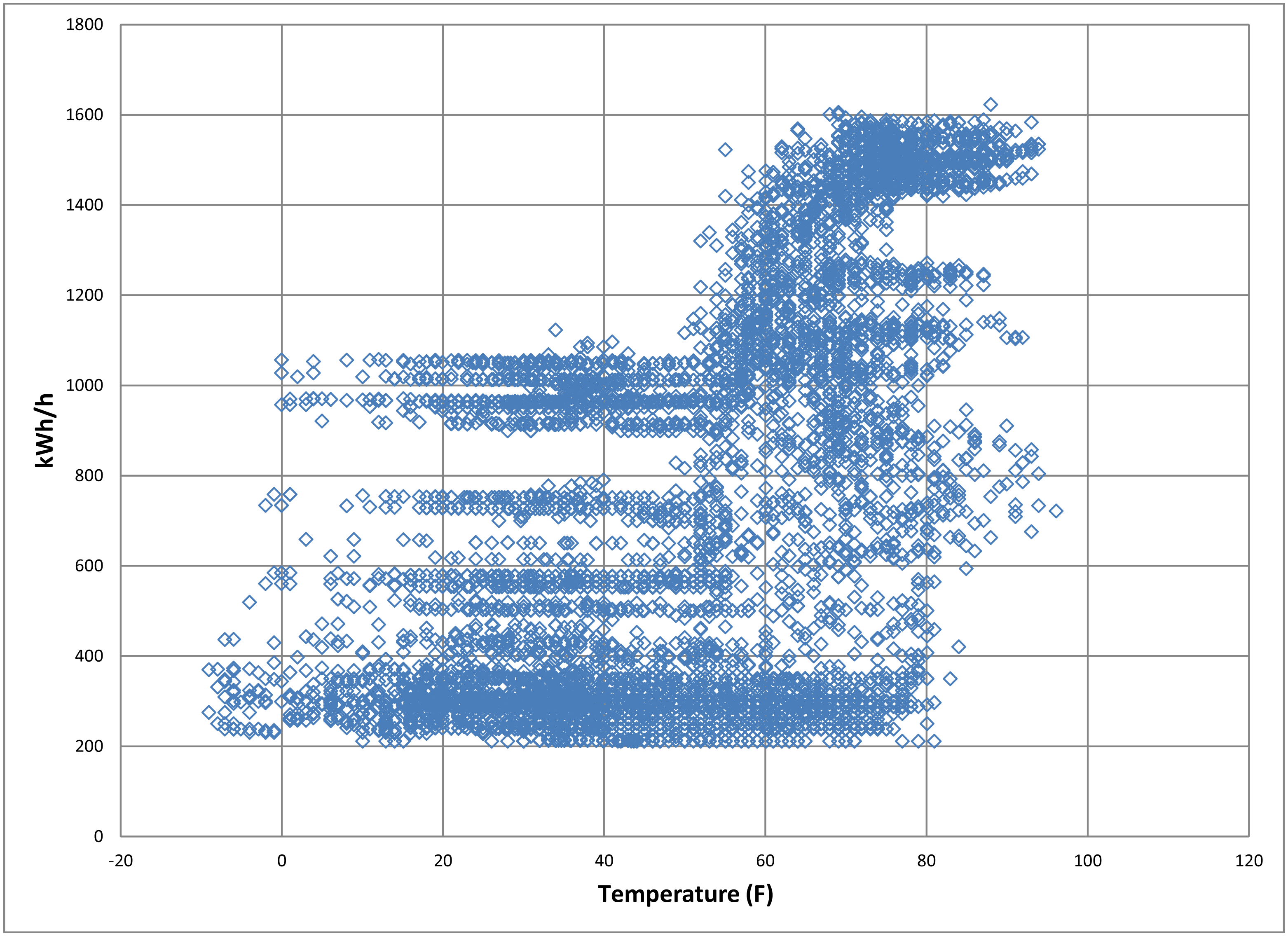
Hourly Hybrid Multivariate Change Point Models Tested



Hourly Hybrid Multivariate Change Point Model Flowchart



Large Office Building located in Chicago - WBE



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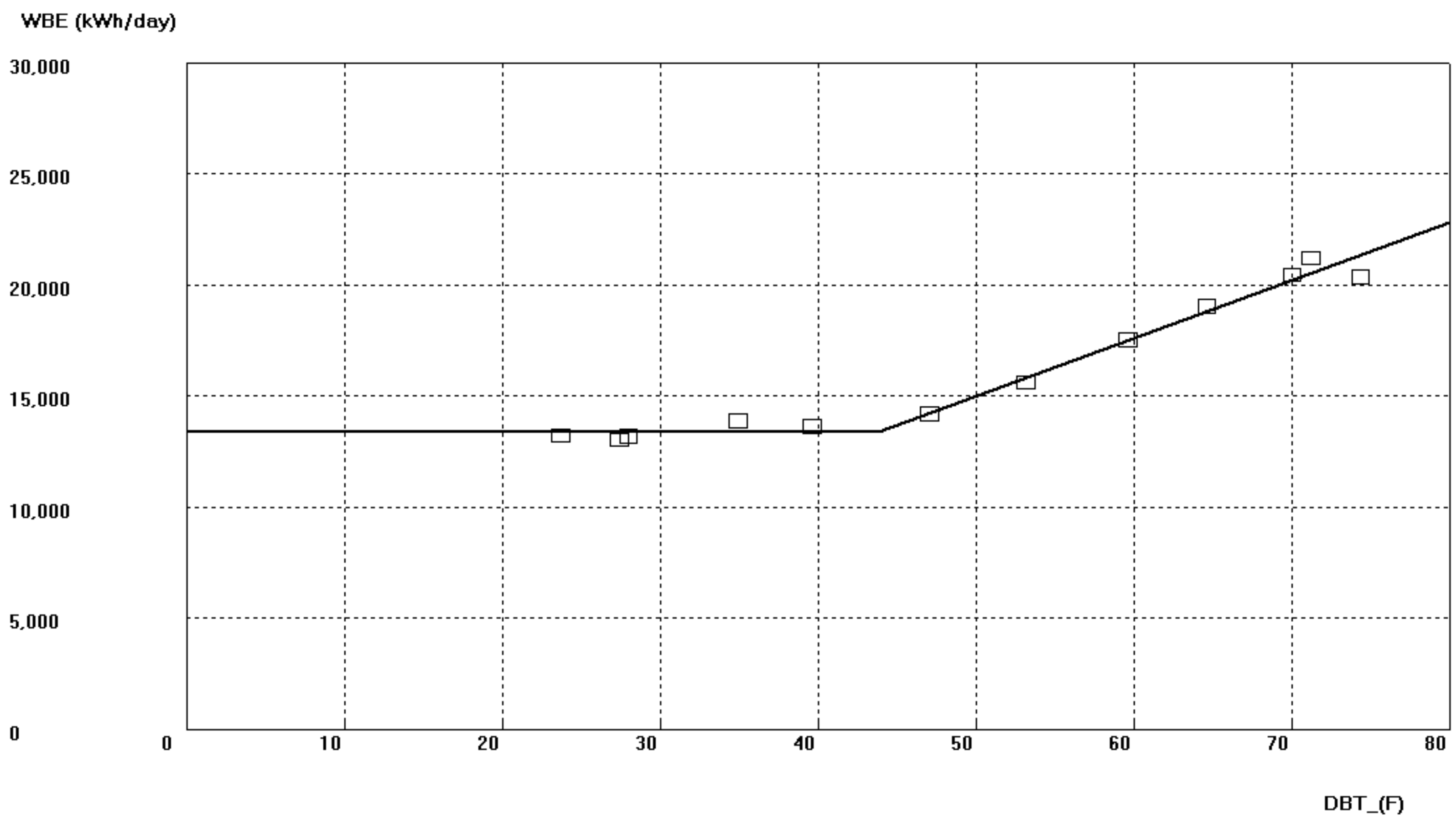


