

**Mid-range, Average, and Hourly Estimates of Heating Degree Days:  
Implications for Weather Normalization of Energy Demand**

by

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This paper examines the theoretical and empirical properties of three methods to calculate heating degree days (HDDs). The first method relies on hourly data, the second method relies on the average daily temperature, and the third method uses the average of the minimum and maximum daily temperature. The latter method is commonly used by the National Oceanic and Atmospheric Administration (NOAA) for their published HDD estimates. We find that there is a theoretical ordering for the first pair of measures and an empirical ordering between the second pair of measures that depends on the degree of hourly temperature skewness. Using hourly data from Washington's Sea-Tac airport for the period 1971 through 2005, we find that HDD normals are under-estimated by 2.6 percent due to differences between mid-range and daily average methods, and a further 3.1 percent due to the difference between daily average and hourly methods. We explore the implications for weather normalization and rate making as a consequence of using NOAA published normals. We find that the degree of weather normalization is nearly identical between normal and test-year periods as long as the HDD measurement methodology is consistently applied.

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## **I. Introduction**

Heating Degree Days (HDDs) and Cooling Degree Days (CDDs) have been reported for locations all over the world for decades. HDDs and CDDs represent the number of degrees over a period in which the ambient temperature is lower (or higher) than a base level. HDDs are intended to proxy the thermal load requirements to maintain the interior dwelling temperature when exterior temperatures are lower than interior temperatures.

In practice, there are various methods to measure this simple concept. One method is based on hourly temperature readings and estimates hourly degree days (HDDs that occur in specific hours), which are then accumulated to the daily level. A second commonly used method relies on average temperature in the day, summarizing the hourly temperature distribution with a single moment of the temperature distribution (the mean value). NOAA uses the average of the minimum and maximum temperatures that occur in a day to estimate the daily average temperature. These differences prove to be important in practice as temperature is the single most important factor in load forecasting. In the short-term, rises in temperature reduce the load carrying capacity of transmission and distribution lines. In the long-term, utilities must plan for the power they need to provide to customers. As temperature extremes affect peak usage, the temperature-load relationship is crucial for forecasting capacity requirements. Finally, weather adjusted sales are used in regulatory proceedings to determine the likely load under “normal” weather conditions.

Temperature adjustment, or weather normalization, estimates electric and gas loads during a rate case test year as if the weather had been “normal” during that test

year. By performing weather normalization, changes in loads over time, such as between test and rate years, can be more accurately attributed to factors other than weather, such as customer growth or changes in use per customer. Additionally, by setting rates based on normalized temperature, prices are more stable over time and more accurately reflect the costs to serve customers because they are not based merely on weather conditions that happened to prevail during a test year for a given rate case. Millions of dollars are literally at stake based on the degree of weather normalization.

In this paper, we examine the theoretical and empirical properties of alternative HDD measures and the consequences for rate normalization. We find that there is an ordering of HDD estimates based solely on the method used to define HDDs, wherein hourly based measures are larger than daily average based measures, which are in turn either larger or smaller than the NOAA mid-range based method (utilizing the average of the minimum and maximum daily temperatures) depending on the degree of hourly temperature skewness. For instance, the NOAA mid-range estimate of HDDs will typically be smaller than HDDs (based on hourly observations) in geographic regions with positive hourly temperature skewness and, consequently, will indicate that these regions were warmer for certain periods than was really the case.

Our empirical analysis relies on over 2 million hourly temperature measurements from over 200 locations in the United States. We find that the degree of hourly temperature skewness varies across the U.S. and that the degree of skewness is correlated with the divergence between the average and mid-range (NOAA) based measures of HDDs. Our study also utilizes hourly data from 1971 through 2005 from the Pacific Northwest. We find that the degree of weather normalization under differing methods of

heating degree measurement is nearly constant, provided that a common methodology is employed to calculate normal and test-year degree-days. However, when HDDs are computed between “normal” and “test year” periods in utility rate cases, the degree of weather adjustment can be overstated when NOAA’s published measure of HDDs is relied upon.

The paper proceeds as follows. First we discuss weather normalization and its importance in utility rate making. Then, we review theoretical properties of the HDD estimates. We then examine the empirical relationship between hourly temperature skewness and HDD measures. Finally, we compare the HDD estimates and the consequences for rate normalization of a typical Northwest utility.

## **II. Weather Normalization**

Weather normalization is the process of adjusting forecasted utility revenues and sales to reflect normal weather conditions. Weather normalization has historically been important to utilities and regulators in establishing utility rates and, more recently, as part of “rate decoupling.”

