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MISSOURI PUBLIC SERVICE COMMISSION

COMMISSION STAFF DIVISION

TARIFF/RATE DESIGN

REBUTTAL TESTIMONY

OF

SEOUNG JOUN WON, Ph.D.

UNION ELECTRIC COMPANY
d/b/a AMEREN MISSOURI

CASE NO. GR-2019-0077

Jefferson City, Missouri
June 2019

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Q. Please state your name and business address.

A. My name is Seoung Joun Won and my business address is Missouri Public Service Commission, P. O. Box 360, Jefferson City, Missouri 65102.

Q. Who is your employer and what is your present position?

A. I am employed by the Missouri Public Service Commission ("Commission") and my title is Regulatory Economist III in the Tariff and Rate Design Department of the Commission Staff Division.

Q. Are you the same Seoung Joun Won who prepared the Weather Variables section of Staff's Cost of Service Report ("Staff Report")?

A. Yes, I am.

EXECUTIVE SUMMARY

Q. What is the purpose of your rebuttal testimony?

A. The purpose of my rebuttal testimony is to address issues with the weather variables that Union Electric Company d/b/a Ameren Missouri ("Ameren Missouri" or "Company") witness Mr. Ryan P. Ryterski used to calculate weather normalization adjustments and the weather sensitivity of gas usage of some customer classes.

Q. Which aspects of the weather variables used by Mr. Ryterski are you going to address?

A. I am addressing three issues: (1) the weather data used for calculating normal heating degree days ("HDDs"), and (2) the time period of 30-year normals, and (3) the definition of 30-year normals.

Q. Which aspect of the weather sensitivity of gas usage of some customer classes will you be addressing?

A. I am addressing the inhomogeneity of the weather sensitivity of gas usage in the Large Volume Transportation ("LVT") class.

WEATHER DATA

Q. What weather data did Mr. Ryterski use for calculating actual and normal HDD?

A. According to the Company's response of Staff's data request No. 0089, Mr. Ryterski used weather data sourced from "The Weather Company," an IBM Business, formerly known as WSI. Weather data from the Columbia Regional Airport ("COU") and the Cape Girardeau Municipal Airport ("CGI") were used for actual and normal weather variables. To calculate HDDs, the Company used the actual weather data sets consisting of daily maximum temperature ("Tmax") and daily minimum temperature ("Tmin") observations from the Weather Company and developed a set of mean daily temperature ("MDT") values which consist of the average of Tmax and Tmin for each day. HDDs are based on the difference of the MDT from a comfort level of 65°F.[1] HDDs are calculated as the difference between 65°F and the MDT when the MDT is below 65°F, and are equal to zero when the MDT is above 65°F.

Q. What are Staff's concerns about the data sourced from the Weather Company?

[1] Where MDT < 65°F, HDD = 65 – MDT; otherwise, HDD = 0.

A. The Weather Company's raw data sets include missing data and other observation anomalies in the temperature time series for the 30-year period of January 1, 1981 through December 31, 2010. Generally, there are inconsistencies and biases in the time series data of daily temperature observations (e.g. such as the relocation, replacement, or recalibration of the weather instruments). In addition, changes in observation procedures or in an instrument's environment had also occurred.

Q. What are the missing observations in the data sets used by Mr. Ryterski?

A. For example, according to the Company's response of Staff's Data Request No. 0089, both Tmax and Tmin of June 27, 2010 in CGI is recoded -99, so that the Weather Company's HDD on June 27, 2010 is 164. However, -99 is a numerical representation of missing observation. Because of this miscalculation the Company's normal HDD of June 27, 2010 in Cape Girardeau is unrealistically higher than the actual HDD.

Q. Are there any other known anomalies in the temperature data series used by Mr. Ryterski?

A. According to NOAA's Historical Observing Metadata Repository, there are multiple location and equipment changes.[2] The location of the weather station at COU changed on February 10, 1988, February 8, 2002, and November 1, 2010; the equipment was changed on September 1, 1995.[3] The location of the weather station at CGI changed on May 21, 2001 and July 18, 2009; the equipment was changed on March 5, 1997.[4] However, these anomalies are disregarded in the Company's calculation of normal HDD.

Q. How does NOAA recognize and eliminate these anomalies?

[2] Retrieved on August 22, 2017, https://www.ncdc.noaa.gov/homr/.
[3] See Schedule SJW-1.
[4] See Schedule SJW-2.

A. NOAA recognizes that there are inconsistencies and biases in the weather time series data. This is especially the case if there are changes at a weather station such as instruments being relocated, replaced, or recalibrated. Changes in observation procedures or in an instrument's environment may also occur during the time period for normal weather. NOAA accounted for these anomalies in calculating the normal temperatures it has published.[5] NOAA confirmed that the serially-complete monthly minimum and maximum temperature data sets have been adjusted to remove all inconsistencies and biases due to changes in the associated historical database.[6] NOAA produced the serially-complete monthly temperature ("SCMT") data series.[7] The statistical soundness of NOAA's methodology for removing documented and undocumented anomalies is published in the Journal of Climate.[8]

Q. What is Staff's recommendation for weather data?

A. Staff recommends utilization of the SCMT published in July 2011 by the National Climatic Data Center ("NCDC") of the NOAA for the purposes of normalizing the test year gas usage and revenues. In addition, Staff recommends utilization of the adjusted Tmax and Tmin daily temperature series that are consistent with NOAA's SCMT during the most recent NOAA 30-year normal period ending 2010 for the COU and CGI weather stations.

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[5] Arguez, A., I. Durre, S. Applequist, R. S. Vose, M. F. Squires, X. Yin, R. R. Heim, Jr., and T. W. Owen, 2012: NOAA's 1981-2010 U.S. Climate Normals: An Overview. Bulletin of the American Meteorological Society, 93, 1687-1697.

[6] Retrieved on July 10, 2014 from NOAA website, http://www1.ncdc.noaa.gov/pub/data/normals/1981-2010/documentation/.

[7] Retrieved on October 17, 2013, http://www1.ncdc.noaa.gov/pub/data/normals/1981-2010/source-datasets/. The SCMT, computed by the NOAA, includes adjustments to make the time series of daily temperatures homogeneous.

[8] Menne, Matthew J., and Claude N. Williams Jr. "Homogenization of temperature series via pairwise comparisons." Journal of Climate 22, no. 7 (2009): 1700-1717.

TIME PERIOD

Q. What are Staff's concerns regarding Mr. Ryterski's time period used to calculate normal weather?

A. Mr. Ryterski calculated the average HDDs over the 30 years using the time period 1981-2010 for weather normalization of gas sales during the test year. However, this time period does not properly represent the trend of current weather changes.

Q. What is the trend of current weather changes?

A. There is a downward trend of HDD time series data 1981 through 2017 in both COU and CGI weather stations. Figure 1 and Figure 2 shows trend analysis results.

Figure 1 Yearly HDD and Trend in COU

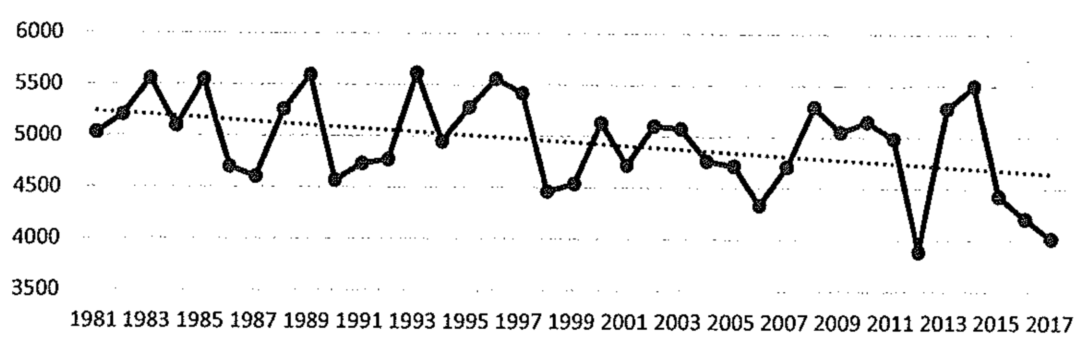
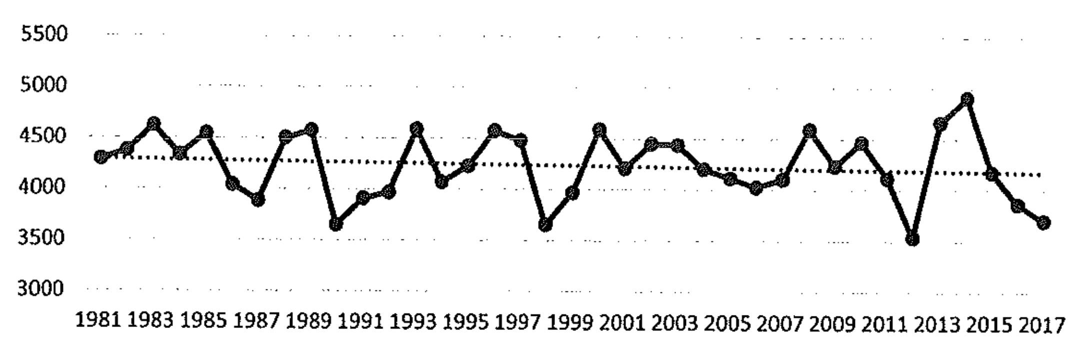


Figure 2 Yearly HDD and Trend in CGI



Q. What is the difference between 1981-2010 and 1987-2016 of 30-year average HDD?

A. The 1987-2016 time period shows a lower average HDD than the time period 1981-2010. Table 1 below presents the comparison of average HDD of COU and CGI.

Table 1. The Average HDD Comparison of COU and CGI

Weather Station	1981-2010	1987-2016	Difference
COU	5,018	4,923	95
CGI	4,256	4,225	32

Q. Were there any gas rate cases that utilized the billing determinants that were decided by normal HDD from the time period of 1987-2016?

A. Yes. The three most recent gas rate cases have utilized the time period 1987-2016 for calculating normal HDD to decide the billing determinants. The rate cases are GR-2017-0089 of Liberty Utilities (Midstates Natural Gas) Corp. d/b/a Liberty Utilities, GR-2017-2015 of Spire East, Spire Missouri, Inc., and GR-2017-2016 of Spire West, Spire Missouri, Inc.

Q. What is Staff's recommendation for the 30-year normal weather time period?

A. Staff recommends to utilize the 30-year time period of 1987-2016 for considering the trend of current weather changes and consistency with other recent rate cases.

RANKED AVERAGE

Q. What is Staff's concern in the Company's method of calculating normal HDDs?

A. The Company utilized the definition of the National Oceanic and Atmospheric Administration ("NOAA") normals to accurate normal HDDs. However, NOAA's daily normal temperatures are not directly usable for Staff's purposes. NOAA's dated average method calculates a simple arithmetic mean of MDTs of the same calendar date for each year in the 30-year normal period. Staff's calculated daily normal temperatures are based on the ranking of the actual temperatures of the accumulation period and the daily actual temperatures do not follow smooth patterns from day to day.