Large Office Building located in Chicago - WBE

$$Y = A + B\left(DBT - cp\right)^{+}$$

$$WBE_{(kWh/day)} = 13{,}393 + 259.7\left(DBT_{(F)} - 43.8\right)^{+}$$

$$\text{Hourly Residuals} = Y - \left(B/24\right)\left(DBT - cp\right)^{+}$$

$$\text{Hourly Residuals} = WBE_{(kWh/h)} - \left(259.7/24\right)\left(DBT_{(F)} - 43.8\right)^{+}$$

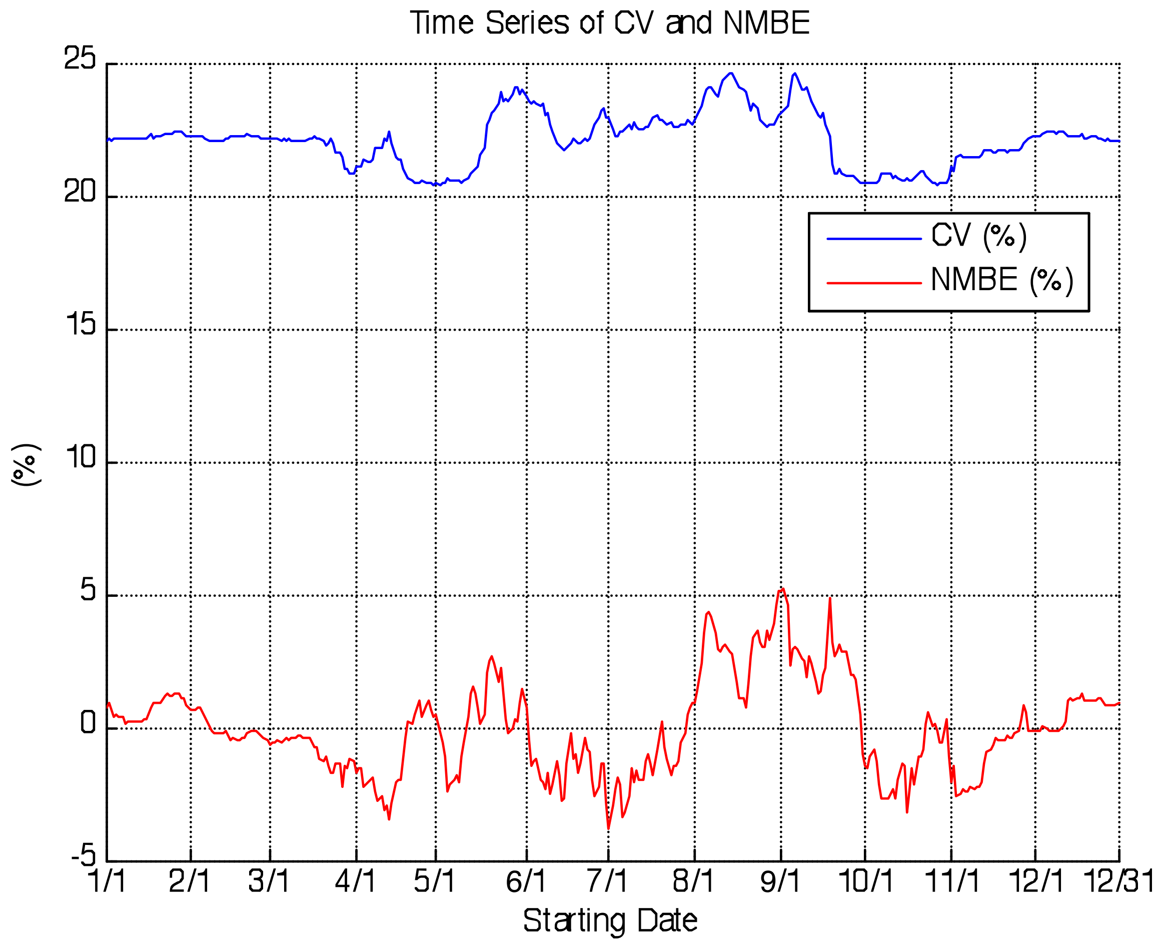
$$\text{Hourly Residuals} = D + E\left(LTEQ\right)$$

$$\text{Hourly Residuals} = 17 + 1.2\left(LTEQ_{(kWh/h)}\right)$$

$$\text{Final Model: } Y = D + \left(B/24\right)\left(DBT - cp\right)^{+} + E\left(LTEQ\right)$$

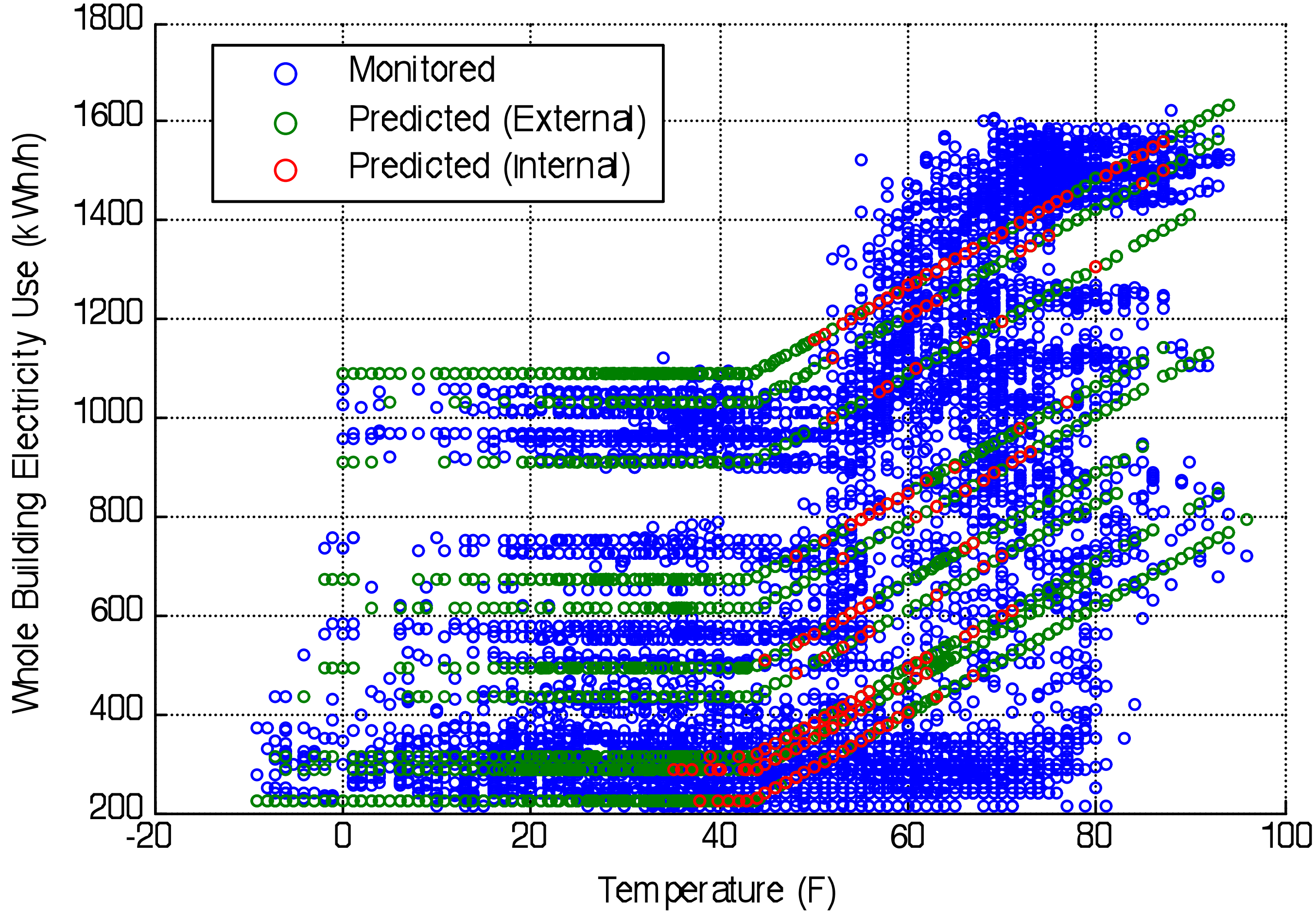
$$\text{Final Model: } WBE_{(kWh/h)} = 17 + \left(259.7/24\right)\left(DBT_{(F)} - 43.8\right)^{+} + 1.2\left(LTEQ_{(kWh/h)}\right)$$

