Load Forecast Uncertainty Modeling: New York Temperature Distribution Analysis

A Report by the
New York Independent System Operator

March 2021

Table of Contents

1 Executive Summary

A key component in the reliability planning of electric power systems is the development of load forecasting models to estimate the amount and variability characteristics of future energy demand. Load Forecast Uncertainty (LFU) models are developed to evaluate the system load forecast response due to varying weather conditions. The results from the LFU models are used in reliability modeling simulations to create many years of peak load conditions that are representative of the long-term variation in weather conditions. The New York State Reliability Council (NYSRC) Installed Capacity Subcommittee (ICS) has requested the support of the New York Independent System Operator, Inc. (NYISO) to perform an analysis of the long-term peak load producing weather conditions across the New York Control Area (NYCA). The analysis presented in this study is broken down into three main topic areas: 1) a comparison of the temperature-humidity data sets used in LFU modeling and an overview of their impacts on LFU model results, 2) an analysis of long-term historical weather (temperature and humidity) distributions for the NYCA and modeling areas, and 3) a review of the inter-annual trends in sensitivity between weather and system load. The topics were selected based on discussions with NYSRC ICS and the NYISO's Load Forecasting Task Force in order to enhance the understanding of LFU modeling and help the NYISO to identify where areas of additional study on LFU modeling are recommended.

1.1 Comparison of Temperature-Humidity Indices used in LFU Modeling

The weather variable analysis compiled 20 years of weather data sets used in the LFU modeling areas between the NYISO, Long Island Power Authority (LIPA), and Con Edison (ConEd). The study found that the NYISO weather variable (CTHI) and ConEd weather variable (TV) are similarly structured and generally interchangeable for use in LFU modeling in Zone J (New York City). The LIPA weather variable (THI4) correlates well with CTHI and regresses better against peak load conditions in Zone K (Long Island). The NYISO, LIPA, and ConEd compare the results from more complex LFU models during each model development cycle for use in the Installed Reserve Margin (IRM) studies. The NYISO typically finds that the NYISO and LIPA models produce comparable results. Additional investigation may be useful in order to identify potential reasons for differences in the load weather relationships between the NYISO and LIPA weather variables.

1.2 Long-term Historical Weather Distributions and Co-Incident vs. Non-Coincident LFU Trends

The analysis of the long-term historical temperature and humidity index distributions compiled 70 years of historical peak weather data (1950-2019). The NYISO compared regional coincident and non-coincident peak load producing weather over the last 20-years (2000-2019). The study showed that extreme weather events in the LFU modeling areas (Zones A-E, F&G, H&I, J, K) are coincident with the

NYCA composite peak load producing weather. When the NYCA coincident peak load weather is at its 99th percentile, the reliability regions are all above the 95th percentile of their respective NYCA coincident peak load producing distributions on average. The results show that in general, assuming extreme weather coincidence across all regions is an appropriate assumption in resource analysis studies.

The NYISO also analyzed the coincidence of peak loads across the NYCA. Simplified NYCA-wide and individual LFU area models were constructed and compared over the 2010 through 2019 period. The study showed the results from the NYCA-wide models generally produced tighter LFU distributions and lower load values (and multipliers) at the upper extreme temperatures. A review of the NYCA-wide versus the sum of the area models reveals a diverging trend in the evolution of LFU multipliers. The sum of the area models produced increasing LFU multipliers with time while the NYCA-wide models showed LFU multipliers that decreased over time. A review of the LFU area model results indicate an increase in the variation of the weather/load sensitivity among the various modeling regions. Specifically, LFU multipliers at the higher temperatures rose in Zone J and K, remained steady in Zones A-E and F&G, and decreased in Zones H&I throughout the study period.

A review of extreme temperature values at the NYCA, LFU modeling area, zonal, and weather station levels over a 70-year period was performed. The study showed that the extreme values currently used to define extreme events (e.g., Bin 1 temperature-humidity values) are reasonable and do not exceed physical/observed thresholds. The results also showed that the distribution of peak-producing temperature-humidity values is wider than the distribution of seasonal maximum temperature and humidity values. However, the results also suggest that the extreme weather conditions currently used in the highest levels (e.g., Bin 1) are not excessive for the respective LFU modeling areas. The results also indicate that temperature values that exceed annual extreme weather limits are not being incorporated in the temperature and humidity distributions used in LFU modeling.

Using 70 years of weather station data, the NYISO reviewed the coincident weather patterns across the zones and NYCA along with an assessment of the use of the normal distribution for modeling temperature and humidity extremes. The results revealed the most coincident patterns of temperature and humidity occur in the downstate regions, while the least coincident areas are generally upstate, and particularly in the western portion of the state (Zones A-E). A series of goodness-of-fit tests were compiled using pooled (combined) weather station data by LFU area. The test results were consistent for the NYCA and the five LFU modeling regions and showed that applying the assumption that peak temperature data is normally distributed is a reasonable assumption in LFU modeling.

1.3 Inter-Annual Trends in System Load and Weather

Finally, a detailed review of the inter-annual trends in sensitivity between weather and load across the NYCA was explored in order to assess changes in weather sensitivity over the most recent 20-year period. Consistently defined and simple NYCA-wide LFU models simulated year over year were employed for this examination. The study results showed increasing design and extreme peak load values through the mid-2010s, before dropping in recent years through 2019. The extreme LFU load per-unit multipliers followed a similar trend indicating a general increase in weather sensitivity as peak load levels increase.

1.4 Recommendations for Future LFU Modeling Studies

This whitepaper provides key background information on the temperature distributions used in LFU modeling. The statistical analysis of the temperature distribution data confirms that the distributions established for use in the modeling of LFU in the NYSRC Installed Reserve Margin and the NYISO Reliability Needs Assessments are valid and robust. Recommendations for future LFU modeling studies include using models with added complexity (i.e., with additional exploratory variables) to further evaluate the trends uncovered in this analysis and provide even better fits to the load weather relationship. A zonal or expanded reliability region analysis of the inter-annual weather sensitivity and LFU trends (e.g., including more years of data) may be warranted to identify any significant differences from the current NYCA and regional level analyses presented thus far. An extension of the analysis to include examining the implications of calibrating LFU area model results to a NYCA-wide model may also be warranted. Furthermore, given the recent trend in declining loads across the NYCA coupled with increasing regional LFU values, a comparison of net and gross loads (e.g., with BTM solar added back onto the load values) to further examine the last four years of peak load patterns is warranted, in order to potentially explain the recent downward trend shown in the simple model analyses.

Finally, the analysis presented focused on summer peak load producing weather conditions, specifically daily temperature-humidity values. Expanding this evaluation to a more granular level may be important with the increasing complexity of the power grid and the associated changes in hourly load shapes. Specifically, an evaluation of the current hourly load response against historical hourly weather conditions is warranted for the creation of model-based load shapes for potential use in future reliability studies. Exploration of these topics will be discussed with both the NYISO stakeholders and the NYSRC ICS working groups in order to define the scope of a follow-on (e.g., Phase 2) study on updated LFU modeling techniques that will develop as the complexity of the New York power grid increases.

2 Introduction

At the request of the New York State Reliability Council (NYSRC), the New York Independent System Operator (NYISO) presents this whitepaper on Load Forecast Uncertainty (LFU) modeling, focusing on an analysis of temperature distributions and load weather sensitivity across the New York Control Area (NYCA). The findings presented in this whitepaper will be used to assist the NYSRC and the NYISO in defining future areas of investigation on LFU modeling approaches and associated impact analyses of the modeling changes on resource adequacy analysis.

This study focuses on long-term temperature and humidity distributions across multiple regions of the NYCA. Historical distributions between multiple temperature-humidity variables currently used in LFU modeling are presented and compared. Furthermore, this study augments existing work, performed to date, on the Cumulative Temperature and Humidity Index (CTHI) variable, including extreme value analysis, regional versus local temperature distributions, and regional correlation of extreme weather (coincident / non-coincident variability). An analysis of the long-term inter-annual variability of load weather sensitivity for the NYCA and LFU modeling regions (i.e., LFU modeling composite areas: Zones A-E, F&G, H&I) is also presented. Finally, recommendations for future work on LFU modeling and impact analyses with the General Electric Multi-Area Reliability Simulation (MARS) software are discussed.

3 Background

Planning for the growth and increasing complexity of electric power systems requires the development of load forecasting models to estimate the amount of future energy demand. These models assist power system planners, engineers, and system managers in making decisions on changes to generation and transmission facilities along with the approaches used in demand management programs. When building models to forecast long-term (greater than one year ahead) system load requirements, trends in the economy, demographics, and end-use technologies are typically considered [1]. In general, these trends evolve slowly (e.g. quarterly to yearly) and incrementally alter the annual energy and peak load requirements of the system. Short-term (one hour to one week ahead) and medium-term (one week to a year ahead) load forecast models are used for facility scheduling, electricity pricing, mid-term production planning, and fuel purchasing. In both short- and medium-term forecast models, hour-to-hour, day-to-day, and weekly weather fluctuations imbue a significant impact on the system load requirements and are the predominant driver of uncertainty in forecasting peak system demands.

A key aspect of modeling and evaluating the medium- and long-term reliability of power systems is calculating the loss of load expectations (LOLE). The General Electric (GE) Multi-Area Reliability Simulation (MARS) Power System modeling software calculates loss of load expectation (LOLE) using hourly chronological loads. MARS currently models up to ten different load levels using per-unit (PU) multipliers that can vary by month, season, or year. PU multipliers are derived from Load Forecast Uncertainty (LFU) models, and represent the ratio of the predicted load at each Bin temperature to the predicted load at the design temperature. LFU models are probabilistic models that represent the probability of occurrence of monthly, annual or seasonal peak loads. Long-term peak load forecast uncertainty can come in the form of the expected changes in the economy, end-use technologies, demographics, and the proliferation of distributed energy resources (DERs) across the system. These changes generally result in more predictable, systematic trends in peak demand over the long-term forecast period (e.g., 1-20-years ahead). Daily weather fluctuations are much more random and imbue more uncertainty in the NYCA-wide and regional peak demands. LFU models are developed to evaluate the system load forecast uncertainty due solely to the varying weather conditions. These probabilistic models require many years of hourly weather conditions coupled with tested methods used for translating the weather conditions into peak loads. These probabilistic models have been referred to as the "LFU Curves" in previous NYSRC literature [2] and are an important input in the reliability studies performed each year to determine the required installed reserve margin (IRM) for New York State. The LFU models are also key inputs for the NYISO's Short-Term Assessment of Reliability (STAR) and long-term Reliability Needs Assessment (RNA) studies.

Throughout the course of a year, load increases towards peak conditions during the summer and winter months as weather conditions move away from comfortable levels. Several weather variables have historically been leveraged for understanding the uncertainty surrounding peak producing loads. Dry bulb temperature (measuring the thermal content of dry air) has been shown to have good explanatory power in predicting peak loads (Figure 1). The third order polynomial regression between summer dry-bulb temperatures and daily peak loads shown in Figure 1 has an R-squared value of 0.904. The R-squared value is a goodness-of-fit measure for regression models. This statistic indicates the percentage of the variance in the dependent variable (e.g., daily peak load) that the independent variables (e.g., dry-bulb temperature) explain collectively. The R-squared metric represents the strength of the relationship between a model and the dependent variable on a convenient 0–1 (0-100%) scale with values closer to unity representing a generally well-fit model. In Figure 1, 2013 summer weekday NYCA peak loads are plotted against daily maximum dry bulb temperature. We plot 2013 because it contains the all-time NYCA peak load day (7/19/2013), and contains representative information about load levels at upper extreme temperatures. Note that estimated demand response impacts have been added back into the load values.

Figure 1: NYCA-Wide Model between Peak Load and Daily Maximum Dry Bulb Temperature.

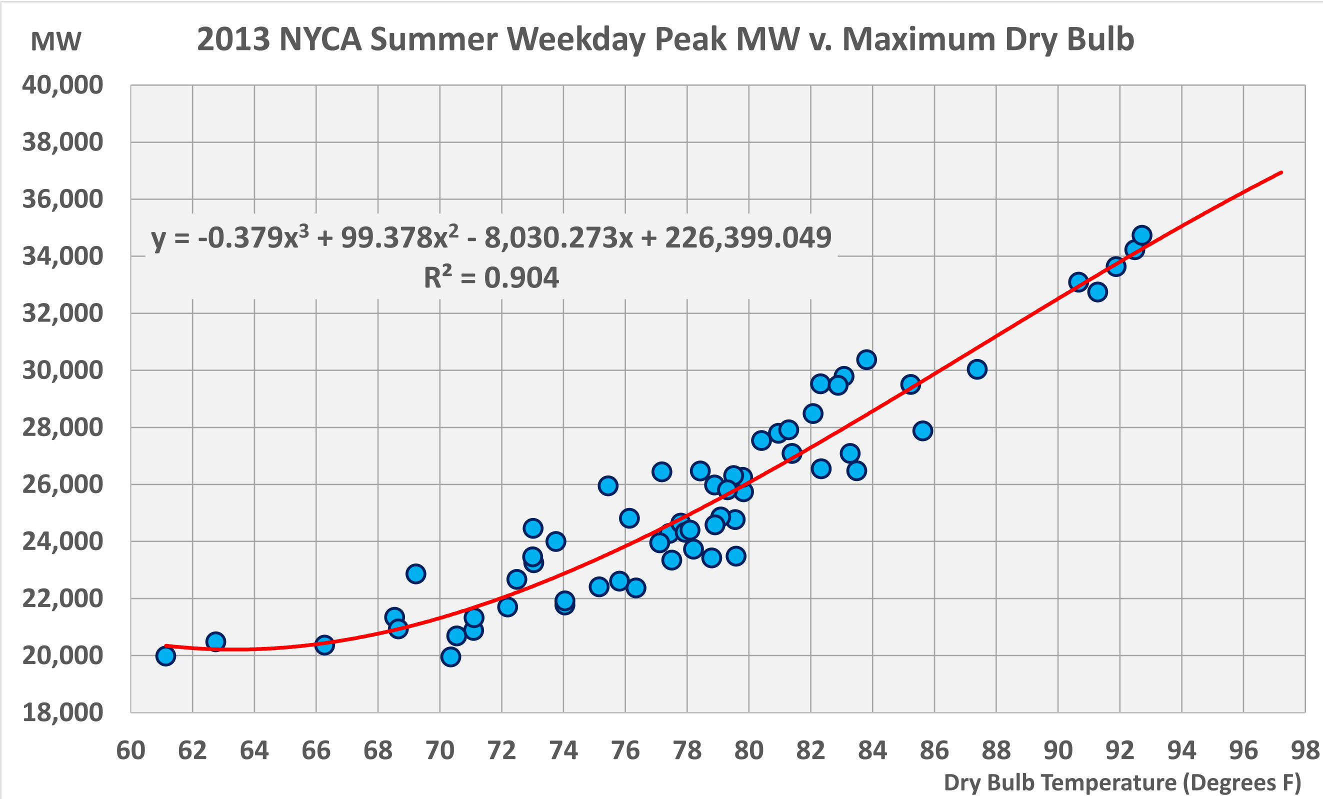
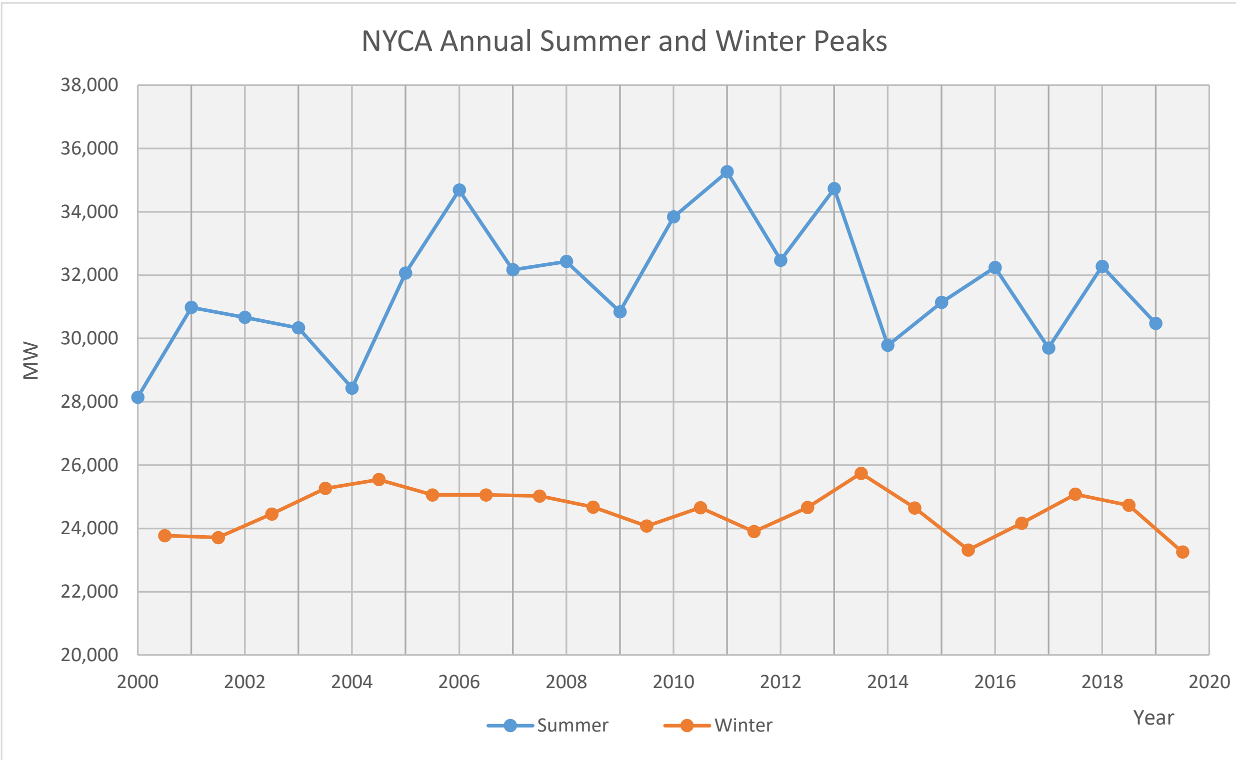


Figure 2, below, shows the annual summer and winter peak demand values for the NYCA over the 20-year period from 2000-2019. Summer peaks during the 20-year period range from a minimum of 28,138 MW to a maximum of 35,262 MW (with special case resources added back), whereas winter peaks ranged from a minimum of 23,253 MW to a maximum of 25,738 MW. The average year over year change in summer (winter) peak load is 2,095 MW (660 MW) respectively indicating a significant amount on inter-annual variability in peak loads. The strong inter-annual variability is largely due to the randomness in the arrival time and duration of peak load producing weather conditions. Finally, it is important to note that the NYCA is a summer peaking system. Therefore, the majority of LFU modeling in the NYCA is focused on modeling the load weather sensitivity during summer peak load producing weather conditions. The NYISO recently analyzed the impacts of beneficial electrification required to meet the emissions reduction targets outlined in the 2019 New York State Climate Leadership and Community Protection Act (CLCPA) [3]. As gas and oil-based residential and commercial heating are converted into fully electric heating systems the NYCA has the potential to switch from a summer peaking system to a winter peaking system. The LFU modeling methods discussed in this section can and have been applied to winter peak producing weather conditions.

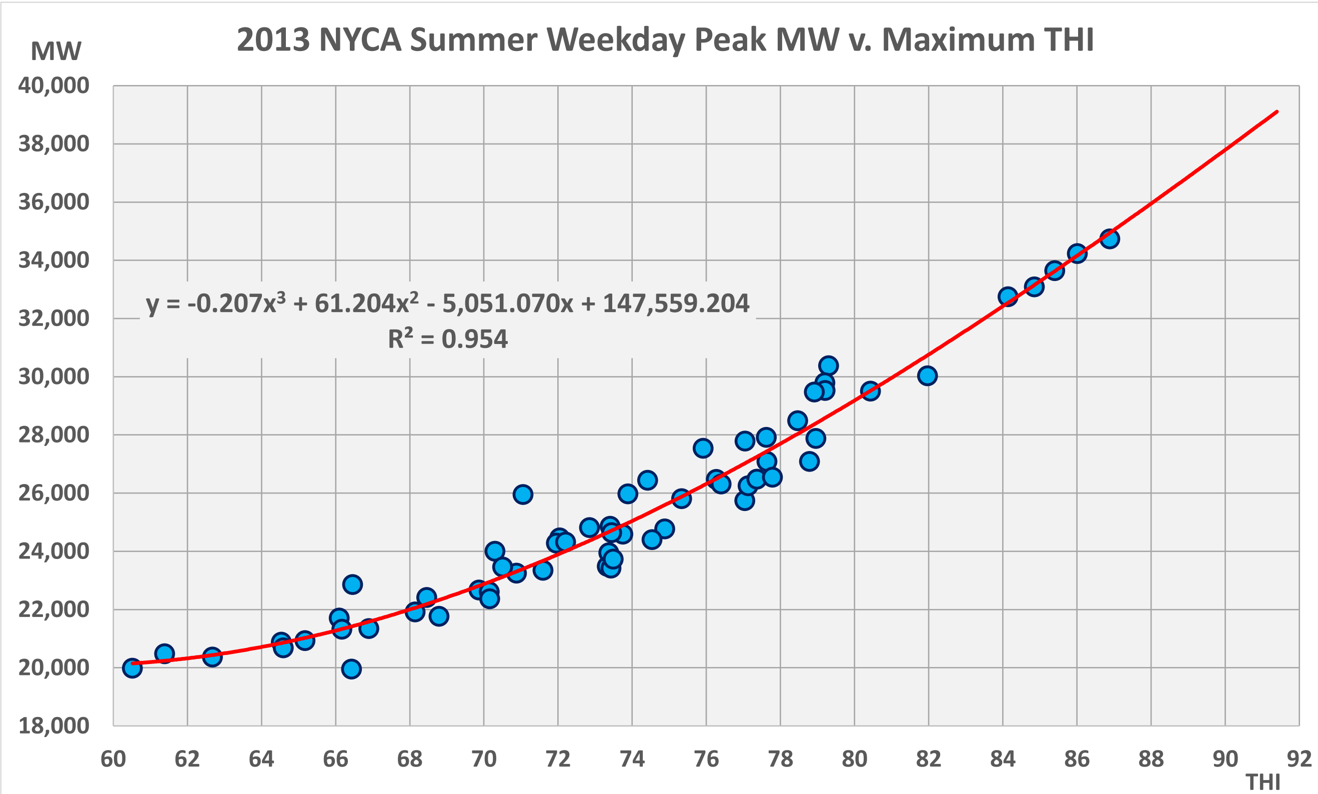
Figure 2: Time Series of NYCA Summer and Winter Peak Demand Values.



Note: Demand Response has been added back to the Peak Demand values shown.

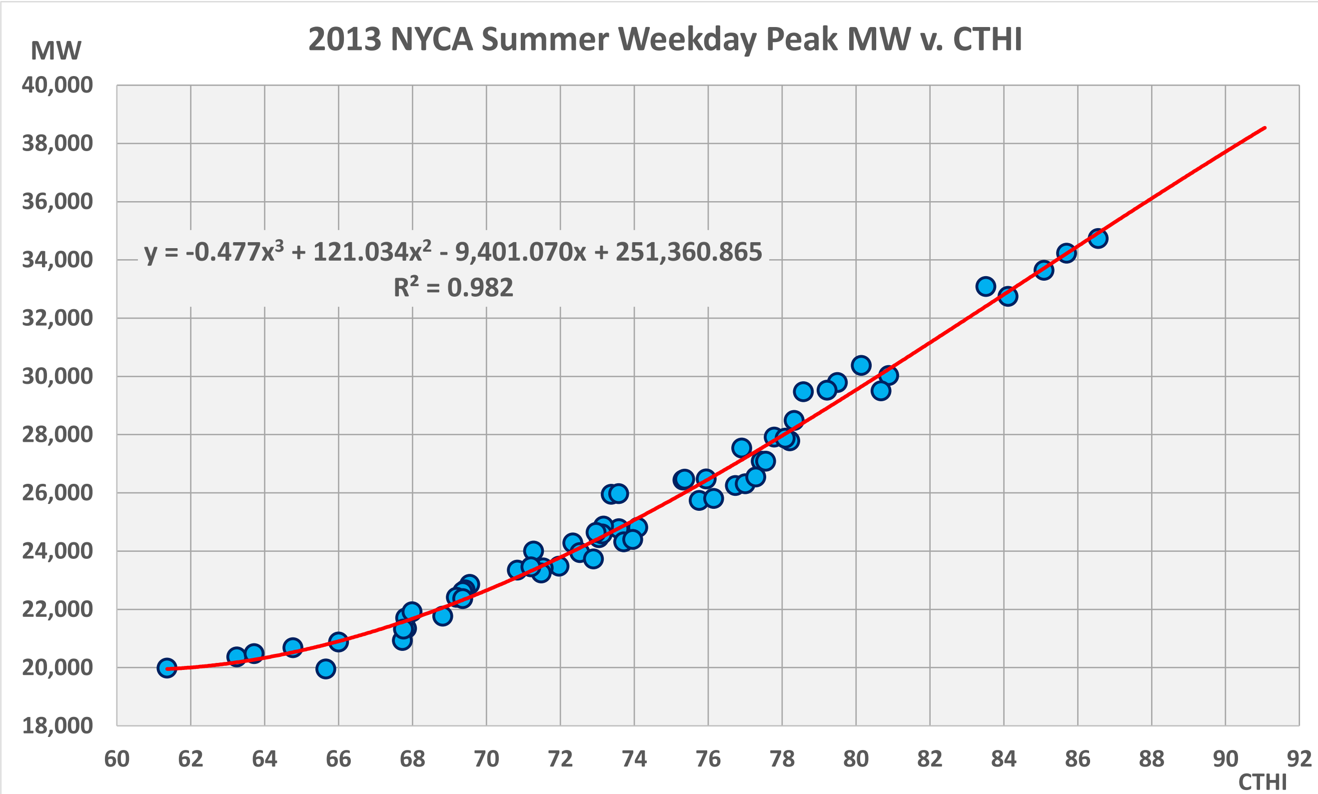
Dry bulb temperature combined with wet bulb temperature (a measure of humidity) in the form of a Temperature-Humidity Index variable (THI) exhibits additional explanatory power (**Figure 3**). During extreme hot and humid summer conditions, air conditioning (AC) equipment will approach its full capacity and its load requirements will begin to level off as the temperature and humidity increase. The slowing of load growth with increasing temperatures is called saturation and is observed in **Figure 3**.