In other words, the NOAA daily normal temperatures and HDD values are derived by statistically "fitting" smooth curves through these monthly values. As a result, the NOAA daily normal HDD values reflect smooth transitions between seasons and do not directly relate to the 30-year time series of MDT as used by Staff. However, in order for Staff to develop adjustments to normal HDD for gas usage, Staff must calculate a set of normal daily HDD values that reflect the actual daily and seasonal variability. More details of a ranked average method for normal weather are explained in a peer-reviewed publication which I co-authored and attached as Schedule SJW-3.[9]

Q. What is the evidence that a ranked average method is more appropriate than a dated average method?

A. The evidence is demonstrated by a comparison of the results of the two different methods. If the ranked average method is used, the range of daily temperatures is 10°F through 85°F and 15°F through 85°F in COU and CGI, respectively. In contrast, if the dated average method is used, the range of daily temperatures is 27°F through 79°F and 31°F through 80°F in COU and CGI, respectively. Therefore, the ranked average method produces a more realistic daily temperature variation. Figure 3 and Figure 4 show the distribution of daily normal temperature series of COU and CGI using the ranked average method.

[9] Won, S. J., Wang, X. H., & Warren, H. E. (2016). Climate normals and weather normalization for utility regulation. Energy Economics, 54, 405-416.

Q. What would the result be if the dated average method is used instead of the ranked average method?

A. Because elimination of extreme temperatures occurs using the dated average method, the weather normalization adjustment of corresponding gas usage will be biased as shown in Figure 3 and Figure 4.

Figure 3 Daily Average Temperature Normal – COU

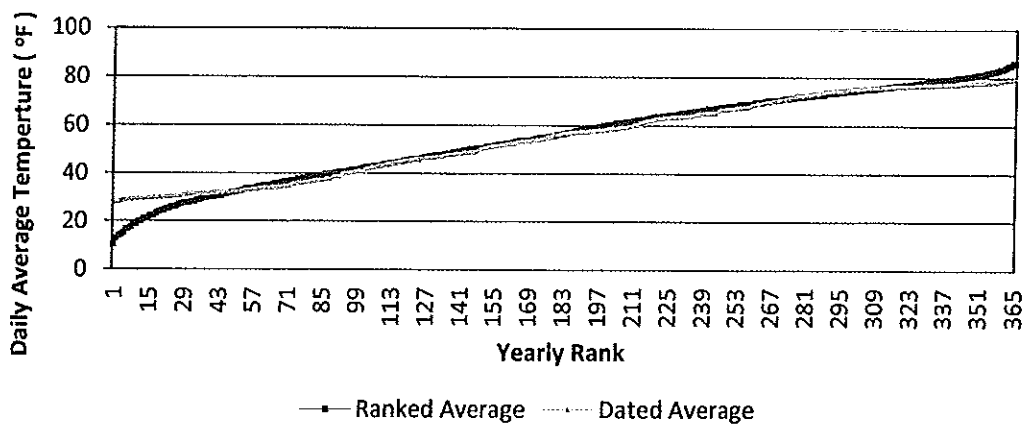
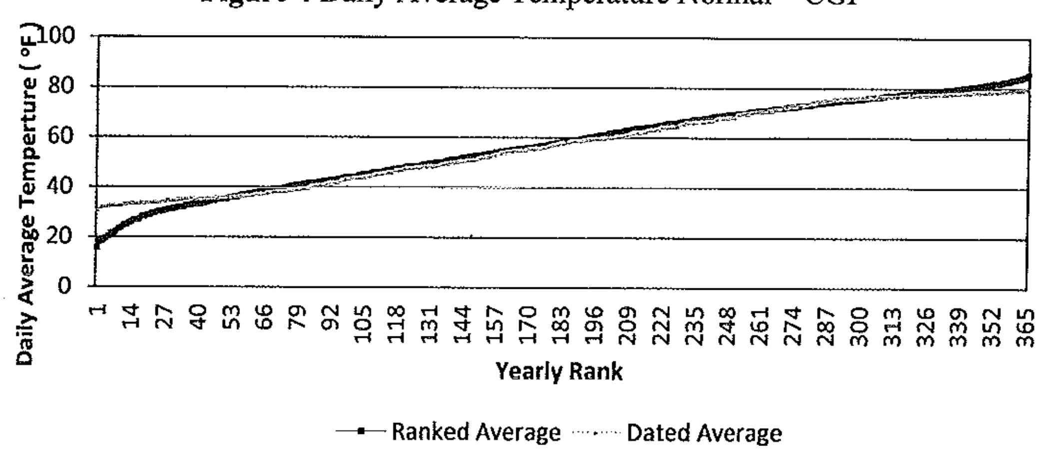


Figure 4 Daily Average Temperature Normal – CGI



Q. Were there any gas cases in which the Commission decided to utilize Staff's ranked average method?

A. In Page 13, Report and Order of gas cases GO-2019-0058 of Spire East, Spire Missouri, Inc., and GO-2019-0059 of Spire West, Spire Missouri, Inc., the Commission stated:

> The Commission finds that the tariff sheets to adjust Spire's WNAR rate should be rejected and that Spire should file tariff sheets based on **Staff's ranked method** for determining daily normal weather.

Q. What is Staff's recommendation regarding a method of calculating normals?

A. Staff recommends the Commission utilize the ranked average method to preserve the variation of peak gas usages.

WEATHER SENSITIVITY

Q. What are Staff's concerns about the Company's weather normalization of the LVT class?

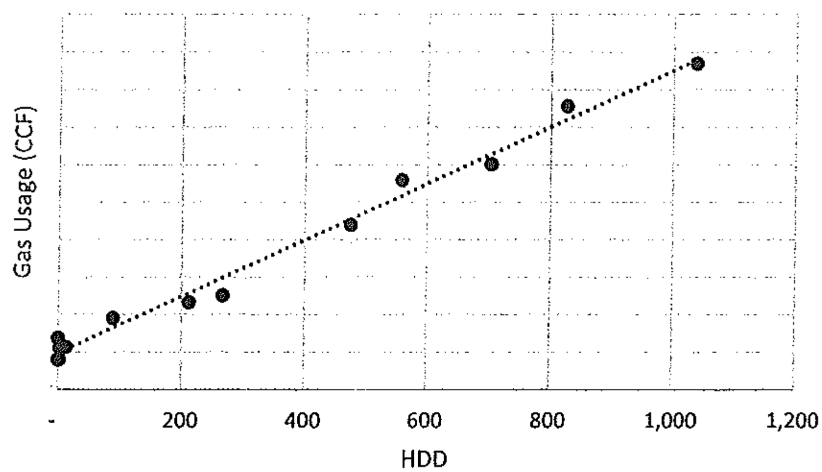
A. The Company weather normalized LVT customer gas usage in aggregate class level although each customer's gas usage uniquely reacts on weather. Moreover, among 21 LVT customers, only 13 customers' gas usage shows a significant relationship with weather. Staff classified 13 customers as weather sensitive customers. The other 8 LVT customers' gas usage charges are difficult to explain by weather variation, so that the Company's aggregated class level weather normalization can introduce a bias to the weather normalization adjustment of LVT customer usage.

Q. How did Staff test the weather sensitivity of LVT customers?

A. Staff has conducted a regression analysis and a chart analysis. Both analysis results are provided in Staff's rebuttal workpapers. According to the result of regression analysis, the gas usage variation of weather sensitive customers is explained more than 80% by weather. In addition, the chart analysis result is matched to the regression analysis.

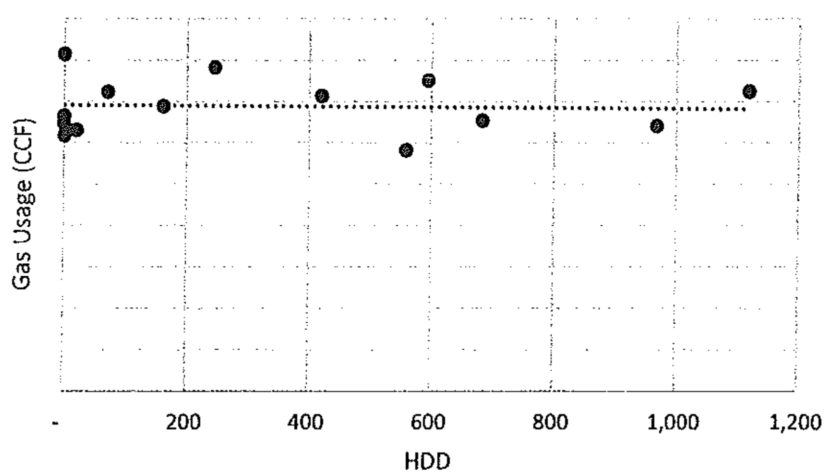
Figures 5 and Figure 6 are examples of the chart analysis for weather sensitive customers and non-weather sensitive customers, respectively. In Figure 5, the gas usage of a customer increases with a higher HDD, and more than 98% of gas usage variation is explained by HDD.

Figure 5 Weather Sensitive LT Customer



In Figure 6, the gas usage of a customer does not change with HDD, and more than 99% of gas usage variation is not explained by HDD.

Figure 6 Non-Weather Sensitive LT Customer



Q. What is Staff's conclusion regarding the LVT customer weather sensitivity test?

A. Based on the result of analysis there are 13 weather sensitive customers and 8 non-weather sensitive customers in the LVT class. In addition, each weather sensitive customer shows a unique relationship between gas usage and actual HDD so that Staff concludes that 13 weather sensitive customers should be weather normalized individually.

CONCLUSION

Q. What is the conclusion of Staff's rebuttal testimony?

A. For normal HDD calculations, Staff recommends the Commission utilize the ranked-average method with NOAA's homogenized weather data in the time period 1987 through 2016. For LVT customer gas usage weather normalization, Staff recommends the Commission utilize individual weather normalization for the 13 weather sensitive LVT customers.

Q. Does this conclude your rebuttal testimony?

A. Yes, it does.

BEFORE THE PUBLIC SERVICE COMMISSION

OF THE STATE OF MISSOURI

In the Matter of Union Electric Company d/b/a Ameren Missouri's Tariffs to Increase its Revenues for Natural Gas Service	)))	Case No. GR-2019-0077

AFFIDAVIT OF SEOUNG JOUN WON, PhD

STATE OF MISSOURI)
) ss.
COUNTY OF COLE)

COMES NOW SEOUNG JOUN WON, PhD and on his oath declares that he is of sound mind and lawful age; that he contributed to the foregoing *Rebuttal Testimony*; and that the same is true and correct according to his best knowledge and belief.

Further the Affiant sayeth not.