Large Office Building located in Chicago - WBE



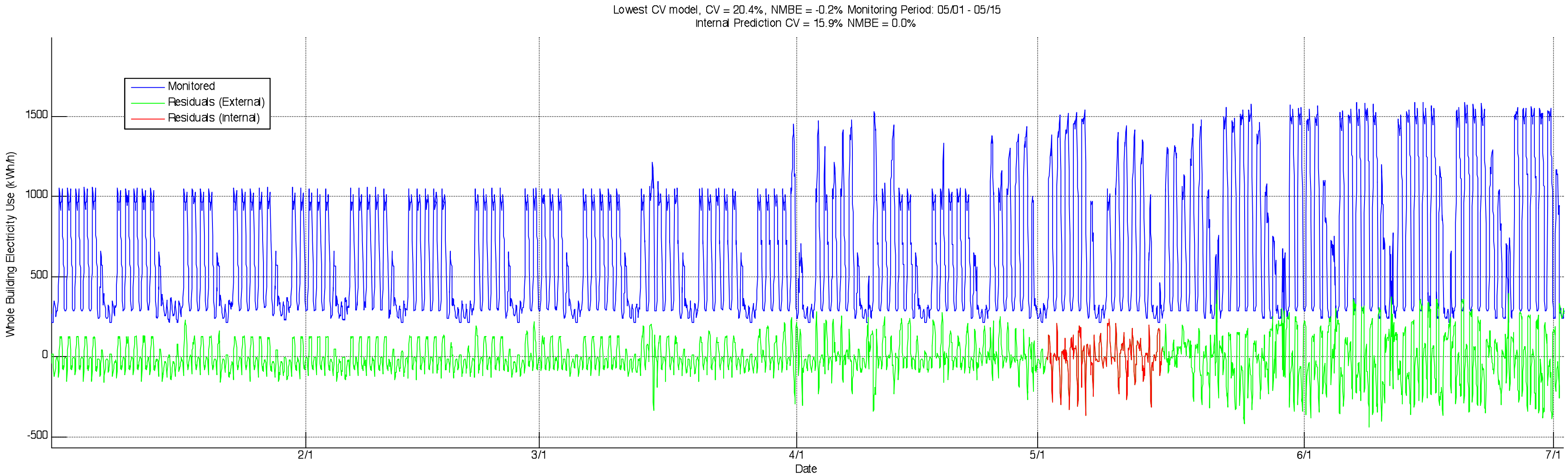
Large Office Building located in Chicago- WBE

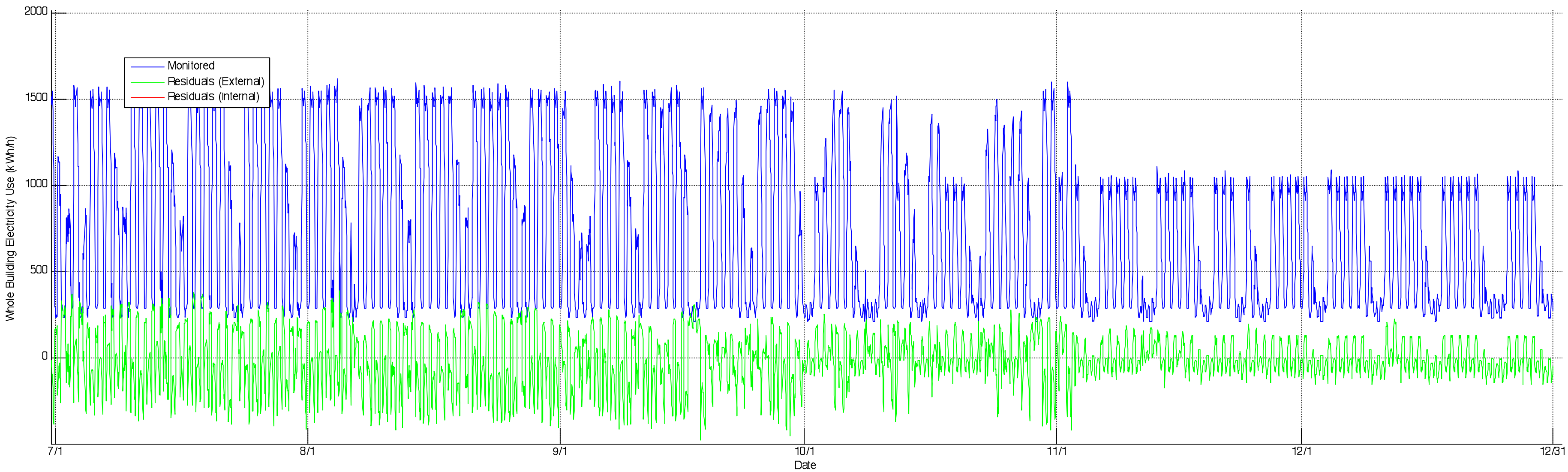
Lowest CV model, CV = 20.4%, NMBE = -0.2% Monitoring Period: 05/01 - 05/15
Internal Prediction CV = 15.9% NMBE = 0.0%



