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Witness:	*Hari K. Poudel*
Sponsoring Party:	*MoPSC Staff*
Type of Exhibit:	*Direct Testimony*
Case Nos.:	*GR-2022-0179*
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MISSOURI PUBLIC SERVICE COMMISSION

INDUSTRY ANALYSIS DIVISION

TARIFF AND RATE DESIGN DEPARTMENT

DIRECT TESTIMONY
Revenue Requirement

OF

HARI K. POUDEL

SPIRE MISSOURI INC., d/b/a Spire

Case No. GR-2022-0179

Jefferson City, Missouri
August 2022

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DIRECT TESTIMONY OF

HARI K. POUDEL

SPIRE MISSOURI, INC., d/b/a Spire

Case No. GR-2022-0179

DIRECT TESTIMONY

OF

HARI K. POUDEL

SPIRE MISSOURI INC., d/b/a Spire

CASE NO. GR-2022-0179

Q. Please state your name and business address.

A. My name is Hari K. Poudel, and my business address is Missouri Public Service Commission, P.O. Box 360, Jefferson City, Missouri, 65102.

Q. By whom are you employed and in what capacity?

A. I am employed by the Missouri Public Service Commission ("Commission") as an Economist in the Tariff/Rate Design Department in the Industry Analysis Division.

Q. Please describe your educational and work background.

A. I received a Ph.D. in Public Policy and a master's degree in Public Health from the University of Missouri, Columbia, and another master's degree in Agricultural Economics from the University of Hohenheim, Germany.

In January of 2020, I began working for the Missouri Department of Health and Senior Services as a research/data analyst. I was employed with the Division of Community & Public Health from January 2020 until October 2021. I started my career with the Missouri Public Service Commission as an Economist in October 2021.

Q. Have you previously testified before the Missouri Public Service Commission ("Commission") or any other regulatory agency?

A. Yes. Please refer to Schedule HKP-d1 for a list of my prior testimony, recommendations, or memorandums filed with the Commission.

I. EXECUTIVE SUMMARY

Q. What is the purpose of your testimony?

A. The purpose of my direct testimony is to describe the weather variables and to present the results of the weather normalization analysis of natural gas usage for Spire Missouri.

Q. Please summarize your testimony.

A. Each year's weather is unique; consequently, test year usage and revenue need to be adjusted to "normal" weather so that rates will be designed on the basis of normal weather rather than any anomalous weather in the test year. In the quantification of the relationship between test-year weather and energy sales, Staff used weather data observations for the period June 1, 2021 through May 31, 2022.

I calculated the Staff's weather normalization adjustment. These calculations relied on the weather data obtained from the Midwestern Regional Climate Center ("MRCC")[1] and monthly revenue data provided by the Company through data requests. The results were given to Staff witness Nancy L. Harris for use in her revenue calculation.

II. WEATHER VARIABLES

Q. Where did Staff obtain its weather data?

A. The weather data set was produced by MRCC. MRCC is a cooperative program between the National Centers for Environmental Information ("NCEI") and Purdue University, Indiana. The NCEI is a part of the US Department of Commerce's National Oceanic and

[1] https://mrcc.purdue.edu/CLIMATE/

Atmospheric Administration ("NOAA")[2]. The weather data sets consist of actual daily maximum temperature ("T_{max}") and daily minimum temperature ("T_{min}") observations. As is customary, "mean temperature" (T_{avg}) is defined as the average of T_{max} and T_{min} for the day. For the purposes of normalizing the test year energy usage and revenues, Staff used the actual maximum and minimum daily temperature series for the 30-year period of January 1, 1990, through December 31, 2019, at St. Louis Lambert International Airport ("STL") and Kansas City International Airport ("MCI").

Weather data from STL was used for the service territories of Spire East and MCI was used for the service territories of Spire West. STL and MCI weather data were used for actual and normal weather variables. These weather stations were selected based on the availability and reliability of the weather data as well as their approximate location to Evergy's customer base.

Q. What is a climate normal?

A. According to NOAA, a climate "normal" is defined as the arithmetic mean of the temperature computed for a uniform and relatively long period comprising at least three consecutive ten-year periods.[3] In developing climate normal temperatures, NOAA focuses on the monthly maximum and minimum temperature time series to produce the serially-complete monthly temperature ("SCMT") data series.[4]

Q. Why does Staff use NOAA's SCMT?

A. NOAA's published climatic normals are not directly usable by Staff, since the daily normal is based on a calendar date average rather than the ranked daily average that Staff uses.

[2] https://www.ncei.noaa.gov/about
[3] Retrieved on August 23, 2022, https://www.ncei.noaa.gov/products/land-based-station/us-climate-normals
[4] Retrieved on August 1, 2022, https://www1.ncdc.noaa.gov/pub/data/normals/1981-2010/source-datasets/.

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. The ranked average method produces a more realistic daily temperature variation.

The SCMT, computed by NOAA, includes adjustments to make the time series of daily temperatures homogeneous. NOAA performed the homogeneity of observed data with respect to non-climatic influences. The adjusted data set will reflect a uniform observing environment for a 30-year period. The SCMT is an intermediate product that includes adjustments for inconsistencies and biases that may occur in the 30-year time series of daily temperature, (e.g., such as the relocation, replacement, or recalibration of the weather instruments). Changes in observation procedures or in an instrument's environment may also occur during the 30-year period. NOAA accounted for documented and undocumented anomalies in calculating its SCMT[5]. The meteorological and statistical procedures used in NOAA's homogenization for removing documented and undocumented anomalies from the T_{max} and T_{min} monthly temperature series are explained in a peer-reviewed publication.[6] To Staff's knowledge, NOAA is the only entity that provides reasonably reliable weather data for both the 30-year historical period and the test year period for the Kansas City and St. Louis regions.