SEOUNG JOUN WON, PhD

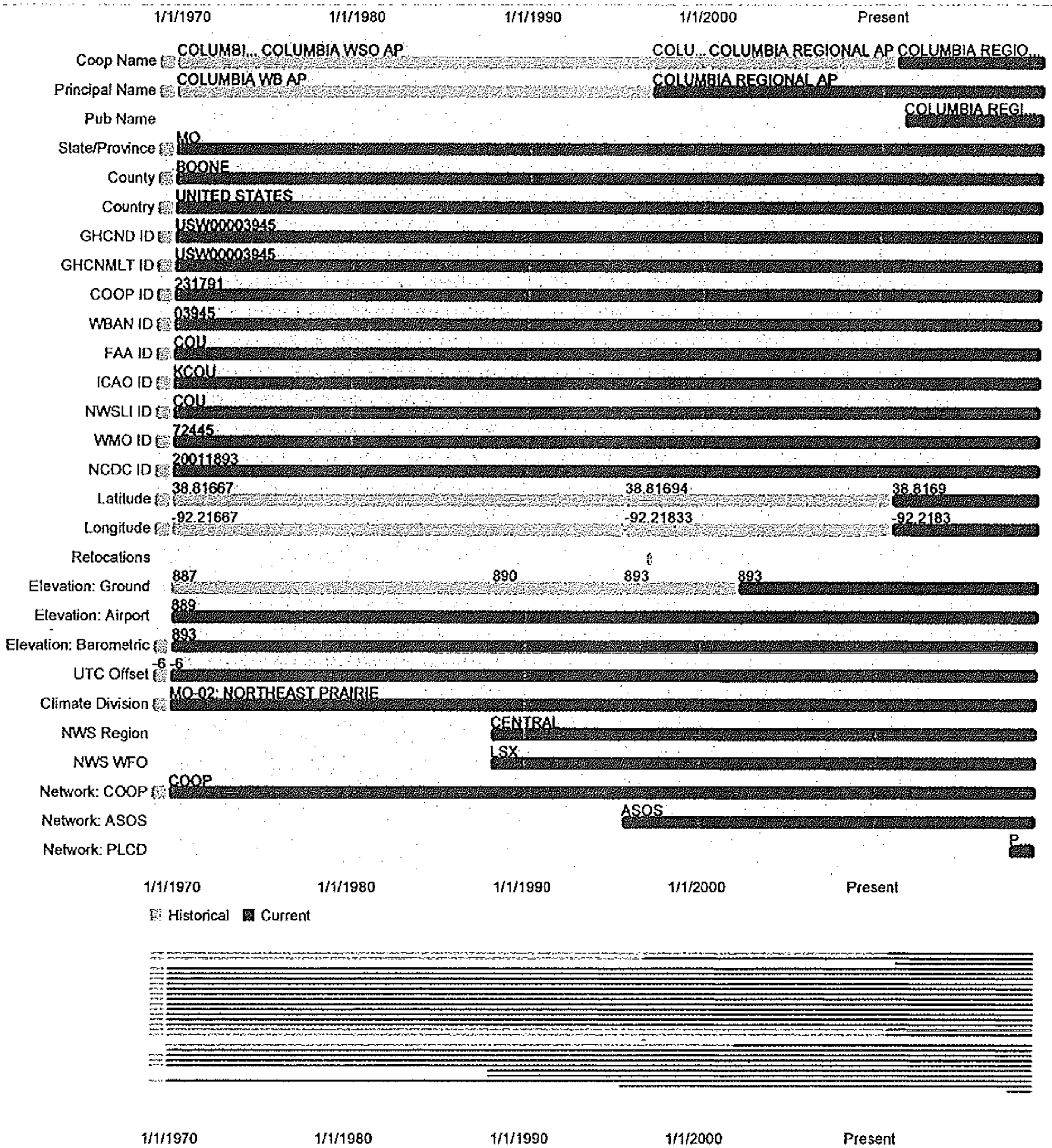
JURAT

Subscribed and sworn before me, a duly constituted and authorized Notary Public, in and for the County of Cole, State of Missouri, at my office in Jefferson City, on this 5th day of June 2019.

D. SUZIE MANKIN
Notary Public - Notary Seal
State of Missouri
Commissioned for Cole County
My Commission Expires: December 12, 2020
Commission Number: 12412070

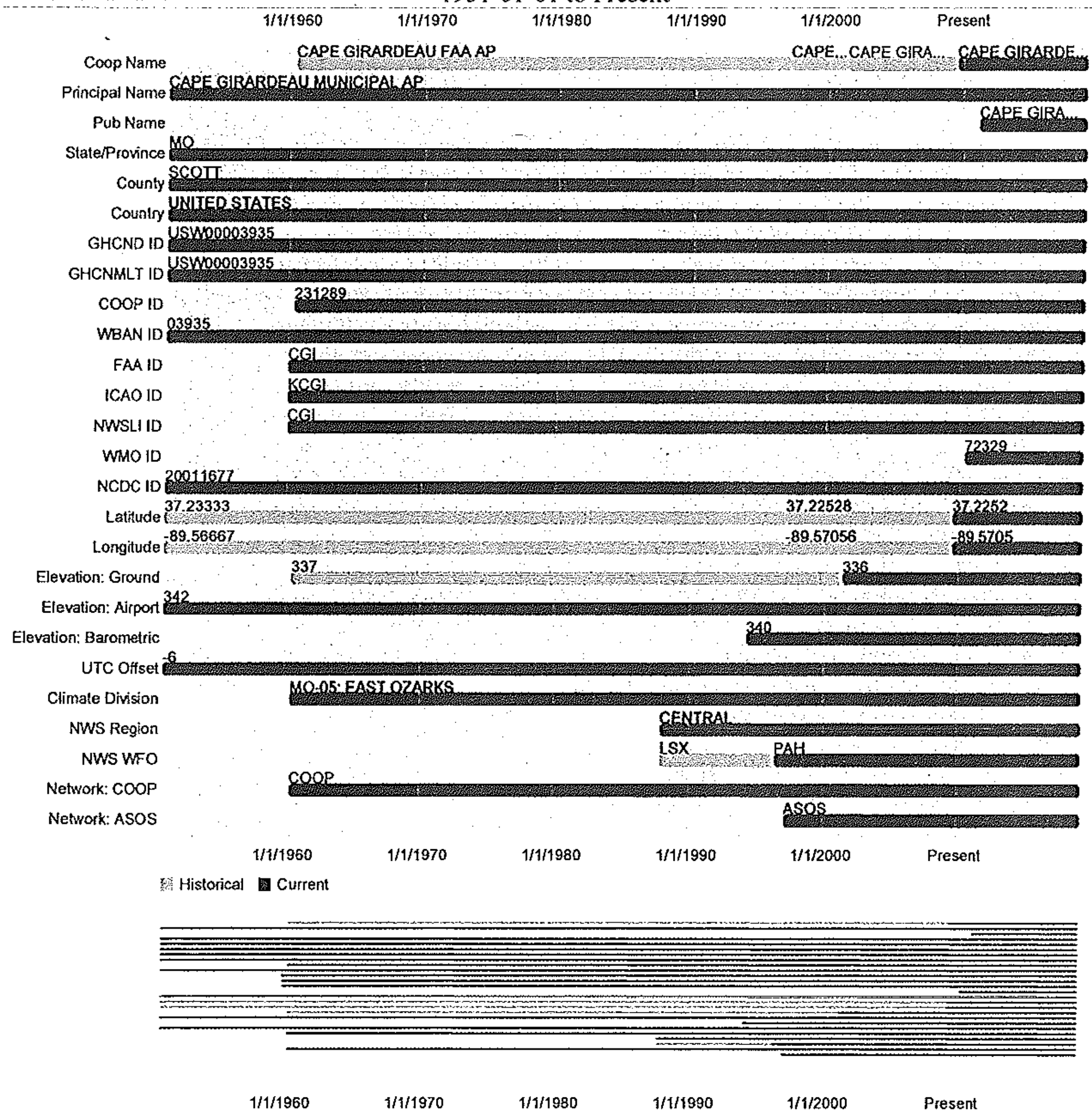
Notary Public

COLUMBIA REGIONAL AIRPORT, MO
1968-10-01 to Present



CAPE GIRARDEAU FAA AP, MO

1951-01-01 to Present



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Climate normals and weather normalization for utility regulation☆

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ABSTRACT

In the regulation of natural gas and electric utilities, the determination of rate revenues commonly involves a sales adjustment to reflect the difference between actual weather and normal weather. This adjustment process, commonly known as weather normalization, is required to properly determine a set of rates which yields the revenue requirement under the assumption of normal weather. Normal weather values that characterize long-term weather patterns are critical component of weather normalization. Conventionally, normal weather values are calculated using the Standard Climate Normal (SCN). The SCN for any given calendar day is the 30-year average of the associated weather observations for that calendar day. In the regulatory process the SCN can inadvertently introduce biases in the weather normalization adjustment. This study investigates the sources and mitigation of these biases.

1. Introduction

In the United States, rates for regulated natural gas and electric utilities (energy utilities) are periodically reset through administrative proceedings commonly known as rate cases. In a rate case, rates are established which recover the revenue requirement. However, an energy utility's sales vary year to year. This variation can occur for many reasons: weather, economic conditions, and other events that influence customer behavior (Dergiades and Tsoulfidis, 2008). In the regulatory process, the actual energy sales need to be adjusted for any unusualness during the test year (Monts et al., 1989).[1]

The temperature pattern is one of the primary determinants of energy usage and revenues for most energy utilities (Bower and Bower, 1985). Unusual levels of energy sales, due to an unusual temperature pattern, must be adjusted to levels consistent with the normal temperature pattern (Elkhafif, 1996). For the rate design to be just and reasonable this weather normalization adjustment is determined using a model that quantifies the relationship between sales and temperature.

In the weather normalization of test year energy sales, developing a data set of normal weather values that characterizes long-term weather patterns in the utility service territory is critical. Weather-normalized energy sales are calculated using weather during the test year that is adjusted to normal. In this calculation, daily normal weather values replace actual daily weather values during the test year in a model of energy sales. Depending on the model of energy sales, the data set of normal weather may need to reflect a more complete set of statistical properties, including monthly and yearly temperature variation. If the statistical properties of normal weather are inconsistent with the statistical properties of the test year weather, then the subsequent calculation of weather normalized sales will be biased. The total U.S. energy utility operating revenue was over $300 billion in 2009 (US Census Bureau, 2012).[2] A weather normalization adjustment to utility revenue may be more than 2% of annual operating revenues (Croucher, 2011). So, any miscalculation in the weather normalization adjustment to sales could have a significant impact on rate.

Conventionally, the Standard Climate Normal (SCN) is used for determining the daily normal weather values. Climate normals are based upon the average of associated weather variables in a certain time period. According to the National Oceanic and Atmospheric

☆ Disclaimer: The views expressed in this paper are those of the authors and do not necessarily reflect the views of the Missouri Public Service Commission.

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[1] A test year in the context of a utility rate case is a consecutive 12-month period used to calculate normalized and annualized costs and revenues which serve as a basis for calculating appropriate new rates. A test year could be a forward test year using projected data or a historical test year using verifiable actual data with some adjustments for known and measurable changes. Normal weather is appropriate for either type of test year, because the historical time series uses verifiable actual data for calculating normal weather, and it is assumed to be the most likely expectation for future years in which the new rates will be effective.

[2] See http://www.census.gov/compendia/statab/cats/energy_utilities.html.

http://dx.doi.org/10.1016/j.eneco.2015.12.016
0140-9883/

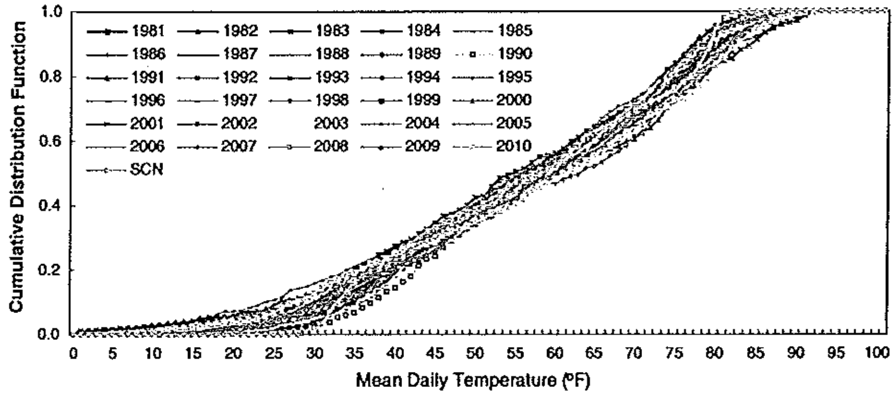

Fig. 1. Cumulative distribution functions of each year MDT and the daily SCN temperatures (1981–2010).