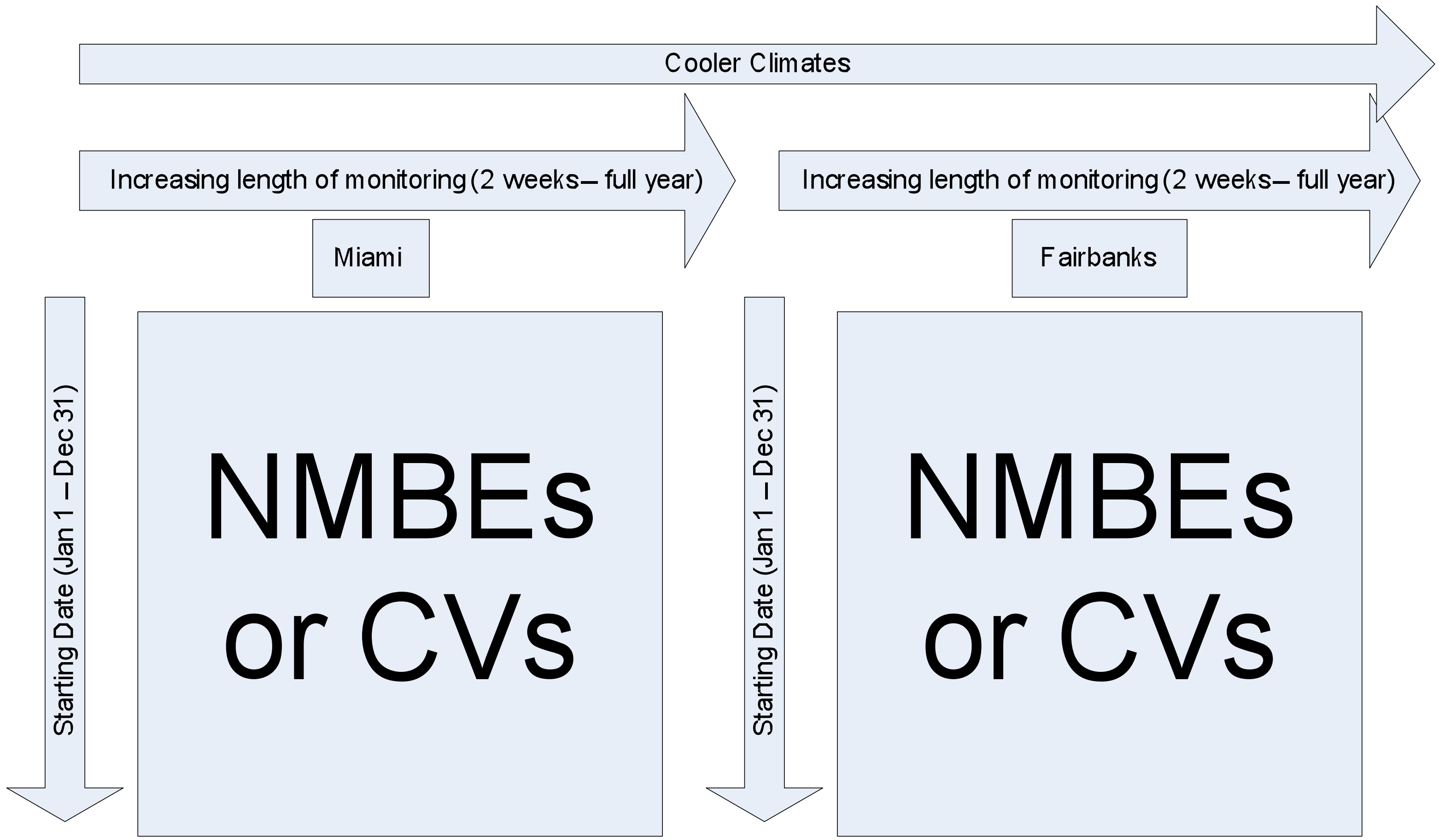
Equation: $E = (260/24)(T-43.8)^{+} + (0/24)(43.8-T)^{+} + 1.2(LTEQ) + 17$

Large Office Building located in Chicago - WBE





Color Area Plots



Color Area Plots (CAP's)

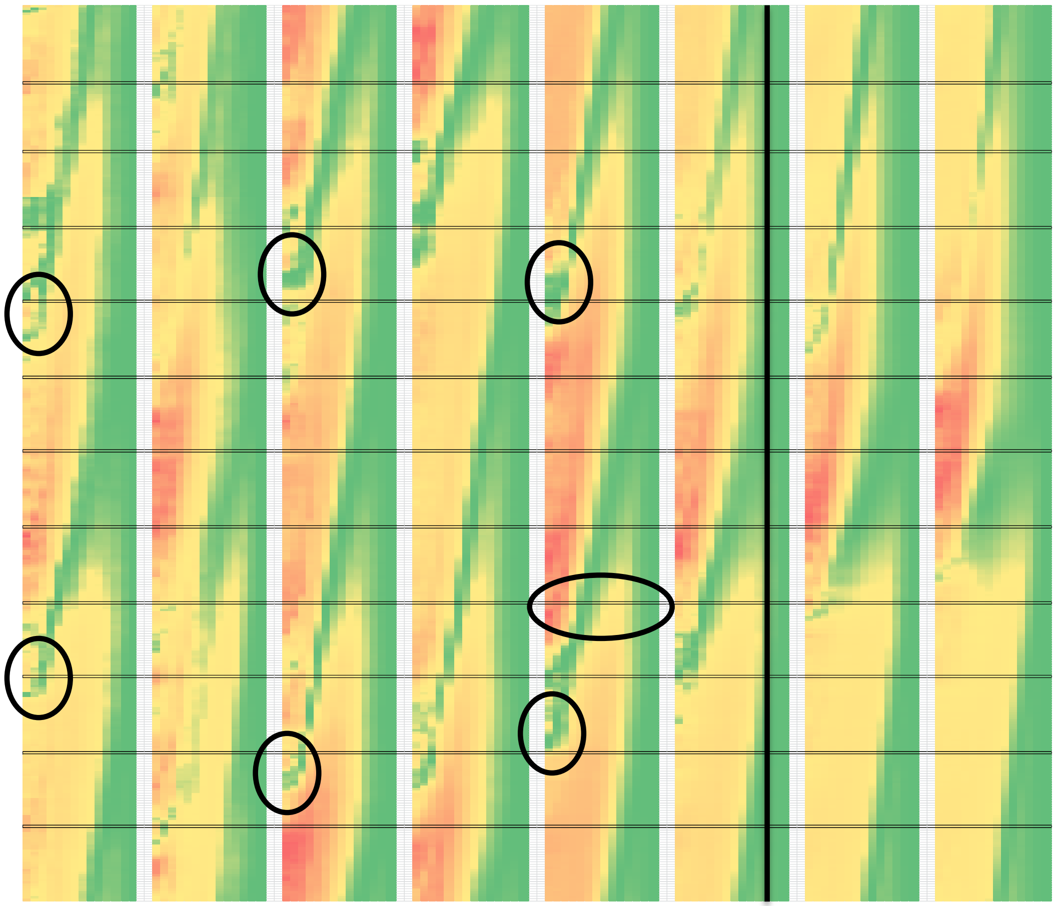
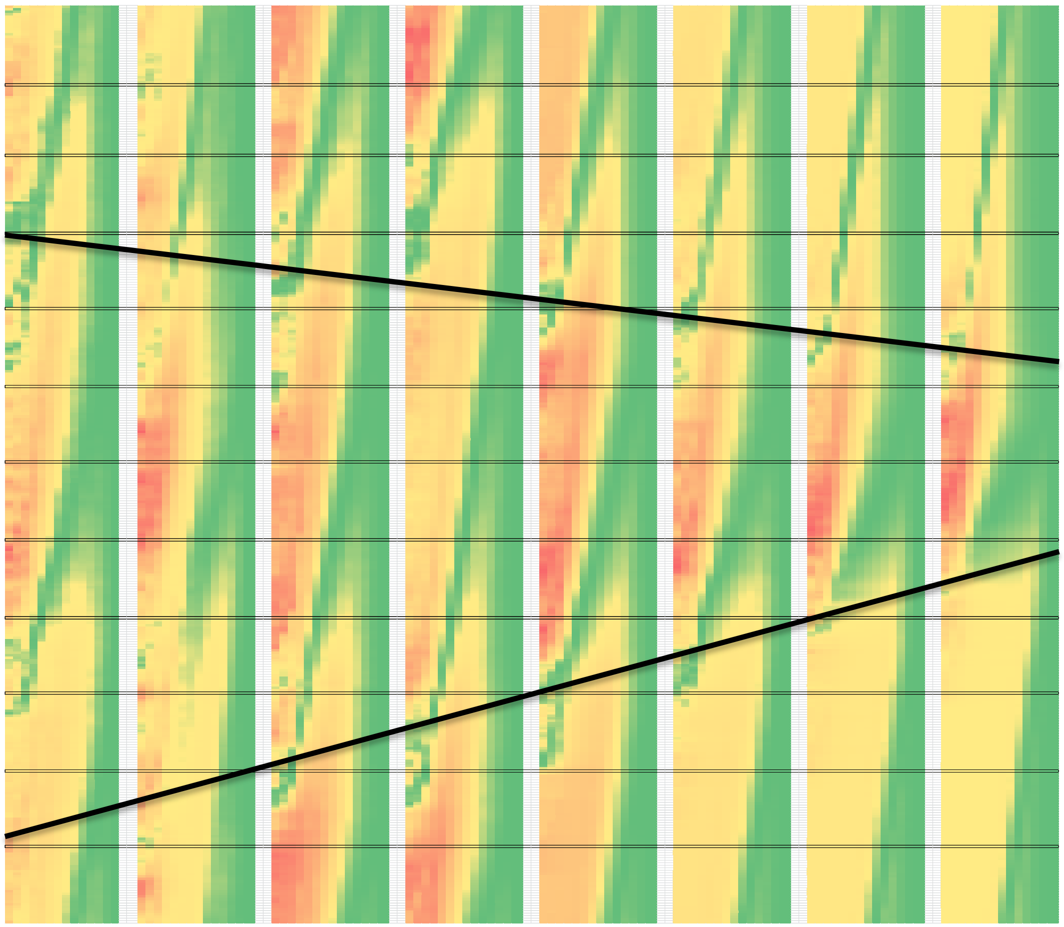