Q. How did Staff calculate daily normal weather?

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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] Menne, M.J., and C.N. Williams, Jr., (2009) Homogenization of temperature series via pairwise comparisons. *J. Climate, 22*, 1700-1717.

A. Staff used a ranking method to calculate normal weather estimates of daily normal temperature values, ranging from the temperature that is "normally" the hottest to the temperature that is "normally" the coldest, thus estimating "normal extremes." Normal weather is used to build the base forecast of future energy use. The Staff ranked MDTs for each month of the 30-year history from hottest to coldest and then calculated the normal daily temperature values by averaging the ranked MDTs for each rank, irrespective of the calendar date. The ranking process results in the normal extreme being the average of the most extreme temperatures in each month of the 30-year normal period. The second most extreme temperature is based on the average of the second most extreme day of each month, and so forth. Staff's calculation of daily normal temperatures is not the same as NOAA's calculation of smoothed daily normal temperatures because Staff calculated its normal daily temperatures based on the rankings of the actual temperatures of the test year, and the test year temperatures do not follow smooth patterns from day to day. NOAA provides daily normals. More details of Staff's ranked average method for normal weather are explained in a peer-reviewed publication and attached as Schedule HKP-d2.[7]

III. WEATHER NORMALIZATION

Q. What is weather normalization?

A. Weather normalization is the process of measuring the impact of weather on energy consumption and removing abnormal weather influence from the test period in order to provide a more accurate representation of "normal" gas usage. Since the primary use of natural gas is for the purpose of space heating, the level of natural gas sales is dependent upon weather conditions. It is important to remove abnormal weather influences from the test year in order to

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

provide a more accurate representation of "normal" natural gas usage. For example, if natural gas sales are overstated because the weather in the test period was colder than normal, then the Company may under-recover its revenue requirement, and if natural gas sales are understated because the weather in the test period is warmer than normal, then the Company may over-recover its revenue requirement.

Q. How did Staff calculate weather normalized sales?

A. Staff's weather normalized adjustments of natural gas sales account for deviations from what are considered normal weather conditions that occurred during the test year. Normal weather conditions are at or near the average climatological value over a certain period. Staff adjusted monthly natural gas volumes to normal by first adjusting the annual number of days for each billing cycle[8] to 365. If the annual number of days in a billing cycle is below or above 365, Staff adds or subtracts the difference from the non-heating season.[9] This adjustment is made so that each billing cycle is set to the same total number of days. Since natural gas utilities are winter peaking, any heating degree days (HDD) that are removed based on the 365 day adjustment are added back to June since it is a non-heating season. HDDs are based on the difference of the mean daily temperature (MDT) from a comfort level of 65°F.[10] HDDs are calculated as the difference between 65°F and the MDT when the MDT is below 65, and are equal to zero when the MDT is above 65°F.

After each billing cycle is adjusted so that it contains the proper number of calendar days, the next step is to calculate the difference between normal and actual HDDs for each

[8] Customers are divided up over 18 separate billing cycles within a billing month. For example, a percentage of the Company's customers are billed on the 1st of the month, which is the 1st billing cycle, and another percentage of customers are billed on another day of the month. Billing cycles are used to spread out the number of meters read and bills issued on any specific day of the month.

[9] The non-heating season is generally referred to as the months of May, June, July, August, and September.

[10] Where MDT <65°F, HDD=65-MDT; otherwise, HDD=0.

billing cycle. Then, Staff multiplies these differences by the estimate rendered from the regression analysis to determine the changes in sales volumes in each billing cycle due to abnormal weather. The next step is to sum up each of the changes in sales volumes per month due to abnormal weather. Lastly, Staff added the monthly adjustments in sales volumes to the total monthly natural gas sales to calculate the normalized volumes.

IV. WEATHER NORMALIZATION ADJUSTMENT VALUE

Q. How does Staff calculate weather normalization adjustment values for different customer classes?

A. Staff provides the daily actual and daily normal HDDs for Spire East and Spire West separately. In its first step, Staff used a regression analysis to estimate the relationship between the average usage per customer per day and the average HDD per day for each billing cycle month for each class separately. Staff seeks regression analyses to estimate a relationship between a dependent variable (in this case, the energy consumption) and two or more independent variables (the predictors) in the form:

$$y_{gas} = \beta_0 + \beta_1 x_{1+}\ \beta_2 x_{2+\ldots+} \beta_n x_n + \varepsilon,$$

where $\beta_{0\ \ldots}\ \beta_n$ are the regression coefficients to be estimated based on the weather data. The output of the regression analyses develops quantitative measures that describe the relationship between daily space-heating sales per customer in Ccfs (Hundred Cubic Feet) and the actual daily HDD. The regression equation estimates a change in the daily natural gas usage per customer whenever the actual daily average weather changes by one unit of HDD.