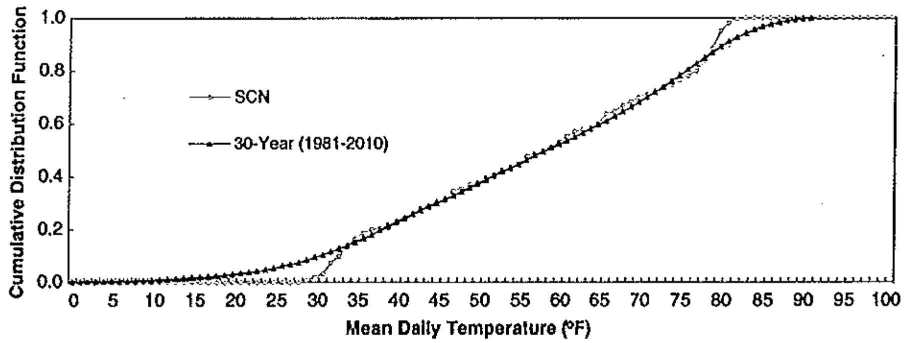

Fig. 2. Cumulative distribution functions of the daily temperature SCN and the 30-year (1981–2010) MDT.

Administration (NOAA), the SCN is defined as the arithmetic mean of a climatological element computed over 30-year period, usually three consecutive decades.[3] The SCN has also been the international standard for calculating normal weather for more than 70 years (Livezey and Hanser, 2013).

For several years, there has been ongoing debate concerning the SCN in energy utility rate design (Angel et al., 1993; Livezey et al., 2007; Livezey and Hanser, 2013). Recently, NOAA held a workshop on alternative climate normal calculations and the subsequent impact to the energy industry rates and revenues (Arguez et al., 2013). These issues are related to climate changes. However, there are more fundamental problems to define normal weather for the utility regulation.

Normal weather variables are statistical expectations of weather variables calculated using a long-term historical data. According to the National Climate Data Center (NCDC) the current daily SCN is based upon a 30-year (1981–2010) average of the yearly associated weather observations for the calendar day. If the goal is to define the most plausible temperature of a given calendar date using historical data, the daily SCN provides a statistically well-defined expectation. However, if we want to calculate the most plausible set of temperature values for the 365 days in a year, the suitability of the 365 daily SCN temperature values is questionable. Although each daily SCN is a good expectation for each calendar day, the set of 365 daily SCN values may not be the expectation for the days in an SCN year. Fig. 1 contains the 30 cumulative distribution functions of the mean daily temperatures (MDT) for the years 1981–2010 and the daily SCN for the normal period 1981–2010.

Fig. 1 illustrates that the annual proportion of MDT below 28 °F or above 82 °F, ranges from 5% to 25% of the calendar days in the years 1981–2010, but none of the 365 daily SCN temperatures for 1981–2010 are in those ranges. Since these temperatures are significant in determining daily energy sales and load forecasts, use of the daily temperature SCN in calculating weather normalized sales in utility rate cases will result in lower winter and summer sales. The source of this bias can be defined in terms of distribution similarity.

According to the Finkelstein–Schafer statistic (Finkelstein and Schafer, 1971), if any number, n, observations of a weather index $X_1, X_2, \ldots, X_n$ are available, a monotonic increasing function, $F(x)$, defined by

$$F(x) = (\text{number of } X_i \text{ such that } X_i \le x)/n.$$

$F(x)$ is a cumulative distribution function (CDF) based on the time series of the weather index with size n. The comparison statistics, FS, between CDF for the long-term (F_{LT}) which is used for calculating the climate normal and CDF for the climate normal (F_{CN}) are calculated by the following equation:

$$FS(F_{LT}, F_{CN}) = \int |F_{LT}(x) - F_{CN}(x)| dx.$$

We define the temperature distribution bias of a climate normal as the FS statistics. In Fig. 2, it can be seen that the SCN series has significant bias in the lower temperatures (25 °F–35 °F) and the higher temperatures (75 °F–85 °F).

This study investigates the effect of the SCN bias in the weather normalization process in the economics of electric utility rate design. An unbiased alternative procedure is developed for calculating daily normal temperatures. Weather normalization adjustments to energy sales and revenues are computed using the SCN and the alternative procedure. The results show that the alternative procedure of daily normal test year temperatures are preferred to the SCN because their distribution is closer to actual daily temperature distribution and there is a

[3] See http://www.ncdc.noaa.gov/oa/climate/normals/usnormals.html.

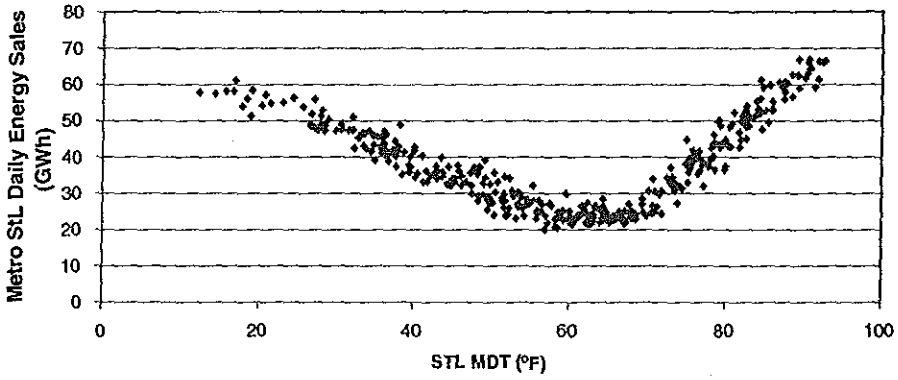

Fig. 3. Metropolitan St. Louis (Metro StL) 2011 daily residential electric energy sales and the corresponding STL MDT.

significant difference in the weather normalization adjustments to sales and revenues adjustments.

Section 2 introduces a weather normalization process for electric utility revenues. Section 3 discusses the computation and application of daily normal temperatures. Section 4 identifies the SCN biases and proposes alternative unbiased daily normal temperatures. In Section 5 SCN and alternative normal test year electric energy sales and revenues are simulated. Section 6 discusses implications of alternative daily normal temperatures for electric rate design.

2. Weather normalization

Energy sales for space heating and cooling are highly responsive to ambient temperature. The object of weather normalization is to find the level of energy sales consistent with the normal temperature pattern, assuming ceteris paribus. During the cooling season, as the temperature reaches higher levels, electricity sales increase as the demand for cooling such as air conditioning, ventilation, and refrigeration increases. During the heating season, as temperature falls the demand for additional space heating also results in increased energy sales.

A regulated energy utility is authorized to recover its fixed costs and variable costs as the result of a rate case or another regulatory process. The amount of revenue authorized is based on a specified rate-of-return and allowed expenses. The weather normalization of sales and revenues is a fundamental calculation in this regulatory process. An initial step in rate design is to determine the normal level of rate revenue and the quantification of associated variable costs.

Weather normalization uses load research data to determine the relationship between class specific sales and temperature variation. These relationships may include different base usage parameters for different days of the week and months of the year. For instance, for residential and commercial energy sales models, the variation in daily average temperature is the independent variable that determines the day-to-day variation in energy sales.

The relationship between daily residential electricity usage in the St. Louis metropolitan area (Metro StL) and the corresponding mean daily temperature (MDT) at Lambert – St. Louis International Airport (STL) in the test year 2011 is illustrated in Fig. 3. MDT is the simple average of the day's maximum daily temperature (Tmax) and minimum daily temperature (Tmin). The equation form of the daily mean temperature of dth day is as follows:

$$\mathrm{MDT}_d = \frac{1}{2}\,\mathrm{Tmax}_d + \frac{1}{2}\,\mathrm{Tmin}_d. \tag{1}$$

It is generally recognized that the response of electric energy sales to temperature is not uniformly linear as seen in Fig. 3 (Train et al., 1983). A rise in temperature 65 °F to 70 °F will not usually elicit the same response in electric energy sales as a rise from 80 °F to 85 °F, and a drop from 65 °F to 60 °F will not have the same effect as a drop from 50 °F to 45 °F.

In this study, we assume a test year is historical and a model of test year sales is developed from the relationship between energy sales and weather in the test year.[4] The model quantifies a change in energy sales during a specified time period, resulting from a change in the weather variable. The weather normalized sales adjustment is based on the difference between normal weather and actual weather during these periods in the test year.

A general model (Eq. (2)) characterizes the relationship between energy sales in a defined time period in the test year to weather and non-weather variables. The model parameters can be statistically estimated then the empirical model can be used to weather normalize energy sales:

$$E_t = F(w_t, x_t, \varepsilon_t) \tag{2}$$

where E is the amount of energy sales, w is a vector of weather variables that determine energy sales, x is a vector of non-weather variables that determine energy sales, ε is unexplained variation in energy sales, t is the time-period such as an hour, a day, a month, or billing cycle, and F is a function that relates the energy sales to the observed explanatory variables. This model is general and needs further specification for practical use in weather normalization.

If it is assumed that the energy response is invariant in the specified time period, and no interactivity among variables w, x, and ε, then the independent variables can be expressed as additively separable (Eq. (3)),

$$E_t = f(w_t) + g(x_t) + \varepsilon_t \tag{3}$$

where $E(t)$ is the amount of energy usage at time t,[5] w_t is a weather vector at time t, $f(.)$ is the amount of weather sensitive energy sales, x_t is a non-weather vector at time t, $g(.)$ is the amount of non-weather

[4] If a rate case adopts a forward test year, normal weather is used to forecast utility's future energy sales.

[5] Usually, weather normalization is conducted on daily level base. One reason is that the shortest time span available for climate normals is daily data. In some cases, the amount of energy usage is given for each billing month which is different from any given calendar month. Yet there are 21 different billing cycles so that eventually we need daily temperature normals. Therefore, average daily usage and average daily temperature for a given billing month are used for calculating weather normalization of energy consumption. In some cases, hourly load should be weather normalized. Because there is no official hourly climate normal data, daily peak load and daily average load are first normalized and then normalized hourly load shape is extrapolated from the daily normal loads. In summary, daily temperature normals are the fundamental units for most weather normalization calculations.

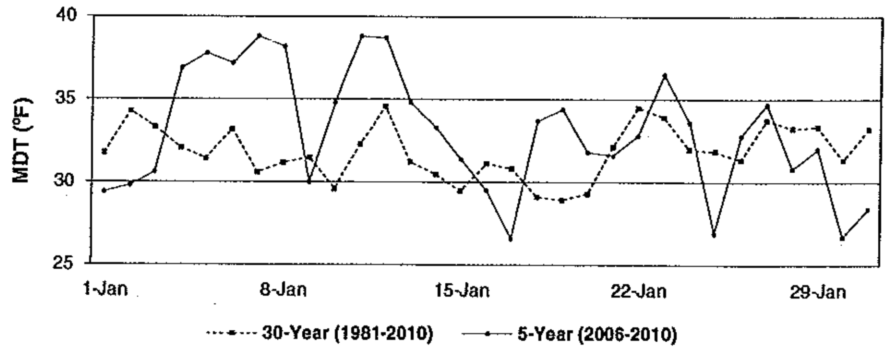

Fig. 4. STL 30-year and 5-year normal January MDT.

sensitive energy sales, and ε_t is the amount of the unexplained energy consumption at time t.

