

# Weather Variable for Winter Load

## LFU Phase 3 Analysis

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# Agenda

- **Background and Objectives**
- **Problem Statement**
- **Methodology**
- **Results**

# Background and Objective

- NYISO has historically been a summer peaking system
- Primary emphasis has been on summer Load Forecast Uncertainty (LFU) modeling
- With more electrification of heating load in the future, the system is projected to transition to winter peaking
- The objective is to develop an improved weather variable for predicting winter peak load
  - Univariate approach provides simple framework for defining uncertainty and calculations are simpler than multivariate approach
  - Simple weather normalization calculation
  - Simple interpretation of weather sensitivity

*Preliminary analysis was presented at the 9/27/2022 LFTF ([Link](#))*

# Assumption

- Winter peak load is a quadratic function of weather variable

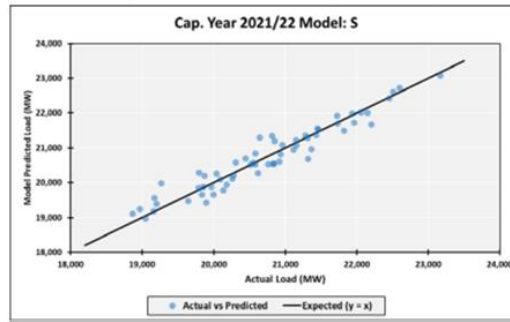
- $$peak = \beta_0 + \beta_1 X + \beta_2 X^2 + \text{binary terms} + e$$

Where  $X$  is weather variable

- 2020 variable: HDD\_55
- 2022 variable: Combination of daily maximum, minimum and 6pm temperature
- In both cases, the winter peak load showed a quadratic relationship with the winter variable

2022 Winter LFU ([Link](#))

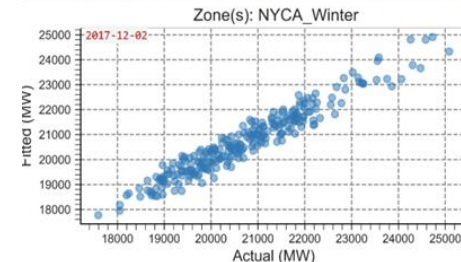
Mult. R: 96.2%		R-sq: 92.5%		Adj R-sq: 91.8%	
	Coef.	Std.Err.	t - Stat	p - Value	
Intercept	19343.2	175.6	110.17	0.00%	
WinterVar	62.3	14.0	4.46	0.00%	
WinterVar_2	0.8	0.3	2.37	2.13%	
Fri	-379.43	96.45	-3.93	0.02%	
Dec	-198.4	113.0	-1.76	8.47%	
Feb	-374.2	101.5	-3.69	0.05%	



2020 Winter LFU ([Link](#))

Adjusted R-Squared: 0.927

	Coef.	Std.Err.	t	P> t
Intercept	19500.95	128.6435	151.5891	0
HDD_55	43.0524	9.7942	4.3957	0
HDD_552	1.308	0.1968	6.6479	0
CP_2017_18	651.6266	59.6048	10.9324	0
CP_2018_19	387.0183	58.3658	6.6309	0
Jan	-255.984	58.6974	-4.3611	0
Feb	-795.702	58.551	-13.5899	0
WkEnd	-1489.18	53.9265	-27.615	0
Fri	-425.439	69.1682	-6.1508	0



# Problem Statement

- Main Assumption: Winter peak load ( $Y$ ) is a function of variable, say  $X$  and  $X^2$  and other non-weather sensitive variables
  - $X$  is a linear combination different weather variables  
 $X_1, X_2, X_3, \dots, X_n$

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \text{other non weather terms} + e$$

$$X = \sum_{i=1}^n w_i X_i = w_1 X_1 + w_2 X_2 + w_3 X_3 + \dots + w_n X_n$$

Our goal is to find optimal set of weights ( $w_1, w_2, w_3, \dots, w_n$ )