Second, Staff calculates the difference between normal and actual HDDs for each billing cycle. Third, Staff multiplies the differences from the second step by the estimate rendered from the regression analysis in the first step. The fourth step is to sum the billing cycles' adjusted volumes by billing month. Fifth, Staff adds the monthly adjustments in Ccfs to the total monthly natural gas sales to calculate normalized volumes. The billing month averages are calculated from the data provided by the utility on the number of customers, natural gas usage, and summed HDD from the billing cycles for each billing month by customer class. The daily average HDD in each billing month and billing cycle is weighted by the percentage of customers in that billing cycle. Thus, the billing cycles with the most customers are given more weight when computing the daily average HDD for the billing month. Staff uses the 12 monthly average-usage-per-customer amounts across the billing cycles to calculate the daily average usage for one month. The usage and weather billing month averages are used to study the relationship between space-heating natural gas usage and cold weather, which is used to estimate the change in usage related to a change in HDD.

Q. Please describe the Weather Normalization Adjustment values for the three customer classes- Residential General Service (RES), Small General Service (SGS), and Large General Service (LGS) of Spire East.

A. Staff conducted an analysis of weather normalization for RES, SGS, and LGS for the test year as updated through May 31, 2022 (Table 1). Staff did not perform a weather normalization calculation for Large Volume Service (LV) and Transportation classes, as explained in more detail by Staff witness Michael Stahlman in his direct testimony[11] .Staff's overall weather normalization analyses determined that the weather during the test year was warmer than normal, so actual sales were also lower than normal. In order to account for the reduced sales and warmer weather, Staff made an adjustment to increase natural gas sales to reflect sales for "normal" weather conditions. Staff's analysis resulted in an approximate

[11] Page 2, Q 4, "*Did Staff review class usage for the transportation customers?*"

increase of 5.46% for RES class, an approximate increase of 5.37% for SGS class, and an increase of approximately 4.12% for LGS class. These adjustments account for changes in sales to reflect normal weather and the annual number of days in a billing cycle.

Table 1. Actual energy usage and weather adjustment among different rate classes of Spire East

Spire East	RES		SGS		LGS	
Billing Month	Actual Usage (Ccfs)	Weather Adj. (Ccfs)	Actual Usage (Ccfs)	Weather Adj. (Ccfs)	Actual Usage (Ccfs)	Weather Adj. (Ccfs)
June	12,984,417	-1,407,975	2,026,748	-423,918	5,354,742	-796,314
July	8,963,935	26,866	1,620,184	7,179	4,211,048	16,875
August	8,215,559	0	1,496,376	0	4,117,392	0
September	8,707,391	506,677	1,611,356	70,399	4,026,083	90,562
October	9,786,138	4,065,543	1,598,130	650,265	4,558,950	899,955
November	31,777,763	4,384,233	4,060,631	758,850	8,399,945	1,191,046
December	56,788,153	13,629,821	8,343,997	2,125,275	14,315,414	2,679,143
January	82,576,127	12,283,725	13,149,577	2,287,932	20,094,115	3,675,364
February	93,371,198	-6,812,233	16,162,786	-1,168,870	23,828,553	-1,681,649
March	67,562,925	-341,730	11,848,785	-124,287	21,057,256	-317,837
April	45,229,716	1,334,553	7,311,904	303,633	13,460,975	568,084
May	21,406,355	-3,316,114	3,430,288	-598,030	8,164,614	-954,630

Q. Please describe the Weather Normalization Adjustment values for the three customer classes- RES, SGS, and LGS of Spire West.

A. Staff conducted an analysis of weather normalization for RES, SGS, and LGS for the test year as updated through May 31, 2022 (Table 2). Staff did not perform a weather normalization calculation for Large Volume (LV) and Transportation classes, as explained in more detail by Staff witness Michael Stahlman in his direct testimony. Similar to the weather normalization analysis for Spire East, Staff's weather normalization analysis of Spire West gas sales resulted in an increase in natural gas sales because the weather during the test year was warmer than normal. The analyses resulted in an approximate increase of 8.44% for RES class, an approximate increase of 5.09% for SGS class, and an increase of approximately 3.81% for LGS class. These adjustments account for changes in sales due to abnormal weather and the annual number of days in the billing cycle.

Table 2. Actual energy usage and weather adjustment among different rate classes of Spire West

Spire West	RES		SGS		LGS	
Billing Month	Actual Usage (Ccfs)	Weather Adj. (Ccfs)	Actual Usage (Ccfs)	Weather Adj. (Ccfs)	Actual Usage (Ccfs)	Weather Adj. (Ccfs)
June	8,875,407	0	1,487,691	-289,774	2,464,144	-272,225
July	6,321,573	33,708	1,208,367	3,416	2,317,783	3,780
August	5,795,533	58,816	1,112,094	0	2,046,245	0
September	5,933,432	959,683	1,180,430	71,777	2,822,954	85,848
October	6,929,412	2,816,881	1,339,154	537,868	2,724,563	484,412
November	23,212,583	5,221,288	3,412,490	602,774	5,186,695	502,474
December	39,296,193	12,532,430	6,275,097	1,726,711	7,117,039	1,488,285
January	67,938,091	12,705,146	11,461,230	1,596,837	12,073,616	1,304,605
February	69,385,224	-1,190,529	12,622,254	-835,403	9,849,256	-757,616
March	57,053,286	-1,985,932	10,480,500	-80,795	10,113,753	-34,444
April	38,786,855	-491,491	6,729,972	192,850	7,354,766	130,352
May	17,221,132	-1,431,781	2,860,697	-473,402	3,814,139	-380,185

Q. How did Staff obtain energy usage data for this analysis for each customer class?

A. Staff relied upon Spire Missouri's response to data requests.[12]

Q. Was the data provided by Spire Missouri in Data Request 0076 and Data Request 0076.1 identical?

A. No. There were discrepancies between the monthly bill count figures and the client charge total in some of the billing months. For example, the Data Request 0076 reported 29,387 bills including Non-Billing Cycles (NBCs), but the Data Request 0076.1 reported 29,447 bills including NBCs for the West Small General Class in October 2021. Similarly, the Data Request 0076 reported 1,376,856.27 Ccfs but the Data Request 0076.1 reported 1,339,153.85 Ccfs for the West Small General Class in October 2021.