If we define the weather normal function, $N(w_t)$, as the normal weather value at time t of the observed weather value w_t then the normalized energy usage NE_t can be expressed as follows:

$$NE_t = f(N(w_t)) + g(x_t) + \varepsilon_t. \tag{4}$$

Therefore, the weather normalization adjustment $WNA(w_t)$ of energy usage at time t can be expressed as follows:

$$WNA(w_t) = f(N(w_t)) - f(w_t). \tag{5}$$

For instance, if at time t, we observe the actual energy usage, E_a, with the actual weather, w_a, then weather normalized energy usage, E_n, satisfies the following:

$$E_n = E_a + WNA(w_a). \tag{6}$$

Hence, the accuracy of the weather normal function, $N(w_t)$, is important, because bias in the normal weather function will result in a bias in the normalized energy usage estimate.

3. Climate normals

To define a precise weather normal function and estimate normalized energy usage, we need to have well defined climate normal calculations. The World Meteorological Organization (WMO) has defined climate normals as "period average computed for a uniform and relatively long period comprising at least three consecutive ten-year periods" and the SCN as "averages of climatological data computed for consecutive periods of 30 years (WMO, 2009)." The equation form of the SCN is as follows:

$$N^{30}(m,d;y_1) = \frac{1}{30}\sum_{y=y_1}^{y_1+29} O(y,m,d). \tag{7}$$

Here, $N^{30}(m,d;y_1)$ is the 30-year climate normal for a climate element of month, m, day, d, with normal period starting year, y_1, and $O(y,m,d)$ is the observed daily value for the climate element of year, y, month, m and day, d. This definition assumes that if the climate is not stationary any trend will be captured in the decadal update of the 30-year normal.

Technically, weather normalization is not forecasting. In load forecasting on the reliability of the 30-year normal has been broadly challenged recently (Livezey et al., 2007; Milly et al., 2008). A profusion

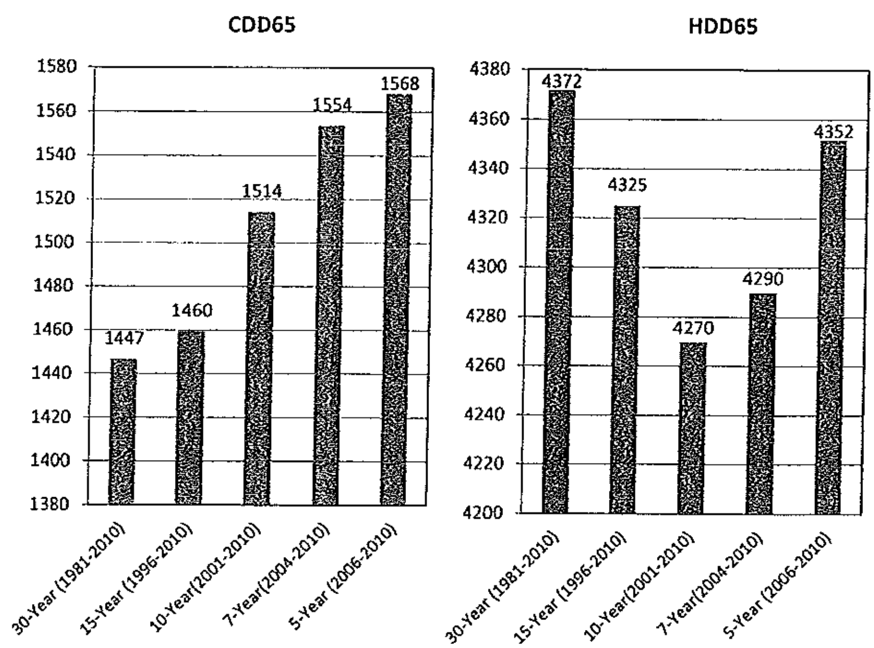

Fig. 5. STL annual CDD65 and HDD65 normals.

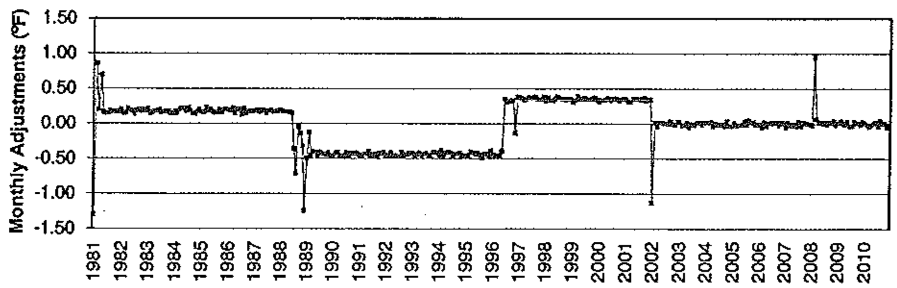

Fig. 6. Monthly adjustments to STL MDT (1981–2010). Note: Monthly adjustment = Homogenized monthly MDT of NOAA 1981–2010 normals – Observed monthly MDT.

of studies suggest that utilities and regulatory agencies in the U.S. energy industry are moving to shorter-term averages for forecasting (Arguez and Vose, 2011). Optimal Climate Normals, Least Squares Linear Trend Fits, and Hinge Fits are examples of alternative forecasting methodologies (Wilks, 2013). The appropriate methodology cannot be uniformly prescribed but needs to be evaluated in the context of the application and whether the application is normalization or forecasting.

The more general equation form of a climate normal is:

$$N^n(m,d;y_1) = \sum_{y=y_1}^{y_1+n-1} W(y)O(y,m,d). \tag{8}$$

Here, $N^n(m,d;y_1)$ is the n-year climate normal of month, m, day, d, with normal period starting year, y_1, $W(y)$ is a weight for year, y, and $O(y,m,d)$ is the observed daily value of year, y, month, m, and day, d. Using the STL temperature data set from January 1, 1981 to December 31, 2010, 30-year (1981–2010) and 5-year (2006–2010) normal MDTs for January were computed (Fig. 4). The 5-year normal January MDT has a larger day to day variation. The 5-year normal January MDT reflects recent weather trends and in some applications may be better for a short term forecasting (Angel et al., 1993), but it is not better in terms of characterizing the variation in ambient temperature over a longer period time.

In energy utility regulation, heating degree days with a base of 65 °F (HDD65) and cooling degree days with a base of 65 °F (CDD65) are conventionally used in revenue requirement calculation. HDD65 and CDD65 are calculated as the difference between the MDT and a chosen base 65 °F.[6] HDD65 is calculated as the difference between 65 °F and the MDT when the MDT is below 65 °F, and is equal to zero when the MDT is above 65 °F: HDD65 for day d is defined as

$$\text{HDD65} = \mathbf{max}[0,(65-T_d)], \tag{9}$$

where T_d is the MDT for day, d. Similarly, CDD65 is calculated as the difference between 65 °F and the MDT when the MDT is above 65 °F, and is equal to zero when the MDT is below 65 °F. CDD65 for day d is defined as.

$$\text{CDD65} = \mathbf{max}[0,(T_d-65)]. \tag{10}$$

Because of weather cycles, the normal for HDD65 and CDD65 will vary according to the length of time period (Fig. 5).

After determining that weather normalization is the appropriate methodology the next question to be confronted is which climate normal period is the better for weather normalization. The goal of the Missouri Public Service Commission (MPSC) is to balance the interests of ratepayers and company stockholders. There are often competing economic interests in choosing the normal time period for weather normalizing energy sales and revenues. These competing stakeholder interests may result in protracted administrative proceedings involving countervailing testimony resulting in added time and costs to the regulatory process. Since the 1990's the position of the MPSC Staff has been that the WMO and the NOAA 30-year normal is the most practical and authoritative due to the effort of NOAA to provide a 30-year weather station time series for the normal calculation that includes adjustments for any changes in the station location and/or instrumentation.

4. Biases and mitigation procedure

4.1. Homogenization

Even if the 30-year climate normal period is accepted by all regulatory stakeholders there are often problems with the time series of weather observations that lead to disagreements about how to identify biases in and calculate adjustments to the time series. For instance, if the weather instruments were relocated, replaced, or recalibrated, the observed weather data series may be inconsistent and biased. Changes in observation procedures or in an instrument's environment may also occur during the normal period. Any inhomogeneity in the climate data series needs to be identified and quantified to achieve a reliable adjustment to weather observation time series.

In the calculation of the 1981–2010 climate normals, NOAA developed an automated homogenization algorithm based on the pairwise comparison of monthly temperature series from nearby weather stations. As described in Menne and Williams (2009), the National Climatic Data Center (NCDC) developed a robust quality control and standardization methodology which yielded consistent monthly maximum and minimum temperature time series for each weather station (Arguez et al., 2012). The monthly homogenization algorithm for the temperature observations was applied to the daily maximum and minimum temperature observations (Vincent et al., 2002).

Usually the 30-year time series has been statistically evaluated and adjusted for consistency. These statistical techniques identify and adjust for missing data values and discontinuities. The discontinuities may include documented and undocumented changes in instruments, location, elevation, observation schedule, and site characteristics. The equation form of climate normal that includes adjustments in the observed daily data series is:

$$N_A^{30}(m,d;y_1) = \frac{1}{30}\sum_{y=y_1}^{y_1+29} A(y,m,d). \tag{11}$$

$N_A^{30}(m,d;y_1)$ is the 30-year climate normal of month, m, day, d, with normal period starting year y_1, and $A(y,m,d)$ is the adjusted observed daily value of year, y, month, m, and day, d.[7]

The STL 1981-2010 time series has adjustments for documented and undocumented changes in the MDT observations as a result of the

[6] For the consistency, degree day values are calculated by the definition of degree day using the associated average of MDT for the given calendar date.

[7] The homogenization of historic data is conducted using monthly data series. For calculating daily adjustments, please see Vincent et al. (2002).

Table 1
STL Meta Data (NOAA Multi-Network Metadata System).

Begin date	End date	Latitude	Longitude	Elevation	Equipment
1/18/2002	3/31/2012	38.752500 (38°45′09″N)	−90.373610 (90°22′24″W)	GROUND: 531 FEET	ASOS HYGROTHERMOMETER
6/1/1996	1/18/2002	38.752500 (38°45′09″N)	−90.373610 (90°22′24″W)	GROUND: 568 FEET	ASOS HYGROTHERMOMETER
7/1/1995	6/1/1996	38.750000 (38°45′00″N)	−90.366670 (90°22′00″W)	AIRPORT: 618 FEET	MAX-MIN THERMOMETERS
7/11/1988	7/1/1995	38.750000 (38°45′00″N)	−90.366670 (90°22′00″W)	GROUND: 535 FEET	MAX-MIN THERMOMETERS
1/1/1980	7/11/1988	38.750000 (38°45′00″N)	−90.366670 (90°22′00″W)	GROUND: 535 FEET	UNKNOWN - TEMP