# Initial Summary Variables

Variable	Explored in 9/27/2022 Analysis
Average Morning Dry Bulb (DB) Temperature	X
Average Morning Wind Chill (WC)	
Average Afternoon Dry Bulb Temperature	X
Average Afternoon Wind Chill	
Average Evening Dry Bulb Temperature	X
Average Evening Wind Chill	
Average Lag Evening Dry Bulb Temperature	X

$$X_{Mor} = Avg(X_{HB06} \sim X_{HB11})$$

$$X_{Aft} = Avg(X_{HB12} \sim X_{HB17})$$

$$X_{Eve} = Avg(X_{HB18} \sim X_{HB23})$$

Wind Chill,  $WC = f(DB, WS)$

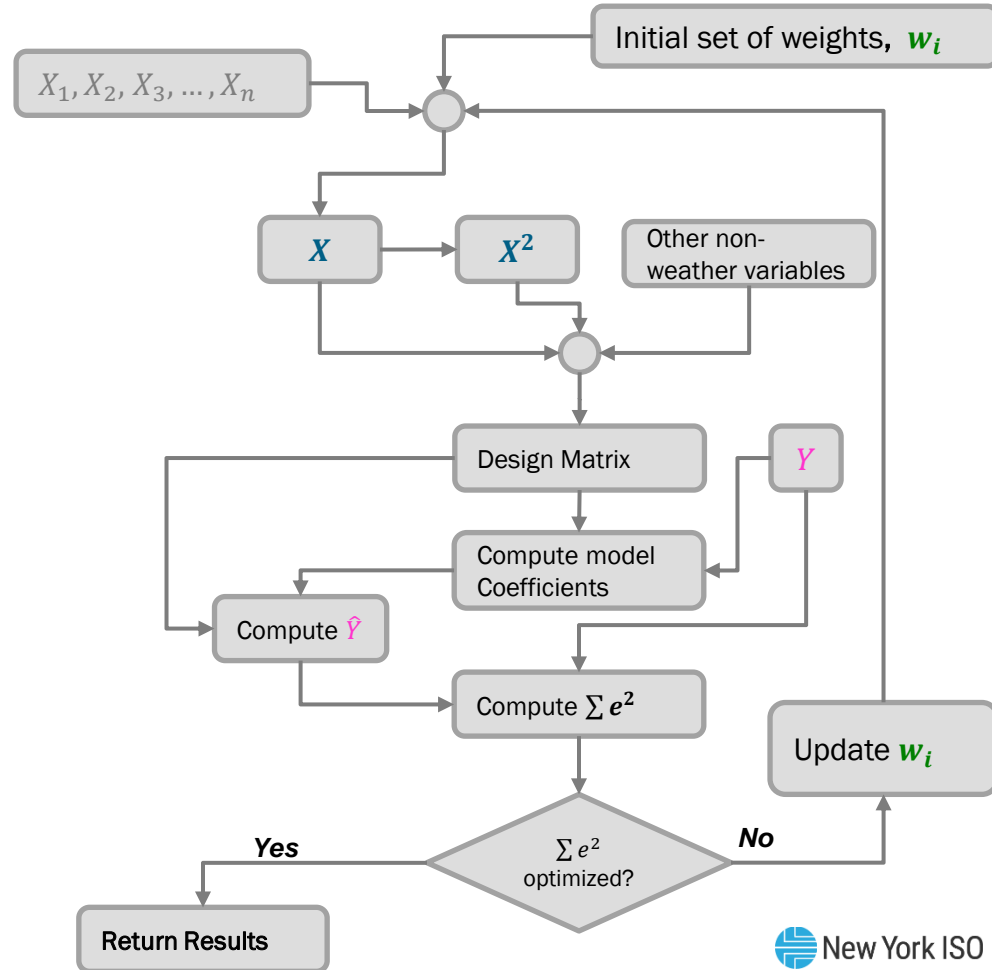
- $DB$  = Dry Bulb Temperature ( $^{\circ}F$ )
- $WS$  = Wind Speed (mph)