Q. Was Staff given sufficient data to calculate the weather normalization adjustment?

[12] Data Request 0076, Data Request 0076.1

A. Not initially. Staff was not provided the updated version of Data Request 0076.1 until 8/5/2022.[13]

V. CONCLUSION

Q. Please summarize your testimony.

A. I calculated Staff's weather normalization adjustment factor for each month for each class of data. The results of my calculation were then provided to Staff witness Nancy L. Harris to calculate the amount of the adjusted non-gas operating revenues.

Q. Does this conclude your direct testimony?

A. Yes. It does.

[13] The Data Request 0076.1 was requested on 5/10/2022. Spire responded on May 31 (21 days elapsed), July 19 (70 days elapsed) and August 5, 2022 (87 days elapsed). The Data Request 0076 was requested on 4/18/2022 and it was responded on May 5 (17 days elapsed), May 25 (37 days elapsed), and June 14 (57 days elapsed).

BEFORE THE PUBLIC SERVICE COMMISSION

OF THE STATE OF MISSOURI

In the Matter of Spire Missouri, Inc. d/b/a Spire's Request for Authority to Implement a General Rate Increase for Natural Gas Service Provided in the Company's Missouri Service Areas	)))))	Case No. GR-2022-0179

AFFIDAVIT OF HARI K. POUDEL, PhD

STATE OF MISSOURI)
) ss.
COUNTY OF COLE)

COMES NOW HARI K. POUDEL, PhD and on his oath declares that he is of sound mind and lawful age; that he contributed to the foregoing *Direct Testimony of Hari K. Poudel, PhD*; and that the same is true and correct according to his best knowledge and belief.

Further the Affiant sayeth not.

HARI K. POUDEL, 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 26th day of August 2022.

D. SUZIE MANKIN
Notary Public - Notary Seal
State of Missouri
Commissioned for Cole County
My Commission Expires: April 04, 2025
Commission Number: 12412070

D Suzie Mankin
Notary Public

Hari K. Poudel, PhD

Case History

Direct Testimony

SN	Case Number	Company Name	Issue
1.	ER-2022-0129 & ER-2022-0130	Evergy Missouri West and Evergy Missouri East	Weather Variables

Recommendation/Memorandum

SN	Case Number	Company Name	Issue
1.	ER-2022-0146	Ameren Missouri	Rider Energy Efficient Investment Charge (EEIC)
2.	GR-2022-0235	Spire Missouri, Inc.	Weather Normalization Adjustment Rider (WNAR)
3.	GT-2022-0233	Liberty Utilities	Weather Normalization Adjustment Rider (WNAR)

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Climate normals and weather normalization for utility regulation☆

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A R T I C L E   I N F O

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A B S T R A C T

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/

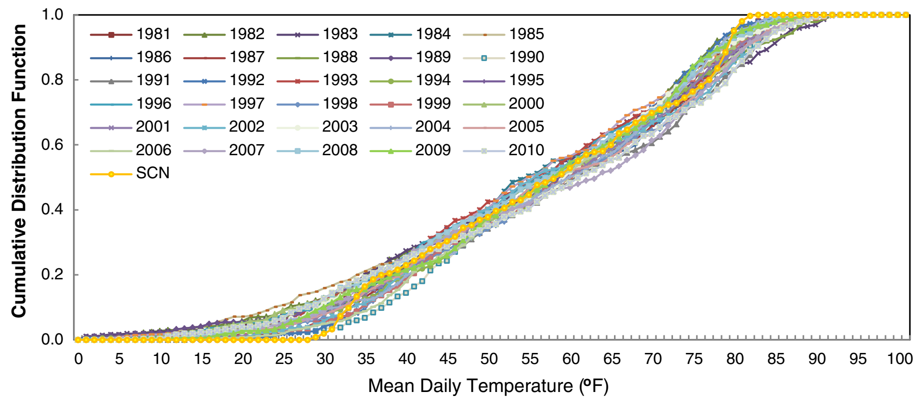

Fig. 1. Cumulative distribution functions of each year MDT and the daily SCN temperatures (1981–2010).

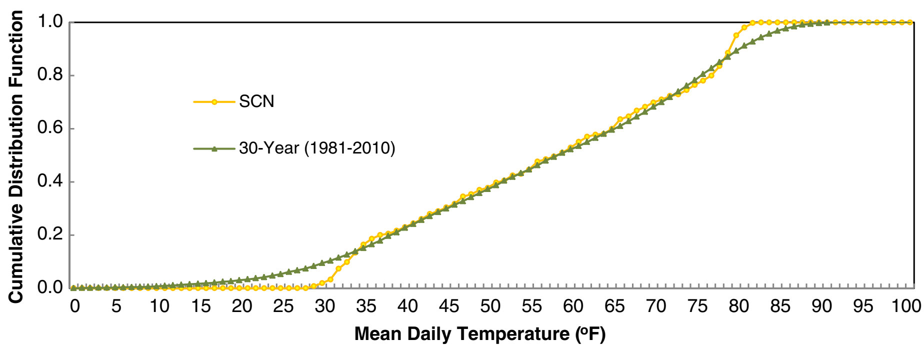

Fig. 2. Cumulative distribution functions of the daily temperature SCN and the 30-year (1981–2010) MDT.

