

Weather Variable for Winter Load – LFU Phase 3 Analysis

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Agenda

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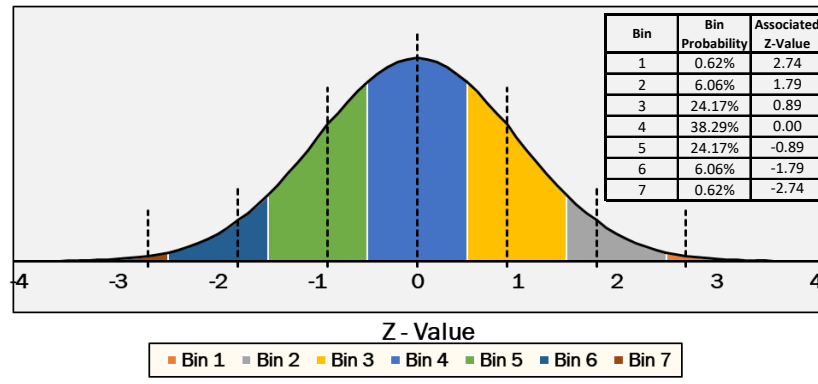
Background and Objective

- NYISO has historically been a summer peaking system
- Primary emphasis has been on summer Load Forecast Uncertainty (LFU) modeling
- With more electrification in the future, the system will likely transition to winter peaking
- The objective is to develop an improved weather variable for predicting winter peak load

Motivation of Univariate Approach

- Univariate approach provides simple framework for defining uncertainty and calculations are simpler than multivariate approach
- Simple weather normalization calculation
- Simple interpretation of weather sensitivity

LFU 7-Bin Structure



Simple bi-variate system

- X1, X2 are two independent random variables
- Can take integer values between 1 and 10 (inclusive) with equal probability

		X1									
		1	2	3	4	5	6	7	8	9	10
X2	1	(1,1)	(2,1)	(3,1)	(4,1)	(5,1)	(6,1)	(7,1)	(8,1)	(9,1)	(10,1)
	2	(1,2)	(2,2)	(3,2)	(4,2)	(5,2)	(6,2)	(7,2)	(8,2)	(9,2)	(10,2)
	3	(1,3)	(2,3)	(3,3)	(4,3)	(5,3)	(6,3)	(7,3)	(8,3)	(9,3)	(10,3)
	4	(1,4)	(2,4)	(3,4)	(4,4)	(5,4)	(6,4)	(7,4)	(8,4)	(9,4)	(10,4)
	5	(1,5)	(2,5)	(3,5)	(4,5)	(5,5)	(6,5)	(7,5)	(8,5)	(9,5)	(10,5)
	6	(1,6)	(2,6)	(3,6)	(4,6)	(5,6)	(6,6)	(7,6)	(8,6)	(9,6)	(10,6)
	7	(1,7)	(2,7)	(3,7)	(4,7)	(5,7)	(6,7)	(7,7)	(8,7)	(9,7)	(10,7)
	8	(1,8)	(2,8)	(3,8)	(4,8)	(5,8)	(6,8)	(7,8)	(8,8)	(9,8)	(10,8)
	9	(1,9)	(2,9)	(3,9)	(4,9)	(5,9)	(6,9)	(7,9)	(8,9)	(9,9)	(10,9)
	10	10% area									

		X1									
		1	2	3	4	5	6	7	8	9	10
X2	1	(1,1)	(2,1)	(3,1)	(4,1)	(5,1)	(6,1)	(7,1)	(8,1)	(9,1)	(10,1)
	2	(1,2)	(2,2)	(3,2)	(4,2)	(5,2)	(6,2)	(7,2)	(8,2)	(9,2)	(10,2)
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	7	(1,7)	(2,7)	(3,7)	(4,7)	(5,7)	(6,7)	(7,7)	(8,7)	(9,7)	(10,7)
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	9	(1,9)	(2,9)	(3,9)	(4,9)	(5,9)	(6,9)	(7,9)	(8,9)	(9,9)	(10,9)
	10	(1,10)	(2,10)	(3,10)	(4,10)	(5,10)	(6,10)	(7,10)	(8,10)	(9,10)	(10,10)

$$P(X1 \leq 10, X2 \leq 9) = 0.9$$

$$P(X1 \leq 9, X2 \leq 10) = 0.9$$

- P90 scenario can be reached in multiple ways
- Calculations become very complex when random variables are continuous and correlated