$$WC = 35.74 + 0.6215(DB) - 35.75(WS^{0.16}) + 0.4275(DB)(WS^{0.16})$$

<https://www.weather.gov/ama/windchill>

# Methodology

- Start with a random set of values of  $w_1, w_2, w_3, \dots, w_n$  and calculate  $X$  as  $\sum_{i=1}^n w_i X_i$
- Make a regression model with winter peak as dependent variable  $Y$  and  $X, X^2$  as independent variables, along with other non-weather variables.
  - Data:
    - Dec, Jan, Feb
    - 2017-18, 2018-19, 2021-22, 2022-23
    - Weekends included
    - Holidays removed
- Calculate coefficients of the regression model.
- Using the coefficients and design matrix, calculate predicted peak load  $\hat{Y}$
- Calculate sum of squared error, as  $\sum e^2 = \sum (Y_i - \hat{Y}_i)^2$
- Vary  $w_1, w_2, w_3, \dots, w_n$  so that  $\sum e^2$  is minimized



# Candidate Variables

Candidate 1	Candidate 2
<p><b><u>Pass 1</u></b></p> <ul style="list-style-type: none"><li><input type="checkbox"/> All seven summary variables (including lag evening temperature) were considered for initial optimization</li><li><input type="checkbox"/> Optimization was performed for all zones</li><li><input type="checkbox"/> A weight set was chosen based on the load weighted average</li><li><input type="checkbox"/> Initial optimization provided an “in-day” metric</li></ul> <p><b><u>Pass 2</u></b></p> <ul style="list-style-type: none"><li><input type="checkbox"/> Second round optimization was performed to investigate lag impact of the initial optimized weather metric</li><li><input type="checkbox"/> A weight set (applicable for the in-day and 2 lag terms) was chosen based on the load weighted average</li></ul>	<ul style="list-style-type: none"><li><input type="checkbox"/> Initially 6 variables (w/o lag evening temperature) were used to the in-day metric</li><li><input type="checkbox"/> Final weather metric was built by taking a weighted average of three days (in-day metric and 2 lag terms)</li><li><input type="checkbox"/> One round of optimization</li><li><input type="checkbox"/> Weight set was guided by the load weighted average</li></ul>



# Results – Candidate 1

## ■ Candidate 1 – Pass 1

Zone	Morning		Afternoon		Evening		Lag 1 Evening
	DB	WC	DB	WC	DB	WC	DB
A	0.0%	6.6%	0.0%	85.4%	0.0%	7.8%	0.2%
B	7.9%	0.0%	1.2%	48.3%	0.0%	17.4%	25.3%
C	12.3%	0.0%	12.2%	35.6%	0.0%	15.4%	24.6%
D	9.3%	3.2%	0.0%	27.0%	16.8%	14.3%	29.4%
E	0.0%	1.6%	0.0%	45.2%	0.0%	13.2%	40.0%
F	0.0%	0.0%	44.5%	26.7%	0.0%	3.1%	25.7%
G	6.0%	0.0%	54.3%	6.6%	0.0%	13.4%	19.6%
H	0.0%	0.0%	72.7%	2.5%	0.0%	4.9%	19.8%
I	0.0%	11.5%	36.2%	16.5%	0.0%	12.3%	23.4%
J	0.0%	0.0%	46.1%	8.5%	0.0%	14.2%	31.1%
K	0.0%	1.1%	32.2%	26.3%	7.9%	11.7%	20.7%

Load Wgt Avg	2.5%	1.4%	29.7%	27.9%	1.6%	12.4%	24.5%
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Recommended	0.0%	0.0%	35.0%	25.0%	0.0%	15.0%	25.0%
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Zone	R-Sq Value	
	Optimized	Recommended
A	86.9%	85.4%
B	89.1%	88.9%
C	91.2%	91.0%
D	92.0%	91.8%
E	88.5%	87.1%
F	89.4%	88.9%
G	90.0%	89.6%
H	77.5%	75.8%
I	83.1%	82.9%
J	95.2%	95.0%
K	93.1%	93.0%