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.

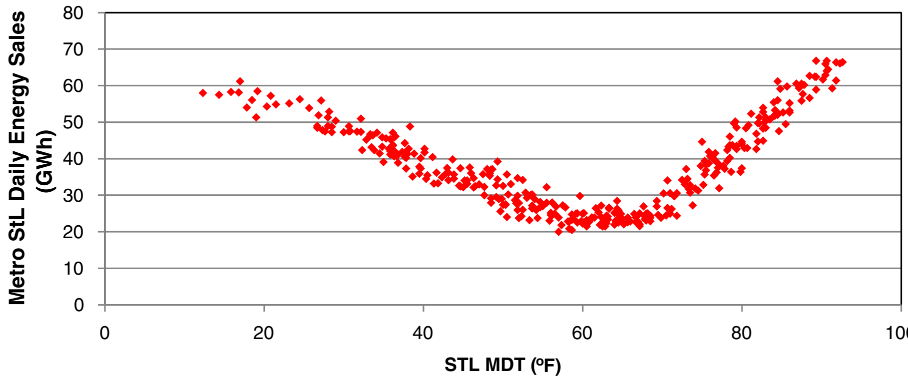

Fig. 3. Metropolitan St. Louis (Metro StL) 2011 daily residential electric energy sales and the corresponding STL MDT.

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:

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

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:

$$E_t = F(w_t, x_t, \varepsilon_t) \qquad (2)$$

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)),

$$E_t = f(w_t) + g(x_t) + \varepsilon_t \qquad (3)$$

where $E(t)$ is the amount of energy usage at time t,[5] $\mathrm{w_t}$ 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.

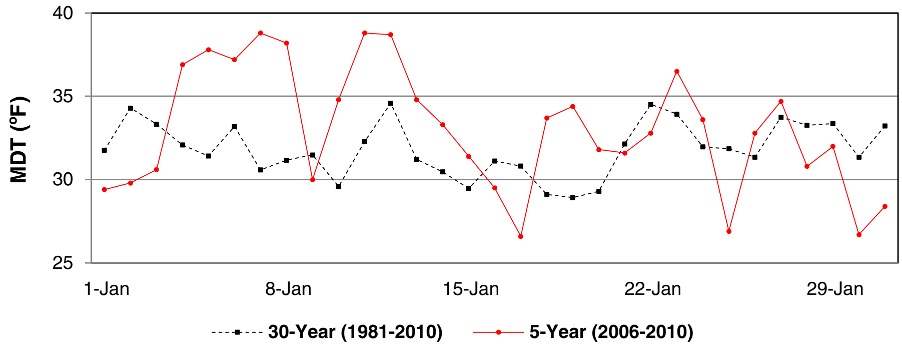

Fig. 4. STL 30-year and 5-year normal January MDT.

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

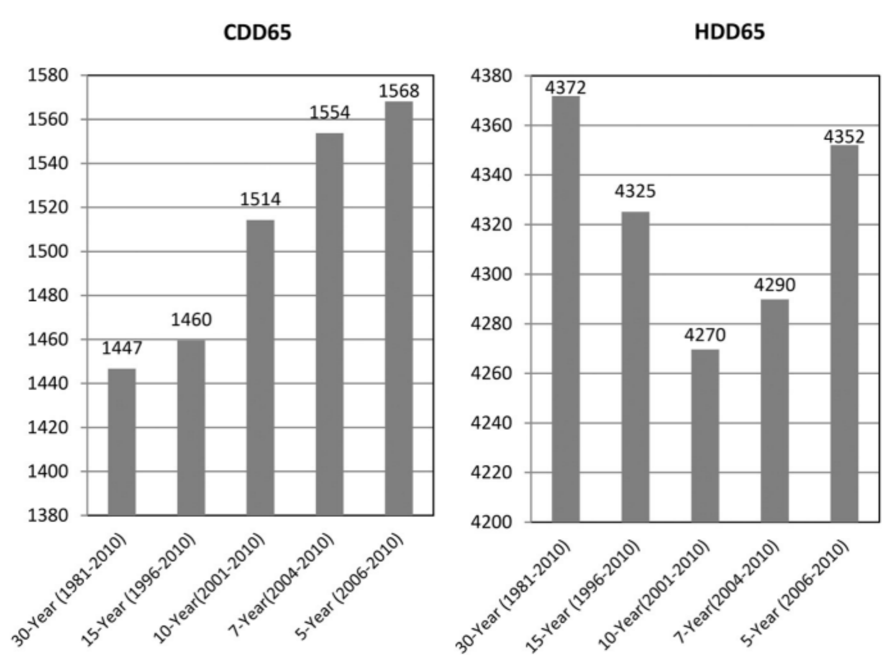

Fig. 5. STL annual CDD65 and HDD65 normals.