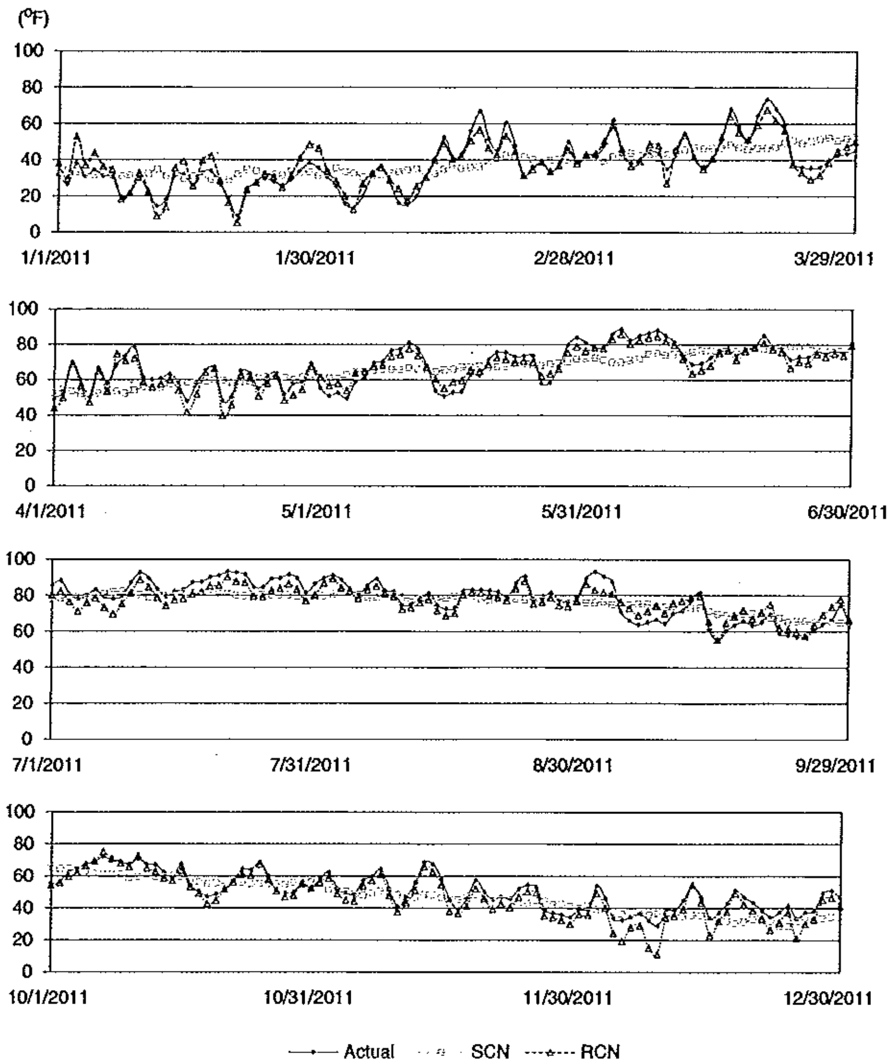

Fig. 7. STL 2011 MDT, SCN, and RCN.

NOAA's homogenization (Fig. 6). Adjustments indicate difference between the NOAA's monthly homogenized temperature and the monthly average of observed temperature, January 1, 1981 to December 31, 2010, at the STL.

Documented changes during the normal period are reported in Multi-Network Meta Data System of the NOAA.

System of the NOAA.[8]

The changes in instruments and locations documented in Table 1 are reflected in the time series (Fig. 6). There are significant adjustments in 1988, 1996, and 2002.

[8] See http://www.ncdc.noaa.gov/homr/.

4.2. Preserving variation

The goal of electric power system load research is to accurately characterize daily peak load and daily average load, which are very temperature dependent. To properly determine the temperature normalized daily peak load, daily temperature variation should be consistent with the variation in the daily climate normal time series. As explained in introduction, this variation is lost in the SCN which is calculated using the typical averaging process which eliminates extremes in the time series of observations. If the SCN set of MDT is used in a load research model, the result is a set of normalized daily peak loads in which the daily variation is suppressed. Thus, the monthly and annual series of SCN daily temperature series have a bias in their variation which results in a

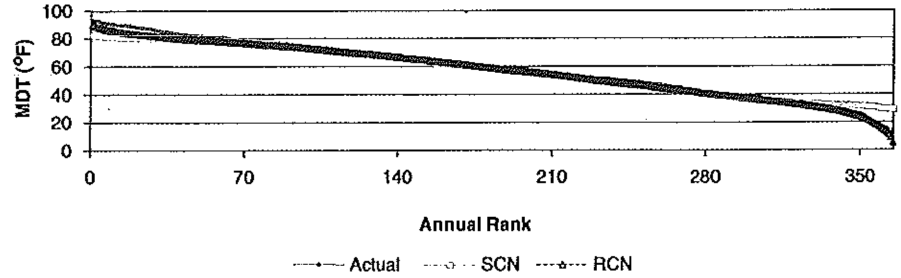

Fig. 8. STL Ranked 2011 MDT, SCN, and RCN.

bias in the variation of any monthly or annual time series estimates of daily peak load. Subsequently in any related analysis of the potential variation in generation, transmission, or distribution is suppressed.

The daily temperature pattern in months and years should be reflected in the normalized test year daily temperature time series used for the weather normalization of energy sales, there is a non-linearity in the response of energy sales to MDT. So, the normalized daily energy sales need to reflect the test year daily temperature variation. More importantly, because of the non-linear relationship between temperature and energy sales (Fig. 3), removing variation in daily temperatures could lead to a significant error in the weather normalization adjustment to test year sales. Therefore, the set of daily normal temperatures in a month should approximate the range of observed daily temperatures in a set of monthly and annual MDT.

To capture the historic MDT pattern for each test year month and filter any anomalies, the staff of MPSC developed a computational procedure based on the Monthly Climate Rank (MCR) of the test year observed MDT. The MCR is an intermediate calculation used in the compilation of the final Ranked Climatological Normal (RCN) series. It is used for assigning yearly ranked temperature values from the 30-year time series to the corresponding test year date which has the same monthly temperature rank.

A more general equation form for a temperature in the MCR series is:

$$N^{30}_{MR}(m,d;y_1) = \frac{1}{30}\sum_{y=y_1}^{y_1+29} A_{MR}(y,m,d). \tag{12}$$

$N^{30}_{MR}(m,d;y_1)$ is a ranked temperature for a day in the MRC series i.e. the dth highest daily temperature in month, m, in the MCR series for the 30-year climate normal period starting year, y_1, and $A_{MR}(y,m,d)$ is dth highest daily temperature of the adjusted daily temperature in month, m, year, y. The MCR series preserves the normalized daily temperature pattern each month of the test year.

The normal daily temperatures need to properly reflect the variation of the test year daily temperatures. The RCN series is based upon a 30-year average of the ranked daily temperature in each year assigned to the corresponding the monthly ranked test year temperature using the MCR. The equation form of a normal MDT in the RCN series is calculated using the monthly and yearly rank:

$$N^{30}(m,d;y_1,y_T) = \frac{1}{30}\sum_{y=y_1}^{y_1+29} A_{YR}(y,m,D). \tag{13}$$

Here, a rank in the RCN, $N^{30}(m,d;y_1,y_T)$, is the 30-year daily normal of month, m, day,d, normal period starting year, y_1, assuming the temperature of month, m, day, d, in the test year, y_T, has Dth monthly rank. $A_{YR}(y,m,D)$ is a temperature value which yearly rank in temperature data series of year, y, is the same as the yearly rank of the temperature value, $N^{30}_{MR}(m,D;y_1)$, in the MCR, $\{N^{30}_{MR}(.,.;y_1)\}$.

The main reason the monthly rank is employed in this procedure is that weather normalized consumer usage will be used in calculating monthly revenues and monthly expenses related to monthly characteristics of the test year. If we just use yearly rank then the daily normal pattern of temperature variation in a month will reflect an abnormal temperature variation in a month in the test year. Therefore, the RCN methodology not only preserves both monthly and annual temperature variation but also minimizes the difference between test year daily temperatures and normal daily temperatures (Turner and Lissik, 1991).

The daily RCN, which is calculated by the rank and average method explained above and the daily SCN are compared in Fig. 7. The variation in the daily RCN reflects the variation in the test year daily temperature observations whereas the daily SCN variations in temperature values are dampened.

Comparison of yearly ranked daily test year, RCN and SCN temperature series are graphed in Fig. 8. At the upper end and lower end of the plot it can be seen that both hot and cold extreme temperatures are dampened in the SCN data series, but are reflected in the RCN data series. The RCN has a relatively similar shape compared to the test year daily temperature series in both the higher and lower ranked temperature values.

For each year of the normal period (1981–2010) the average of the upper 95th percentile (warmest 18 days) MDT is plotted in Fig. 9. Similarly the average of lower 5th percentile (coldest 18 days) MDT for each year are plotted in Fig. 10. The corresponding average of the

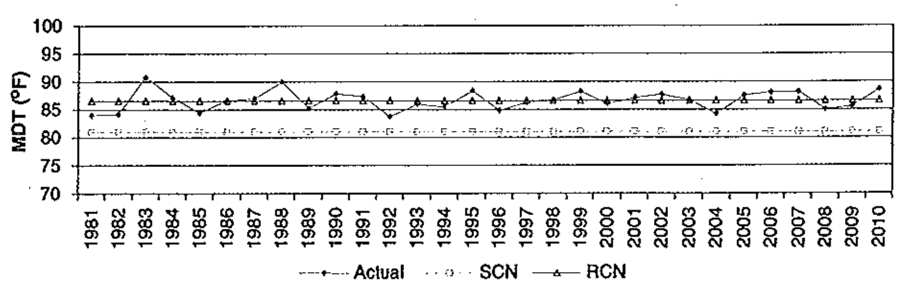

Fig. 9. STL 95th percentile (18th warmest) MDT – actual, SCN, and RCN.

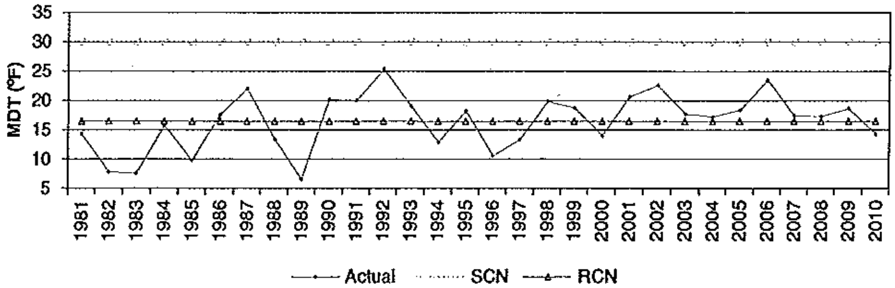

Fig. 10. STL 5th percentile (18th coldest) MDT — actual, SCN, and RCN.

highest 18 days of the SCN and RCN are plotted in Fig. 9 each year, and the average of the lowest 18 days of the SCN and the RCN are plotted each year in Fig. 10. In both figures it can be seen that the average SCN is offset from the lower 5th percentile average and upper 95th percentile average of the years in the period, 1981–2010, whereas the RCN, by design, goes through the average of the lower 5th percentile and upper 95th percentile respectively.

The histograms of the distribution of Actual MDT for the normal period (1981–2010), the distribution of the SCN, and the distribution of the RCN are plotted in Fig. 11. The distribution of the RCN MDT has a better fit to the distribution of MDT of 30-year period from 1981 to 2010 than the distribution of the SCN MDT. In Fig. 11, the distribution of the RCN MDT is almost the same as the distribution of the Actual MDT from 1981 to 2010. The distribution of the SCN MDT shows that extremes lower than 20 °F and higher than 90 °F are removed. The SCN distribution also shows abnormally high density in the intervals from 30 °F to 40 °F and 70 °F to 80 °F. In Fig. 12, it can be seen that cumulative distribution function of RCN and the 30-year MDT series are almost coincidental while the SCN series deviates in the lower temperatures (25 °F–35 °F) and the higher temperatures (75 °F–85 °F).