Load Wgt Avg	91.2%	90.8%
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In-Day Var for day  $i$ ,  $v_i = 0.35DB_{aft_i} + 0.25WC_{aft_i} + 0.15WC_{eve_i} + 0.25DB_{aft_{i-1}}$

# Results – Candidate 1

- Candidate 1 – Pass 2

Zone	Variable v		
	In Day (i)	Lag 1 (i-1)	Lag 2 (i-2)
A	100.0%	0.0%	0.0%
B	88.8%	0.0%	11.2%
C	87.4%	0.0%	12.6%
D	87.3%	6.9%	5.8%
E	80.1%	5.4%	14.5%
F	84.1%	0.0%	15.9%
G	88.0%	0.0%	12.0%
H	88.1%	2.2%	9.7%
I	85.4%	0.0%	14.6%
J	83.8%	5.7%	10.5%
K	88.8%	0.0%	11.2%

Load Wgt Avg	87.1%	2.3%	10.6%
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Recommended	85.0%	0.0%	15.0%
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Zone	R-Sq Value	
	Optimized	Recommended
A	85.4%	84.2%
B	89.6%	89.5%
C	92.0%	92.0%
D	91.9%	91.9%
E	88.9%	88.8%
F	90.6%	90.6%
G	90.5%	90.4%
H	76.5%	76.4%
I	83.8%	83.8%
J	95.7%	95.7%
K	93.6%	93.5%

Load Wgt Avg	91.6%	91.4%
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$Candidate_1$  for day  $i = 0.85v_i + 0.15v_{i-2}$

# Results – Candidate 2

- Single Pass

Zone	Morning		Afternoon		Evening	
	DB	WC	DB	WC	DB	WC
A	0.0%	6.6%	0.0%	85.7%	0.0%	7.7%
B	27.0%	0.0%	3.1%	51.3%	0.0%	18.6%
C	31.2%	0.0%	16.7%	35.8%	0.0%	16.3%
D	30.2%	0.1%	0.0%	33.4%	17.2%	19.1%
E	6.0%	23.4%	0.0%	57.4%	0.2%	13.0%
F	24.8%	0.0%	1.6%	61.0%	0.0%	12.6%
G	22.8%	0.0%	54.9%	7.7%	0.0%	14.7%
H	3.6%	0.0%	90.6%	2.4%	1.3%	2.1%
I	0.0%	30.0%	46.8%	10.3%	0.0%	12.9%
J	17.4%	4.6%	53.3%	9.4%	0.0%	15.3%
K	8.1%	7.0%	40.0%	28.6%	3.6%	12.7%

Load Wgt Avg	16.4%	5.4%	30.9%	32.2%	1.1%	14.0%
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Recommended	15.0%	0.0%	35.0%	35.0%	0.0%	15.0%
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Lag 1 Evening		
In-Day	Lag 1	Lag 2
99.8%	0.2%	0.0%
81.6%	7.8%	10.6%
81.4%	7.1%	11.4%
75.5%	21.9%	2.6%
70.2%	17.6%	12.2%
78.5%	9.5%	12.1%
82.4%	5.0%	12.7%
80.2%	11.4%	8.4%
77.4%	6.7%	15.9%
74.9%	15.1%	10.1%
80.3%	5.4%	14.3%

79.8%	10.0%	10.2%
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80.0%	10.0%	10.0%
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Zone	R-Sq Value	
	Optimized	Recommended
A	86.9%	85.2%
B	89.5%	89.3%
C	91.8%	91.5%
D	92.1%	91.7%
E	88.5%	87.3%
F	89.7%	89.9%
G	90.8%	90.2%
H	77.9%	75.9%
I	84.1%	83.6%
J	95.6%	95.3%
K	93.9%	93.7%