Figure 3: NYCA-wide Model between Peak Load and Daily Maximum THI



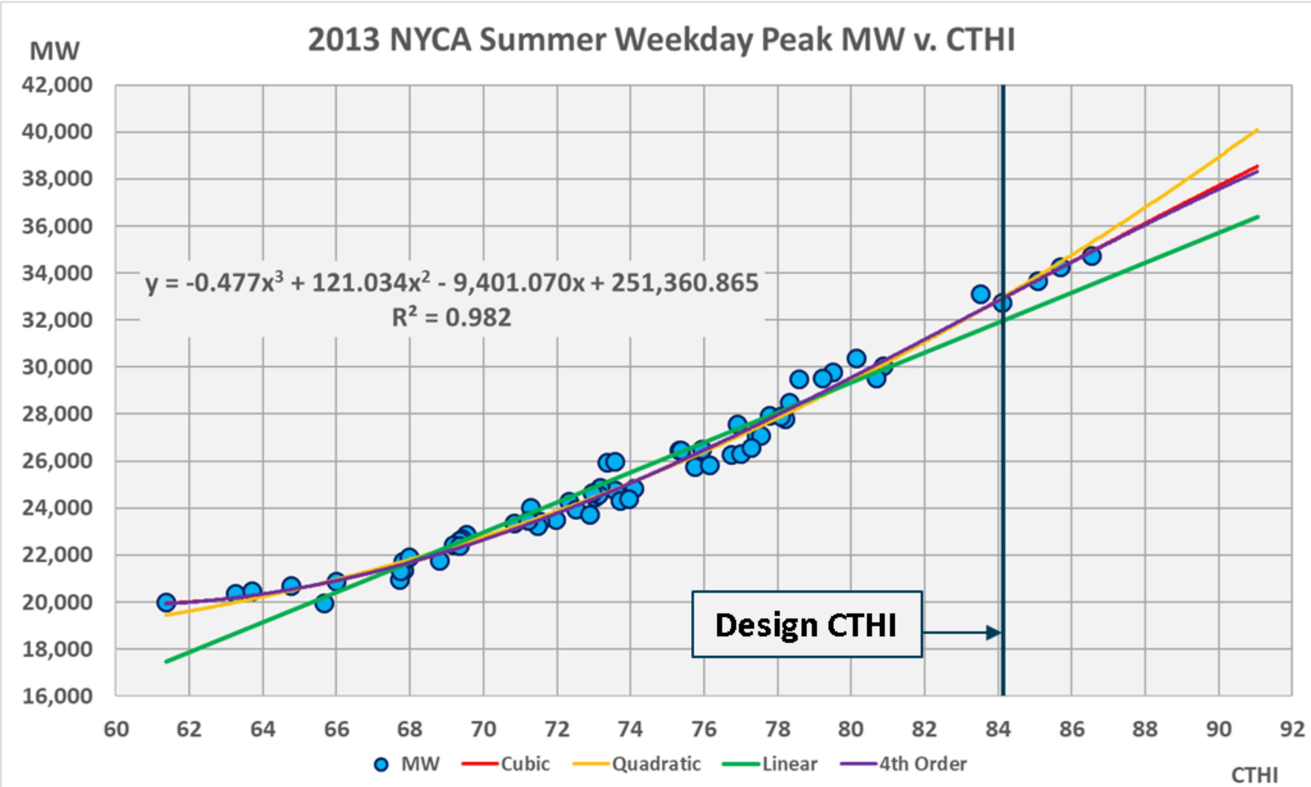
During heatwaves, the AC equipment must run more hours to keep up. As heat buildup within building structures occurs during a heatwave, AC equipment can run throughout the nighttime hours causing peak loads to increase in each successive day of the heatwave. This behavior aids in aligning multi-day heat waves with summer peak load producing conditions. Thus, the duration of extreme weather should also be considered in the modeling of peak load forecast uncertainty. Figure 4, below, shows that a cumulative measure (using a three-day trailing weighted average) of the THI variable (CTHI) exhibits even more explanatory power than the hourly (instantaneous) THI variable.

Figure 4. NYCA-wide Model between Peak Load and Cumulative THI Variable



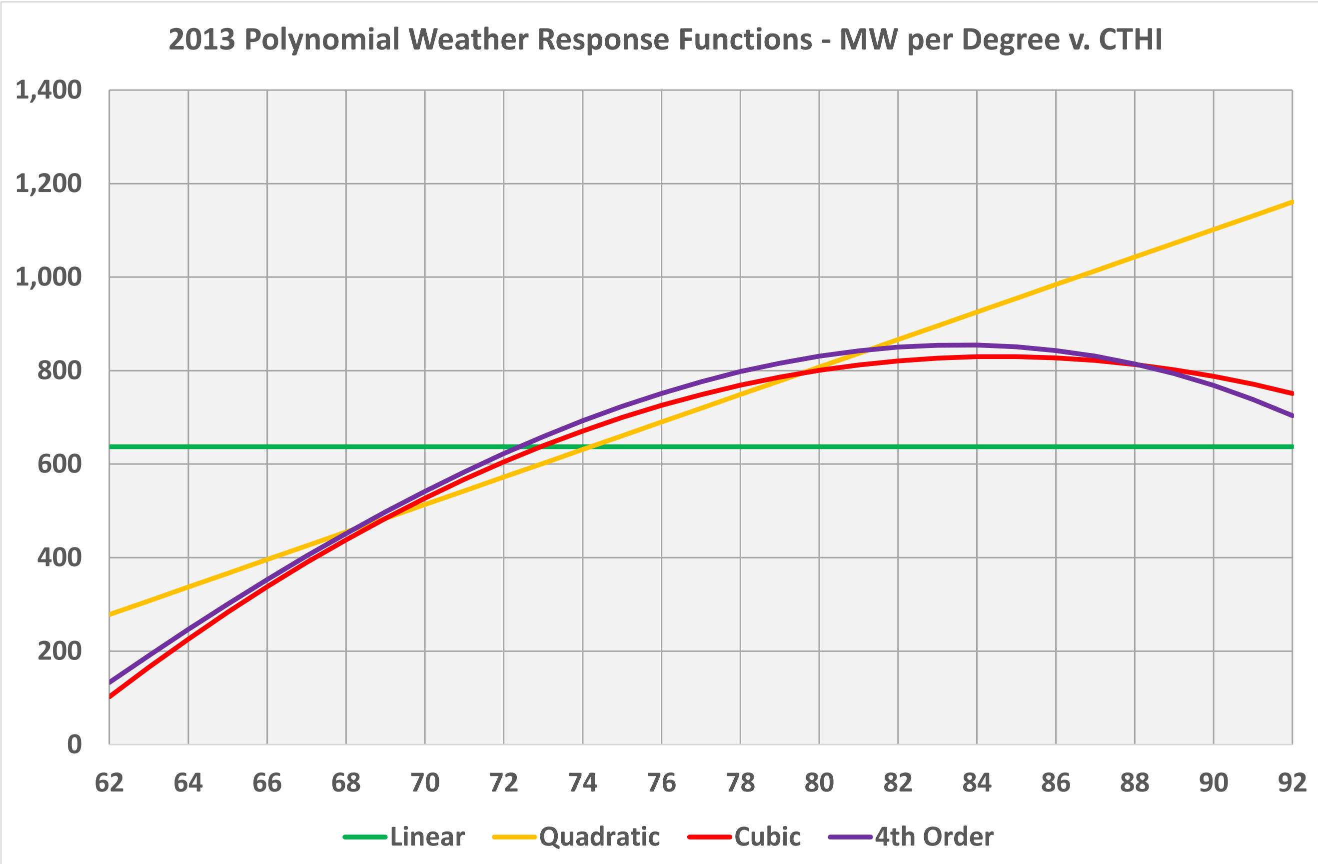
The modeled load and weather relationship given in Figure 4 above are constructed using a 3rd order polynomial regression model. Linear or piecewise linear models can be used. In the New York Control Area (NYCA), however, these models may not provide an optimal fit. Quadratic (2nd order polynomial) models fit the loads well between low to medium-high temperatures but tend to over predict the peak load at extreme THI values. Cubic (3rd order) functions fit well over a wide range of temperatures, their derivatives are easy to calculate, and these functions have been shown to have good explanatory power in the NYCA. Finally, sigmoid functions (neural networks) have the advantage of a good fit over a wide range of temperatures and good explanatory power. Whether a third, fourth, or neural network model is used depends largely which one has more explanatory power for the weather and load data being evaluated. Figure 5, below, compares linear, quadratic, 3rd and 4th order models for CTHI values across the New York Control Area.

Figure 5: NYCA-wide Model between Peak Load and Cumulative THI Variable with Linear, Quadratic, Cubic, and 4th Order Fits



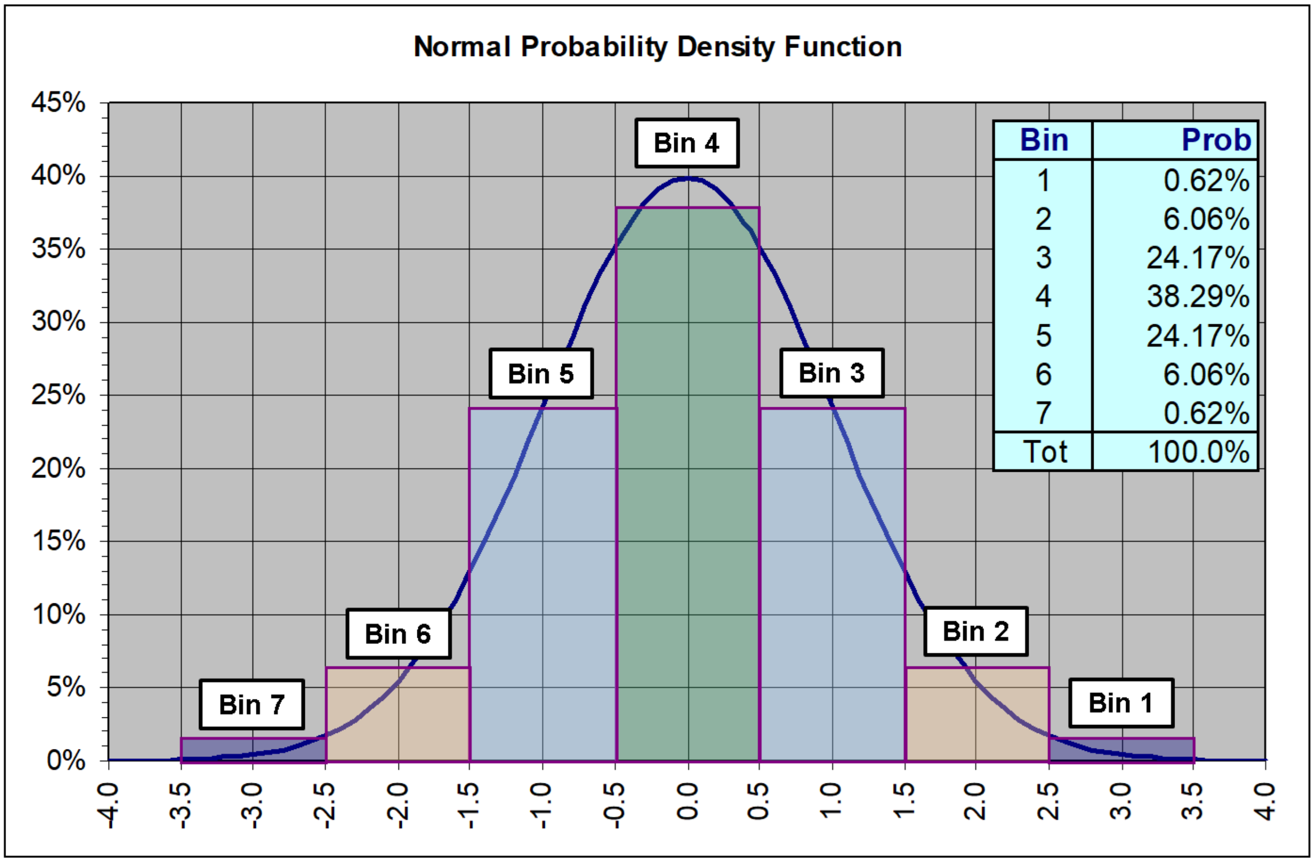
Once the load and weather relationship is developed, the load and weather response function should also be examined. The weather response function is the first derivative with respect to the weather variable. Significant differences can emerge in the weather response function between the different load weather models. Figure 6, below, compares the weather response function between linear, quadratic, 3rd (cubic) and 4th order polynomial weather functions. It is important to note, that the 3rd and 4th order polynomial curves in Figure 6 describe a weather response that begins to decrease at the highest temperatures as equipment begins to reach full load, while the weather response functions of the linear and quadratic models are monotonically increasing. An examination of the weather response at high temperature and humidity values is a key step in LFU modeling so that an assessment of the model to handle the saturation of load can be performed [4, 5].

Figure 6: NYCA-wide Model Weather Response Functions for Linear, Quadratic, Cubic, and 4th Order Fits.



Another important consideration in the development of LFU models is the examination of the design weather conditions that coincide with peak producing loads. The distribution of the weather dataset should be tested for symmetry, skewness, and normality. This includes examining the longer-term mean and standard deviation (e.g., at least 20-years). Assessments of normality in the weather data set can be accomplished using one or more statistical normality tests such as the Chi-square, Shapiro-Wilk, and/or others [2]. If the aforementioned tests conclude that normality of the peak producing weather cannot be rejected, then the normal distribution is used to define the probability distribution function (PDF) and a representative histogram is constructed for use in the MARS modeling software. For the normal distribution, a three-sigma rule conveys that nearly all (99.7%) weather values lie within three standard deviations of the mean. For example, the cumulative probability of a random normally distributed weather observation falling between the -0.5 and +0.5 standard deviations from the mean equals approximately 38.29%. Figure 7, below, shows the full normal distribution divided into seven probability Bins along with the respective probabilities of each Bin.

Figure 7: Probability Bins associated with a Normal Distribution



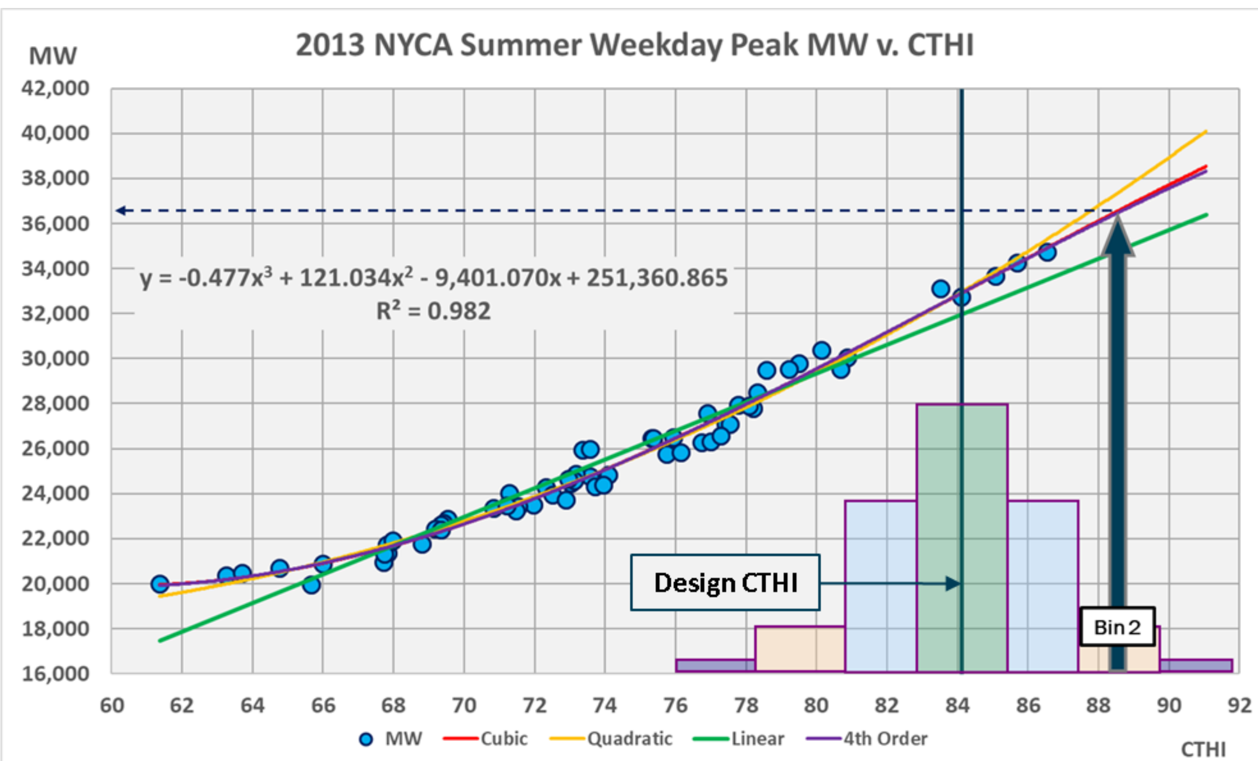
After the probability Bins are defined, the peak producing weather values are assigned to each Bin of the PDF. In order to relate the PDF to the peak load model a z-transformation (also referred to as standardization or auto-scaling) can be used to make two sampled data sets comparable with one another. The z-transformation has the property of centering and scaling the data to a zero mean and z-values (z-scores) representing multiples of the standard deviation of the sample [2]. Using a Bin spacing of 1.0 standard deviation and applying the standard z transformation yields the probability distribution function shown in Table 1, below, for a 20-year sample of the NYCA CTHI data. An example of this process is given in

Figure 8, below (note: the annual peak load producing CTHI distribution superimposed on the chart is an approximate representation and provided for illustrative purposes).

Table 1. NYCA-wide Distribution of CTHI Fit to the Normal Distribution, 2000 - 2019

Bin	Mid-Point	Z Begin	End	Cumulative Probability	Bin Probability	CTHI
1	3	2.5	3.5 ->	1.00000	0.00621	90.80
2	2	1.5	2.5	0.99379	0.06060	88.54
3	1	0.5	1.5	0.93319	0.24173	86.28
4	0	-0.5	0.5	0.69146	0.38292	84.02
5	-1	-1.5	-0.5	0.30854	0.24173	81.77
6	-2	-2.5	-1.5	0.06681	0.06060	79.51
7	-3	<- -3.5	-2.5	0.00621	0.00621	77.25

Figure 8: NYCA-wide Model between Peak Load and Cumulative THI Variable



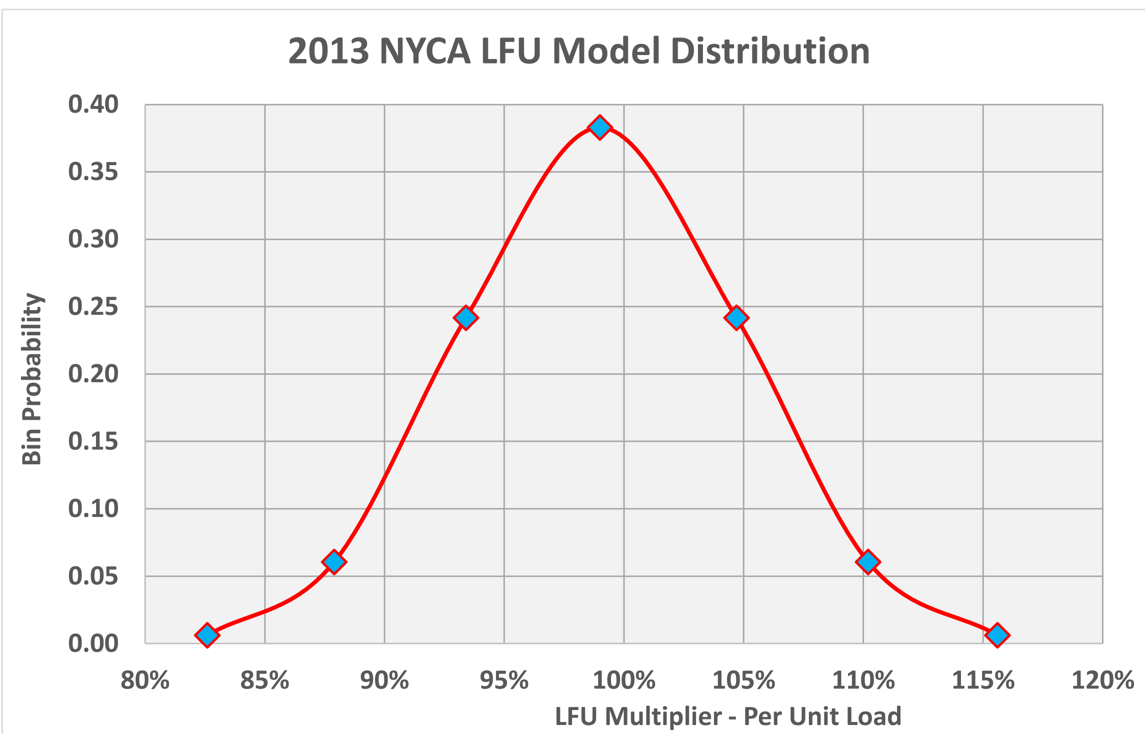
Once the peak load producing weather distribution is assembled, the weather response function (

Figure 8) can be used to tabulate both the peak loads in the distribution and the PU multipliers for use in MARS. Table 2, below, provides an example of the peak loads, their respective probabilities, and the PU load multipliers. The results shown in Figure 9 visualize the data in Figure G and are the result of the LFU modeling process. These results are based upon a simple 2013 NYCA-wide LFU model, and do not reflect actual LFU results used for modeling areas in historical reliability studies.

Table 2: Example of NYCA LFU Distribution Data using the 2013 Weather/Load Relationship

		Z						
Bin	Mid-Point	Begin	End	Cumulative Probability	Bin Probability	CTHI	Load	PU Load
1	3	2.5	3.5 ->	1.00000	0.00621	90.80	38,399	115.6%
2	2	1.5	2.5	0.99379	0.06060	88.54	36,549	110.2%
3	1	0.5	1.5	0.93319	0.24173	86.28	34,701	104.7%
4	0	-0.5	0.5	0.69146	0.38292	84.02	32,827	99.0%
5	-1	-1.5	-0.5	0.30854	0.24173	81.77	30,969	93.4%
6	-2	-2.5	-1.5	0.06681	0.06060	79.51	29,143	87.9%
7	-3	<- -3.5	-2.5	0.00621	0.00621	77.25	27,390	82.6%

Figure 9: Example of 2013 NYCA LFU Distribution



The use of a normal distribution to model load forecast uncertainty has been shown to be a reasonable assumption. Common practice to date involves describing the epistemic uncertainty by a normal distribution with a given standard deviation [6, 7]. The potential load/weather scenarios at the tail ends of the distribution are meant to represent extremely rare events that have a very low probability of occurrence. The use of normal curves to model load forecast uncertainty captures the possibility of these extremely rare events and properly assigns them a very low probability of occurrence. In LFU modeling, it remains difficult to obtain sufficient historical data to fully ascertain the distribution type. The NYISO recently completed a climate change study that included a compilation and analysis of over 70 years of weather variable information and trends over the New York Control Area [3]. In order to further refine and determine updates to current LFU modeling methods, the NYSRC Installed Capacity Subcommittee (ICS), with support of the NYISO, elected to engage in a study on LFU modeling. This study on LFU modeling builds upon the analysis and data obtained during the NYISO climate change study with a goal of compiling updated information on the statistical variation in peak load producing weather conditions.

4 Study Topics and Methods

This whitepaper examines three main study areas: 1) a comparison of temperature-humidity indices used in LFU modeling, 2) an analysis of long-term historical CTHI distributions for the NYCA and the LFU modeling areas, and 3) a review of the inter-annual trends in sensitivity between weather and load. These three topics were selected based on discussion with the NYSRC to enhance the understanding of LFU modeling and to help the NYISO identify where areas of additional study on LFU modeling are recommended. A brief introduction of each study topic and the associated methods used are provided below:

4.1 Comparison of Temperature-Humidity Indices

Historically, the Zones H&I and Zone J Load Forecast Uncertainty (LFU) models have often used Con Edison's Temperature Variable (TV) rather than the NYISO's CTHI variable. Likewise, the Zone K model has often used LIPA's Temperature and Humidity Index (THI4), which includes a different specification than CTHI. This section analyzes and assesses the relationship between CTHI, TV, and THI4 to determine whether there are any significant differences between these variables and their impact on LFU, or they are similar enough that any LFU impacts are insignificant. The NYISO uses CTHI alone for the other LFU areas, namely Zones A-E and Zones F&G.

4.2 Long-Term Historical CTHI Distribution Analysis

This section analyzes the characteristics of long-term CTHI weather distributions during peak load producing days. Up to 71 years of historical peak weather are examined (1950-2020). LFU area CTHI is calculated using a weighted average of station level weather variables from weather stations in the region. This section analyzes and compares observed peak temperatures from 1950 through current relative to the temperatures defined in the LFU Bins. For example, Bin 1 temperatures, representative of an approximately one in 160-year occurrence, are contrasted against historically observed peak temperatures in order to provide an updated look at the extreme end of the distribution.

Separate LFU models are made for five LFU modeling areas: 1) Zones A-E, 2) Zones F&G, 3) Zones H&I, (4) Zone J, and 5) Zone K. Historical patterns of peak weather across the LFU areas are analyzed, to determine the level of historical coincidence in extreme temperatures across zones during New York Control Area (NYCA) peak load days. The LFU results from a NYCA-wide LFU model are compared against the sum of area LFU models to assess the evolution of peak weather and load diversity across the NYCA.

This analysis also compares extreme temperatures at individual stations to extreme temperatures at the composite LFU area level. Information on historical station level maximums may provide more insight to the theoretical maximum possible temperature in a given area. LFU modeling is currently based on the distribution of peak-producing CTHI, i.e., the CTHI during the NYCA peak load day. Another measure of extreme weather is the summer seasonal maximum temperature, i.e. the maximum summer CTHI. These two measures of peak CTHI have slightly different historical distributions, both in average and variance. This section analyzes and describes the historical distributions of both variables and their potential differences and impacts on LFU modeling.

4.3 Inter-Annual Weather Sensitivity and LFU Trends

This section will explores changes in weather sensitivity over recent years. Changes in LFU multipliers over time are generally driven by the changing response of peak load relative to peak weather. The slope of the LFU model represents the average MW of load increase caused by a rise of one degree in temperature or CTHI, or another temperature variable. Using a single consistently defined and simple NYCA LFU model simulated year over year, this section will explore how this average slope has evolved over the past 20-years, and whether there are any clear trends in the resulting LFU multipliers.