Chart Details	
Building:	DOE Benchmark Large Office Building
Location:	8 Locations
Regression Statistic:	Coefficient of Variation, CV (%)
Building Type:	Large Office
Dependent Variable:	CHW
Monitoring Period:	All Monitoring Periods (2 weeks – Full Year)
Model Type:	Hybrid
Data Type:	Synthetic
Model Form:	$WBE = A + \frac{B}{24}(T - cp)^{+} + C(LTEQ)$

Color Area Plots (CAP's)



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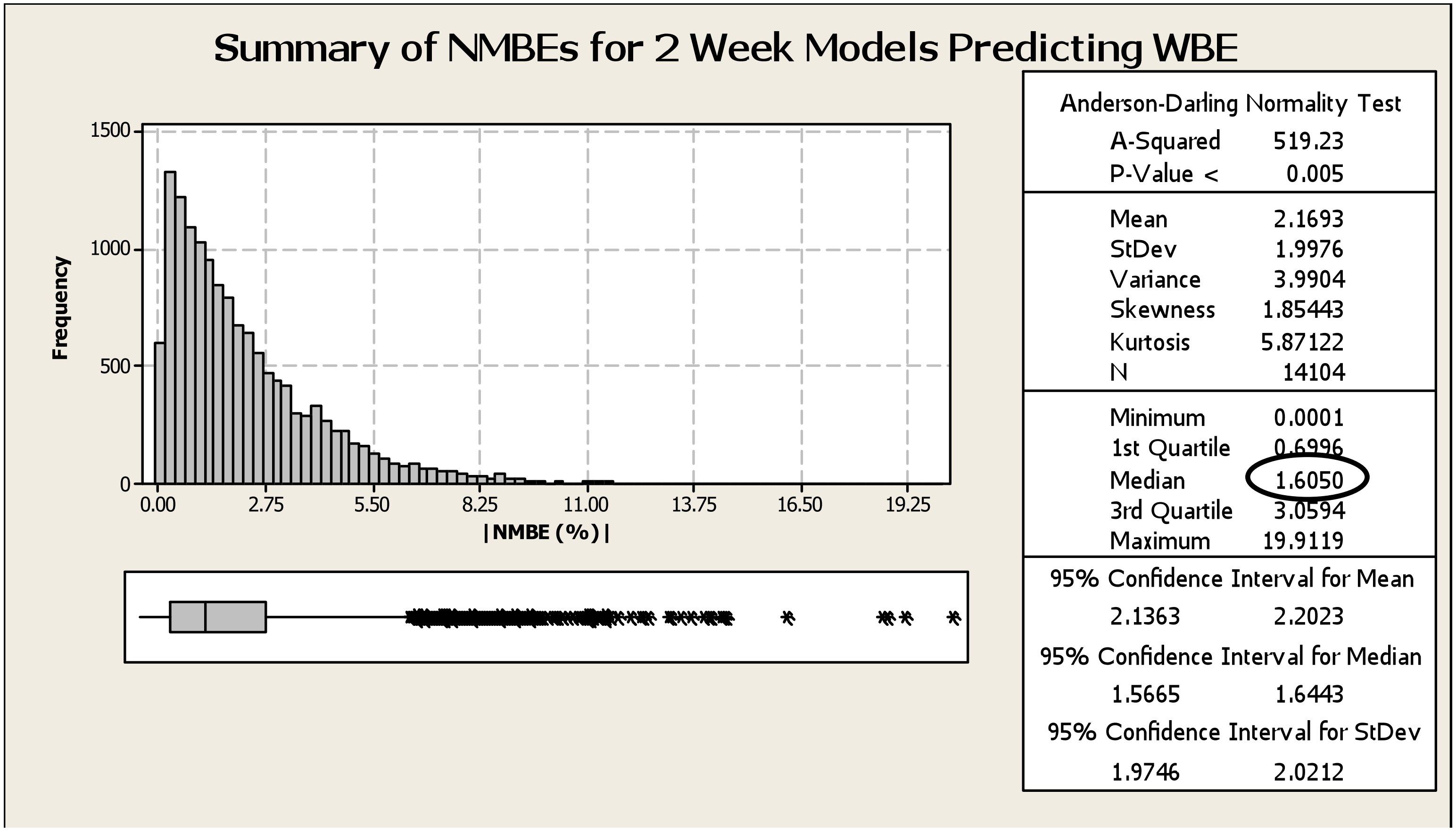
Location:	8 Locations
Regression Statistic:	Coefficient of Variation, CV (%)
Building Type:	Large Office
Dependent Variable:	CHW
Monitoring Period:	All Monitoring Periods (2 weeks – Full Year)
Model Type:	Hybrid
Data Type:	Synthetic
Model Form:	$Cooling\ Demand = A + {}^{B}\!/_{24}(T - cp)^{+} + C(w - 0.009)^{+} + D(LTEQ)$