Load Wgt Avg	91.7%	91.2%
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$$\text{In-Day Var for day } i, v_i = 0.15DB_{mor_i} + 0.35DB_{aft_i} + 0.35WC_{aft_i} + 0.15WC_{eve_i}$$

$$\text{Candidate}_2 \text{ for day } i = 0.8v_i + 0.1v_{i-1} + 0.1v_{i-2}$$

# LFU Model Comparison

<i>WinVar = HDD55</i>				
	Coefficient	StdErr	T-Stat	P-Value
CONST	18429.006	151.477	121.662	0.00%
WinVar	88.405	14.472	6.109	0.00%
WinVar_sq	0.411	0.354	1.159	24.89%
HDD55.CY_21_22	356.84	67.683	5.272	0.00%
Calendar.Feb	-548.651	78.55	-6.985	0.00%
Calendar.Jan	-136.782	79.359	-1.724	8.75%
Calendar.Fri	-187.627	82.982	-2.261	2.57%
<b>R-Sq</b>	<b>88.80%</b>			

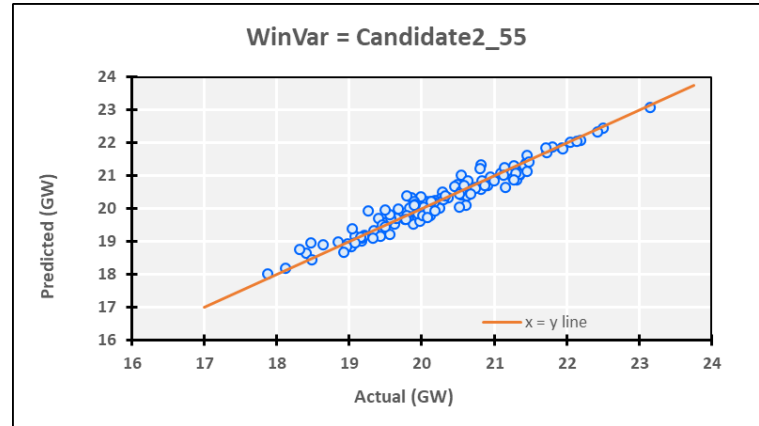
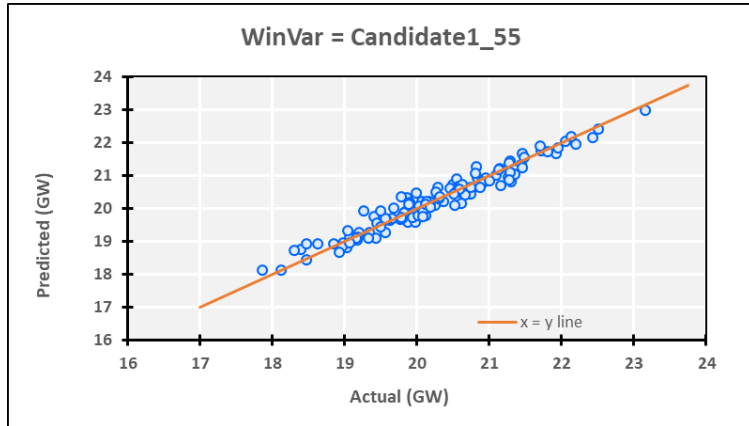
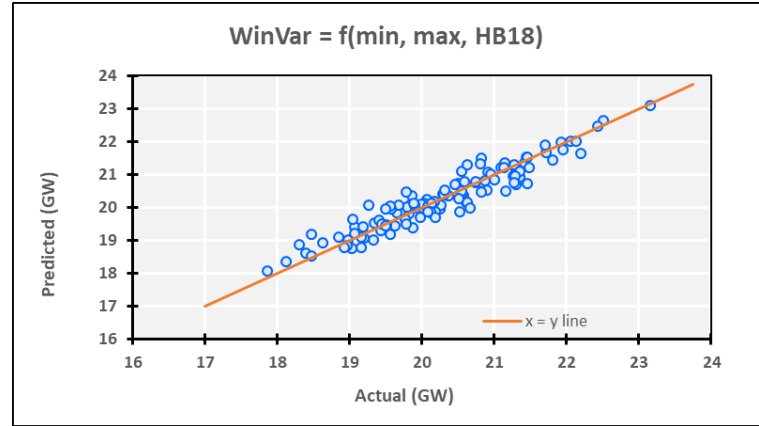
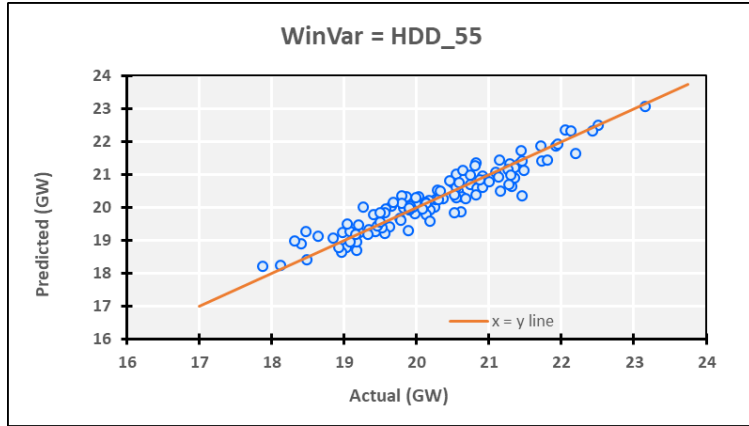
<i>WinVar = combination of max, min and HB18 temp</i>				
	Coefficient	StdErr	T-Stat	P-Value
CONST	18626.267	121.082	153.832	0.00%
WinVar	87.623	12.585	6.963	0.00%
WinVar_sq	0.491	0.344	1.427	15.63%
HDD55.CY_21_22	372.534	64.236	5.799	0.00%
Calendar.Feb	-499.481	74.582	-6.697	0.00%
Calendar.Jan	-148.708	75.563	-1.968	5.15%
Calendar.Fri	-353.113	78.495	-4.499	0.00%
<b>R-Sq</b>	<b>89.90%</b>			