4.3. *The cumulative effect*

A persistent weather pattern (such as a "heat wave" or a "cold air mass") has a cumulative effect on daily energy use for space cooling and heating. Thus, in summer, a warm day after one or more warm days has greater total daily energy sales than the same warm day preceded by cool or temperate days. For example, during the cooling season, even if the MDT is the same for two Wednesdays in different weeks, more air conditioning would be used on the Wednesday with the warmer preceding Tuesday. Assuming a positive linear load and sales response of a weather observation, such as temperature in the summer, the cumulative effect of weather can be measured by a regression model,

$$\text{Energy Sales} = \beta_0 + \beta_1 W_t + \beta_2 W_{t-1} + \gamma NW_t + \varepsilon_t \tag{14}$$

where W_t is a weather observation on day t, W_{t-1} is the weather observation on the previous day, NW_t is a non-weather variable, ε_t is an error. Both $\beta_1$and β_2 are anticipated to be positive. In the weather normalization process, a regression model with weather lag variable is problematic because the relationships between two days in a test year and in climate normal are different.

Another way to internalize the cumulative temperature effect is to calculate a two-day weighted mean daily temperature (TWMDT) series for the test year. The equation form of TWMDT for day d is:

$$\text{TWMDT}_d = \alpha_1 \text{MDT}_{d-1} + \alpha_1 \text{MDT}_d \tag{15}$$

where

$$\alpha_1 = \frac{\beta_1}{\beta_1 + \beta_2} \text{ and } \alpha_2 = \frac{\beta_2}{\beta_1 + \beta_2}.$$

Based on empirical analysis of weighting alternatives a set of TWMDT is calculated using the previous day's mean daily temperature with a one-third weight and the current day's mean daily temperature with a two-thirds weight ($\beta_1 = 1$ and $\beta_2 = 2$). The model using the TWMDT series shows a higher explanatory power than regression model using the MDT series. In other words, when the other independent variables are the same, the regression model of daily electric energy sales with the TWMDT series shows a higher R-square than the model with the MDT series. For instance, as demonstrated by the regression model in the next section, adjusted R-square is 0.9643 in the regression with the TWMDT series but the same regression model with

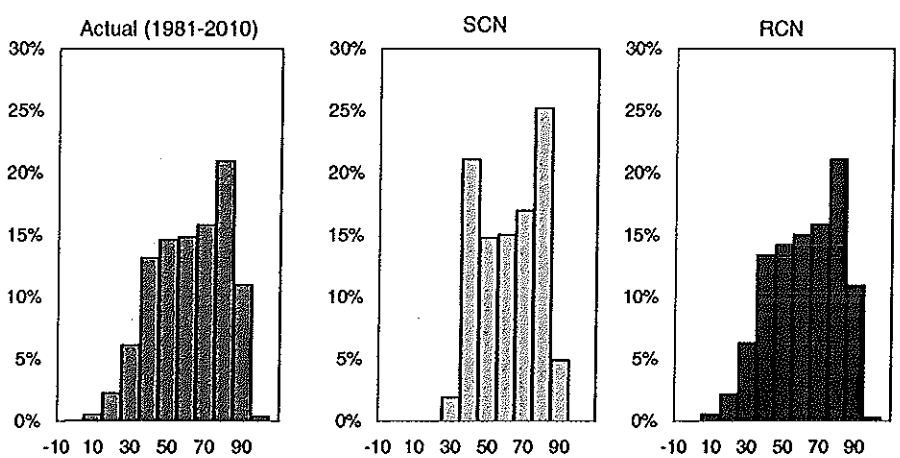

Fig. 11. STL density distributions of 1981–2010 MDT, SCN, and RCN.

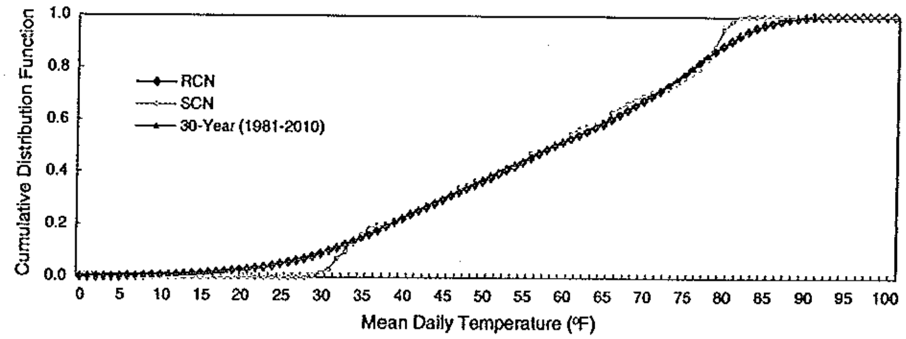

Fig. 12. Cumulative distribution functions of the daily temperature RCN and SCN series and the 30-year (1981–2010) MDT series.

the MDT series has an adjusted R-square of 0.9545. It is also demonstrated that for weather normalization the ranked normal TWMDT is more appropriate than the two day weighted mean of ranked normal MDT. The TWMDT accounts for the some of the cumulative effects of persistent temperatures on energy sales, but further investigation of the cumulative effect on sales needs to be conducted.

4.4. Mitigation of other anomalies

Further refinement of the daily energy sales model must be made for weekends and holidays (non-workdays), when energy sales responses to TWMDT are significantly different due to variations in economic activity. Therefore, if the monthly extreme temperature occurs on a non-workday in the test year, the relationship between test year weather and energy sales will diverge. Consequently, test year days with temperature extremes are reassigned to a workdays with a similar TWMDT rank.

In test years that are non-leap years the observations on February 29 in the thirty year period are excluded from the normal series of MDT in the calculation of the daily climate normal. If the test year is a leap year, the observations on February 29 are included in the normal series, and the non-leap years in the normal series is augmented using the average of February 28 and March 1, to generate a value for February 29 to complete the 30 year period to calculate the daily climate normal.

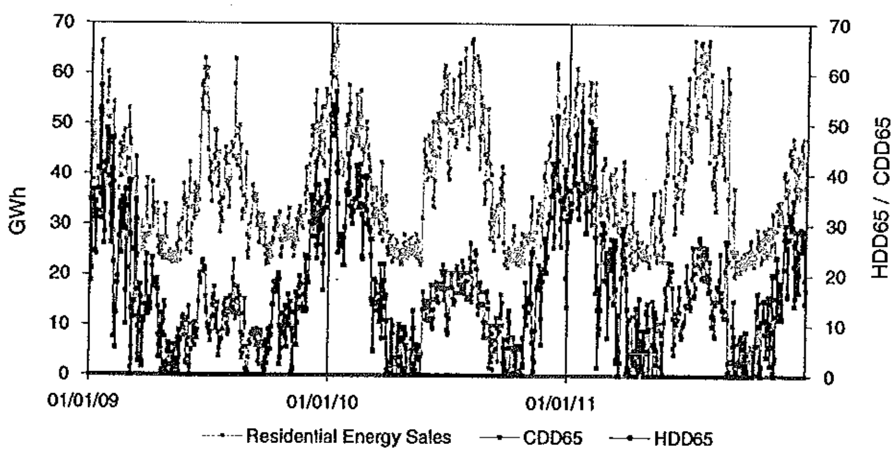

Fig. 13. Metro StL Daily Residential Energy (GWh) sales and STL HDD65 and CDD65 (2009–2011).

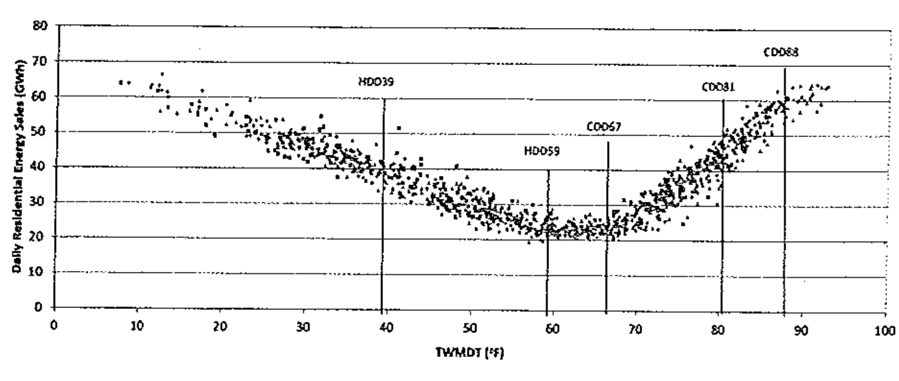

Fig. 14. Piecewise linear inflection points for Metro StL daily residential electric energy sales vs. STL TWMDT used to calculate HDD and CDD.

Table 2
Descriptive statistics for using TWMDT.

Variable	Count	Mean	StdDev	Min	Max	Skewness	Kurtosis	Jarque–Bera	Probability	CorrYX
RESENERGY (GWh)	1095	38,115	11,783	19,978	68,900	0.454	2.195	67	0.000	1.000
HDD39	1095	2.039	5.095	0.000	31.487	2.962	12.028	5319	0.000	0.507
HDD59	1095	8.812	12.264	0.000	51.487	1.247	3.448	293	0.000	0.454
CDD67	1095	4.083	6.470	0.000	25.667	1.420	3.796	397	0.000	0.555
CDD81	1095	0.494	1.698	0.000	11.667	4.009	19.540	15415	0.000	0.527
CDD88	1095	0.047	0.366	0.000	4.667	8.925	88.300	346507	0.000	0.282
EMPLOYMENT (1000)	1095	2517	35	2449	2568	−0.548	2.500	66	0.000	−0.093
PRICE ($/KWh)	1095	0.082	0.018	0.053	0.121	0.306	2.046	59	0.000	0.114

Table 3
Regression Statistics for TWMDT and MDT Models.

	[1] TWMDT	[2] MDT
Adjusted R Squared	0.9643	0.9039
Standard Error	2240	3672
Variable	Coefficient	Coefficient
HDD39	147**	−749**
HDD59	615**	811**
CDD67	1,372**	1,206**
CDD81	844**	765**
CDD88	−1,230**	−834*
EMPLOYMENT	−23**	−31**
PRICE	−90,431**	−102,435**
DJANUARY	−2,323**	1,127
DFEBRUARY	−3,473**	−3,297**
DMARCH	−5,539**	−8,993**
DAPRIL	−6,348**	−9,328**
DMAY	−4,005**	−6,405**
DJUNE	769	−217
DJULY	1,785	1,042
DAUGUST	420	−605
DSEPTEMBER	−5,299**	−7,593**
DOCTOBER	−6,951**	−10,062**
DNOVEMBER	−5,307**	−8,928**
DSUNDAY	1,100**	1,317**
DMONDAY	−873*	−565
DTUESDAY	−1,438**	−855*
DWEDNESDAY	−1,668**	−1,050*
DTHURSDAY	−1,460**	−826*
DFRIDAY	−1,415**	−1,088*
Intercept	96,192**	134,332**

* $P < 0.1$.
** $P < 0.01$.

5. Economic impact

A simulation of electric rate case weather normalized revenue estimates can demonstrate the difference in the economic impact of the SCN and RCN adjustments to daily test year weather. For comparison, the adjustments to normal weather are calculated using both the SCN series and RCN series to determine the revenue difference between the two methods. The statistical relationship between weather and energy sales can be characterized in the regression model:

$$\text{Energy Sales} = \beta_0 + \boldsymbol{\beta} \cdot \mathbf{W} + \boldsymbol{\gamma} \cdot \mathbf{NW} + \varepsilon, \tag{16}$$

where **W** is a vector of weather variables and **NW** is a vector of non-weather variables.