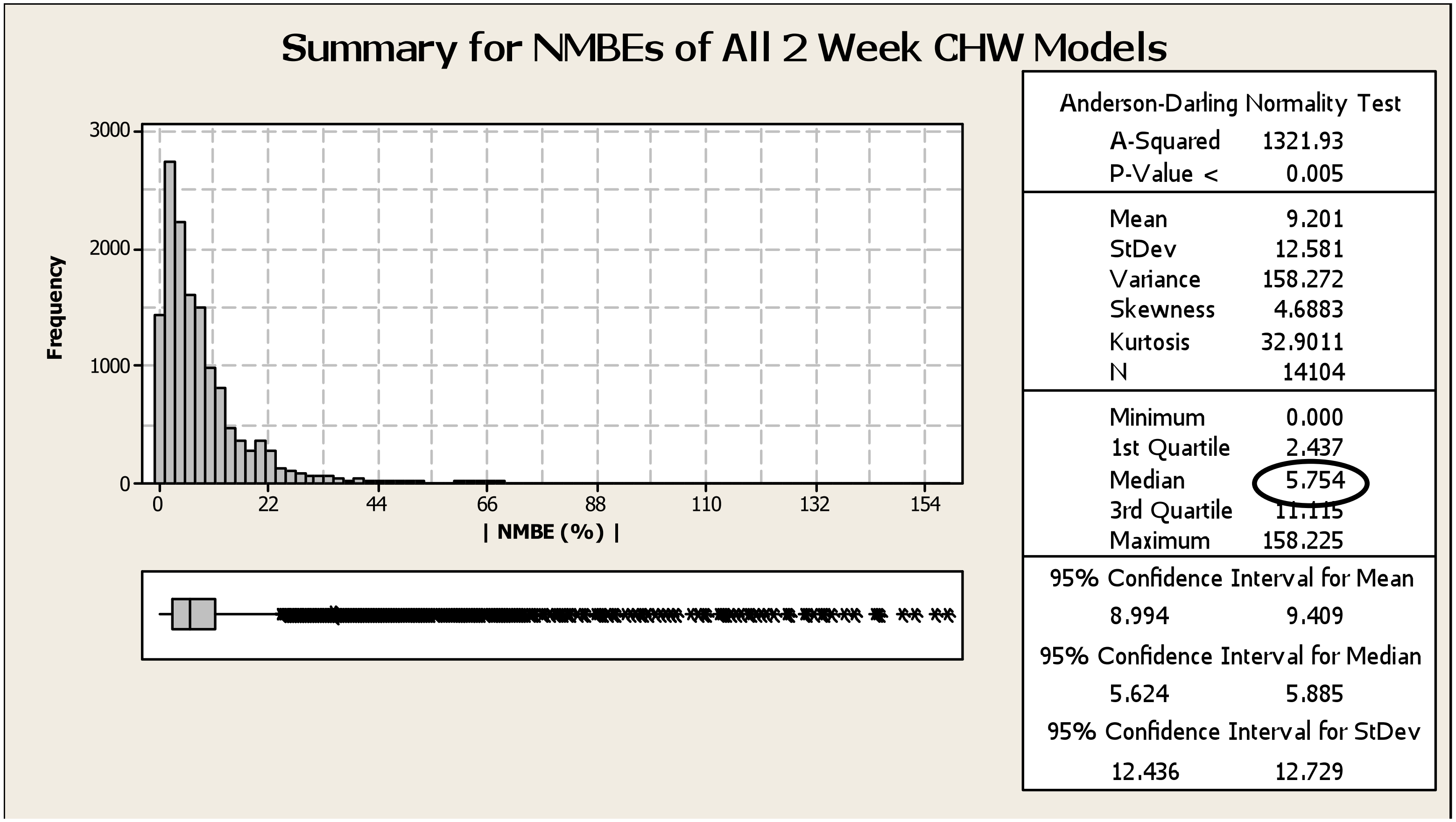
Year Long Utility Bills Combined with a Short Data Set

- At hourly scale, two weeks was found to be an acceptable monitoring length. Many suitable models came from swing seasons (April and October)
- Good flexibility in monitoring time (1.2 million models)
  - WBE, median NMBE ≈ 1.6%
  - CHW, median NMBE ≈ 5.8%
  - HW, median NMBE ≈ 4.5%
  - ASHRAE Guideline 14 suggests +/- 10%

Year Long Utility Bills Combined with a Short Data Set

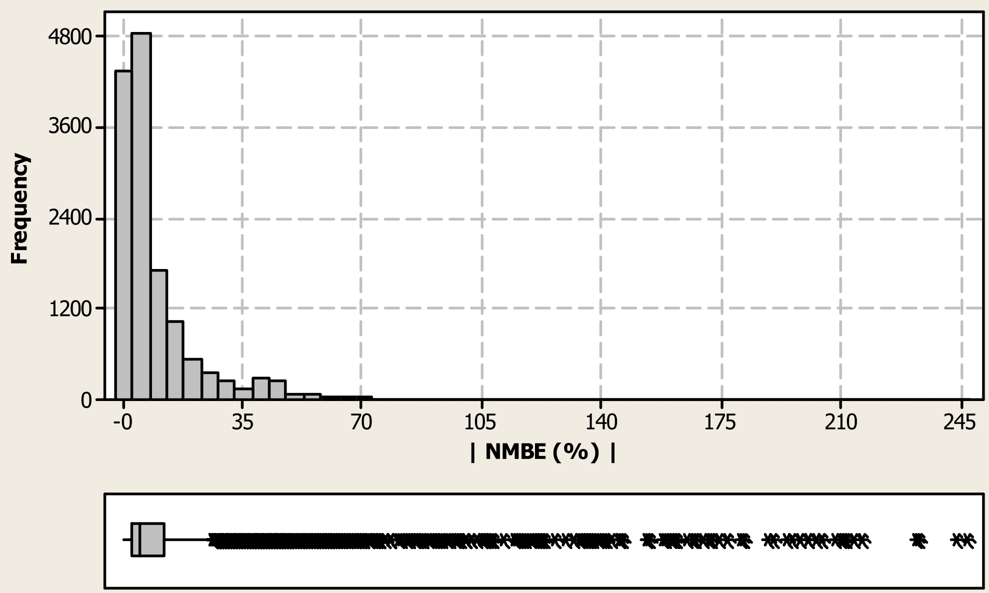


Year Long Utility Bills Combined with a Short Data Set



Year Long Utility Bills Combined with a Short Data Set

Summary for NMBEs of All 2 Week HW Models



Anderson-Darling Normality Test	
A-Squared	1760.89
P-Value <	0.005
Mean	10.317
StDev	17.385
Variance	302.255
Skewness	5.3418
Kurtosis	43.8145
N	14104
Minimum	0.000
1st Quartile	2.009
Median	4.452
3rd Quartile	11.417
Maximum	246.428
95% Confidence Interval for Mean	
10.030	10.604
95% Confidence Interval for Median	
4.349	4.567
95% Confidence Interval for StDev	
17.185	17.591

Year Long Utility Bills Alone

- Coefficient of Variation (CV) was greater without the short term data set (10 – 15% extra CV compared to hybrid)
- Fairly accurate energy estimate at both monthly and annual timescales