5 Comparison of Temperature-Humidity Indices

5.1 Comparison of CTHI and TV

Historically, the Zones H&I and Zone J LFU models have often used Con Edison's Temperature Variable (TV) rather than the NYISO's Cumulative Temperature & Humidity Index (CTHI). The NYISO's CTHI is a three-day weighted average of dry bulb and wet bulb temperatures, as shown in Figure 10 below:

Figure 10: Steps for Calculating the Cumulative Temperature Humidity Index (CTHI)

Step 1: Calculate hourly THI as a weighted average of the dry bulb temperature (DB) and the wet bulb temperature (WB). There are 24 values per day:

For any day d,

$$(\boldsymbol{THI})_{di} = \mathbf{0.6} \times (\boldsymbol{DB})_{di} + \mathbf{0.4} \times (\boldsymbol{WB})_{di}$$

Where $\boldsymbol{i} = \mathbf{0, 1, 2, \ldots, 23}$ indicate the hours of a day

Step 2: Calculate the THI_max for a day. This is the maximum hourly THI value for that day:

$$(\boldsymbol{THI\_max})_d = \max\left((\boldsymbol{THI})_{di}\right)$$

Step 3: Calculate the daily CTHI using a weighted average of three days (the day for which the CTHI is being calculated and the two preceding days):

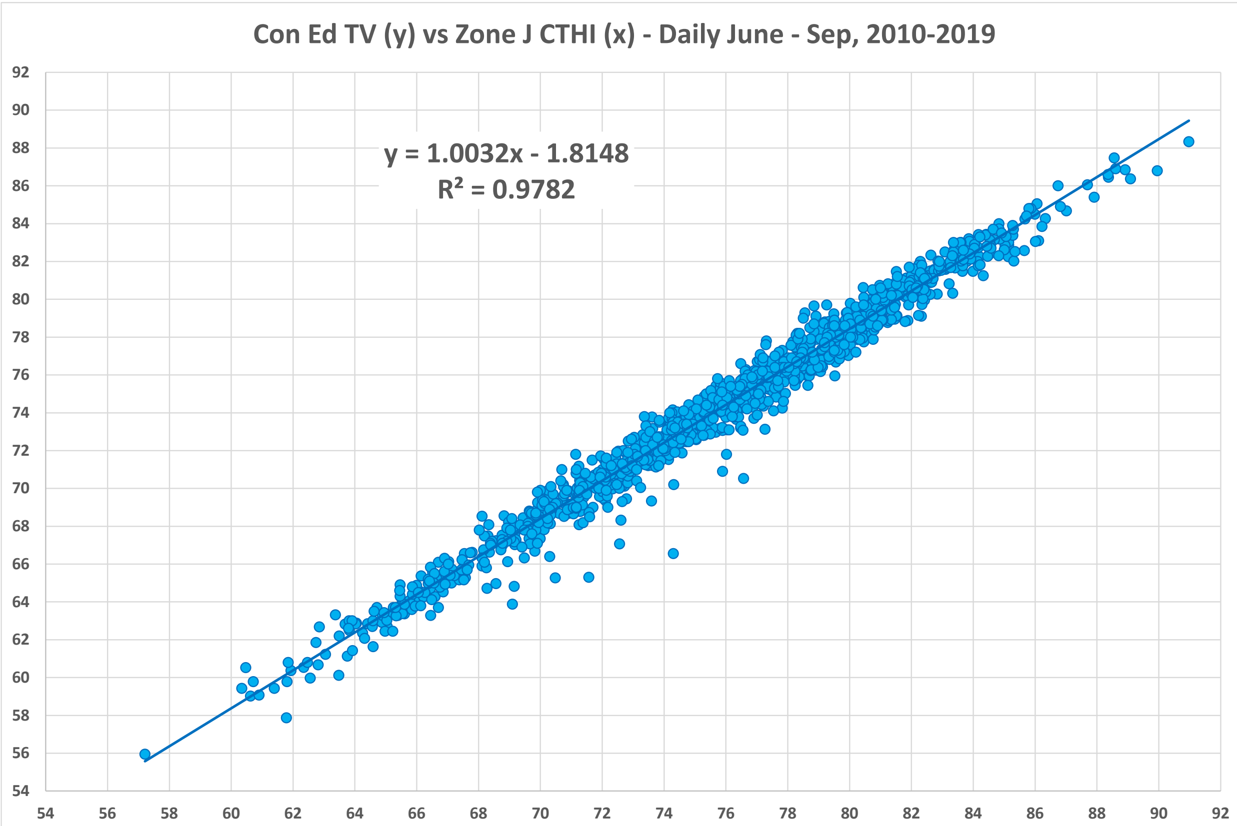
$$(\boldsymbol{CTHI})_d = \mathbf{0.7} \times (\boldsymbol{THI\_max})_d + \mathbf{0.2} \times (\boldsymbol{THI\_max})_{d-1} + \mathbf{0.1} \times (\boldsymbol{THI\_max})_{d-2}$$

The CTHI calculation has multiple important aspects. It takes into account both dry bulb and wet bulb temperatures, adjusting for the load increasing impacts of both heat and humidity. It also incorporates lag values, accounting for the load increasing impacts of heat buildup over multiple days. The CTHI calculation uses the maximum temperature-humidity hour from each day. The CTHI value for Zone J is based upon a weighted average of weather variables from three weather stations: JFK Airport, LaGuardia Airport, and Central Park.

Con Edison's Temperature Variable (TV) is a similar temperature and humidity index. It differs in that it uses the maximum three-hour average of temperature-humidity from each day. It also differs in its weighting of dry bulb and wet bulb, and in its weather station weighting. A 20-year history of daily TV values was obtained from Con Edison staff.

For an initial comparison of CTHI and TV, a daily scatterplot of summer CTHI and TV is depicted in Figure 11 below.

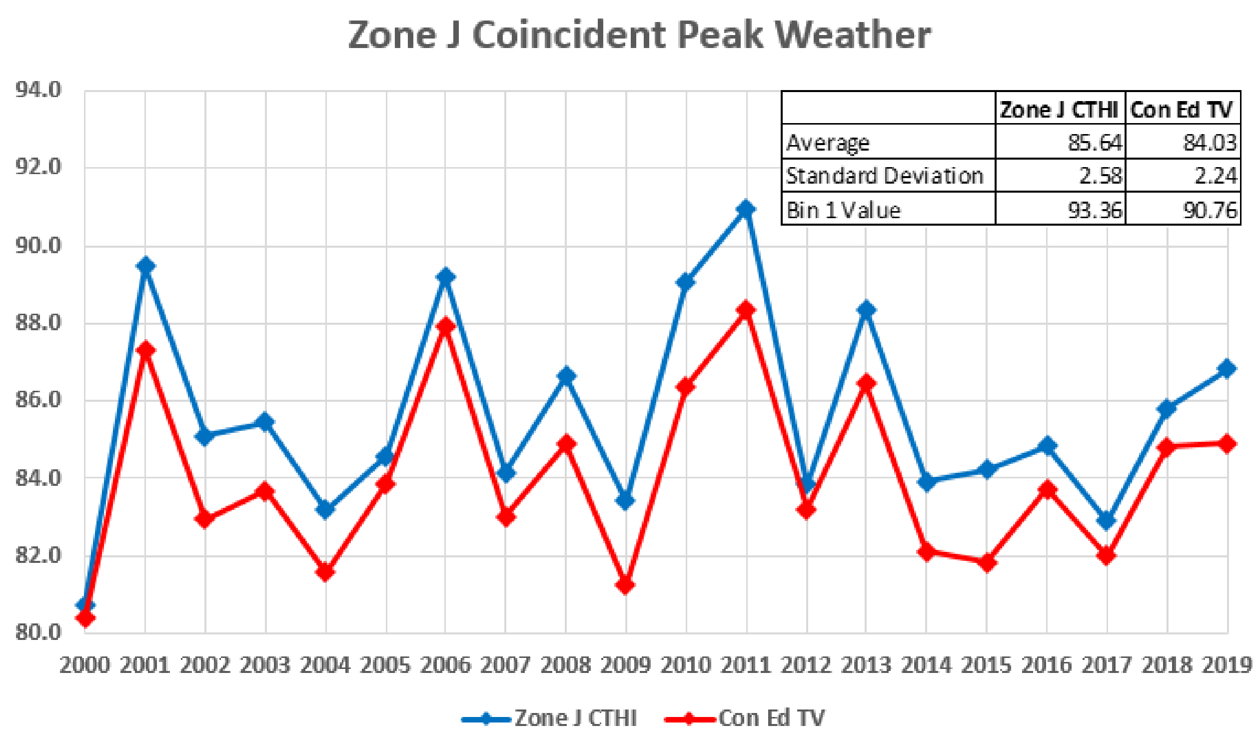
Figure 11: Con Edison TV v. Zone J CTHI



There is a tight scatter between TV and CTHI, as the two variables are very highly correlated, with an R-squared of 0.978. There are a few outlier points, but most observations fit closely around the predicted line. There are no systematic departures from the predicted line, so it is reasonable to assume that the relationship between the variables is linear. On average, one degree of TV yields 1.0032 degrees of CTHI, so the load impact of an additional degree of CTHI should be very similar to the impact of an additional degree of TV.

Next, historical NYCA-coincident peak-producing values of CTHI and TV are compared in Figure 12.

Figure 12: TV and CTHI during the NYCA Peak Load Day



TV and CTHI during the NYCA peak load day track closely to each other on a year-to-year basis, with an R-squared value of 0.943. As expected from the constant of -1.8 degrees shown on the scatterplot, the TV is typically lower than the CTHI; but their patterns are relatively consistent. The average peak-producing CTHI is about 1.6 degrees higher than the average peak-producing TV, based on the 2000-2019 coincident peak load history. Of note, the Bin 1 CTHI value of 93.36 is about 2.6 degrees larger than the Bin 1 TV value of 90.76 degrees due to the increased standard deviation of peak-producing CTHI relative to peak-producing TV. This larger delta at the Bin 1 level relative to the average (Bin 4) level could create a wider LFU distribution and higher upper Bin LFU multipliers for a regression using CTHI.

Finally, simple regression models were calculated for Zone J loads using both CTHI and TV. The models were based on 2011-2013 summer data, and were identical apart from their differing weather variables. The models regressed summer weekday Zone J peak load with demand response impacts added back against daily TV or CTHI, including squared and cubed terms. The 2011-2013 summers were used as they contained two very hot peak load days within a three-year period. The TV-based model (R-squared = 0.975) had a slightly better fit than the CHTI-based model (R-squared = 0.962). The LFU per unit multiplier results for the two models are shown in Figure 13.

Figure 13: Zone J LFU Results using TV and CTHI (simple model)

2011-13 LFU Model Using TV				
Bin	**StDev**	**TV**	**MW**	**LFU**
1	3	90.76	12,565	111.6%
2	2	88.52	12,080	107.3%
3	1	86.27	11,566	102.7%
4	0	84.03	11,032	97.9%
5	-1	81.78	10,487	93.1%
6	-2	79.54	9,942	88.3%
7	-3	77.29	9,407	83.5%
Design	0.43	84.99	11,263	100.0%

2011-13 LFU Model Using CTHI				
Bin	**StDev**	**CTHI**	**MW**	**LFU**
1	3	93.36	12,563	111.7%
2	2	90.79	12,097	107.6%
3	1	88.21	11,567	102.9%
4	0	85.64	10,990	97.8%
5	-1	83.06	10,386	92.4%
6	-2	80.48	9,771	86.9%
7	-3	77.91	9,163	81.5%
Design	0.43	86.74	11,243	100.0%

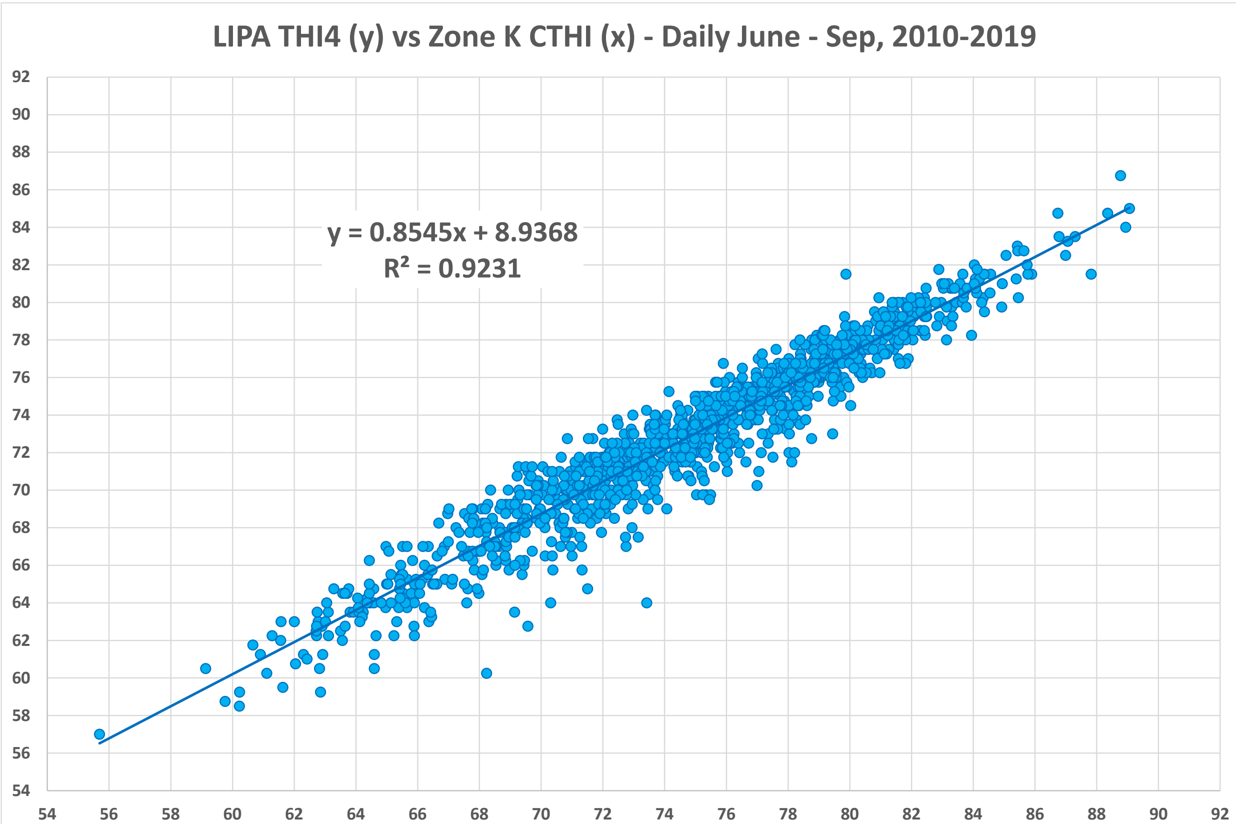
Note that Con Edison uses a 1-in-3 design condition, meaning that peak load producing temperatures are defined at the 67th percentile and will only be exceeded once every three years on average. The 1-in-3 design condition means that the reference load level is set at 0.43 standard deviations above the mean, and yields LFU multipliers under 100% in Bin 4. The upper Bin LFU multipliers for the TV model and the CTHI model were very similar, with a Bin 1 difference of only 0.1%. Bin 1 loads and design condition loads between the two models were nearly equivalent, with differences of only 2 MW and 20 MW respectively. This simple model comparison suggests that Zone J LFU results based on TV and based on CTHI are very similar. There are some slightly larger differences in the load levels and per unit multipliers at the lower Bins, but these differences are unlikely to produce any significant changes in LOLE results.

5.2 Comparison of CTHI and THI4

The NYISO's Zone K CTHI is calculated using a weighted average of weather variables from the Farmingdale and Islip weather stations. Historically, the Zone K LFU models have often used a weather variable defined by LIPA rather than the NYISO's CTHI. Recent models have used THI4, which is a temperature-humidity index with a different specification from CTHI. THI4 differs from CTHI in that it is a weighted average of dry bulb and dew point and uses a different weather station weighting. Daily THI4 is calculated using the four hours immediately preceding the LIPA peak load hour. There is no multi-day lagged component of THI4. LIPA staff provided the NYISO with the THI4 formula, which was used to calculate daily THI4 over a 20-year period.

For an initial comparison of CTHI and THI4, a daily scatterplot of summer CTHI and THI4 is shown in Figure 14.

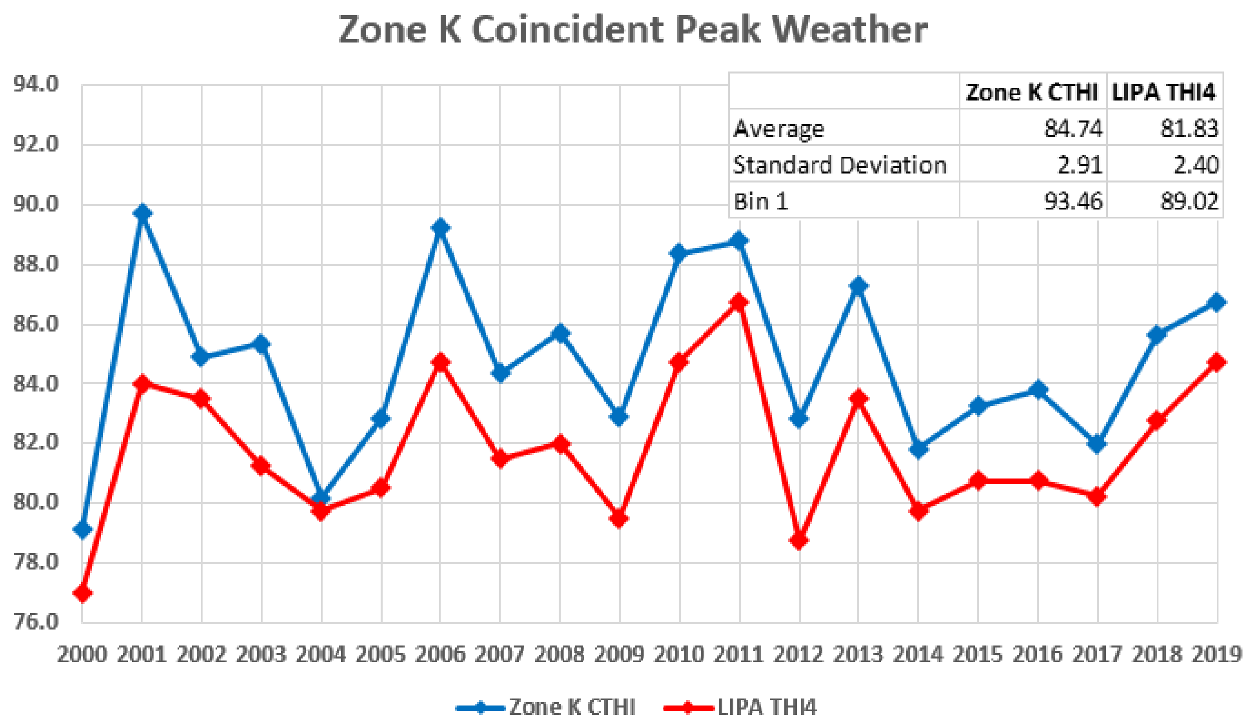
Figure 14: LIPA THI4 versus Zone K CTHI



There is a relatively stable linear relationship between THI4 and CTHI. However, there is considerably more spread between THI4 and CTHI than there is between TV and CTHI. The R-squared value of the relationship is 0.923. The scales of CTHI and THI4 are somewhat different, with a slope of 0.85 degrees of CTHI per degree of THI4.

Next, historical NYCA-coincident peak-producing values of CTHI and THI4 are compared in Figure 15.

Figure 15: THI4 and CTHI during the NYCA Peak Load Day



THI4 and CTHI during the NYCA peak load day track relatively closely to each other on a year-to-year basis, with an R-squared value of 0.840. The average and Bin 1 CTHI values are approximately 2.9 degrees and 4.4 degrees higher than their respective THI4 values. The standard deviation of CTHI is about half a degree higher than THI4. The year-to-year pattern in coincident peak load producing CTHI and THI4 are very similar.

Finally, simple regression models were calculated for Zone K loads using both CTHI and THI4. The models were based on 2011-2013 summer data, and were identical apart from their differing weather variables. The models regressed summer weekday Zone K peak load against daily THI4 or CTHI, including squared and cubed terms. The LFU multiplier results for the two models are shown in Figure 16.

Figure 16: Zone K LFU Results using THI4 and CTHI (Simple Model)

2011-13 LFU Model Using THI4				
Bin	StDev	THI4	MW	LFU
1	3	89.02	6,288	114.9%
2	2	86.62	6,104	111.5%
3	1	84.22	5,826	106.4%
4	0	81.83	5,475	100.0%
5	-1	79.43	5,073	92.7%
6	-2	77.03	4,643	84.8%
7	-3	74.63	4,208	76.9%
Design	0	81.83	5,475	100.0%

2011-13 LFU Model Using CTHI				
Bin	StDev	CTHI	MW	LFU
1	3	93.46	6,450	118.3%
2	2	90.55	6,201	113.7%
3	1	87.64	5,861	107.5%
4	0	84.74	5,453	100.0%
5	-1	81.83	5,003	91.7%
6	-2	78.92	4,535	83.2%
7	-3	76.01	4,075	74.7%
Design	0	84.74	5,453	100.0%

Unlike Con Edison, LIPA employs a 50^{th} percentile or 1-in-2 design condition, meaning that the Bin 4 LFU multiplier is 100% by definition. Upper Bin LFU multipliers for the CTHI model were greater than the LFU multipliers from the THI4 model, with the Bin 1 value being 3.4% higher, translating into about 180 MW in peak load terms. Bin 2 and Bin 3 multipliers were likewise higher in the CTHI model. Generally, the weather response of the THI4 model showed more load saturation at extreme temperatures than did the CTHI model. The THI4 model had a better fit than the CTHI model, with R-squared values of 0.942 and 0.932 respectively. Additional investigation may be useful; both to investigate potential reasons for the apparent difference in the load weather relationships across the two variables and to determine whether this difference holds in further LFU model estimates based on different years.

6 Long-Term Historical CTHI Distribution Analysis

6.1 Coincident versus Non-Coincident Extreme Weather

The analysis presented in this section examines the coincidence of extreme weather across all of the five LFU modeling areas: 1) Zones A-E, 2) Zones F&G, 3) Zones H&I, 4) Zone J, and 5) Zone K. That is, the analysis examines to what degree extreme temperatures are occurring across the state simultaneously. In order to explore the coincidence of extreme weather, NYCA peak load day CTHI was plotted for the five LFU modeling areas over the past 20 summers and is depicted in Figure 17.

Figure 17: NYCA Peak Load Day Reliability Modeling Area CTHI

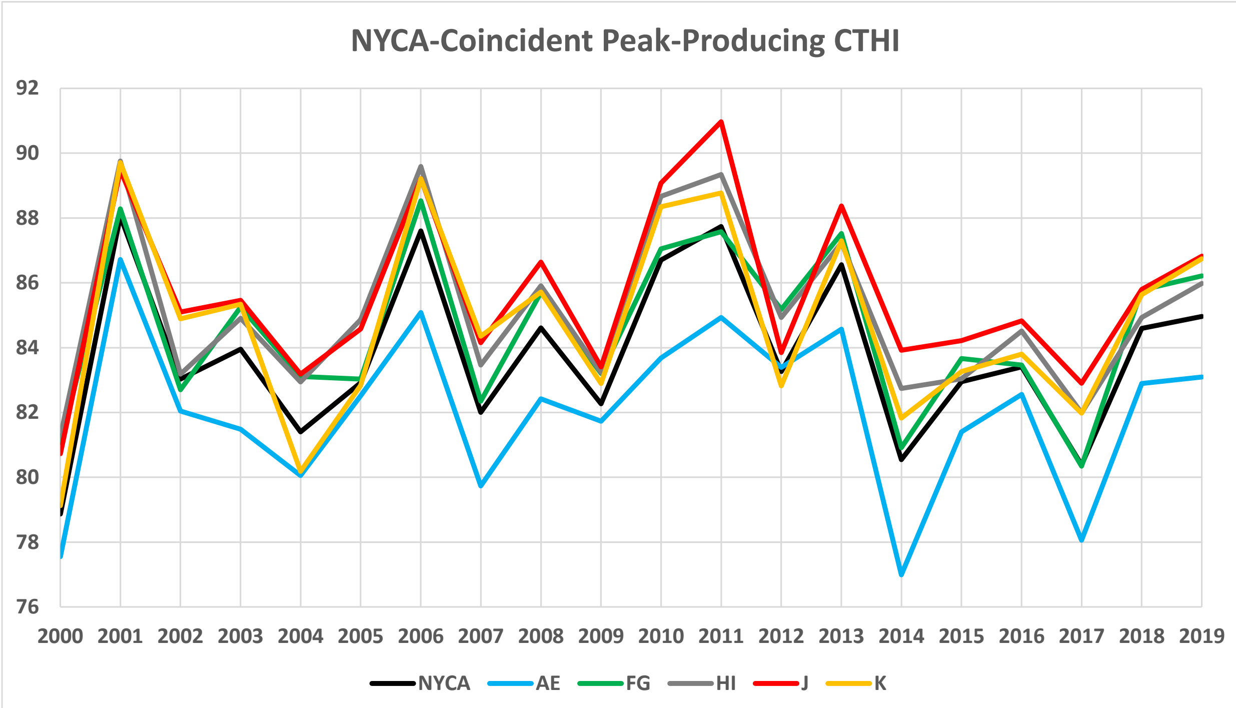
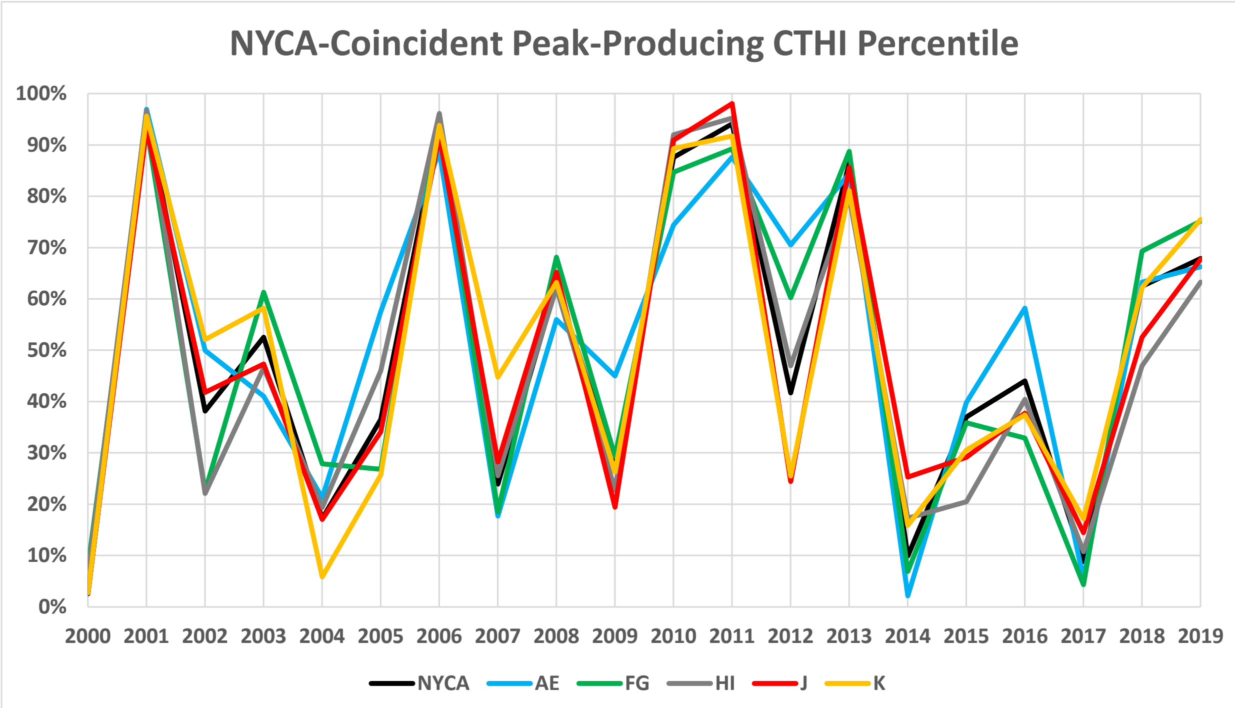


Figure 17 shows that in general, on a year-to-year basis, the CTHI across the LFU modeling regions tend to track fairly well against the NYCA composite CTHI. If peak-producing temperatures are relatively high or low in one region, they are typically likewise in the other regions. Some general trends can be seen in the graph; most clearly that peak load producing weather in the A to E area is typically milder than peak load producing weather in the remaining regions. On average, New York City (Zone J) has the hottest peak weather.