Assumption

Winter peak load is a quadratic function of winter 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

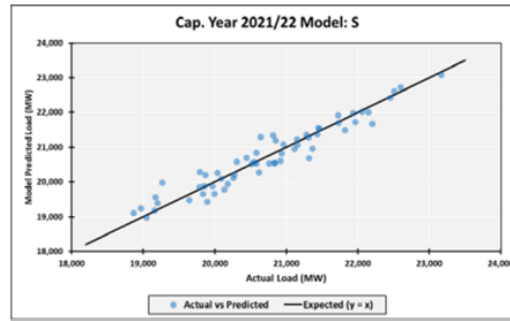
Variables under consideration for this analysis:

- Average Morning Temperature, X_1 (HB6-HB11)
- Average Afternoon Temperature, X_2 (HB12-HB17)
- Average Evening Temperature, X_3 (HB18-HB23)
- Daily Lag Average Evening Temperature, X_4

2022 Winter LFU ([Link](#))

	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%

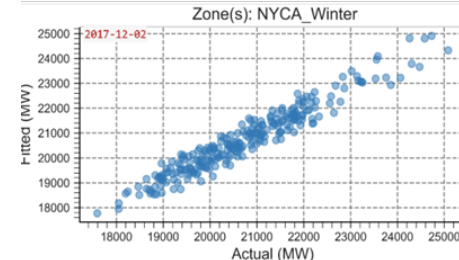
Mult. R: 96.2% R-sq: 92.5% Adj R-sq: 91.8%



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 linear function of variable, say X and X^2 ; where, X is a linear combination of MornDB (X_1), AftDB (X_2), EveDB (X_3), LagEveDB (X_4) and other non-weather sensitive variables

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

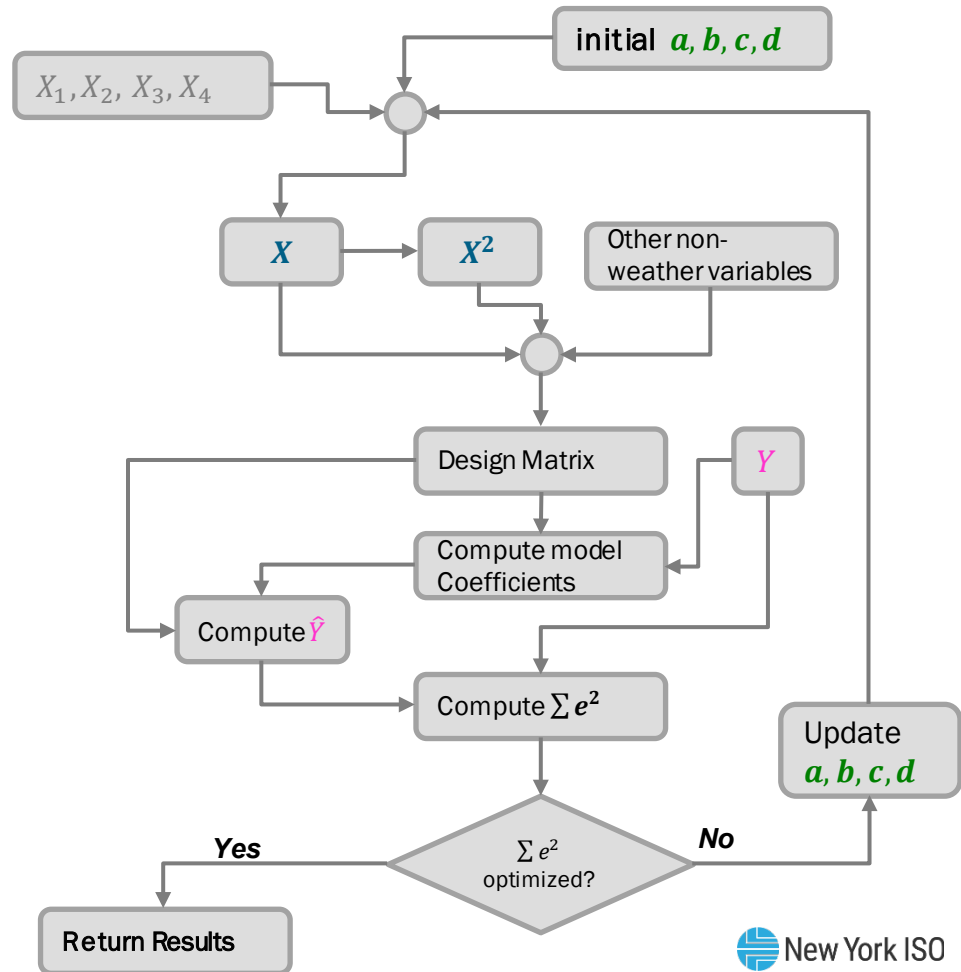
$$\text{Where, } X = aX_1 + bX_2 + cX_3 + dX_4$$