Comparison of Different Models

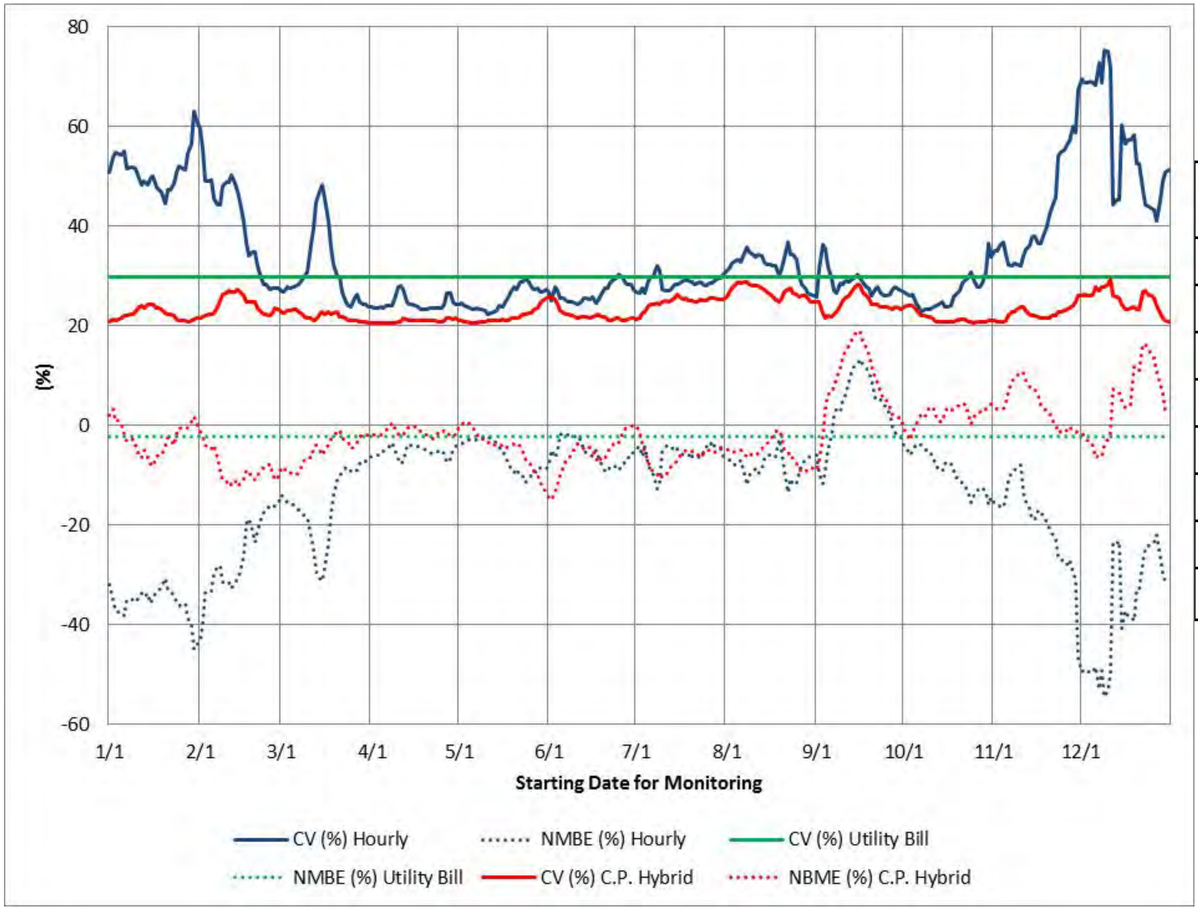
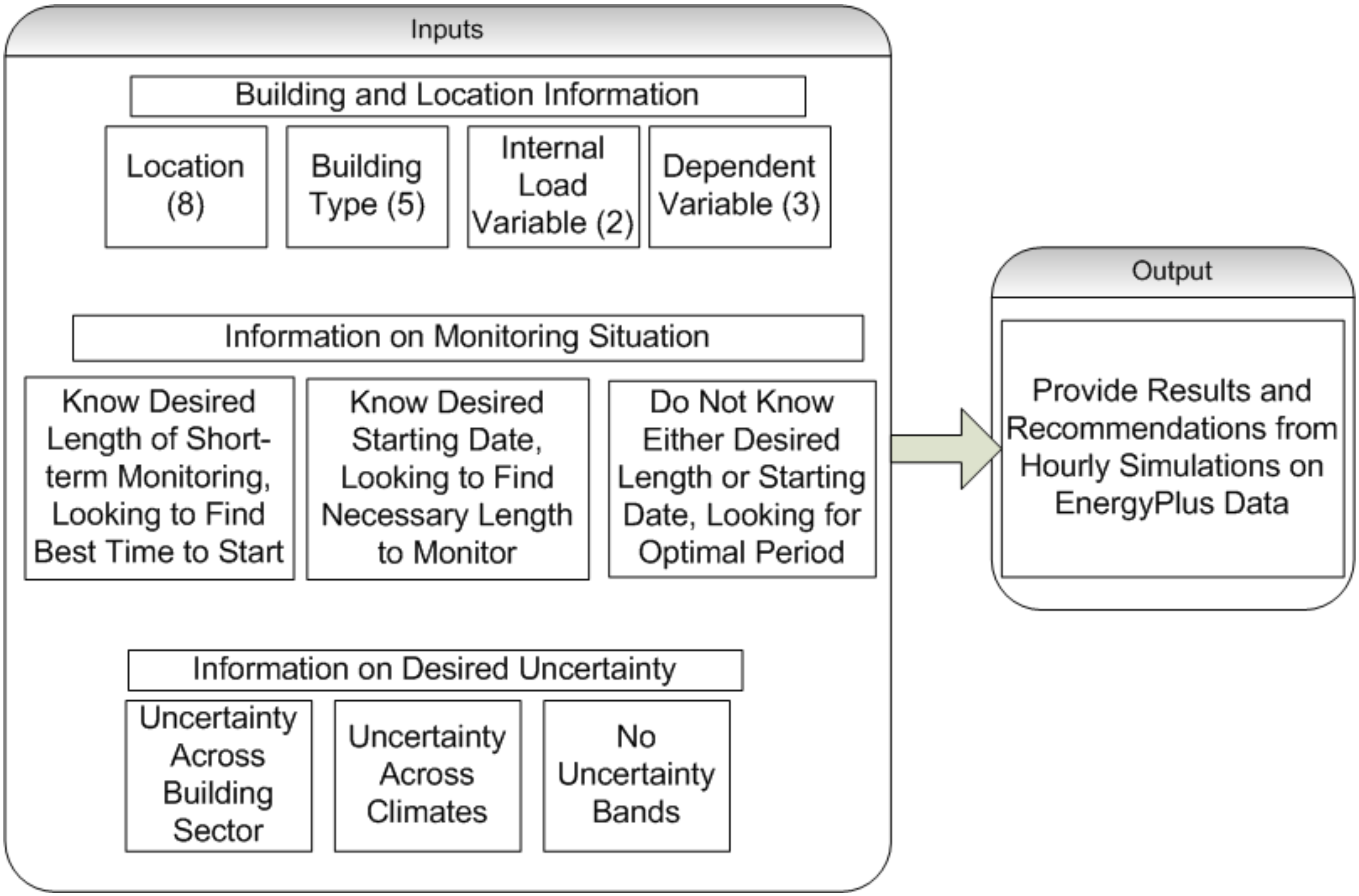
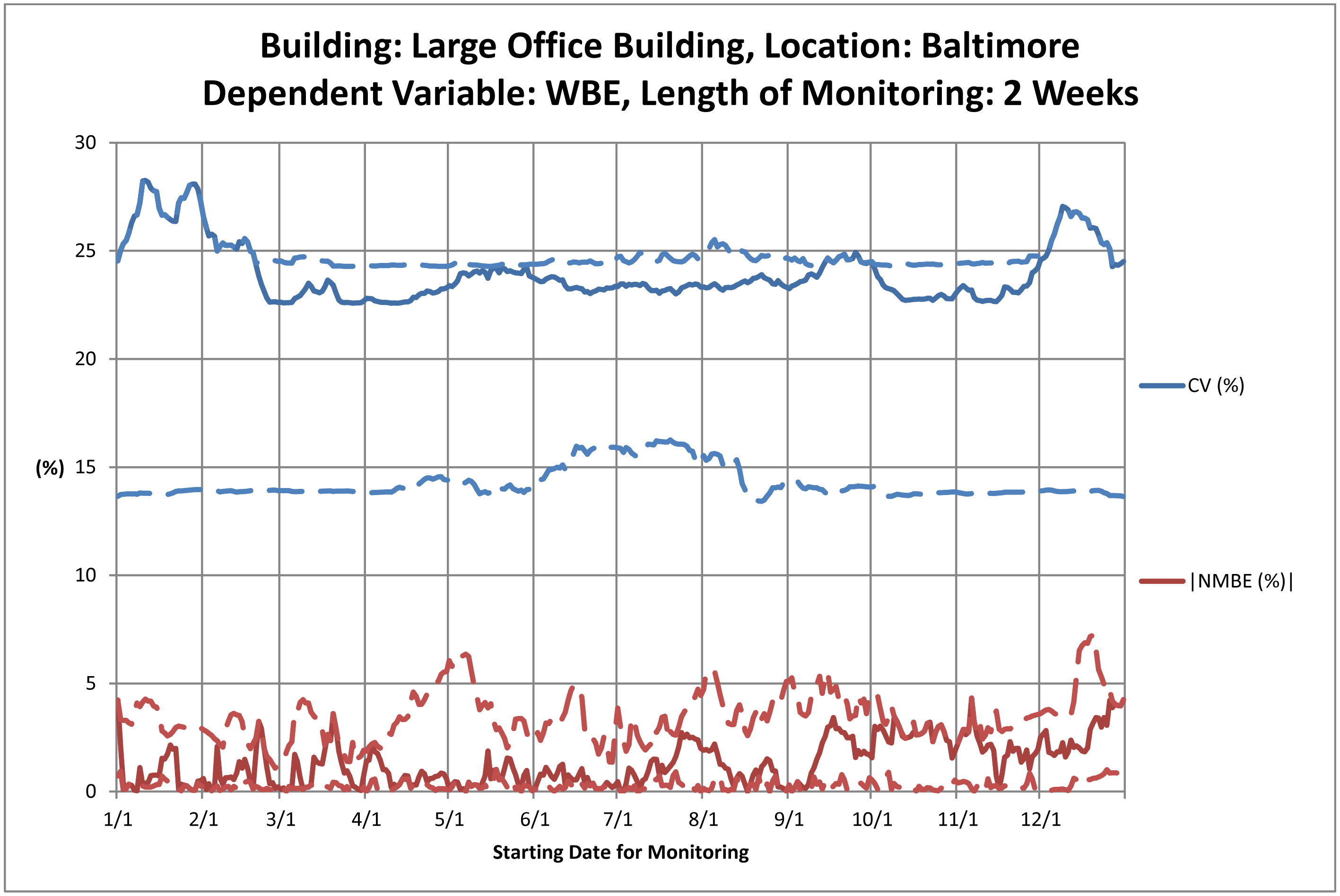