In order to normalize for different average peak weather and variation in peak weather across the regions, the NYCA-coincident peak weather by region was transformed into percentile terms relative to each region's distribution (Figure 18):

Figure 18: NYCA Peak Load Day LFU modeling Area CTHI Percentile



Looking at the percentiles by area, it becomes even clearer that the annual pattern in peak load producing weather is very consistent by area of the state. In extremely warm summers, such as 2001 and 2006, peak load weather is generally at the upper percentiles for all regions simultaneously. Likewise, in relatively mild summers such as 2014 and 2017, peak load weather is generally at the lower percentiles for all regions simultaneously. Additional peak-producing weather metrics are shown in Table 3 below:

Table 3: NYCA Peak Load Day CTHI Statistics

NYCA Peak-Producing CTHI Statistics, 2000 - 2019				
Area	Average CTHI	Standard Deviation	Correlation with NYCA	Percentile at NYCA 99th
A to E	82.04	2.49	0.934	96%
F & G	84.55	2.45	0.961	100%
H & I	85.12	2.53	0.967	96%
Zone J	85.64	2.58	0.967	96%
Zone K	84.74	2.91	0.960	98%
NYCA	83.79	2.52	--	99%

A few interesting observations can be noted from these distributions of NYCA-coincident peak-producing weather statistics. First, Zone J has the hottest typical peak load day weather, at 85.64 CTHI, while A to E has the mildest typical peak load day weather, at 82.04 CTHI. However, these are slight differences, with an overall range of less than 4 degrees. The majority of the areas have NYCA peak load day CTHI distribution standard deviations of approximately 2.4 to 2.6 degrees. The slight outlier is the Zone K standard deviation at 2.91, which suggests the NYCA peak load day weather on Long Island tends to be somewhat more variable. Importantly, the correlation between NYCA and all five areas is very strong, with A to E being 93% correlated and the remaining areas being at least 96% correlated. This confirms the consistent pattern of peak load day weather we observed in the prior figures. Using these distributions, the final column shows the expected percentile of area weather on the NYCA peak load day, given that the NYCA weather is at the 99th percentile. During a Bin 1, or 99th percentile NYCA weather peak load day, we expect the A to E, H&I, and Zone J weather to be at the 96th percentile. The Zone K weather is expected to be at the 98th percentile, and the F&G weather is calculated to be at the 100th percentile. This information suggests that extreme weather coincidence across all areas of the state is a generally viable assumption, since when NYCA is experiencing an extreme temperature event at the 99th percentile; all areas of the state are likewise at extreme conditions of at least the 96th percentile.

6.2 Coincident versus Non-Coincident Extreme Load

The preceding section focused on the coincidence of extreme weather across the state during NYCA peak load days. This section explores the degree to which there is a likewise coincidence of extreme load across the state during NYCA peak load days. This analysis aims to account for any non-weather factors that may impact peak loads at upper Bin levels. A recent example of such a factor was the 2019 NYCA peak load, which occurred on a Saturday. The majority of upstate and non-New York City (NYC) areas were at or near peak load levels during the Saturday peak load day. However, weekend loads are generally much lower in NYC, and coincident peak loads were likewise much lower than they otherwise would have been given the weather conditions.

Currently, the Bin 1 NYCA peak load used in the MARS models is determined by five separate LFU models for the five different areas. The total NYCA coincident peak load assumed for Bin 1 is simply the sum of the Bin 1 coincident peak loads from these five models. Performing LFU modeling for all 11 zones individually and adding up the Bin 1 MWs, or modeling NYCA as a whole to determine the expected NYCA Bin 1 MWs could both produce different results, due to the non-weather impacts on extreme load discussed above.

An initial exploration of this impact tests a NYCA-wide LFU model as a control relative to the total from the five individual area models. For five different two-year periods, simple LFU models were built for each of the five LFU modeling areas and for the NYCA as a whole. Pooled models were constructed for 2010-11, 2012-13, 2014-15, 2016-17, and 2018-19. These simple models were consistent across all years and areas, and regressed summer weekday peak loads against daily CTHI, with squared and cubed terms, with one exception. The 2016-17 Zone F&G model excluded the cubed CTHI term, as it created negative sloping load weather response at the upper Bins. Load values excluded demand response impacts for both the NYCA-wide model and the regional models, yielding a one to one comparison. A comparison of Bin 1 values for the five sets of area and NYCA models is shown in Table 4 below:

Table 4: Bin 1 Values, Sum of Area Models vs. NYCA Control Model

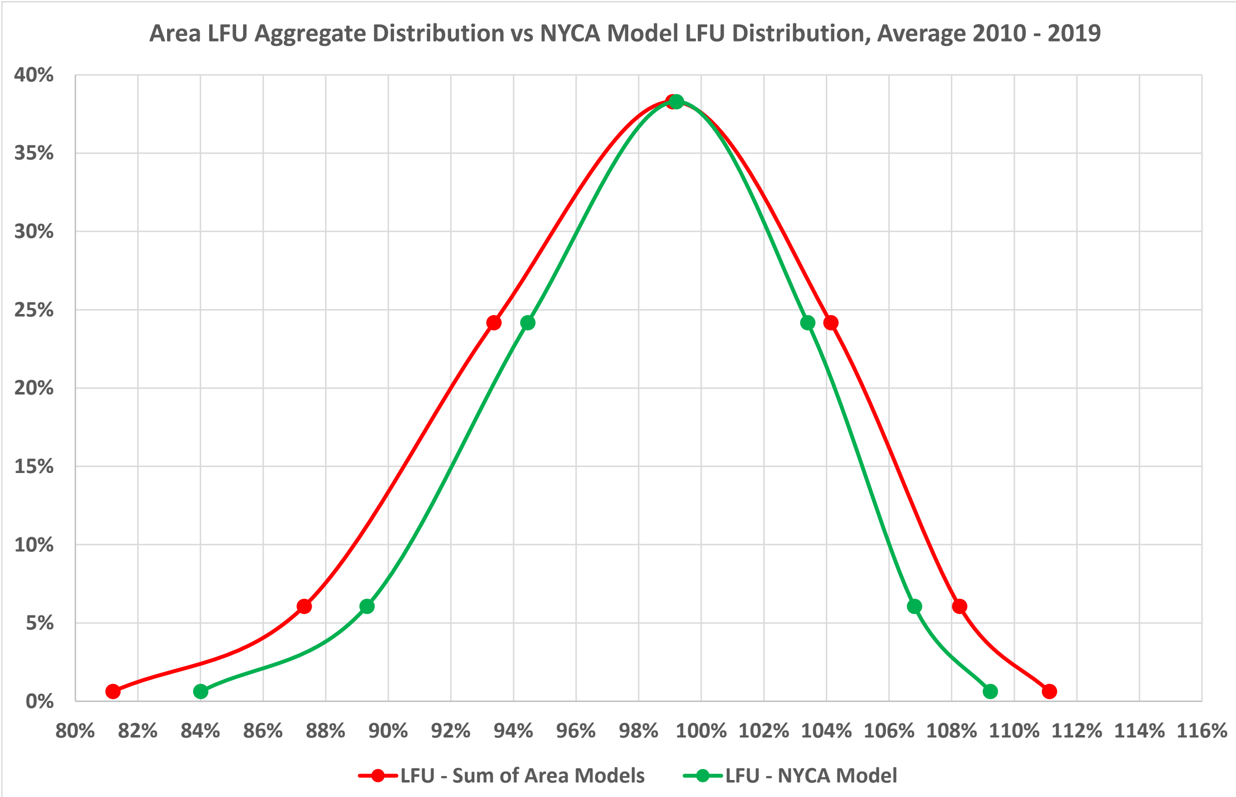
Bin 1 Simple Model LFU Results - Pooled Models						
Model	LFU - Sum of Area Models	LFU - NYCA Model	MW - Sum of Area Models	MW - NYCA Models	Delta %	Delta MW
2010-11	108.6%	107.2%	35,330	34,843	1.5%	487
2012-13	111.3%	111.0%	36,485	36,422	0.2%	63
2014-15	110.5%	113.4%	35,778	36,725	-2.9%	-947
2016-17	114.5%	109.5%	37,038	35,391	5.0%	1,647
2018-19	110.7%	105.1%	35,504	33,677	5.6%	1,827

On average, the sum of the area models produced larger Bin 1 LFU multipliers and MW values than the NYCA control model. The design MWs between the two models were calibrated to equality in order to ensure a one-to-one comparison in Bin 1 values for the two methods. The difference in Bin 1 values (sum of area models less NYCA control model) ranged from -947 MW to +1,827 MW, and the delta in LFU multipliers ranged from -2.9% to +5.6%. In four of the five periods, the NYCA control model produced lower extreme values than the five combined area models. Table 5 and Figure 19 summarize the average distribution of both model types across the entire period:

Table 5: Average Model Results, Sum of Area Models v. NYCA Control Model

Average Simple Model LFU Results (2010 - 2019), Sum of Area Models and NYCA Control Model							
Bin	CTHI	LFU - Sum of Area Models	LFU - NYCA Model	MW - Sum of Area Models	MW - NYCA Models	Delta %	Delta MW
B1	90.8	111.1%	109.2%	36,027	35,412	1.9%	615
B2	88.5	108.3%	106.8%	35,096	34,503	1.4%	594
B3	86.3	104.1%	103.4%	33,763	33,399	0.7%	365
B4	84.0	99.1%	99.2%	32,124	32,043	-0.1%	81
B5	81.8	93.4%	94.5%	30,274	30,508	-1.1%	-234
B6	79.5	87.3%	89.3%	28,310	28,846	-2.0%	-537
B7	77.3	81.2%	84.0%	26,327	27,131	-2.8%	-804

Figure 19: Average LFU Distribution, Sum of Area Models versus NYCA Control Model

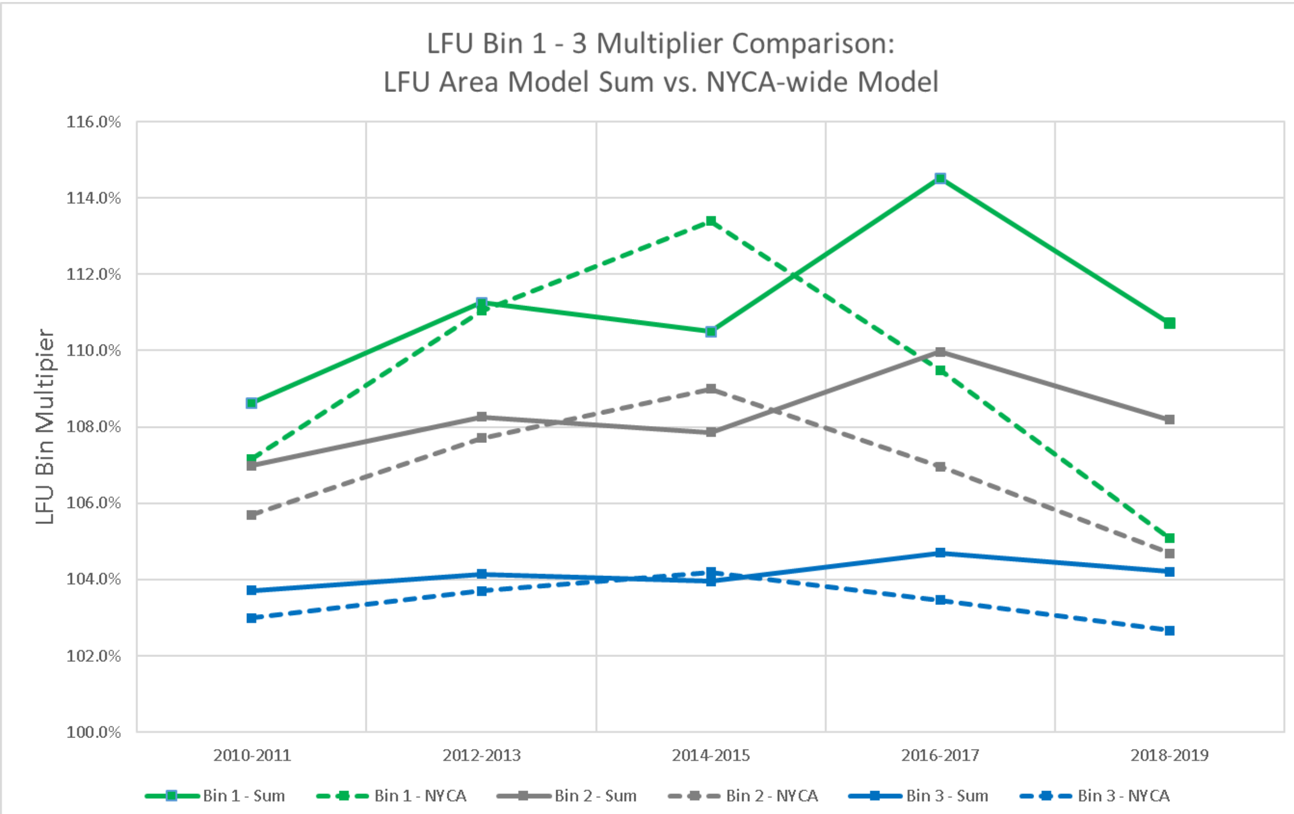


From the above Table 5 and Figure 19, we note that on average, the NYCA standalone model produces a tighter LFU distribution, while the aggregate of the area models produces a more spread distribution. The average Bin 1 LFU for the aggregate area models is 111.1%, while the average for the NYCA standalone model is 109.2%, a difference of 1.9% that translates to an average delta of about 600 MW. On average, upper Bin LFU loads are lower in the NYCA standalone model than for the sum of the LFU area models. However, there are several limiting factors to this general observation. One is that, as seen in Table 4, the NYCA model Bin 1 loads have more year-to-year variation than the aggregate area Bin 1 loads. Another is that the pattern of a narrower NYCA standalone model LFU distribution is not consistent. For 2014-15 the standalone model produced a significantly larger Bin 1 multiplier, and in the 2012-13 models the results were nearly equivalent. Finally, these results are based on simple LFU models as an example, while final LFU models used for reliability analyses tend to include additional variables and complexity.

6.3 Trends in Coincident versus Non-Coincident Extreme Load

A review of the biennial variability in the LFU Bin 1 values shown in Table 4 reveals there is a growing divergence in the Bin 1 LFU ratio and MW values. Figure 20 shows a comparison of Bin 1, 2 and 3 multipliers between the sum of the area models and the NYCA pooled models. The values are diverging in time between all three Bin levels with the sum of the area models growing from 2014-2015 through 2018-2019 while the values for the NYCA model are decreasing in the same period.

Figure 20: Bins 1-3 Values, Sum of Area Models vs. NYCA Control Model

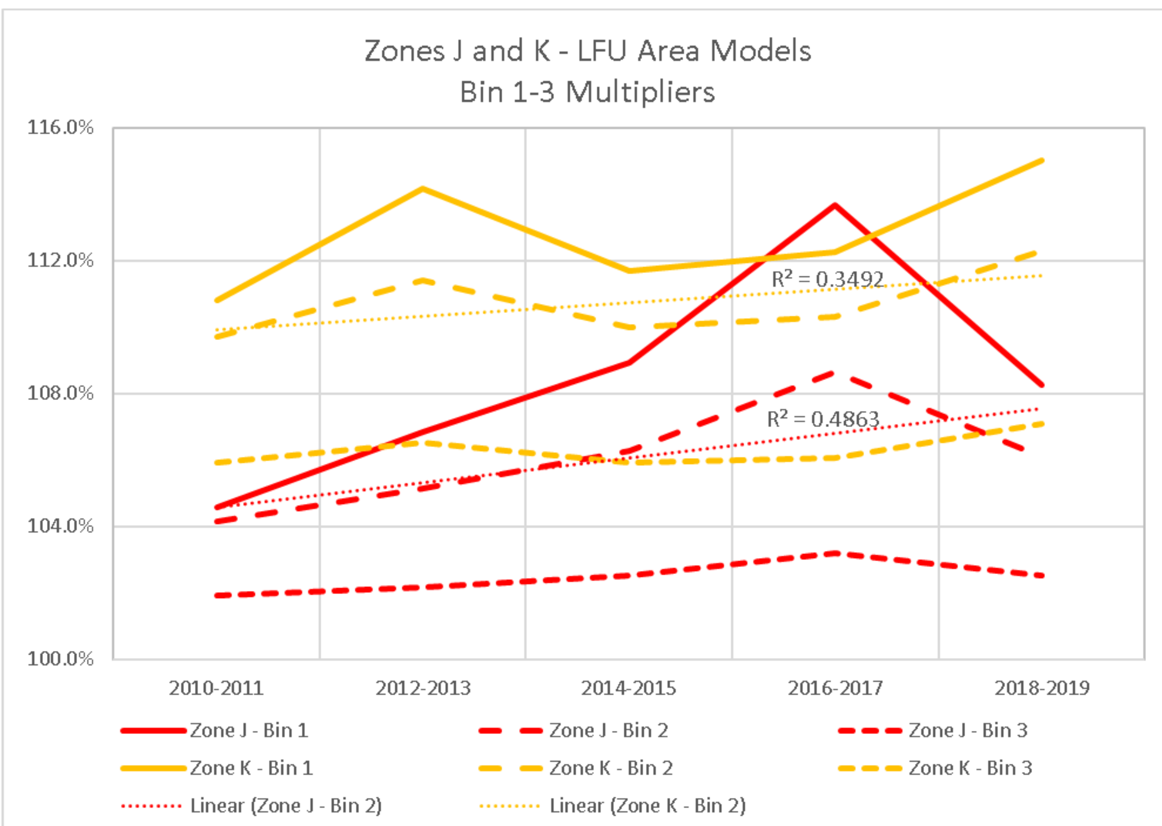


The results in Figure 20 suggest there is increasing variation in the weather/load sensitivity across the various LFU modeling regions. In order to examine further, the LFU area model Bin 1 through 3 multipliers are provided in Table 6 below. Similar to the NYCA-wide model, the LFU area model results for all areas show significant variability between modeling periods in Bins 1 and 2, and a few trends emerge throughout the study period. The LFU area models for Zone J and K show an increasing trend in the Bin multipliers, particularly in Bins 1 and 2 (Figure 21). There are no clearly discernable trends in the LFU area model results in Zones A -E and Zones F and G. However, there is a very slight increase in the LFU multipliers over time in those two areas (Table 6). Lastly, the results of the LFU area model for Zones H and I indicate a clear decreasing trend in the LFU multipliers for Bins 1-3. The regional trends in the LFU area model results (Table 6) support the generally increasing trends in the sum of the areas LFU multipliers shown in Table 4 and demonstrate the load/weather sensitivity varies in both time and space throughout the NYCA.

Table 6: Evolution of Bin 1, 2, and 3 values from 2010-2020, LFU Area Models

LFU Area	Bin	2010-2011	2012-2013	2014-2015	2016-2017	2018-2019
Zones A-E	1	109.2%	113.0%	109.3%	113.9%	109.8%
	2	107.1%	109.1%	107.2%	109.8%	107.7%
	3	104.0%	104.7%	104.0%	105.1%	104.3%
Zones F&G	1	112.4%	113.5%	113.0%	122.1%	113.1%
	2	109.2%	109.7%	109.5%	114.1%	109.6%
	3	104.8%	104.9%	104.9%	106.5%	104.9%
Zones H&I	1	113.4%	114.2%	115.9%	110.8%	111.6%
	2	109.3%	109.7%	110.5%	107.9%	108.2%
	3	104.0%	104.0%	104.3%	103.5%	103.6%
Zone J	1	104.6%	106.9%	108.9%	113.7%	108.3%
	2	104.1%	105.2%	106.3%	108.6%	106.1%
	3	101.9%	102.2%	102.5%	103.2%	102.5%
Zone K	1	110.8%	114.2%	111.7%	112.3%	115.0%
	2	109.7%	111.4%	110.0%	110.3%	112.3%
	3	105.9%	106.5%	105.9%	106.1%	107.1%

Figure 21. Zone J and K LFU Area Model Trends in Bin 1-3 Multipliers



There are benefits from using both the LFU area split models and the NYCA stand-alone or pooled model. The LFU area models were introduced in order to account for the different load to weather relationship across different areas of the state. This is especially important in Zones J and K, which are defined Localities for which associated reliability assessments are currently performed for the NYSRC IRM study and in the NYISO Installed Capacity Market. Conversely, the benefit of calibrating to a NYCA-wide model is that it pools the load to weather relationship across the state, and accounts for the impact of offsetting load impacts to the extent they exist on extreme weather days. In order to explore the merits of a NYCA control model further, more advanced NYCA LFU models similar to the existing LFU models used for reliability studies should be evaluated.

6.4 Historical Extreme CTHI Values

Bin 1 lower bound temperatures, set at +2.5 sigma, represent an approximately one in 160-year occurrence, as the Bin 1 load level is weighted at approximately 0.6%. Bin 1 reference temperatures, set at +3 sigma, represent the 99.87 percentile outcome, occurring approximately one in every 740 years. Since these load levels represent temperatures with such a rare probability of occurrence, the currently defined upper LFU Bins could potentially overstate realistic temperature levels relative to historically observed peak temperatures. This section will analyze and compare observed peak temperatures from 1950 through current relative to the current peak load producing temperatures defined in the LFU Bins.

As we have weather data and calculations spanning a 70-year period, and Bin 1 reference temperatures represent a one in 740-year occurrence, there is theoretically less than a 10% probability that a given LFU modeling area has experienced peak load producing temperatures greater than the Bin 1 reference temperature over the 70-year history. LFU area CTHI is calculated using a weighted average of station level weather variables from weather stations in the region. We can further analyze the Bin 1 reference temperature by area by comparing it to the history of extreme station CTHI for weather stations in the region. Data on historical station level maximums may provide more insight to the theoretical maximum possible temperature in a given area; and into whether the current Bin 1 reference temperatures are within reason, or are too high relative to any historical values.

For this comparison, the composite summer maximum CTHI values from the five LFU modeling areas were compared against the current LFU modeling area Bin 1 reference temperature (Table 7). Station level CTHI values from weather stations carrying at least 10% weight in a given modeling area were also compared to the reference temperature. The stations with at least 10% weight in one or more LFU modeling areas are Binghamton, Buffalo, Elmira, Rochester, Syracuse, and Utica in A to E; Albany, Newburgh, and Poughkeepsie in F&G; Central Park, Poughkeepsie, and White Plains in H&I; Central Park, JFK Airport, and LaGuardia Airport in Zone J; and Farmingdale and Islip in Zone K.