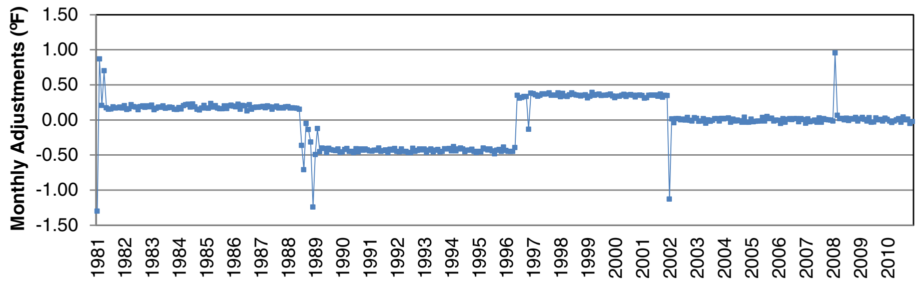

Fig. 6. Monthly adjustments to STL MDT (1981–2010). Note: Monthly adjustment = Homogenized monthly MDT of NOAA 1981–2010 normals − Observed monthly MDT.

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

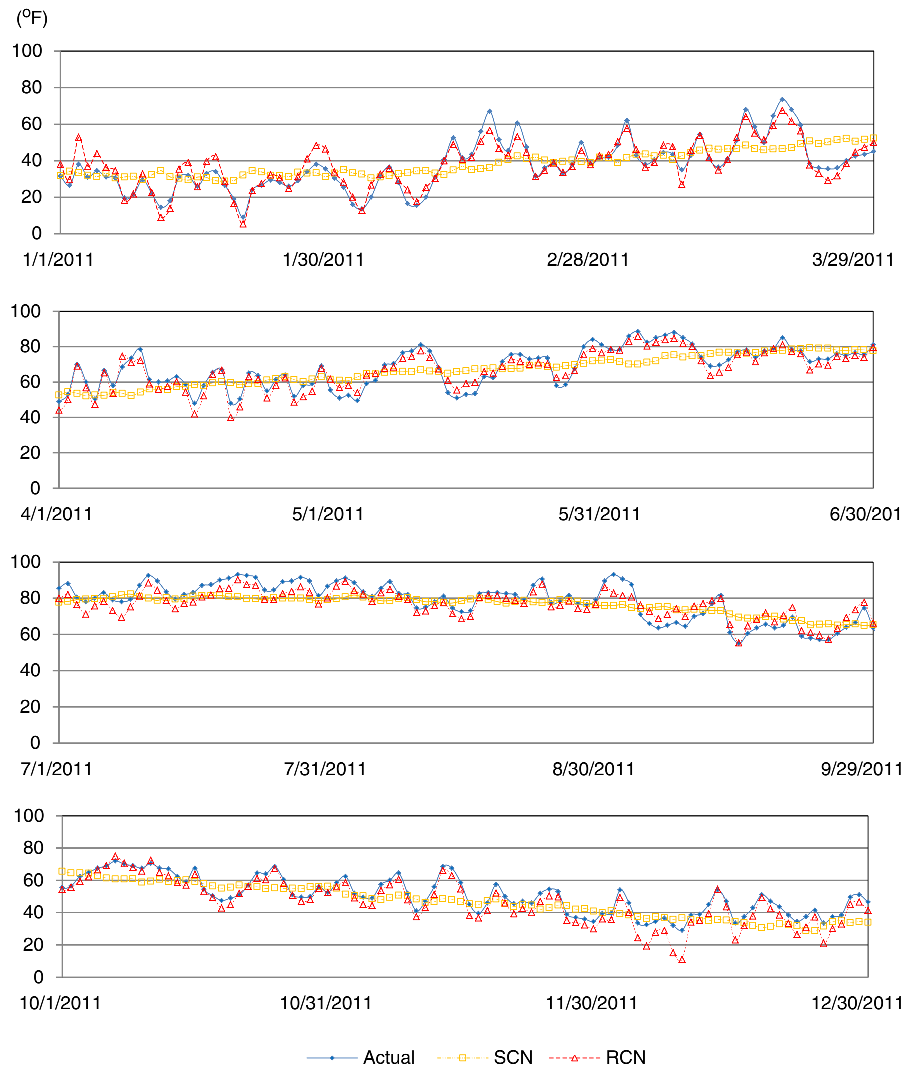

Fig. 7. STL 2011 MDT, SCN, and RCN.

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

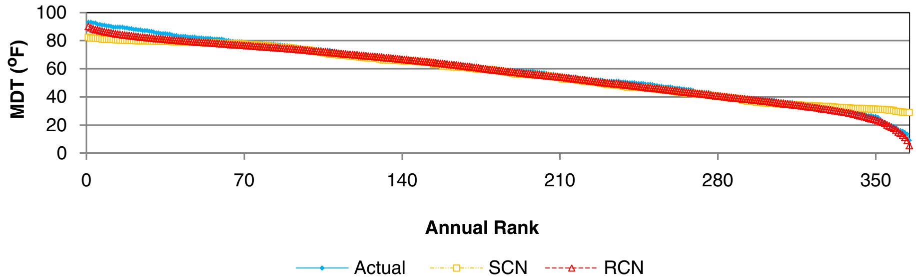

Fig. 8. STL Ranked 2011 MDT, SCN, and RCN.

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:

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

$N_{MR}^{30}(m,d;y_1)$ 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, $N_{MR}^{30}(m,D;y_1)$, in the MCR, $\{N_{MR}^{30}(.,.;y_1)\}$.