Our goal is to find optimal set of weights (a, b, c, d)

- Combining the variables will provide a univariate framework for easy computation of uncertainty
- Will eliminate multicollinearity problem and hence unstable estimation
- Will eliminate the need of checking for possible interaction of the candidate variables

Methodology

- Start with a random set of values of a, b, c, d and calculate X as $aX_1 + bX_2 + cX_3 + dX_4$
- Make a regression model with winter peak as dependent variable Y and X, X^2 as independent variables, along with other non-weather variables.
 - Included months: Dec, Jan, Feb
 - Data period: Dec 2018 – Feb 2022
- 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 a, b, c, d so that $\sum e^2$ is minimized



Results

		X1	X2	X3	X4	
Zone/Area	Regression R-Sq	MornDB_%	AftDB_%	EveDB_%	LagEveDB_%	R-Sq
A	80.7%	0.0%	91.4%	5.5%	3.1%	80.7%
B	87.2%	0.0%	80.8%	3.2%	16.1%	87.2%
C	87.7%	0.0%	66.5%	11.9%	21.6%	87.7%
D	86.5%	0.0%	40.2%	29.2%	30.7%	86.5%
E	88.6%	1.7%	62.2%	6.0%	30.0%	88.6%
F	87.8%	0.0%	70.5%	8.4%	21.1%	87.8%
G	85.0%	0.0%	62.9%	17.0%	20.1%	85.0%
H	84.4%	0.0%	60.6%	23.8%	15.6%	84.4%
I	78.0%	0.0%	64.2%	19.1%	16.7%	78.0%
J	92.2%	0.0%	48.6%	28.3%	23.1%	92.2%
K	90.1%	0.0%	70.4%	19.5%	10.0%	90.1%
S	93.2%	0.0%	58.9%	20.9%	20.1%	93.2%
AE	90.1%	0.0%	76.8%	5.5%	17.6%	90.1%
FG	88.8%	0.0%	64.9%	15.7%	19.4%	88.8%
HI	86.3%	0.0%	60.2%	23.6%	16.2%	86.3%
Avg	87.1%	0.1%	65.3%	15.8%	18.8%	87.1%

- Optimization was performed for all Zones and LFU areas
- Afternoon temperature, evening temperature and lag evening temperature were found to be important components of the winter variable
- Afternoon temperature was found to be the most important contributor across all Zones/LFU areas (contributing to 50-90% of the winter variable weight)
- Fairly good model strength across regions

Results (cont'd)

- The weights of the variables showed general consistency across regions
- A consistent set of weights (60% afternoon temperature, 20% evening temperature and 20% lag evening temperature) was applied and models were re-run
- The consistent weights resulted in modest changes in model accuracy relative to optimal weights of corresponding Zones/LFU areas.

Zone/Area	R-Sq	R-sq (60-20-20)	R-sq Reduction
A	80.7%	80.1%	0.6%
B	87.2%	87.0%	0.2%
C	87.7%	87.6%	0.1%
D	86.5%	86.3%	0.3%
E	88.6%	87.6%	1.0%
F	87.8%	87.6%	0.2%
G	85.0%	85.0%	0.0%
H	84.4%	84.3%	0.1%
I	78.0%	78.0%	0.0%
J	92.2%	92.1%	0.0%
K	90.1%	89.6%	0.5%
S	93.2%	93.2%	0.0%
AE	90.1%	90.0%	0.1%
FG	88.8%	88.8%	0.0%
HI	86.3%	86.2%	0.1%
Avg	87.1%	86.9%	0.2%

Key Takeaways and Future Work

Key Takeaways

- Least Square based optimization provides an effective way to get optimal weight set to combine multiple correlated variables
- This method can be used for examining any potential candidate variable
- This method can be utilized for complex model structures

Future Work

- Apply wintervariable to all LFU areas and analyze results
- Apply the least square based optimization method to other possible variables of interest (e.g., wind chill)

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