Table 7: Zones A to E Weather Station Summer Maximum CTHI, 1950 – 2019

Station / Area	A to E	Binghamton	Buffalo	Elmira	Rochester	Syracuse	Utica	Total Stations
Maximum	87.13	87.34	88.36	90.22	89.38	90.98	90.54	90.98
Bin 1 Value	89.67	--	--	--	--	--	--	89.67
Observations Above	0	0	0	5	0	1	1	7
Percent	0.0%	0.0%	0.0%	6.7%	0.0%	1.3%	1.3%	1.3%

Figure 22: Distribution of Zones A to E Weather Station Summer Maximum CTHI, 1950 – 2019

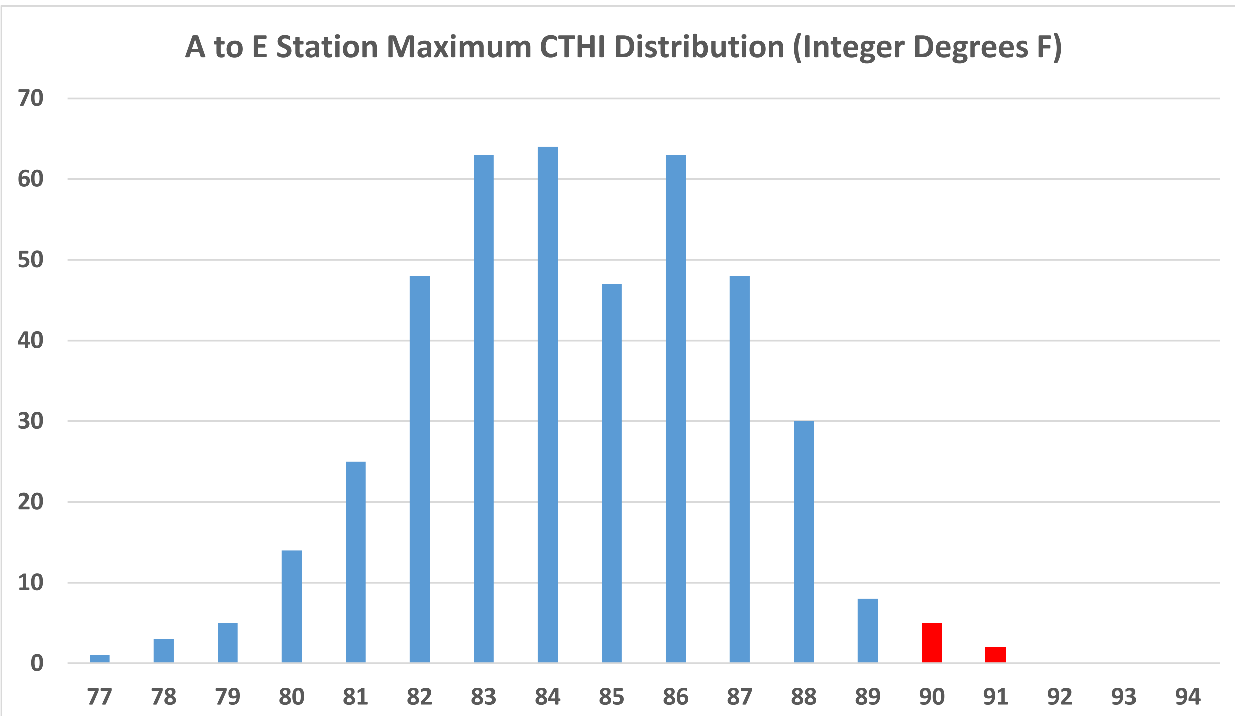


Table 7 and Figure 22 above show the CTHI distribution and the Bin 1 values for the Zones A to E region. The Bin 1 CTHI value for A to E is 89.7 degrees, and the maximum composite A to E CTHI observed over the last 70-years is 87.1, about 2.6 degrees below the Bin 1 temperature. However, the individual station maximums observed for the six weather stations with at least 10% weight in the A to E calculation have historical CTHI maximums ranging from 87.3 degrees in Binghamton to 91.0 degrees in Syracuse. The graph shows the distribution of the 420 weather station maximum CTHI observations (six weather stations over 70 summers) rounded to the nearest integer, with the station observations exceeding the Bin 1 value highlighted in red. The overall distribution appears to be fairly normal and un-skewed. There are seven historical observations exceeding the Bin 1 value (1.3% of all observations); five in Elmira, one in Syracuse, and one in Utica.

Table 8: Zones F & G Weather Station Summer Maximum CTHI, 1950 - 2019

Station / Area	F & G	Albany	Poughkeepsie	Newburgh	Total Stations
Maximum	88.67	90.46	93.64	90.86	93.64
Bin 1 Value	91.94	--	--	--	91.94
Observations Above	0	0	1	0	1
Percent	0.0%	0.0%	1.3%	0.0%	0.3%

Figure 23: Distribution of Zones F & G Weather Station Summer Maximum CTHI, 1950 - 2019

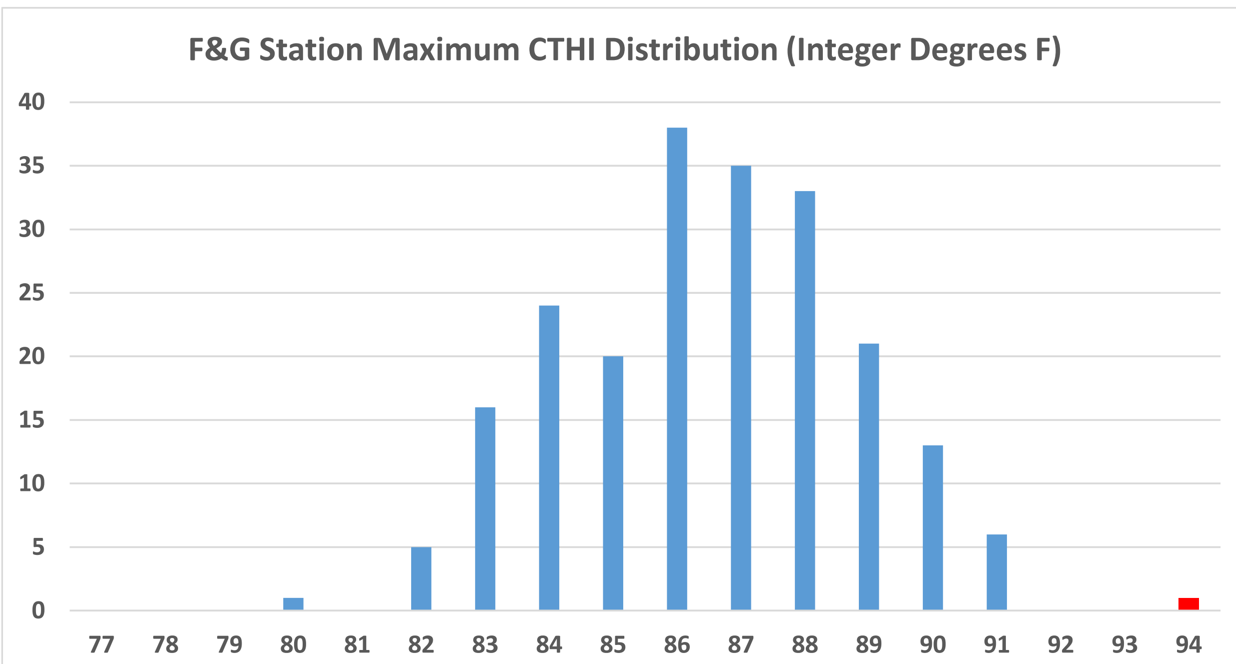


Table 8 shows the Bin 1 CTHI value for F & G is 91.9 degrees, and the maximum composite F & G CTHI observed over the last 70-years is 88.7, about 3.2 degrees below the Bin 1 value. However, the individual station maximums observed for the three weather stations with at least 10% weight in the F & G calculation have historical CTHI maximums ranging from 90.5 degrees in Albany to 93.6 degrees in Poughkeepsie (Table 8). Figure 23 shows the distribution of the 210 weather station maximum CTHI observations (three weather stations over 70 summers) rounded to the nearest integer, with the station observation exceeding the Bin 1 value highlighted in red. The overall distribution appears to be fairly normal and un-skewed. There is one historical observation exceeding the Bin 1 value (0.3% of all observations) in Poughkeepsie. Figure 23 shows that this one CTHI value appears to be an extreme outlier relative to the rest of the area history.

Table 9: Zones H & I Weather Station Summer Maximum CTHI, 1950 - 2019

Station / Area	H & I	White Plains	Poughkeepsie	Central Park	Total Stations
Maximum	91.60	92.32	93.64	93.12	93.64
Bin 1 Value	92.74	--	--	--	92.74
Observations Above	0	0	1	1	2
Percent	0.0%	0.0%	1.3%	1.3%	0.7%

Figure 24: Distribution of Zones H & I Weather Station Summer Maximum CTHI, 1950 - 2019

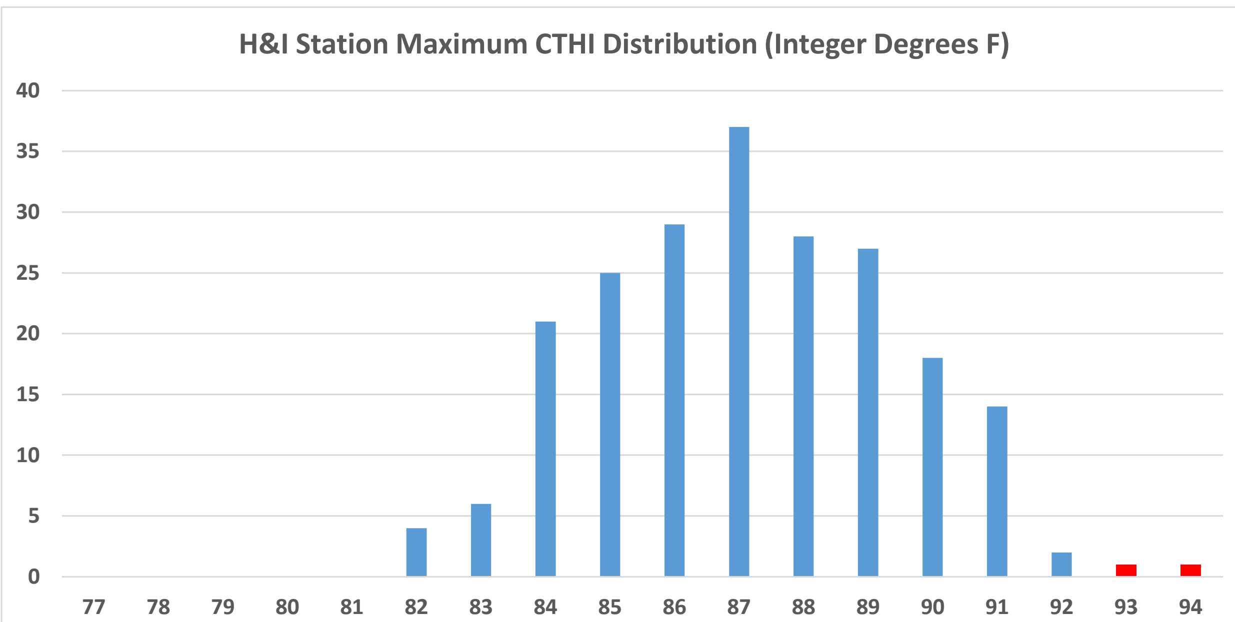


Table 9 shows the Bin 1 CTHI value for H & I is 92.7 degrees, and the maximum composite H & I CTHI observed over the last 70-years is 91.6, about 1.1 degrees below the Bin 1 value. However, the individual station maximums observed for the three weather stations with at least 10% weight in the F & G calculation have historical CTHI maximums ranging from 92.3 degrees in White Plains to 93.6 degrees in Poughkeepsie (Table 9). Figure 25 shows the distribution of the 210 weather station maximum CTHI observations (three weather stations over 70 summers) rounded to the nearest integer, with the station observations exceeding the Bin 1 value highlighted in red. The overall distribution appears to be fairly normal and un-skewed. There are two historical observations exceeding the Bin 1 value (0.7% of all observations); one in Central Park and one in Poughkeepsie. Grouped with the White Plains and Central

Park data, the extreme Poughkeepsie CTHI observation appears to be less of an outlier (Figure 25).

Table 10: Zone J Weather Station Summer Maximum CTHI, 1950 – 2019

Station / Area	Zone J	LaGuardia	JFK	Central Park	Total Stations
Maximum	91.60	93.26	92.12	93.12	93.26
Bin 1 Value	93.36	--	--	--	93.36
Observations Above	0	0	0	0	0
Percent	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 25: Distribution of Zone J Weather Station Summer Maximum CTHI, 1950 – 2019

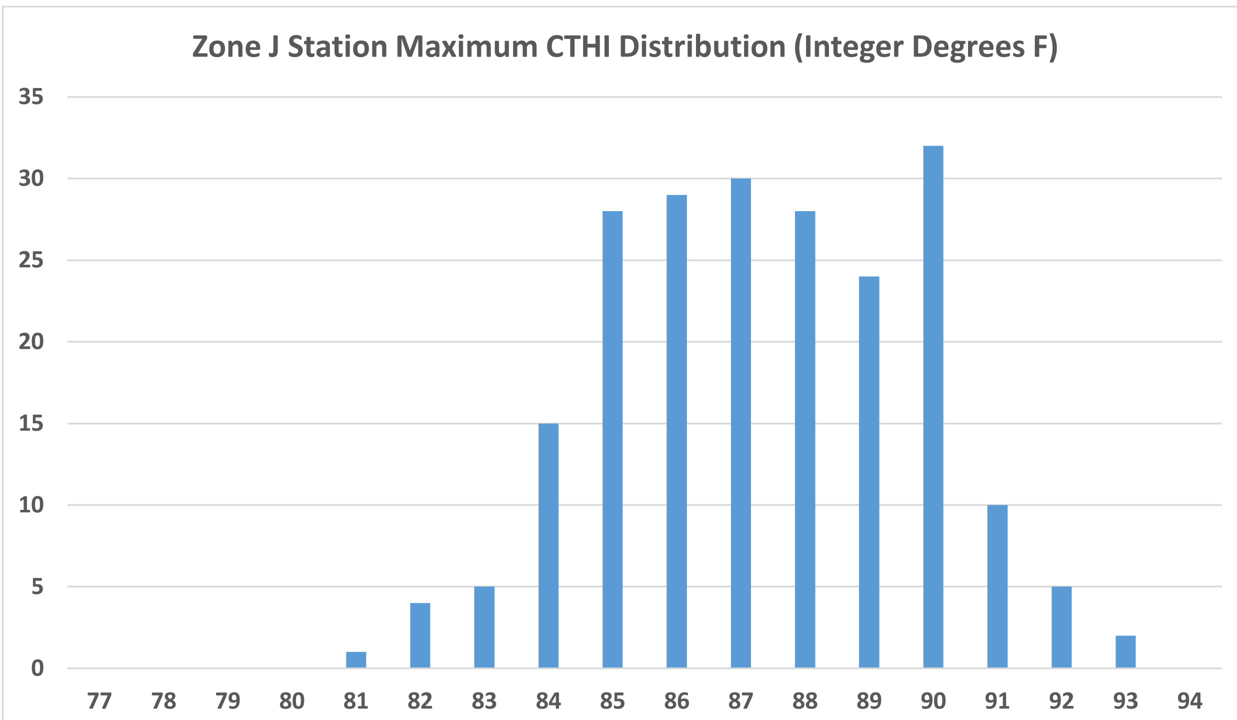


Table 10 shows the Bin 1 CTHI value for Zone J is 93.4 degrees, and the maximum composite Zone J CTHI observed over the last 70-years is 91.6, about 1.8 degrees below the Bin 1 value. The individual station maximums observed for the three weather stations with at least 10% weight in the Zone J calculation have historical CTHI maximums ranging from 92.1 degrees at JFK Airport to 93.3 degrees at LaGuardia Airport. Figure 25 shows the distribution of the 210 weather station maximum CTHI observations (three weather stations over 70 summers) rounded to the nearest integer. The overall distribution appears to be fairly normal and un-skewed. There are no historical observations among the three weather stations exceeding the Zone J Bin 1 value.

Table 11: Zone K Weather Station Summer Maximum CTHI, 1950 - 2019

Station / Area	Zone K	Farmingdale	Islip	Total Stations
Maximum	91.82	92.32	92.00	92.32
Bin 1 Value	93.46	--	--	93.46
Observations Above	0	0	0	0
Percent	0.0%	0.0%	0.0%	0.0%

Figure 26: Distribution of Zone K Weather Station Summer Maximum CTHI, 1950 - 2019

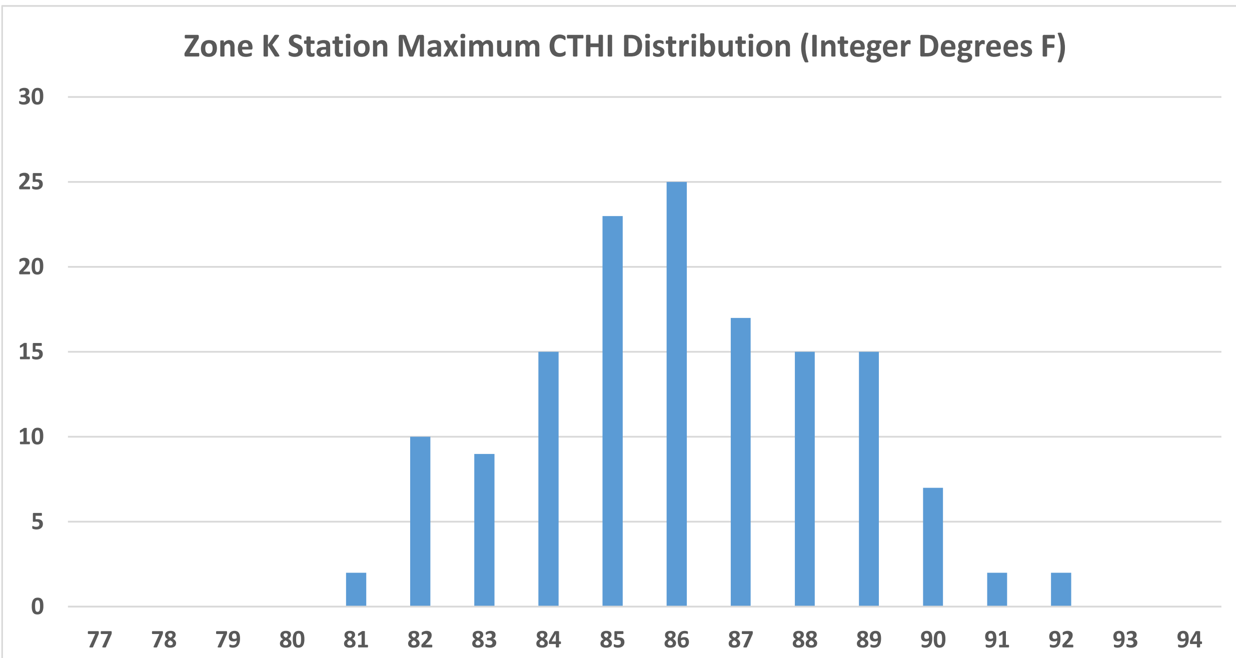


Table 11 shows the Bin 1 CTHI value for Zone K is 93.5 degrees, and the maximum composite Zone K CTHI observed over the last 70-years is 91.8, about 1.7 degrees below the Bin 1 value. The individual station maximums observed for the two weather stations with at least 10% weight in the Zone K calculation have historical CTHI maximums of 92.0 degrees in Islip and 92.3 degrees in Farmingdale. Figure 26 shows the distribution of the 140 weather station maximum CTHI observations (two weather stations over 70 summers) rounded to the nearest integer. The overall distribution appears to be fairly normal and un-skewed. There are no historical observations from the two weather stations exceeding the Zone K Bin 1 value.

Table 12: Summer Maximum CTHI Summary, 1950 - 2019

AVERAGES	Areas Average	Stations Average
Maximum	90.16	92.77
Bin 1 Value	92.23	92.23
Delta	-2.07	0.53
Observations Above	0.0	2.0
Percent	0.0%	0.5%

Table 12 displays the average composite CTHI statistics for the five LFU modeling areas to the left, and the average statistics across the individual weather stations to the right. On average, the five LFU modeling areas have a maximum CTHI of 90.2 degrees, about 2 degrees lower than the average Bin 1 CTHI of 92.2. There are no area composite historical CTHI observations above the Bin 1 value among the five LFU modeling areas. On average across the five LFU modeling areas, the weather station maximum CTHI is 92.8 degrees, about 0.5 degrees higher than the average Bin 1 CTHI of 92.2 degrees. There are an average of two weather station observations above the Bin 1 value, 0.5% of all observations. Even though no area composite CTHI has exceeded its Bin 1 representative value (0 of 350 observations), there were 10 station level observations across the five areas that exceeded their area's representative value. This suggests that the extreme weather conditions currently used for the Bin 1 levels are possible at the station level, and that temperature values that exceed physical extreme weather limits are not being used. However, the weather has not been extreme enough across all weather stations in a given area in any given year for the composite area CTHI to exceed the Bin 1 value.

6.5 Peak-Producing versus Seasonal Maximum Weather

LFU is currently based on the distribution of peak-producing CTHI, i.e. the CTHI during the NYCA peak load day. Another measure of extreme weather is the summer seasonal maximum temperature, i.e. the maximum summer CTHI. These two measures of peak CTHI have slightly different historical distributions, both in average and in variance. This section analyzes and describe the historical distributions of both variables and their potential difference in impact on LFU modeling.

The NYISO has historical NYCA system peak load days available back to 1975. Using these NYCA peak dates, the analysis compares the 45-year histories of NYCA coincident CTHI and summer maximum CTHI:

Figure 27: Area Summer Maximum CTHI v. NYCA-Coincident CTHI Annual Delta

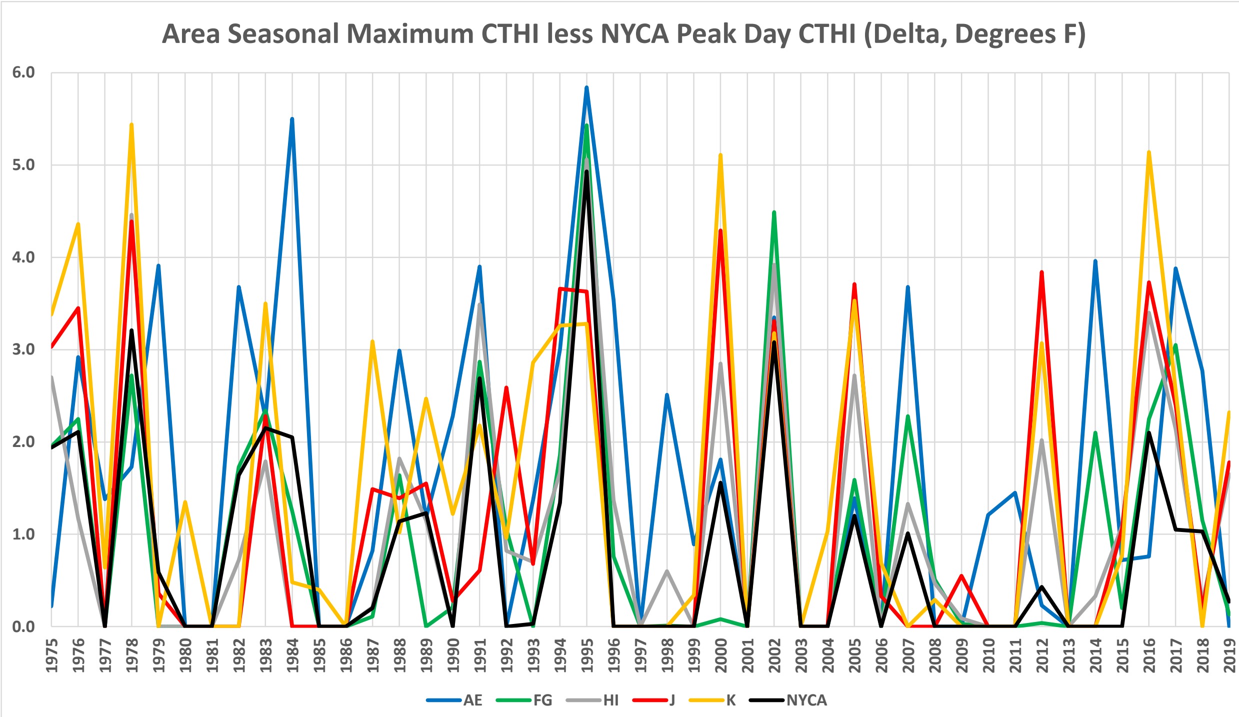


Figure 27 shows the annual difference in seasonal maximum CTHI by area, and the NYCA-coincident peak load day CTHI. We see that in some cases there are significant differences between the two values. For example, in 1995, each of the five LFU modeling areas and the NYCA itself had summer maximum CTHI observations of more than 3 degrees higher than their coincident peak-producing CTHI, with the A to E difference reaching close to 6 degrees. Alternatively, there are summers like 1985 where all of the areas have their maximum CTHI occur on the NYCA peak load day, meaning the delta value for all five areas and the NYCA is zero. Figure 27 shows that there are significant enough differences in maximum and peak-producing CTHI, that the properties of their distributions will be somewhat different, certainly in mean and likely in variance. Thus, using seasonal maximum CTHI rather than NYCA-coincident CTHI for LFU modeling would yield likely differing results to some degree.

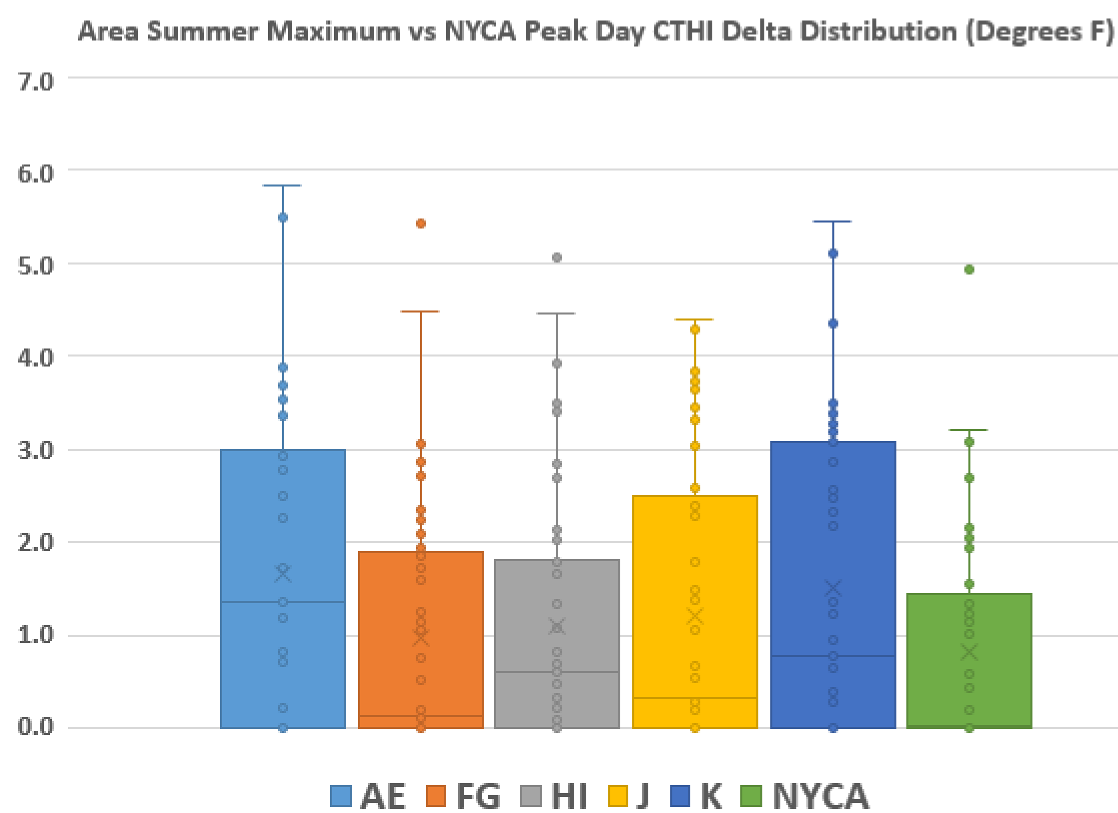
Table 13: Summary Statistics – Maximum CTHI v. Coincident CTHI, 1975-2019

LFU Area	A to E	F&G	H&I	Zone J	Zone K	NYCA
Number Coincident (count)	14	17	17	20	16	22
Average Difference (Degrees F)	1.67	0.98	1.11	1.21	1.51	0.82
90th Percentile Difference (Degrees F)	3.77	2.65	2.84	3.14	3.64	2.27
Maximum Difference (Degrees F)	5.84	5.43	5.06	4.39	5.44	4.93

The statistical summary in Table 13 shows the characteristics of the deltas between summer maximum CTHI and NYCA-coincident CTHI by the LFU modeling area and for the NYCA as a whole. Unsurprisingly, the NYCA maximum weather is most coincident with the NYCA peak load itself. In nearly half (22 of 45) of all summers between 1975 and 2019, the NYCA maximum CTHI occurred on the same day as the NYCA peak load. The average delta between the two variables is 0.8 degrees, with a 90th percentile delta of 2.3 degrees. In terms of LFU modeling area weather, Zones F & G, H & I, and J are all fairly coincident with NYCA peak loads. Zone K is less coincident, with 16 summers coincident and an average delta of 1.5 degrees. The A to E area weather is least coincident with NYCA peak loads, with only 14 summers coincident and an average delta of 1.7 degrees.