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

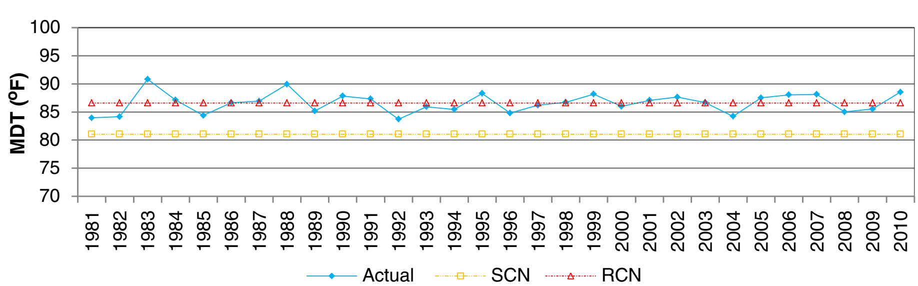

Fig. 9. STL 95th percentile (18th warmest) MDT — actual, SCN, and RCN.

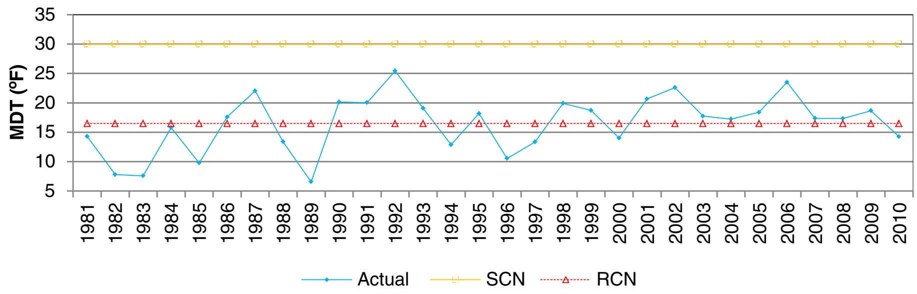

Fig. 10. STL 5th percentile (18th coldest) MDT — actual, SCN, and RCN.

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,

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

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

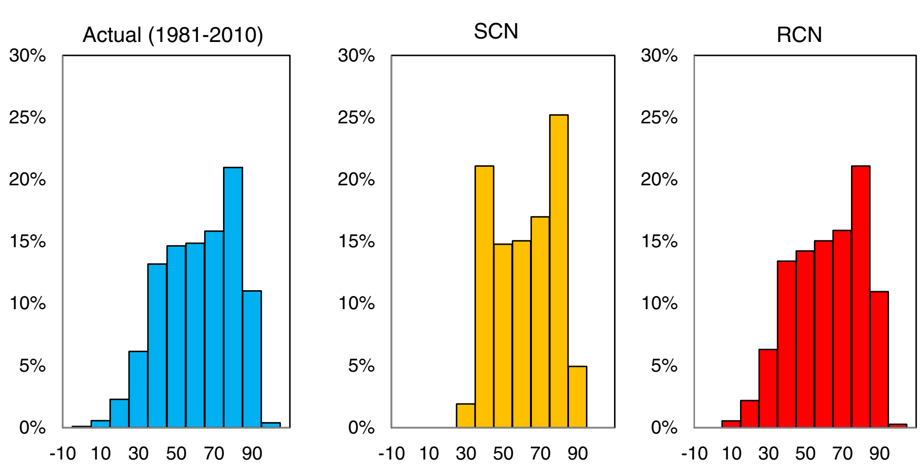

Fig. 11. STL density distributions of 1981–2010 MDT, SCN, and RCN.

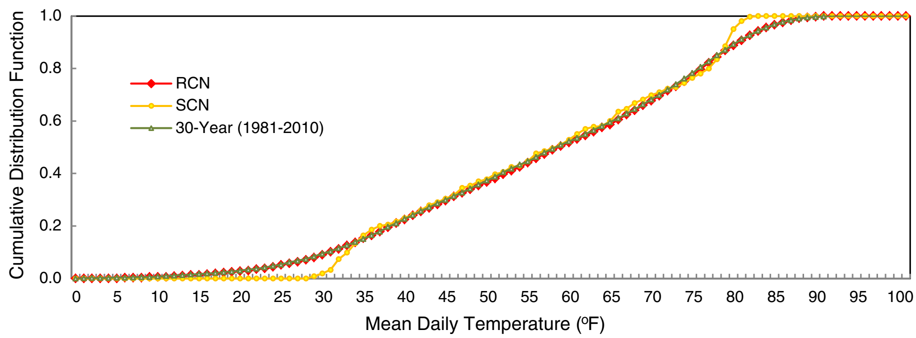

Fig. 12. Cumulative distribution functions of the daily temperature RCN and SCN series and the 30-year (1981–2010) MDT series.

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.

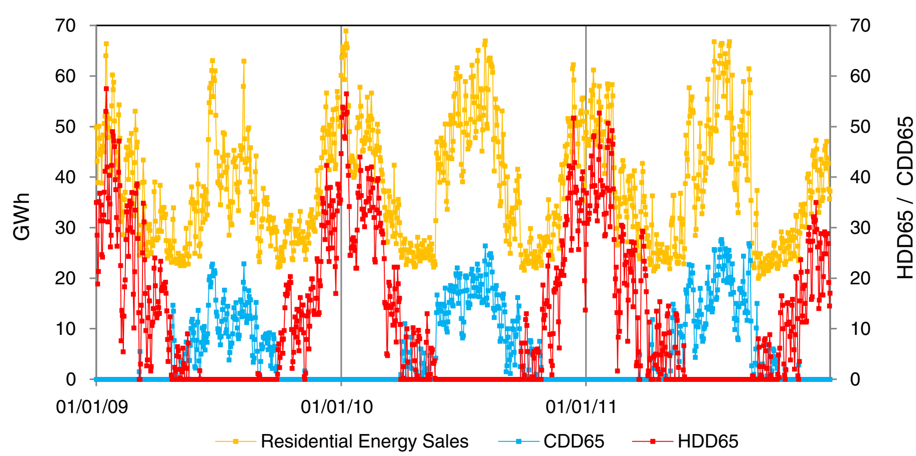

Fig. 13. Metro StL Daily Residential Energy (GWh) sales and STL HDD65 and CDD65 (2009–2011).