Chart Details	
Building:	JBC Building
Location:	8 Locations
Regression Statistic:	CV (%) and NMBE (%)
Building Type:	Large Office
Dependent Variable:	CHW
Monitoring Period:	2 Weeks
Model Type:	Hybrid
Data Type:	Synthetic

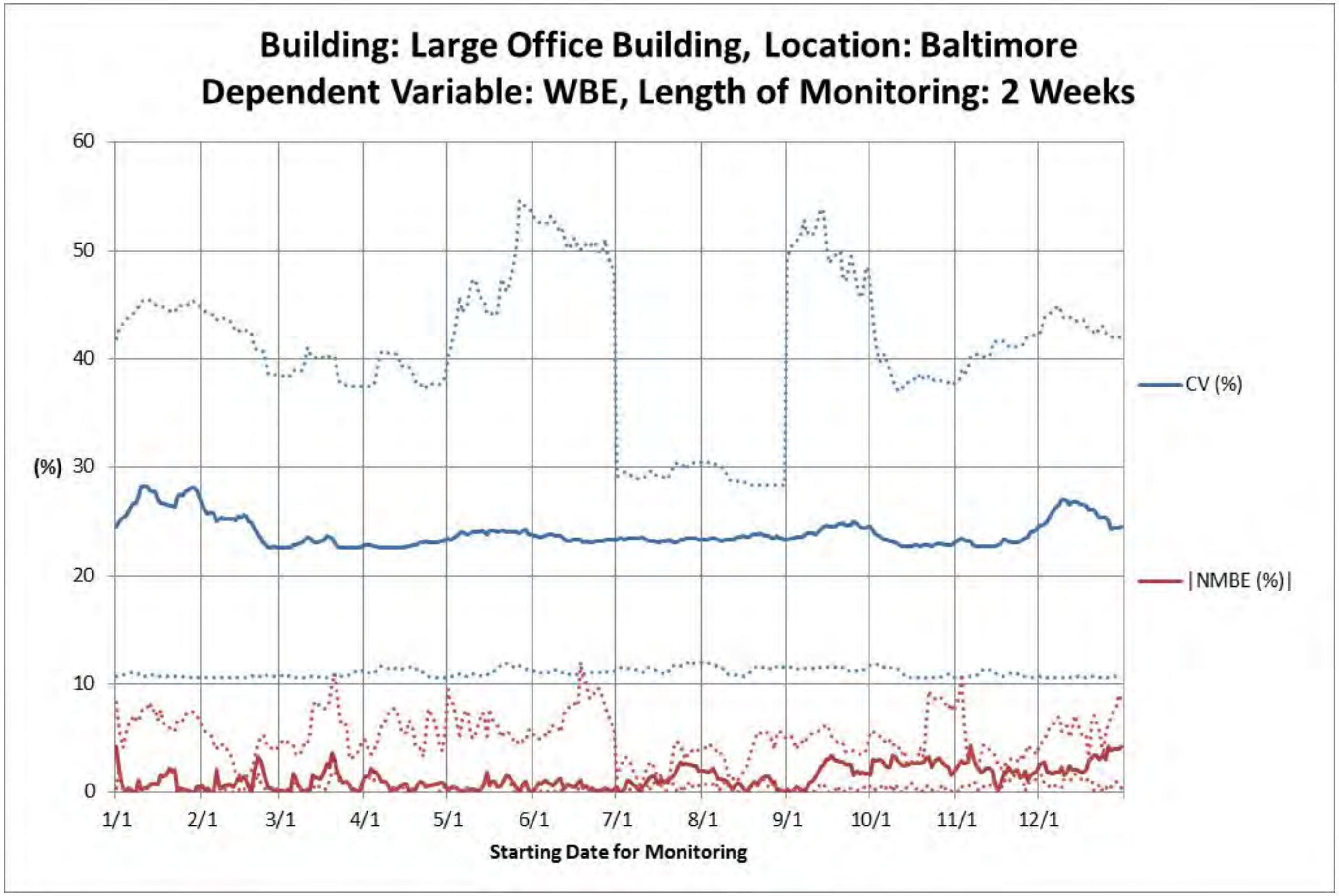
Guidance to Energy Professionals



Uncertainty Methods (Across Climates)



Uncertainty Methods (Across Building Sectors)



Conclusions

- Little to no improvement was found introducing a time lag in the variables used in the hourly models.
- Predictions for cooling energy use were better in warmer climates, and predictions for heating energy use were better in cooler climates.

Conclusions

- For robust models, the temperature change point that exists in many building energy profiles needs to be accounted for.
- Modeling with only utility bills data provided a fairly accurate estimate of the long-term energy use patterns of buildings. A minimum amount of monitoring, however, can improve the results.

Conclusions

- In general, the swing seasons (April and October) have been found to be the best time to complete short term monitoring (1 month or less).
- Extending the monitoring period to cover extreme weather would result in poorer predictions, compared with using much shorter periods taken from the swing seasons.

Conclusions

- The most important factor in the predictive ability of the models has been the closeness of the data set's mean dry bulb temperature to the annual mean, and also that of the data set's temperature range to the annual range.
- The Hourly Hybrid Multivariate Change Point Model (with utility bills) has been found to be the most effective model for annual building energy prediction using data sets covering 1 month or less.