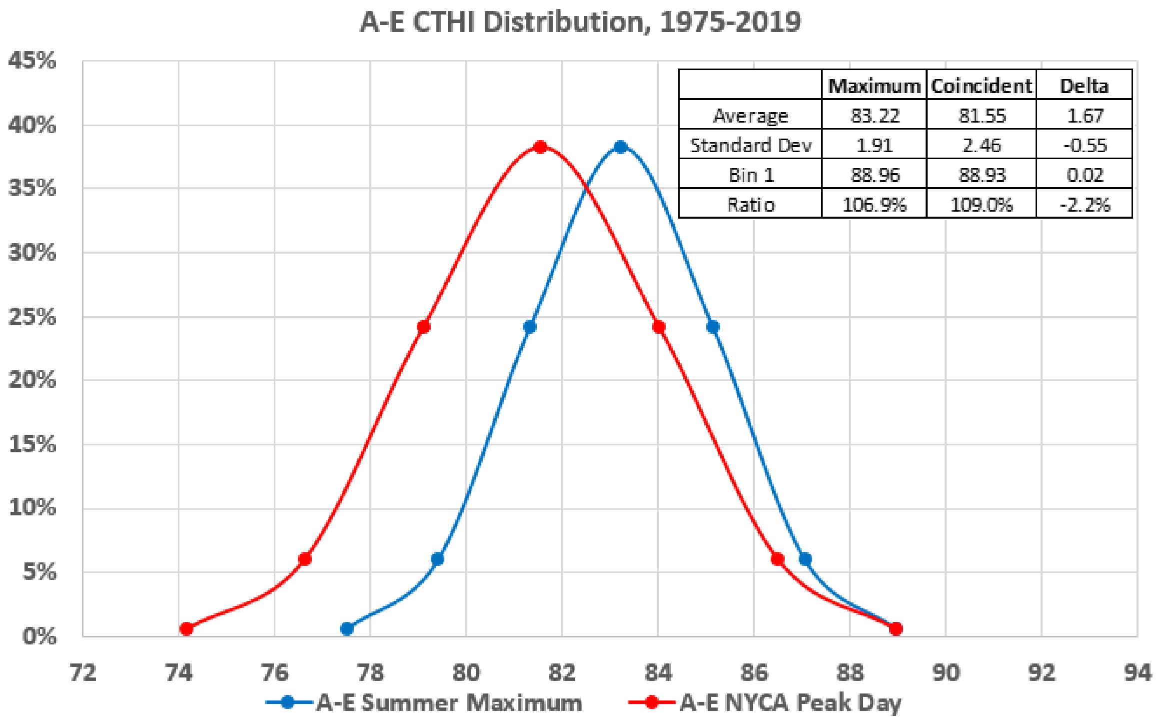
The box & whisker plot in Figure 28 summarizes the distribution of the 45-year delta history for the LFU areas and the NYCA. It shows that the NYCA weather itself is generally most coincident with the NYCA peak load, while Zones A to E and Zone K are generally least coincident.

Figure 28: Area Summer Maximum CTHI v. NYCA-Coincident CTHI Distribution



Next, we compare the LFU area CTHI distributions for both summer maximum and NYCA coincident peak loads. Of particular interest is whether the spread of the NYCA peak producing and summer maximum weather distributions are similar, as this would inform us whether LFU model results would differ significantly by using the maximum CTHI distribution.

Figure 29: NYCA Peak Load Day and Summer Maximum CTHI Distributions, Upstate Areas



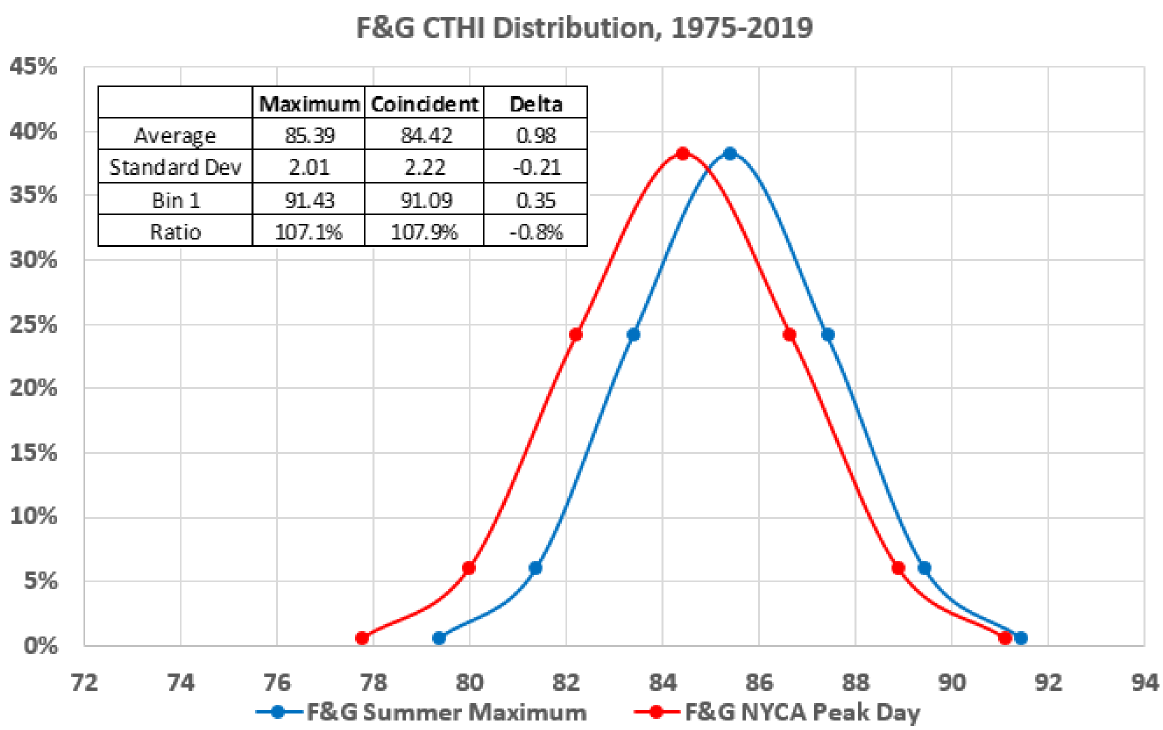
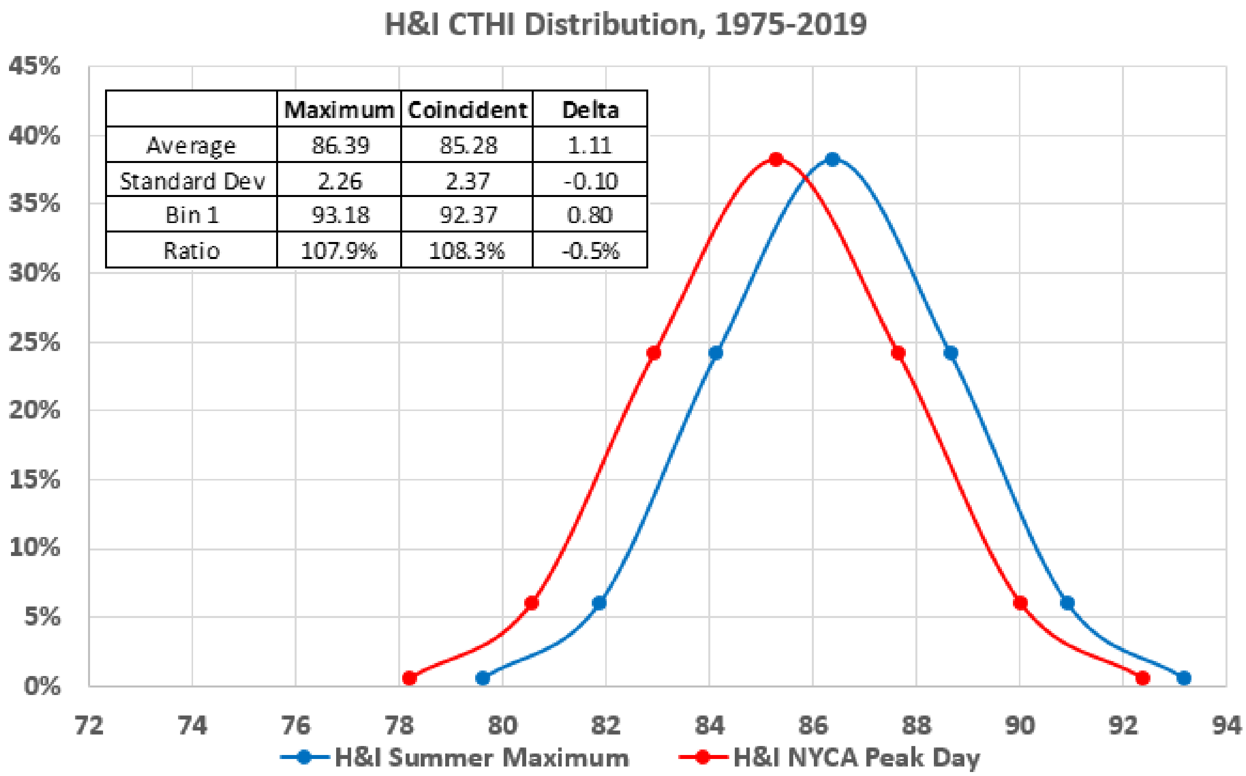


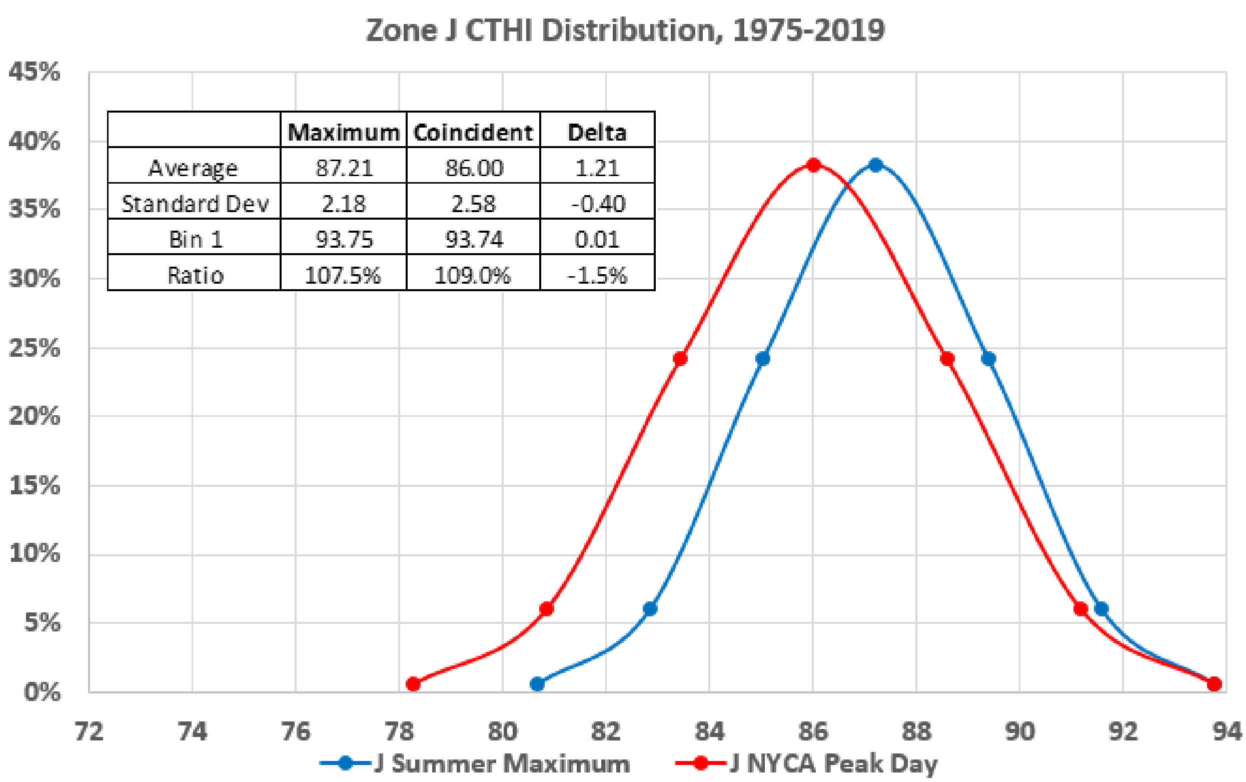
Figure 29 shows that for both Zones A to E and Zones F & G, it is clear that the distribution of NYCA peak load day CTHI is wider than the distribution of summer maximum CTHI. This makes general sense, as maximum weather is a more naturally consistent definition, since it does not include the randomness associated with NYCA peak load relative to CTHI. As stated before, non-weather impacts influence the timing of the peak load. A frequent example would be years during which the peak weather occurred during the weekend, but due to the generally lower load levels during the weekend, the NYCA peak load occurred at a lower CTHI on a weekday. Thus, the standard deviation of the maximum CTHI in a given area will likely be lower than that of its NYCA peak-producing CTHI. This is true historically of both Zones A to E (0.55 degrees lower standard deviation) and Zones F & G (0.21 degrees lower standard deviation).

By definition, the average peak-producing CTHI will be less than the average maximum CTHI. This difference is 1.7 degrees in Zones A to E and 1.0 degrees in Zones F & G. The Bin 1 CTHI of both distributions is simply its average plus three standard deviations. Even though the average peak-producing CTHI is lower, its standard deviation is larger, such that the delta between the Bin 1 values for peak-producing CTHI and summer maximum CTHI converge at the upper tail of the distribution. Comparing the ratio of the Bin 1 value to the average value for both distributions can inform us of how Bin 1 LFU multipliers would look different by using either distribution. This is not a one-to-one comparison, as the load weather relationship is not accounted for, but directionally, the differences in these weather ratios would be expected to translate into final LFU multipliers. For Zones A to E, the ratio of Bin 1 to average weather for the maximum CTHI is 106.9%, and the ratio for peak-producing weather is 109.0%, a delta of -2.2%. For Zones F & G, the ratios are 107.1% and 107.9%, yielding a delta of -0.8%. In both cases, the distribution of summer maximum CTHI is narrower (Figure 29).

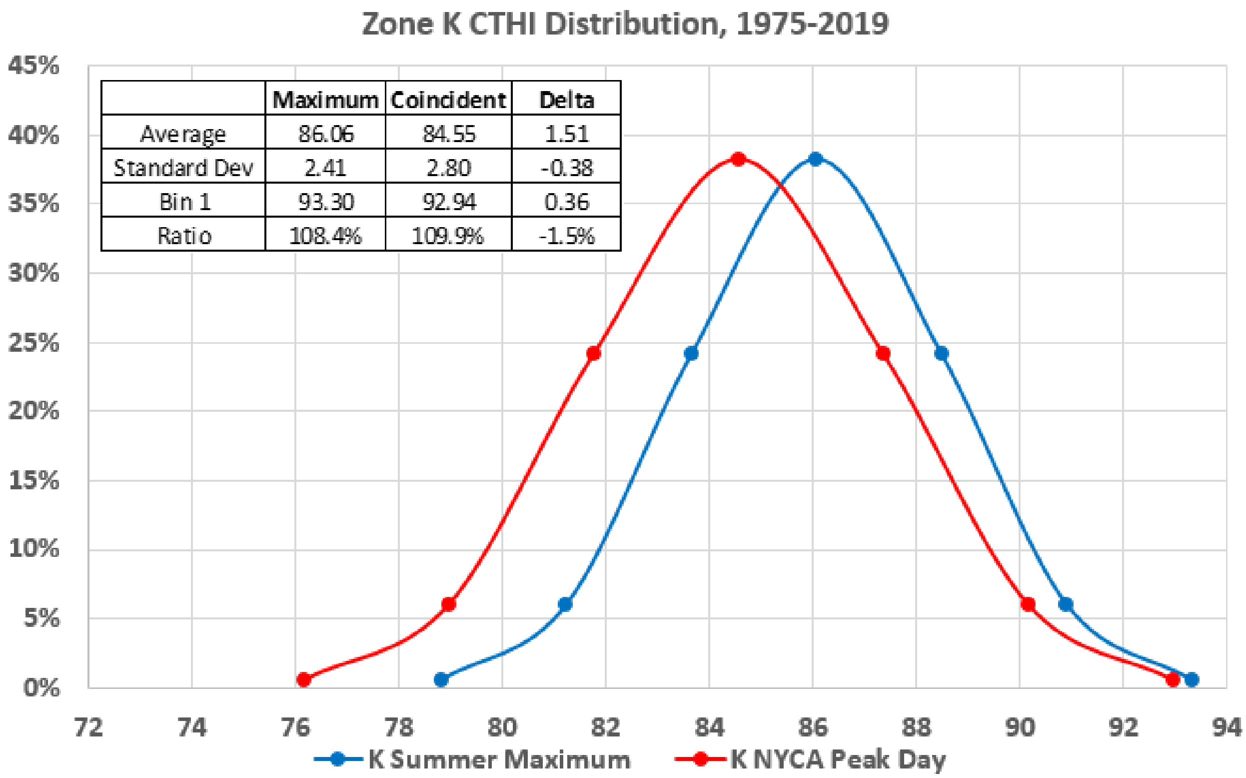
Figure 30: NYCA Peak Load Day and Summer Maximum CTHI Distributions, Downstate Areas



	Maximum	Coincident	Delta
Average	86.39	85.28	1.11
Standard Dev	2.26	2.37	-0.10
Bin 1	93.18	92.37	0.80
Ratio	107.9%	108.3%	-0.5%



	Maximum	Coincident	Delta
Average	87.21	86.00	1.21
Standard Dev	2.18	2.58	-0.40
Bin 1	93.75	93.74	0.01
Ratio	107.5%	109.0%	-1.5%



	Maximum	Coincident	Delta
Average	86.06	84.55	1.51
Standard Dev	2.41	2.80	-0.38
Bin 1	93.30	92.94	0.36
Ratio	108.4%	109.9%	-1.5%

Figure 30 shows that for all three downstate areas, Zones H & I, Zone J, and Zone K, the distribution NYCA-coincident CTHI is wider than the distribution of summer maximum CTHI. The differences in Bin 1 ratios between the two distributions are 0.5% for Zones H & I and 1.5% for Zones J and K.

Figure 31: NYCA Peak Load Day and Summer Maximum CTHI Distributions

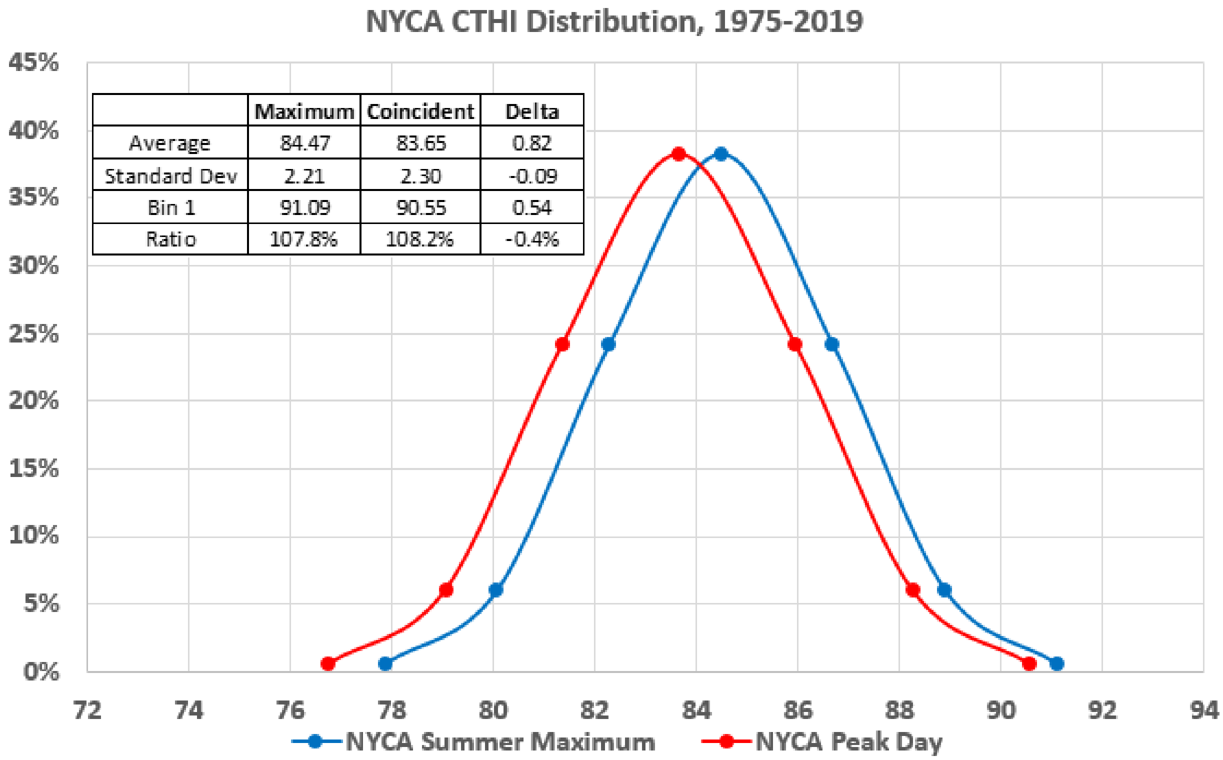
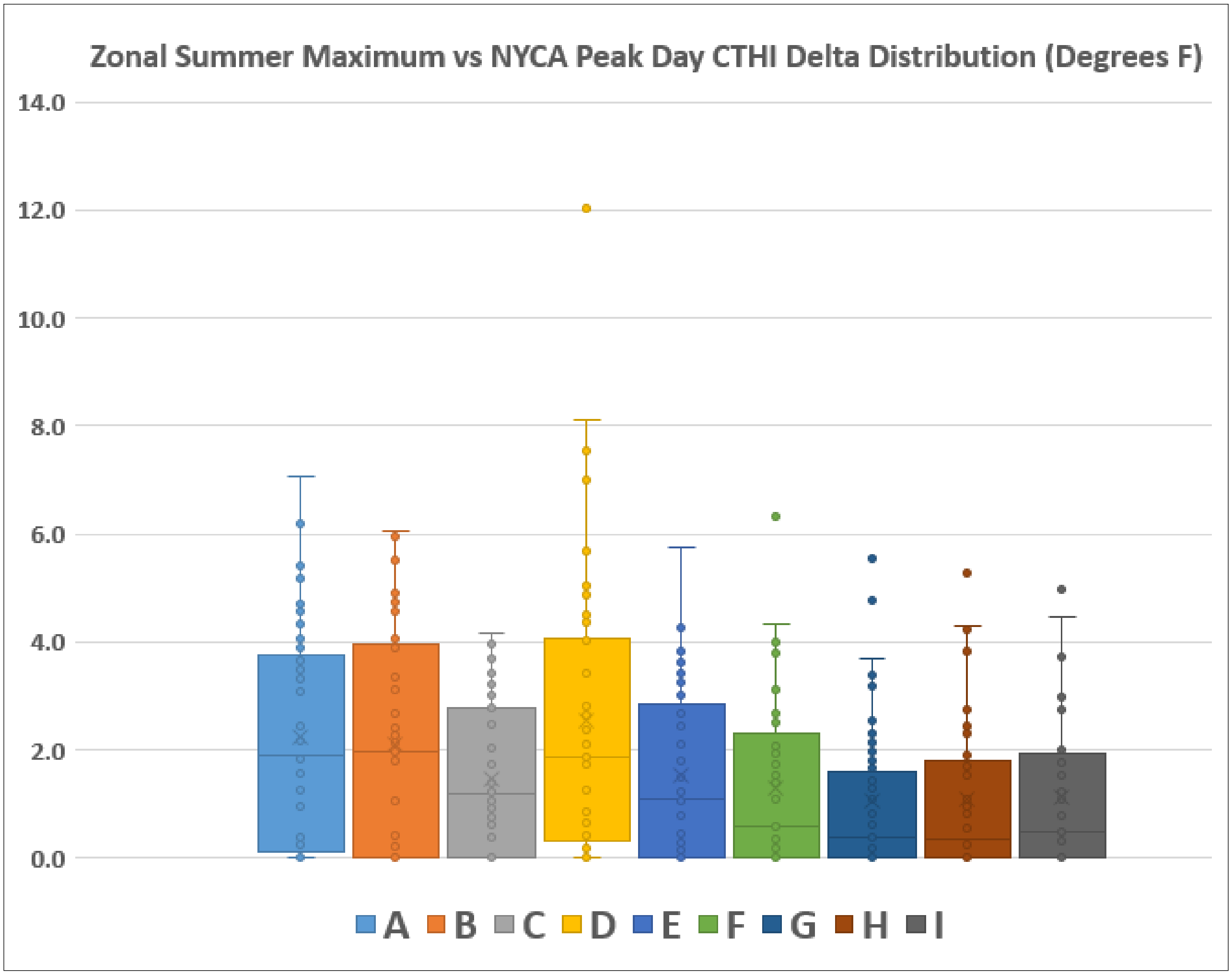


Figure 31 shows that as with all of the area distributions, the NYCA-coincident CTHI distribution is wider than the NYCA seasonal maximum distribution (Figure 31). However, relative to the areas, the delta is smaller, with a 0.1 degree difference in standard deviation and a 0.4% difference in the ratio of Bin 1 to average weather. This is an expected result, as the NYCA weather is more coincident with NYCA loads than is the weather from any one specific region.