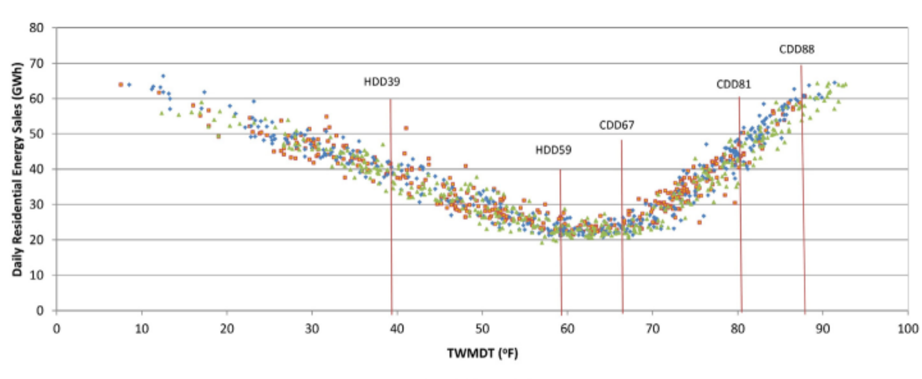

Fig. 14. Piecewise linear inflection points for Metro StL daily residential electric energy sales vs. STL TWMDT used to calculate HDD and CDD.

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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:

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

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:

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

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:

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

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.

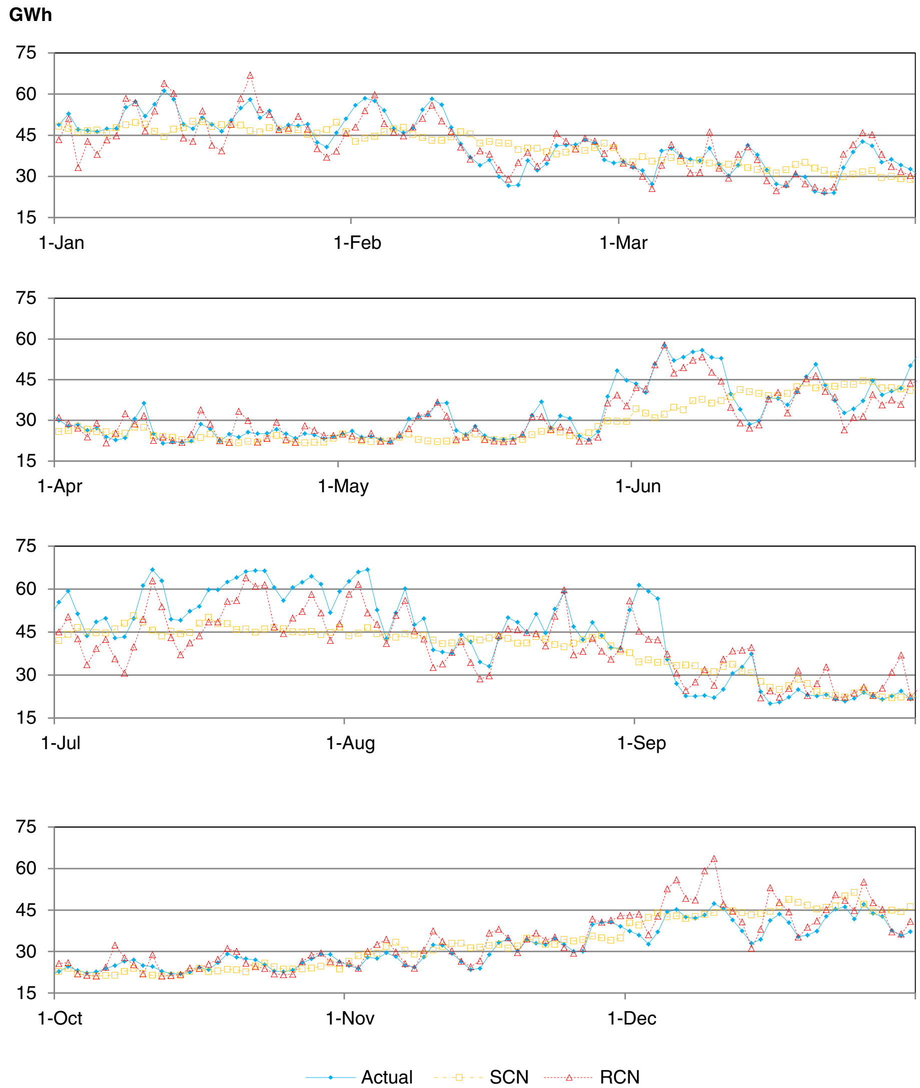

Fig. 15. Metro StL 2011 daily residential electric energy sales and the daily SCN and RCN weather normalized residential electric energy sales.

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

	Actual		SCN Adjustment		RCN Adjustment		Difference	
2011	Usage*	Revenue**	Usage*	Revenue**	Usage*	Revenue**	Usage*	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.

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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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