In the simulation, RESENERGY (GWh), the series of Ameren Missouri daily residential sales are Energy Sales. The STL daily MDTs for the test year are from the Midwest Regional Climate Center (MRCC).[9] The serially complete monthly temperature data series from NOAA[10] are used to compute normal weather, Ameren Missouri daily residential electric energy sales, the daily HDD65 and CDD65, derived from the TWMDT for 2009–2011 are overlaid in Fig. 13.

The quantitative relationship between daily temperature and daily residential electric energy sales varies according to the daily temperature range because electricity is used for heating and cooling. Consequently, the weather variables, HDD and CDD, are calculated with bases other than the standard base of 65 °F that are adjusted to the daily temperature range using MDT and TWMDT. HDD with an adjusted base of *THB* for day *d* are calculated as follows:

$$\mathrm{HDD}_d THB = \mathbf{max}[0, (THB - T_d)] \tag{17}$$

where T_d is one of the daily temperature calculations for day *d* (i.e. MDT or TWMDT). Similarly, CDD with the base of *TCB* for day *d* are calculated as follows:

$$\mathrm{CDD}_d TCB = \mathbf{max}[0, (T_d - TCB)]. \tag{18}$$

Bases were determined by analyzing the relationship between daily energy sales and the daily temperatures. Because of the piecewise linearity of daily energy sales to daily temperature, five bases are used for generating the degree day variables, HDD39, HDD59, CDD67, CDD81, and CDD88. The daily energy sales series, RESENERGY corresponding to the TWMDT series with the five degree day break points are plotted in Fig. 14.

The non-weather factors of season, electricity price and local economic activity are also included. Discrete variables for weeks and months are employed, allowing each time unit a coefficient reflecting factors that are outside the model. The variable, DSUNDAY, is one when the day is Sunday and zero otherwise. Holidays are excluded from the regression because each holiday has a unique characteristic for electric energy sales.

PRICE, P_m, is the average price per kWh paid by residential customers in a month.[11] P_m is calculated from the Ameren Missouri residential class revenue, R_m, per kWh sales, S_m, reported by the U. S. Energy Information Administration,

$$P_m = \frac{R_m}{S_m} - (m =, \ldots, 12). \tag{19}$$

PRICE, P_m, changes monthly for several reasons. First, during the period regulated rate changes occurred in March 1, 2009; June 21, 2010; and July 31, 2011. Second, average rates change as usage changes due to rate designs such as declining block rates and seasonal rates (e.g.

[9] See http://mrcc.isws.illinois.edu/CLIMATE/.

[10] See ftp://ftp.ncdc.noaa.gov/pub/data/normals/1981-2010/source-datasets/.

[11] Ameren Missouri's residential service class rates are not linear. However, evidence from recent studies suggests that electricity consumers respond to average price rather than marginal price or expected marginal price. Customers do not understand complex rate structures (Ito, 2012). Ameren Missouri has an Optional Time-of-Day residential rate, but less than 0.001% of residential customers have requested this rate. The monthly price of electricity used in this study is the monthly average normalized price compiled by the Bureau of Labor Statistics in the quarterly CPI of Metro StL.

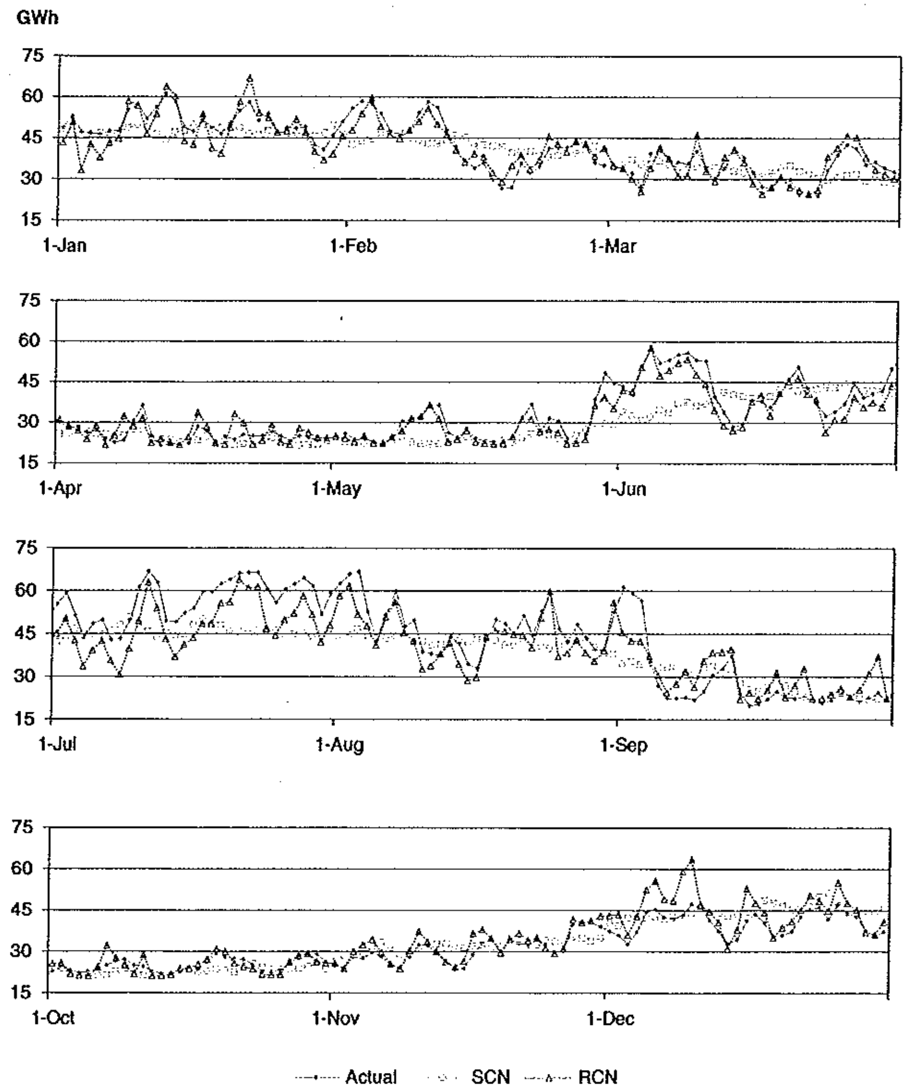

Fig. 15. Metro StL 2011 daily residential electric energy sales and the daily SCN and RCN weather normalized residential electric energy sales.

Table 4
Metro StL energy sales and TWMDT adjustments using SCN and RCN.

2011	Actual Usage*	Actual Revenue**	SCN Adjustment Usage*	SCN Adjustment Revenue**	RCN Adjustment Usage*	RCN Adjustment Revenue**	Difference Usage*	Difference Revenue**
Jan	1,661,987	109,132	(85,303)	(5,175)	(117,476)	(7,127)	(32,173)	(1,952)
Feb	1,434,501	96,953	(86,758)	(5,361)	(81,885)	(5,060)	4,872	301
Mar	1,122,266	80,377	32,566	2,092	(36,735)	(2,359)	(69,301)	(4,451)
Apr	929,098	70,102	(27,892)	(1,856)	6,432	428	34,325	2,284
May	798,299	63,141	(79,947)	(5,495)	17,064	1,173	97,011	6,667
Jun	1,071,000	122,441	(212,035)	(22,603)	(8,075)	(861)	203,960	21,742
Jul	1,411,405	158,725	(112,947)	(12,040)	(143,011)	(15,245)	(30,064)	(3,205)
Aug	1,668,829	186,176	(319,234)	(34,030)	(208,639)	(22,241)	110,595	11,789
Sep	1,301,542	147,016	(119,661)	(12,756)	(169,949)	(18,117)	(50,288)	(5,361)
Oct	779,537	62,063	(20,786)	(1,435)	(56,509)	(3,901)	(35,724)	(2,466)
Nov	777,438	61,744	4,752	327	43,486	2,992	38,734	2,665
Dec	1,099,427	79,421	57,440	3,717	42,802	2,770	(14,638)	(947)
Total	14,055,329	1,237,291	(969,804)	(94,615)	(712,494)	(67,548)	257,309	27,067

Note: Values with red numbers in the parenthesis are negative.
* MWh.
** $1000.

higher rate in summer compared to winter). Third, two components of price, the fuel adjustment clause and purchase power adjustment charge were updated triennially as allowed by regulations.

EMPLOYMENT, quarterly employment in Metro StL from the Bureau of Labor Statistics is used as a proxy for local economic conditions. Interestingly, previous research has found that residential energy sales are negatively correlated with employment (Train et al., 1983). One explanation of this may be that as employment increases fewer people are at home during the work day. The major variables are in Table 2 and the regression results are in Table 3.

In Fig. 15 contains the daily electric energy sales for the test year 2011, along with the weather normalized daily SCN and RCN electric energy sales. The daily RCN electric energy sales tracks seasonal usage patterns of actual sales more closely than the daily SCN electric energy sales. Both magnitude of sales and the seasonal variation of sales are reflected by the RCN electric energy sales. The results of the weather normalization adjustments of monthly electric energy sales and revenues using the SCN and the RCN are presented in Table 4.

The revenue adjustment to 2011 using the SCN, RA_S, is not the same as the revenue adjustment using the RCN, RA_R. Also some monthly adjustments are in different directions, the RA_S is negative and RA_R is positive. Some monthly difference in normalized electric energy sales and revenue for 2011 the SCN and the RCN is more than 17%.

6. Conclusion

This paper investigates the biases in the weather normalization adjustment to test year electric energy sales and revenues using the SCN. The RCN is introduced to provide a more accurate set of normal MDT by preserving MDT variation, and TWMDT is introduced to account for the cumulative temperature effects on energy sales. These weather variables avoid the bias in the weather normalization adjustment that can be introduced when the SCN and MDT are used.

For comparison, adjustments were calculated for 2011 Ameren Missouri daily residential electricity sales. The results reveal that the weather normalization adjustment is significantly improved using the RCN and TWMDT compared to the result using the SCN and MDT. The model using TWMDT has a higher adjusted R-square than the model using MDT (Table 3). The RCN fits the actual 30-year daily temperature distribution better than the SCN (Fig. 12). When the RCN, based on the NOAA-adjusted 30-year set of temperature observations, is used to compute the TWMDT the result is a less biased weather normalization adjustment of daily energy sales and revenue than the MDT from the SCN (Table 4).

Our review of the literature on weather normalization processes indicates that the SCN is the more frequently used climate normal. It has been demonstrated that a naive implementation of the SCN in certain applications such as daily load research, may cause significant biases in the analysis of daily load variation. Even if the mean of the SCN is not biased, the SCN variance is damped, so weather normalization adjustments can be biased. The main reason for this bias is that daily electric sales do not have a uniform response to weather. This non-linear response to weather requires characteristics in a climate normal to be used for energy utility weather normalization that the SCN doesn't have.

The relationship between energy sales and temperature is the most important factor in weather normalization. The daily residential electric sales response to temperature is nonlinear, so if a climate normal does not preserve extremes in daily temperature variation, the weather normalization adjustment will have a bias. Therefore, a daily climate normal for utility regulation should preserve the yearly and monthly weather pattern which corresponds to the test year weather variation. In addition to setting appropriate rates, accurately weather normalized energy sales are also required for evaluating the effectiveness of energy conservation and demand-side management programs. Furthermore, the more realistic climate normal will improve our understanding of energy market asset price dynamics (Mu, 2007).

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2015.12.016.

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