Generally, the major finding is that as expected, coincident peak load day weather is more variable than summer maximum weather for all regions of the state and for the NYCA as a whole. Another key finding is that even though the peak-producing CTHI has a wider distribution, for all areas of the state the Bin 1 weather of the peak-producing CTHI does not exceed the Bin 1 weather calculated using maximum CTHI. This is important, as it shows that we do not overstate Bin 1 weather in the LFU models by using the wider distribution of NYCA peak load day CTHI. However, due to the narrower distributions, using maximum CTHI distributions for the area LFU models rather than the NYCA peak load day weather distributions would likely produce lower LFU multipliers in the upper Bins. Summer maximum CTHI distributions are a purer measure of extreme weather, but further discussion and study are required to determine whether using those distributions as the basis for LFU modeling distributions would be appropriate.

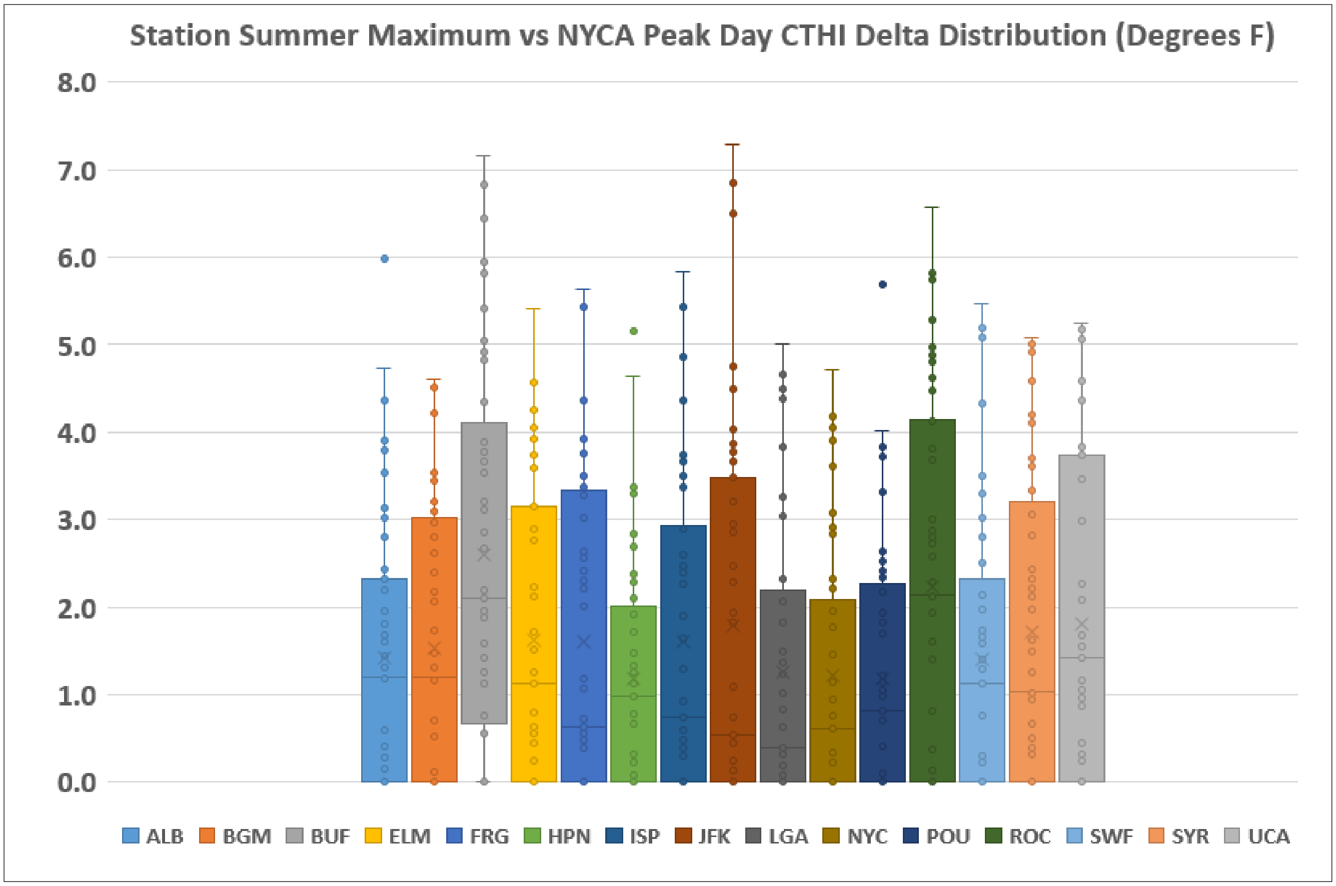
Figure 32: Zonal Summer Maximum CTHI vs. NYCA-Coincident CTHI Distribution



Zone	A	B	C	D	E	F	G	H	I
Number Coincident (count)	10	14	14	9	11	17	16	18	16
Average Difference (Degrees F)	2.26	2.11	1.46	2.53	1.53	1.29	1.05	1.09	1.12
90th Percentile Difference (Degrees F)	4.88	4.60	3.18	5.86	3.52	3.21	2.78	2.85	2.81
Maximum Difference (Degrees F)	7.07	6.06	4.15	12.03	5.76	6.33	5.55	5.29	4.96

To further explore the coincidence of extreme weather to NYCA peak loads, summaries for the remaining A to I zonal delta distributions are shown in Figure 32. Generally, the weather in the Capital District (Zone F), Lower Hudson Valley (Zone G), and Westchester (Zones H & I) is more coincident with the NYCA peak load day than the weather in western parts of upstate. Zones A, B, and D stand out as being fairly non-coincident with NYCA peak loads relative to other zones.

Figure 33: Weather Station Maximum CTHI v. NYCA-Coincident CTHI Distribution



Station Name	Albany	Binghamton	Buffalo	Elmira	Farmingdale	White Plains	Islip
Station Code	ALB	BGM	BUF	ELM	FRG	HPN	ISP
Number Coincident (count)	16	16	9	14	17	16	16
Average Difference (Degrees F)	1.43	1.53	2.59	1.62	1.61	1.19	1.60
90th Percentile Difference (Degrees F)	3.39	3.50	5.35	3.76	3.85	2.89	3.80
Maximum Difference (Degrees F)	5.98	4.60	7.16	5.42	5.64	5.16	5.84

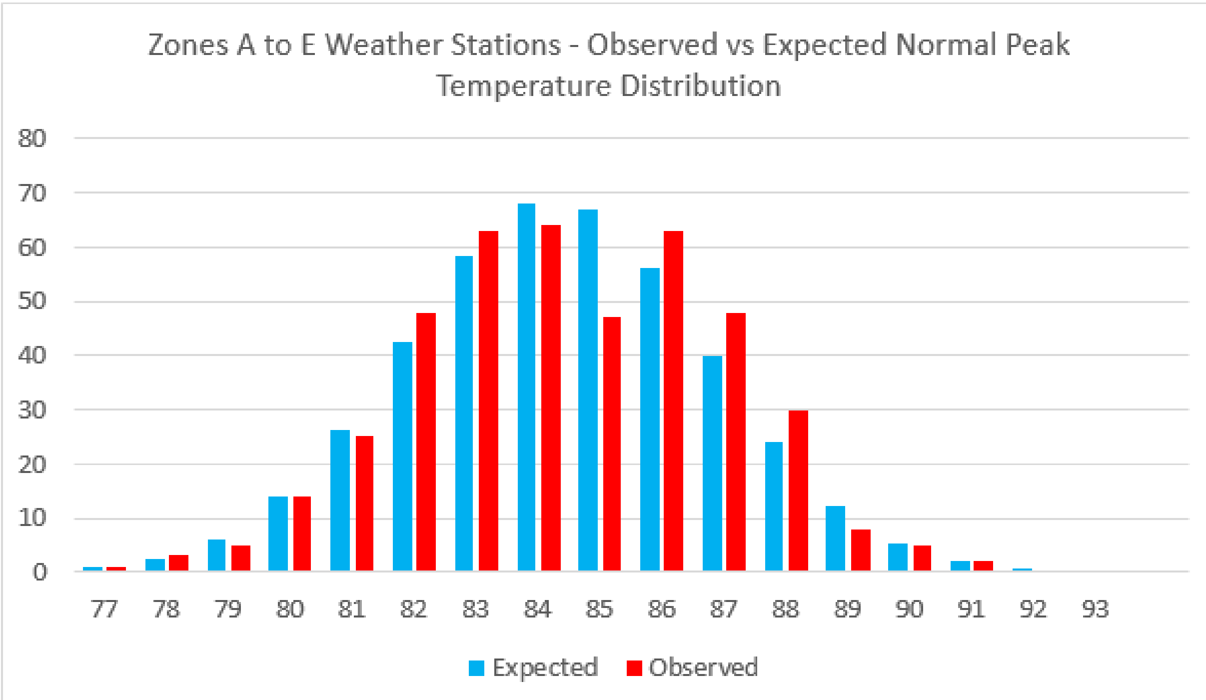
Station Name	JFK	LaGuardia	Central Park	Poughkeepsie	Rochester	Newburgh	Syracuse	Utica
Station Code	JFK	LGA	NYC	POU	ROC	SWF	SYR	UCA
Number Coincident (count)	17	15	16	18	14	16	13	12
Average Difference (Degrees F)	1.79	1.26	1.23	1.18	2.23	1.40	1.71	1.81
90th Percentile Difference (Degrees F)	4.45	3.26	3.05	2.96	4.87	3.42	3.86	4.05
Maximum Difference (Degrees F)	7.28	5.00	4.72	5.68	6.58	5.46	5.08	5.24

For additional information, Figure 33 above shows the coincidence of weather station CTHI to the NYCA peak load day. Generally, the most coincident weather stations are downstate, including Poughkeepsie, with an average CTHI delta of 1.18 degrees and 18 coincident summers; White Plains, with an average CTHI delta of 1.19 degrees and 16 coincident summers; and Central Park, with an average CTHI delta of 1.23 degrees and 16 coincident summers. Interestingly, JFK Airport is historically less coincident than the nearby LaGuardia Airport and Central Park stations. The least coincident areas of the state are generally upstate and particularly to the west. By far the least coincident weather station, relative to the NYCA peak load day, is Buffalo with an average CTHI delta of 2.59 degrees and only 9 coincident summers. Rochester is also noteworthy, with an average CTHI delta of 2.23 degrees and 14 coincident summers. Intuitively, it makes sense that the western areas of the state are less coincident with the NYCA. First, they are farther geographically from the downstate load center of the state, specifically New York City. Second, there are several summer days, which in some cases become NYCA peak load days, where there is extreme hot weather downstate and where a cool front and/or frontal rain showers have already passed through the western part of the state.

6.6 Normality of Historical Temperature Distributions

A key assumption of the current LFU modeling approach is that peak temperatures follow a normal distribution. A number of Chi-squared tests were performed to assess the goodness-of-fit of historical peak temperature distributions relative to the assumed normal distribution. First, the historical seasonal maximum CTHI from weather stations in each of the LFU modeling areas were assessed against the normal distribution. Peak CTHI data from stations with at least 10% weight in a LFU modeling area (6 stations in Zones A to E, 3 stations in Zones F&G, H&I, J, and 2 stations in Zone K) were pooled together and tested. The 1950-2020 actual and expected temperature distributions and Chi-squared test result for the pooled Zones A to E weather stations are shown in Figure 34.

Figure 34: Historical Distribution and Chi-Squared Test Result for Pooled A to E Weather Stations (Seasonal CTHI Maximum)

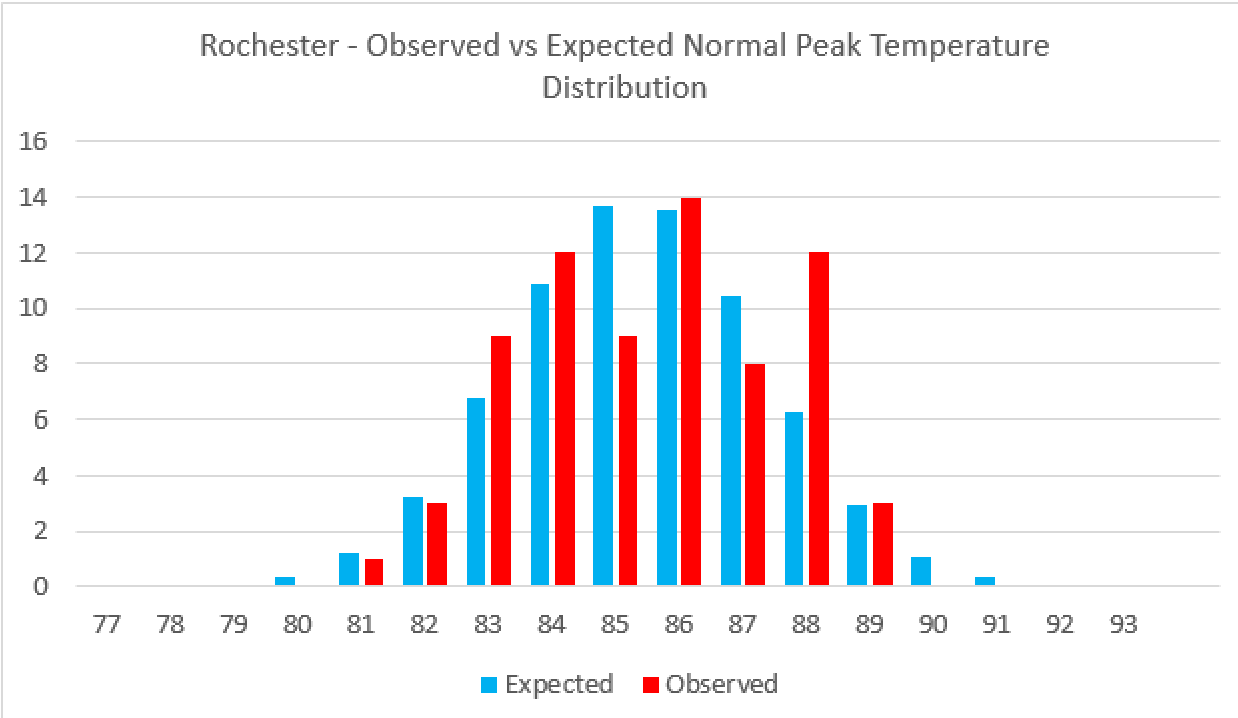


Stat	12.9891
P-value	29.4%

We see that barring a few outliers, the observed distribution of CTHI values generally matches the expected distribution assuming normality. The p-value from the Chi-squared test is 29.4%, meaning we fail to reject the hypothesis that the underlying distribution is normal (i.e. the p-value far exceeds the standard threshold of 5.0%; Figure 34). It is important to note that although the graph shows comparisons for low-count temperature values, for the Chi-squared test the extreme temperature values on both tails were grouped together such that the expected observations in each grouping were near or above five.

This test was repeated for the pooled weather station distributions in the remaining four LFU modeling areas; and as with Zones A to E, we find that we cannot reject the assumption that the underlying peak temperature distribution is normal in any of the four other areas. Pooling weather station data allows for a robust test as the sample size of observed counts is large. However, it is also important to test the data for a single station. We tested the seasonal maximum distribution for Rochester, as it carries the largest weight in the Zones A to E composite weather variable (Figure 35).

Figure 35: Historical Distribution and Chi-Squared Test Result for Rochester (Seasonal CTHI Maximum)

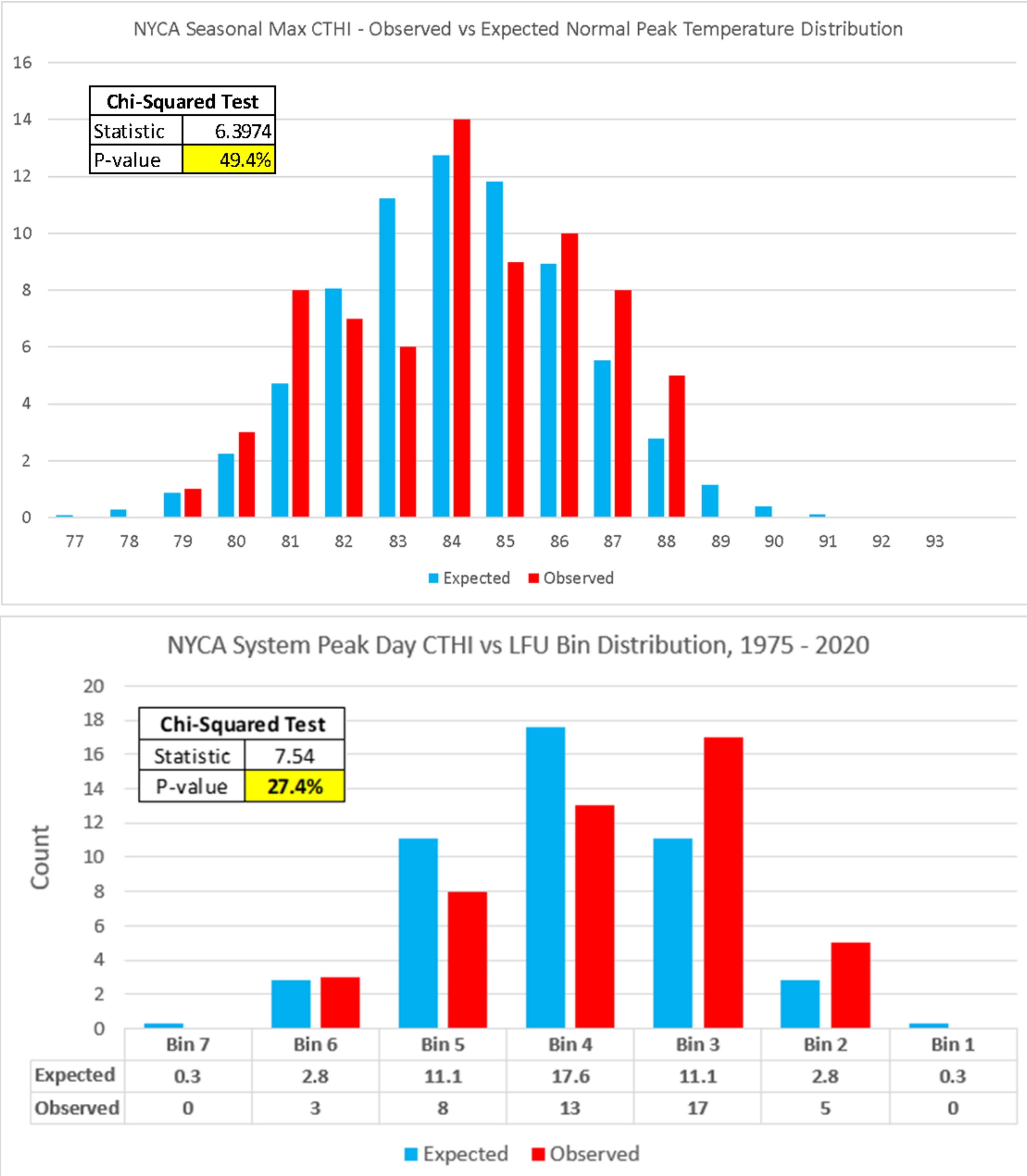


Stat	8.9384
P-value	25.7%

Other than an unusually large number of counts at 88 degrees, and a low number of counts at 85 degrees, we find that the peak CTHI for Rochester between 1950 and 2020 generally follows the normal distribution (P-value of 25.7%; Figure 35).

Next, the historical distribution of NYCA peak CTHI was evaluated in two ways. First, the NYCA-composite seasonal maximum CTHI distribution for 1950 – 2020 was tested against the expected normal integer CTHI counts (Figure 36). Additionally, since LFU weather distributions are defined using NYCA coincident peak producing CTHI values, the NYCA coincident peak producing CTHI distribution was tested against the LFU Bin structure as defined by the most recent 20-year history of peak producing weather (Figure 36).

Figure 36: Historical Distributions and Chi-Squared Test Results for NYCA



In both cases, the assumption that the underlying distribution is normal is shown to be valid. The Chi-square test for the seasonal maximum distribution shows a better goodness-of-fit than for the peak producing CTHI relative to the LFU Bins (Figure 36). This could be due to its longer data sample and its greater categorical granularity.

Finally, a 145-year history (1876 – 2020) of summer maximum hourly dry bulb temperature at the Central Park weather station was tested for normality. This longer data sample allows for a more robust evaluation of the normality assumption, especially in light of the fact that Bin 1 lower bound temperatures are currently defined with a 1 in 160-year probability. Similar to the eight other tests described previously, the Central Park maximum dry bulb temperature over more than a century is shown to adequately follow the normal distribution. A summary of all of the Chi-squared goodness-of-fit tests relative to the normal distribution is shown in Table 14. Based on the results of the nine tests depicted in Table 14, we find the assumption that peak temperatures are normally distributed to be reasonable for the purposes of LFU modeling within the NYCA.

Table 14: Summary of Chi-Squared Goodness-of-fit Test Results Relative to the Normal Distribution

Chi-Squared Test	Bins	Years	Statistic	P-value	Normal
A to E Pooled Stations	Integer Degrees	71	12.99	29.4%	YES
F&G Pooled Stations	Integer Degrees	71	7.17	62.0%	YES
H&I Pooled Stations	Integer Degrees	71	7.81	64.8%	YES
Zone J Pooled Stations	Integer Degrees	71	13.81	18.2%	YES
Zone K Pooled Stations	Integer Degrees	71	4.03	91.0%	YES
Rochester	Integer Degrees	71	8.94	25.7%	YES
NYCA Maximum	Integer Degrees	71	6.40	49.4%	YES
NYCA Coincident Peak	LFU Bins	45	7.54	27.4%	YES
Central Park Dry Bulb	Integer Degrees	145	11.34	50.0%	YES

*CTHI unless noted otherwise
*Seasonal Maximum unless noted otherwise

7 Inter-Annual Weather Sensitivity and LFU Trends

This section explores changes in load weather sensitivity for the NYCA over recent years. Changes in LFU multipliers over time are generally driven by the changing response of peak load relative to peak weather. The slope of the LFU model represents the average MW of load increase caused by a rise of 1 degree in temperature (or CTHI, or another temperature variable). Using a single consistently defined and simple NYCA LFU model simulated year over year, this section explores how this average slope has evolved over the past 20 years, and whether there are any clear trends in the resulting LFU multipliers.

7.1 LFU Trends – Simple Annual Model

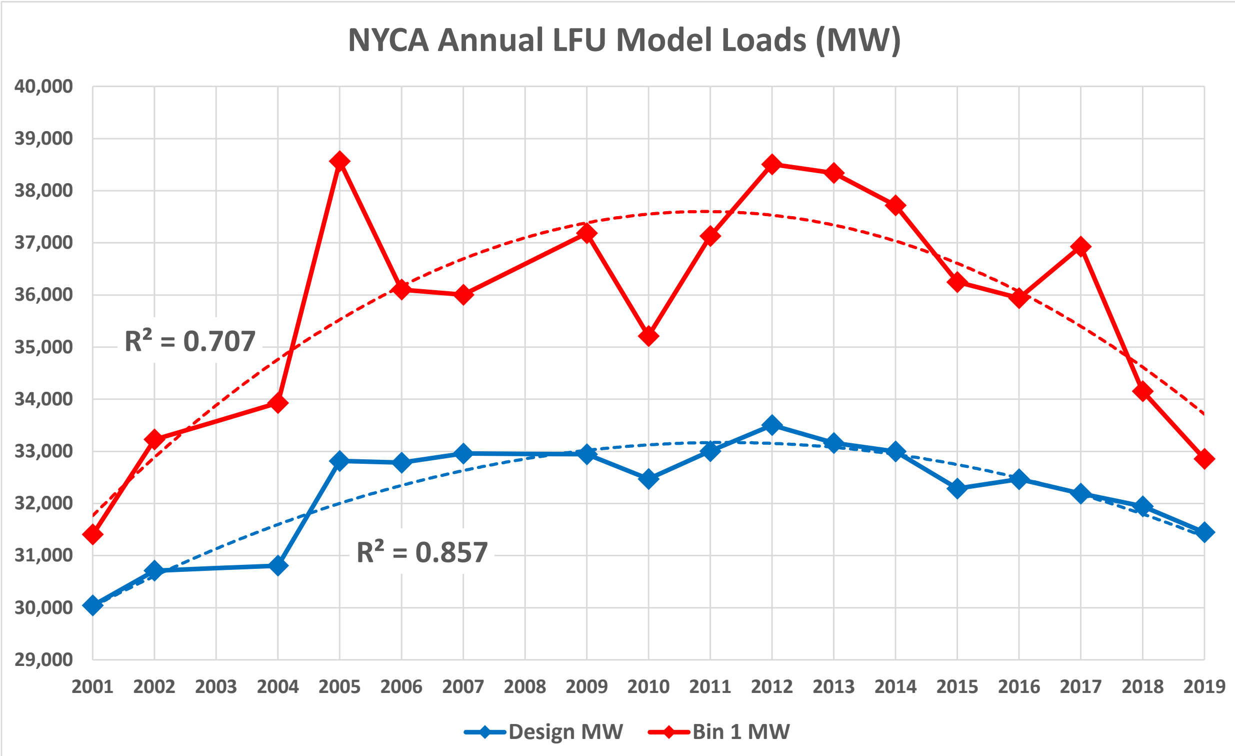
Simple annual LFU models were built at the NYCA level for the 20-year period of 2000-2019. These models regressed summer daily NYCA peak load against NYCA CTHI 60 (CTHI relative to 60 degrees), squared CTHI 60, and cubed CTHI 60. An important aspect was keeping the regression definition consistent across all annual models, in order to discern trends in LFU results, all else being equal. A summary of the annual regression results in tabular form is shown in Table 15. The 2000 and 2008 models were excluded from the analysis due to incorrect signals caused by their cubic terms. The 2003 summer was excluded due to the data impacts of the blackout.