<i>WinVar = Candidate_1_55</i>				
	Coefficient	StdErr	T-Stat	P-Value
CONST	18399.032	124.525	147.754	0.00%
WinVar	85.091	12.128	7.016	0.00%
WinVar_sq	0.607	0.294	2.061	4.16%
HDD55.CY_21_22	326.783	51.046	6.402	0.00%
Calendar.Feb	-550.54	59.546	-9.246	0.00%
Calendar.Jan	-223.657	60.79	-3.679	0.04%
Calendar.Fri	-302.949	62.508	-4.847	0.00%
<b>R-Sq</b>	<b>93.60%</b>			

<i>WinVar = Candidate_2_55</i>				
	Coefficient	StdErr	T-Stat	P-Value
CONST	18467.695	113.095	163.294	0.00%
WinVar	82.464	10.564	7.806	0.00%
WinVar_sq	0.476	0.249	1.914	5.82%
HDD55.CY_21_22	347.808	50.474	6.891	0.00%
Calendar.Feb	-559.535	59	-9.484	0.00%
Calendar.Jan	-229.814	60.228	-3.816	0.02%
Calendar.Fri	-342.889	61.887	-5.541	0.00%
<b>R-Sq</b>	<b>93.70%</b>			

- Data: 2021-22, 2022-23, weekday, Dec – Feb, holidays removed
- Candidate variables were referenced to 55

# LFU Model Comparison



# Recommendation

- Both candidate 1 and 2 show significant improvement in overall fits relative to the variables used in prior years
- Both candidates have “lag” component
- NYISO proposes to use candidate 2 for winter LFU to be used in IRM 2024 LFU
  - Candidate 2 calculation is simpler
  - Candidate 2 lag weights are more intuitive

# Questions?

# Our Mission & Vision



## Mission

Ensure power system reliability and competitive markets for New York in a clean energy future



## Vision

Working together with stakeholders to build the cleanest, most reliable electric system in the nation