Table 15: Annual NYCA Simple LFU Model Statistics

Year	Constant MW	Linear Coef	Squared Coef	Cubed Coef	Slope MW	Design MW	Bin 1 MW	Bin 1 LFU	Bin 2 LFU	Bin 3 LFU
2001	19,725	-181.1	49.7	-1.02	436	30,042	31,404	104.5%	104.0%	102.3%
2002	20,794	-350.6	55.9	-1.02	570	30,710	33,226	108.2%	106.2%	103.1%
2003										
2004	19,439	114.3	25.2	-0.44	559	30,807	33,929	110.1%	106.9%	103.3%
2005	19,304	180.5	18.4	-0.13	842	32,814	38,563	117.5%	111.1%	104.9%
2006	20,556	-191.4	50.3	-0.90	669	32,782	36,103	110.1%	107.3%	103.5%
2007	21,016	-226.3	52.8	-0.96	644	32,958	36,003	109.2%	106.8%	103.4%
2008										
2009	19,703	-59.9	41.1	-0.67	750	32,944	37,183	112.9%	108.7%	104.1%
2010	20,670	-277.5	57.2	-1.07	624	32,470	35,213	108.5%	106.4%	103.2%
2011	20,556	-205.1	49.0	-0.81	751	33,003	37,128	112.5%	108.6%	104.1%
2012	19,342	84.1	31.1	-0.44	812	33,503	38,506	114.9%	109.8%	104.5%
2013	19,930	-31.4	35.1	-0.48	830	33,159	38,339	115.6%	110.2%	104.7%
2014	19,866	-198.0	48.8	-0.77	823	32,996	37,717	114.3%	109.7%	104.5%
2015	18,300	86.1	34.5	-0.60	711	32,285	36,248	112.3%	108.4%	104.0%
2016	19,048	-106.1	48.3	-0.88	694	32,465	35,938	110.7%	107.6%	103.7%
2017	17,694	164.6	27.6	-0.41	778	32,188	36,930	114.7%	109.7%	104.5%
2018	18,917	-226.1	60.6	-1.21	595	31,944	34,154	106.9%	105.7%	103.0%
2019	18,483	-310.4	69.7	-1.44	539	31,446	32,857	104.5%	104.4%	102.6%

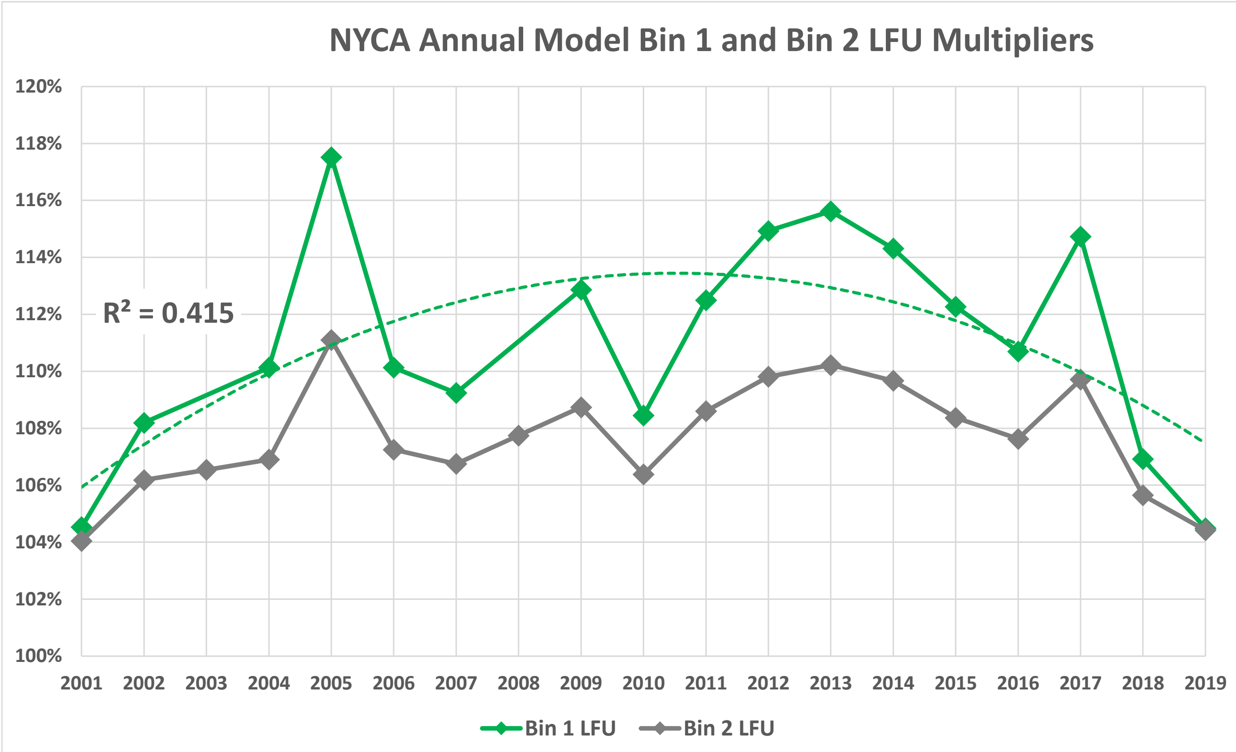
There are clear long-term trends in some of the model outputs. The constant, which represents the predicted peak load during a very cool summer weekday with CTHI equal to 60, has been clearly decreasing over time. This makes sense in light of recent energy efficiency gains throughout the state. The slope, which is more than 98% correlated with the Bin 1 LFU multiplier, had been generally increasing through the mid-2010s, before declining through 2019. The Bin 1 LFU multiplier is calculated as the ratio of Bin 1 temperature predicted MW to design temperature predicted MW. The results are shown in Figure 37.

Figure 37: Annual NYCA Simple LFU Model Peak Load Levels



Both the design peak MW and the Bin 1 peak MW increase across the 2000s, before levelling off and beginning to decline through the late 2010s (Figure 37). Note that there is some year-to-year variability in these results, which is due to the small sample size of one summer per model, some of which do not have peak type or near peak type weather. Nonetheless, the general trends in load levels are reasonably strong as seen in the R-squared values. The difference in these two values drives the scale of the Bin 1 LFU multipliers, which are given in Figure 38.

Figure 38: Annual NYCA Simple LFU Model Bin 1 and Bin 2 Multipliers



Similar to the Bin 1 and design MW values in the prior figure, the LFU multiplier generally rises through 2013 before falling in recent years. This suggests that LFU multipliers may have a positive relationship with peak load levels as they move in tandem.

7.2 LFU Trends – Simple Pooled Models

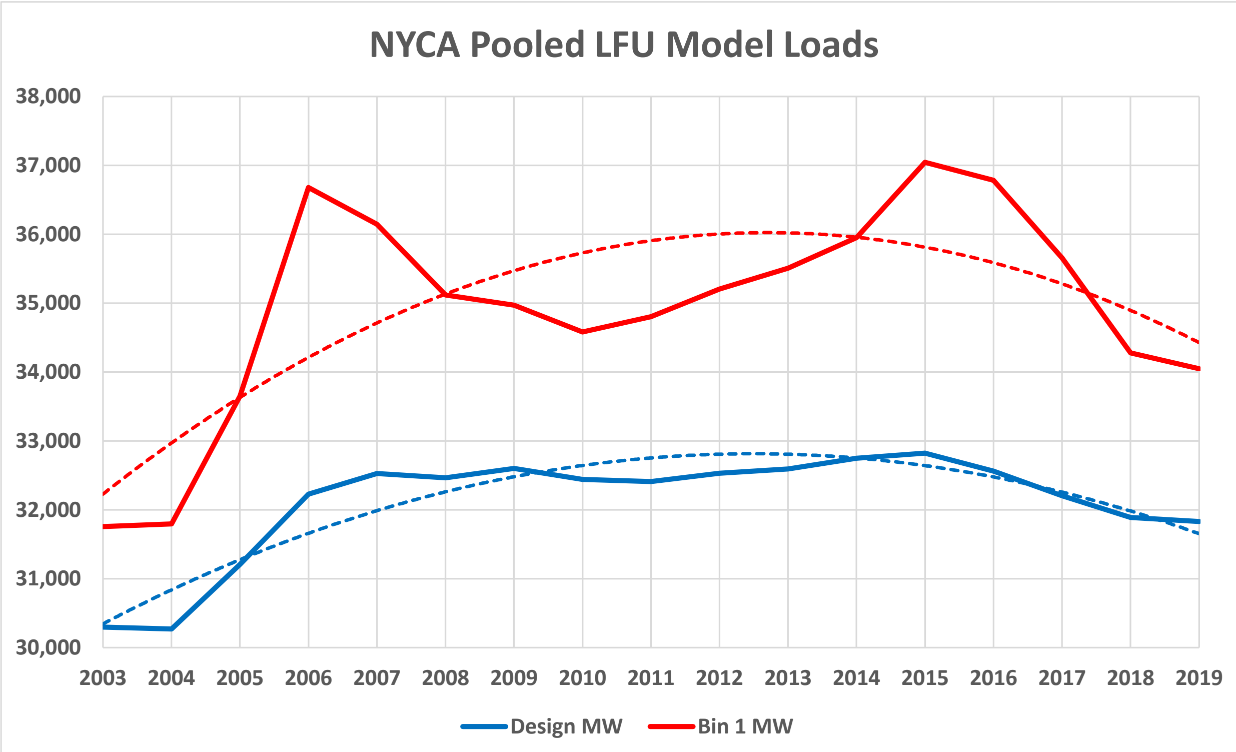
To create a more robust data sample for each model, multi-year pooled models were built for further analysis. Pooled LFU models, each using four summers of data were built at the NYCA level for the 20-year period of 2000-2019. These rolling four-year periods resulted in 17 models: 2000-2003, 2001-2004, and so on, ending with 2016-2019. Models are labeled by their final year; for example, the 2013 label refers to the 2010-2013 model. These models regressed summer daily NYCA peak load against NYCA CTHI 60, squared CTHI 60, and cubed CTHI 60, which was significant across every four-year sample. A summary of the pooled regression results in tabular form is shown in Table 16.

Table 16: Pooled NYCA Simple LFU Model Statistics

Year	Constant	Linear	Squared	Cubed	Slope MW	Design MW	Bin 1 MW	Bin 1 LFU	Bin 2 LFU	Bin 3 LFU
2003	20,057	-206.9	50.9	-1.03	429	30,296	31,755	104.8%	104.2%	102.3%
2004	19,728	-109.0	44.6	-0.92	423	30,269	31,795	105.0%	104.3%	102.3%
2005	19,850	-112.5	44.5	-0.85	533	31,207	33,651	107.8%	105.9%	103.0%
2006	19,436	63.0	29.3	-0.43	729	32,227	36,678	113.8%	109.1%	104.2%
2007	20,600	-162.4	45.7	-0.78	673	32,527	36,147	111.1%	107.8%	103.7%
2008	20,841	-187.7	50.3	-0.95	576	32,466	35,121	108.2%	106.1%	103.1%
2009	20,376	-169.4	52.5	-1.03	558	32,600	34,972	107.3%	105.7%	102.9%
2010	20,378	-178.4	53.4	-1.06	534	32,441	34,582	106.6%	105.3%	102.8%
2011	20,233	-163.6	51.8	-1.01	558	32,409	34,802	107.4%	105.7%	103.0%
2012	20,058	-169.2	52.3	-1.00	594	32,532	35,204	108.2%	106.2%	103.2%
2013	20,244	-181.4	51.7	-0.96	617	32,593	35,509	109.0%	106.6%	103.3%
2014	20,304	-238.4	55.1	-1.00	660	32,751	35,950	109.8%	107.1%	103.5%
2015	19,555	-75.2	42.4	-0.70	746	32,824	37,047	112.9%	108.8%	104.1%
2016	19,292	-47.9	40.4	-0.66	740	32,562	36,786	113.0%	108.8%	104.1%
2017	18,459	-1.1	42.0	-0.77	666	32,204	35,655	110.7%	107.6%	103.7%
2018	18,639	-102.8	51.7	-1.04	571	31,889	34,278	107.5%	105.9%	103.0%
2019	18,669	-181.5	57.8	-1.16	568	31,829	34,050	107.0%	105.7%	103.0%

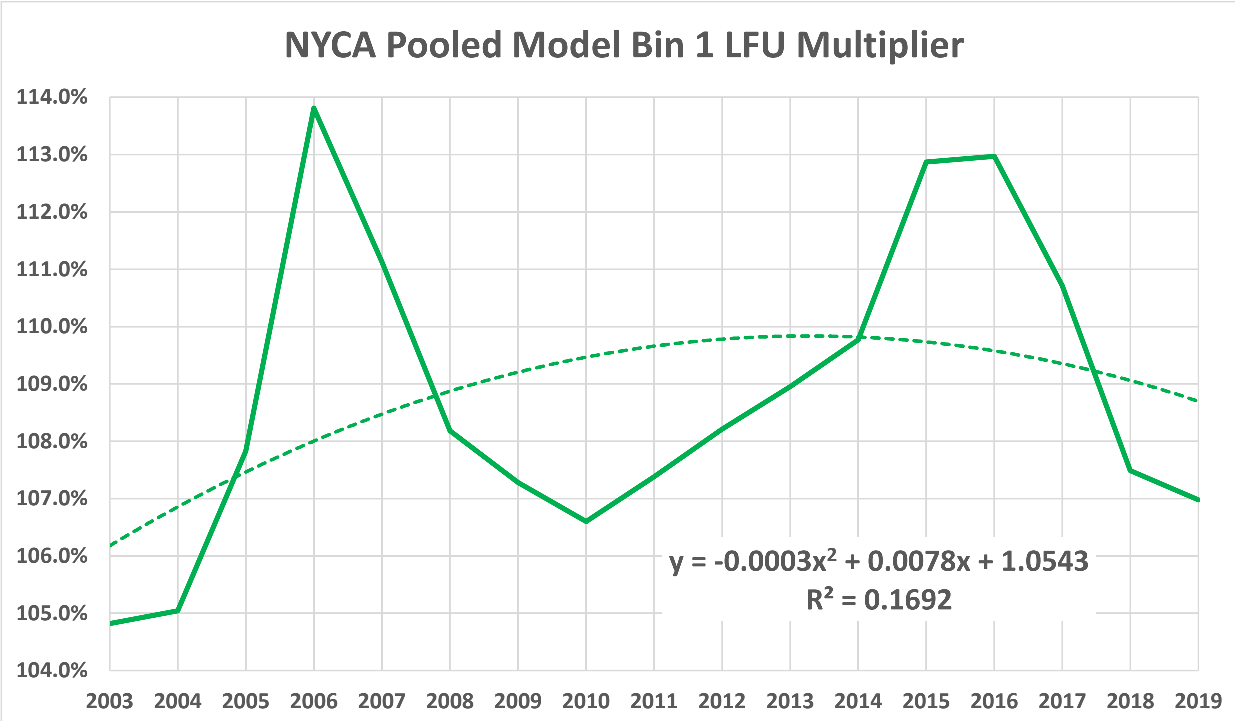
There are again clear long-term trends in some of the model outputs. As with the single-year models, the constant has been clearly decreasing over time. Similar to the annual models, the slope appears to have peaked during the mid-2010s before decreasing in recent years. The design and Bin 1 predicted load values are provided in Figure 39.

Figure 39: Pooled NYCA Simple LFU Model Peak Load Levels



Both the design peak MW and the Bin 1 peak MW generally increase across the early 2000s, before leveling off and then declining through the late 2010s (Figure 39). There is a plateau in design MW predicted values through the middle years. Interestingly, there are two spikes in the Bin 1 MW centered around the 2006 and 2015 pooled models. The resulting Bin 1 LFU multipliers, are depicted in Figure 40.

Figure 40: Pooled NYCA Simple LFU Model Bin 1 Multiplier



The Bin 1 multiplier from the pooled models generally tracks the movement in the Bin 1 MW over time due to the stability in the design MW, yielding a polynomial pattern. The LFU multipliers begin at around 106% in the early 2000s before climbing close to 110%, and then falling back near 109% by 2019. Further analysis would be required to determine the cause of the apparent spikes in LFU multipliers from these pooled models, and to assess the apparent drop in recent LFU multipliers.

The aforementioned sets of NYCA-wide LFU models (both single year and pooled models) show consistent results across the 2003-2019 period. It is important to note that the LFU models developed for and used in the most recent IRM studies are not NYCA-wide models but are instead limited area models. The results from the LFU area models developed for the study are summed and provide the total peak demand values and LFU multipliers for the NYCA. As previously noted in Section 6.3, the trends shown in the sum of the area model results are increasing with time while the NYCA-wide models (decreasing LFU trend) are consistent with the results presented in this section. Furthermore, there exist noticeable trends identified in the various LFU area models. For Bins 1 through 3, the LFU multiplier values have the following overarching regional trends in LFU results. From Section 6.3, based upon a 2010-2019 modeling period, the Zones H&I values are decreasing; Zones A-E and F&G are generally consistent and exhibit a slight upward trend in values; and the Zones J and K values are increasing.

In closing this section, it is important to note two things. First, the true underlying values of Bin 1 LFU multipliers are difficult to estimate, due to the paucity of data at extreme temperatures. Second, the models developed in this section were intentionally simple in order to ensure consistent model specification across the entire period. In reality, final LFU models are much more complex, and their results will not necessarily track the outcomes shown via the simple models constructed for this analysis.

8 Conclusions and Recommendation for Future Work

At the request of the New York State Reliability Council (NYSRC), the NYISO presents this whitepaper on load forecast uncertainty modeling, focusing on New York temperature distribution analysis. The NYISO leveraged over 70 years of weather information and compiled updated information on the statistical variation in peak weather conditions and load response throughout the NYCA and the LFU modeling areas. This whitepaper provides key background information on the temperature distributions used in LFU modeling. The statistical analysis of the temperature distribution data confirms that the distributions established for use in the modeling of LFU in the NYSRC Installed Reserve Margin and the NYISO Reliability Needs Assessments are valid and robust. A summary of the conclusions and recommendations for future Load Forecast Uncertainty (LFU) modeling studies are as follows:

8.1 Comparison of Temperature-Humidity Indices

The load weather relationship for Zone J was compared using NYISO's Cumulative Temperature and Humidity Index (CTHI) weather variable and Con Edison's Temperature Variable (TV) weather variable. Historically, there has been a very high correlation between CTHI and TV values during summer days. NYCA peak-producing values for the two variables are highly correlated over a 20-year period, and produce similar design distributions. Simple LFU models using the two variables produced very similar LFU per unit multiplier results at the upper Bins. Both models had very good fits, with the TV model producing a slightly higher R-squared value. Based on these observations, CTHI and TV appear to be generally interchangeable for LFU analyses.

The load weather relationship for Zone K was compared using NYISO's CTHI weather variable and LIPA's Temperature Humidity Index (THI4) weather variable. Historically, there has been a moderately high correlation between CTHI and THI4 values during summer days. There is a different scale in degrees between the two indices, and they produce somewhat different design distributions. NYCA peak-producing values for the two variables are positively correlated over a 20-year period. Simple LFU models using the two variables produced less similar LFU per unit multiplier results at the upper Bins. Both models had moderately good fits, with the THI4 models producing a slightly higher R-squared value. Additional work comparing these two weather variables and their respective load weather relationships may be prudent for evaluating their impacts on future LFU analyses. At present, each Transmission Owner (Con Edison and LIPA) and the NYISO have discretion to use their own temperature-humidity weather variables in the LFU modeling process. Regular comparisons and discussions of the LFU modeling results between the NYISO, LIPA, and Con Edison [8, 9] show that care is taken to utilize more complex LFU models (each leveraging different temperature-humidity data sets) to produce consistent results.

8.2 Long-Term Historical CTHI Distribution Analysis

Over the past 20-years, extreme weather events in the LFU modeling regions have been very coincident with the NYCA composite peak producing weather. When the NYCA coincident peak weather is at its 99th percentile, the reliability regions are all above the 95th percentile of their respective peak producing distributions on average. This result is important because NYISO's resource adequacy analysis currently assumes extreme weather coincidence across areas, as all regions are assigned Bin 1 temperatures simultaneously. We have assessed that in general, this assumption utilized in resource analysis is appropriate.

The coincidence of peak loads across the system was also evaluated. Simple NYCA level LFU models were built, and their PU multiplier results were compared to the composite PU multipliers derived from summing across LFU area models. This comparison produced mixed results. In general, the results from the NYCA-wide models produced tighter LFU distributions and lower multipliers at the upper Bins. However, this was not a consistent result across all years, with some comparisons producing results with an opposite or negligible signal. A review of the NYCA-wide model versus the sum of the area models revealed a divergent trend in LFU multipliers. An examination of regional LFU model results indicated increasing variation in the weather/load sensitivity across the various modeling regions. We recommend further statistical analysis studying the implications of calibrating LFU area model results to a NYCA-wide model. Extending the analysis to include additional years of regional model results and more complex LFU models may be warranted.

The historical record of extreme temperature values at the NYCA, LFU modeling area, zonal, and weather station levels over a 70-year period was reviewed. There are two primary takeaways from this analysis. First, extreme values currently used to define Bin 1 CTHI are reasonable and do not exceed a physical threshold, as there are multiple historical CTHI observations from individual stations that exceed the defined Bin 1 values. Second, although the distribution of peak-producing CTHI is wider than the distribution of seasonal maximum CTHI, Bin 1 values of peak-producing CTHI do not exceed their respective values from the seasonal maximum distribution, since the average peak-producing CTHI is by definition lower than the average seasonal maximum CTHI. This result suggests that the extreme weather conditions currently used for the Bin 1 levels are not excessive for the LFU modeling area. That is, temperature values that exceed annual extreme weather limits are not being incorporated in the distribution.

Using Chi-squared goodness-of-fit tests, we assessed the validity of the assumption that the underlying distribution of peak weather follows the normal distribution. We tested CTHI distributions for pooled weather station data from the five LFU modeling regions, individual weather stations, and NYCA composite distributions. Each test confirmed the validity of using the normal distribution to describe peak temperatures.

8.3 Inter-Annual Weather Sensitivity and LFU Trends

Simple and consistent year over year annual NYCA LFU models showed increasing design and Bin 1 peak load values through the mid-2010s, before dropping in recent years through 2019. Likewise, the Bin 1 and Bin 2 LFU per unit multipliers followed a similar trend. This result indicates a general increase in weather sensitivity as peak load levels increase. A series of simple four-year pooled NYCA LFU models showed similar results.

In reality, the LFU models employed for reliability planning studies are more complex and include additional explanatory variables beyond CTHI and its polynomial transformations. Additional modeling work using models with added complexity could be used to further evaluate the trends uncovered in this analysis and provide a better fit to the load weather relationship. Further, a comparison of net and gross loads (e.g., with BTM solar added back onto the load values) to further examine the last three to four years of peak load patterns is warranted in order to potentially explain the recent downward trend shown in the simple model analysis. Lastly, a zonal or expanded LFU modeling region (e.g. more years) analysis of the inter-annual weather sensitivity and LFU trends may be warranted in order to identify any significant differences from the current NYCA and regional level analyses presented herein.

8.4 Additional Recommendations

The analyses in this whitepaper focused on metered load, net of behind-the-meter solar impacts. This study focused exclusively on the relationship of and interplay between load and weather (temperature and humidity) across the NYCA and the reliability regions. Behind-the-meter (BTM) generation will continue to have growing impacts to the net load. For example, during the 2020 NYCA summer peak load hour (07/27/2020 hour beginning 17), an estimated 2,000 MW of installed BTM-solar reduced the peak demand on the system by approximately 510 MW. The BTM-solar installed capability is expected to grow to approximately 6,000 MW by the year 2025. The NYISO recommends further analysis to study the potential impacts that BTM solar may have on LFU analyses and results.

This study focused on a review of LFU weather and load relationships given the currently defined temperature distribution and Bin structure. Although this study has shown that historical peak weather distributions fit relatively well to the normal distribution, further exploration of defining different probability distributions for peak temperatures could be beneficial. Additionally, an exploration of different LFU Bin definitions and structures is warranted, including an impact analysis exploring how these alternative definitions would affect reliability metrics such as LOLE.

This analysis focused on summer peak producing weather conditions, specifically daily CTHI values. Expanding this evaluation to a more granular level may be important with the increasing complexity of the power grid and the associated changes in hourly load shapes. An evaluation of the current hourly load response against historical hourly weather conditions is warranted for the creation of model-based load shapes for potential use in future reliability and system planning studies.

These topics will be discussed with both the NYISO stakeholders and the NYSRC ICS working groups in order to define the scope of a follow-on study on updated LFU modeling techniques that may be developed to further represent the increasing complexity of the New York power grid. The results from this next phase of the study will be transformed into updated data and procedure recommendations for consideration in both the 2022-2023 IRM and the 2022 NYISO Reliability Needs Assessment studies.

9 References

1. Soliman Soliman, Ahmad Al-Kandari, "Electrical Load Forecasting: Modeling and Model Construction." Netherlands, Elsevier Science, 2010.
2. Kelvin Chu, Carlos Villalba, "Developing an Electric Load Forecast Uncertainty Curve for the Installed Reserve Margin (IRM) Study.", 2010. [Online]. Available: http://www.nysrc.org/pdf/MeetingMaterial/ICSMeetingMaterial/ICS_Agenda113/Item 1-2010 LFU Modeling Methodology_CV.pdf [Accessed: 22-January-2021]
3. Itron Inc., "New York ISO Climate Change Impact Study Phase 1: Long-Term Load Impact", 2020. [Online]. Available: https://www.nyiso.com/documents/20142/10773574/NYISO-Climate-Impact-Study-Phase1-Report.pdf [Accessed: 22-January- 2021].
4. Arthur Maniaci, "Load Forecast Uncertainty Using Non-linear Weather Response", 2007. [Online]. Available: https://www.nyiso.com/documents/20142/1393070/LFTF_LFU_70607.pdf [Accessed: 22-January- 2021].
5. Arthur Maniaci, "Statistical Validation of Non—Linear Weather Response Models", 2007. [Online]. Available: https://www.nyiso.com/documents/20142/1393142/LFTF_Statistical_Validation_of_Non_Linear_Weather_Response_Model_71707.pdf [Accessed: 22-January-2021].
6. Roy Billinton, Dange Huang, "Aleatory and Epistemic Uncertainty Considerations in Power System Reliability Evaluation. Probabilistic Methods Applied to Power Systems." PMAPS 2008, Proceedings of the 10th International Conference on. May 2008
7. Roy Billinton, Ronald Allan, "Reliability evaluation of power systems." United Kingdom, Springer US, 1996.
8. Maxim Schuler, "Load Forecast Uncertainty Models for the 2020 IRM Study", 2019. [Online]. Available: https://www.nyiso.com/documents/20142/7604453/2020_LFU_Models_LFTF.pdf [Accessed: 22-January-2021]
9. Riaz Khan, "Load Forecast Uncertainty Models for the 2021 IRM Study", 2020. [Online]. Available: https://www.nyiso.com/documents/20142/11883362/LFU_Summary.pdf [Accessed: 22-January-2021].