In traditional electric and natural gas utility ratemaking, rates are set according to an estimate of the costs of providing service, including an allowed rate of return on the utility rate base. Revenue requirements are assumed to equal the cost of service plus a return on historically determined prudent investments. The regulator then sets rates equal to the revenue requirement divided by total volume, typically using some form of fixed plus variable tariff. Except for the flat customer service charge (usually under ten percent

of the typical residential bill), customers pay based on their volumetric consumption.<sup>1</sup>

Regulators set rates in periodic rate cases wherein a utility's projected revenue requirements are determined for a future year along with projected sales for that year. Projections for future periods are typically based on recent historical experience known as "test year" periods. Because electricity and natural gas usage are highly dependent on the weather, weather normalization is used to estimate what electric and gas loads during a rate case test year would have been if the weather had been "normal" during that test year. A corresponding adjustment is then made to the revenues a company collected during the test year in order to better estimate the amount of revenues that the company will require during the rate year. Setting rates based on normalized weather helps keep rates from being set too high if the test year was particularly warm (resulting in test year revenues being lower than normal), and helps keep rates from being set too low if the test year was particularly cold (resulting in test year revenues being higher than normal).<sup>2</sup> Recently, weather normalization has also played a central role in "rate decoupling".

Rate decoupling is a fairly simple concept. Under traditional cost-of-service

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<sup>1</sup> Revenue requirements were historically based on projected levels of prudently incurred capital and operating costs, including the ability to earn a set rate of return on approved capital investments. Restructuring in the late 1990s required many utilities to sell their power plants and buy power on the wholesale market. In this case, regulators allow the realized costs of purchased power to be passed through to customers based on their consumption. Companies recover their cost of purchased power, but do not earn a return on such costs. When purchased power costs differ from levels anticipated in a rate case, adjustments may be made in future years via a power cost adjustment.

<sup>2</sup> Suppose that initially a utility's cost of service is  $C_0$  and sales are  $Q_0$ . Suppose prices are set to recover cost of service with  $P_0 = C_0 / Q_0$  using average cost pricing. If sales are adjusted in the test-year from  $Q_0$  to a higher level  $Q_1$  as a consequence of too much weather normalization, then prices would be set too low at  $P_1 = C_0 / Q_1$  with  $Q_1 > Q_0$ . The revenue shortfall is  $P_0 Q_0 - P_1 Q_0$  (again presuming that actual sales are realized at  $Q_0$ ) or revenue shortfall =  $P_1(Q_1 - Q_0)$ . The degree to which prices are lowered is  $(P_0 - P_1) / P_1 = (Q_1 - Q_0) / Q_0$ .

regulation, after rates are set, if actual sales turn out just as forecast, the utility will recover its fixed costs and earn its allowed rate of return. If actual sales exceed the forecast, the utility over-earns. Thus, traditional cost-of-service regulation provides a regulated utility with an incentive to increase usage because revenues and sales are directly related. This, in turn, provides utilities with a disincentive to promote conservation and energy efficiency because, by definition, those activities would reduce usage and a utility's revenues. One solution to this problem is to "decouple" revenue from sales. The notion is that removing the linkage between sales and revenues makes the utility indifferent to the effects of conservation and energy efficiency measures. This is important as the utilities fixed costs are generally recovered on a volumetric rather than a per customer basis, which means that if volumes decline, revenue and fixed cost recovery suffers. Rate decoupling is essentially a periodic adjustment to fixed costs similar to power cost adjustments which adjust rates for changes in operating costs.<sup>3</sup>

The basic concept is that the regulator will determine a utility's allowed revenue. The difference between the allowed revenue and the actual revenue is the amount of the revenue decoupling, either positive or negative. A positive number means the utility under-recovered and will receive a future rate increase to make up the shortfall. A negative number means the utility over-recovered and there will be a future decrease in rates. Decoupling in terms of energy efficiency and conservation is important in that it removes the disincentives for utilities (although it does not provide any incentive) to engage in conservation or energy efficiency.

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<sup>3</sup> Power cost adjustment and decoupling mechanisms help ameliorate the errors of a weather adjustment that is too large or too small by essentially deferring the true-up to another rate period. Nonetheless, for weather normalization to work properly in rate setting it should at least be correct on average.

Weather normalization can be considered an example of partial revenue decoupling, although its purpose is not necessarily to remove utility disincentives, but to smooth out the effects of weather on a utility's sales. Like decoupling for energy efficiency/conservation, weather normalization adjusts sales volumes to a "normal" level in order to smooth out variations in sales, in this case due to fluctuations in weather. Consequently, weather normalization is important to utilities that want to avoid shortfalls in revenue that are solely related to changes in weather. Weather normalization is a form of decoupling because it adjusts for changes in sales volume, in this case due to weather. In contrast, decoupling associated with energy efficiency/conservation adjusts for changes in sales volume due to actions that the utility is taking to increase energy efficiency and conservation, which if successful will reduce the utility's sales volume. Thus, the underlying effect of weather normalization is the same as decoupling associated with energy efficiency and conservation: to capture changes in margin that result from variations in sales due to weather (or conservation/energy efficiency measures), both positive and negative.

Weather normalization requires four components to compute normalized consumption in the test year: (1) normal temperatures; (2) differences between test year and normal temperature; (3) temperature sensitivity coefficients; and (4) test year number of customers. Normal temperature is determined from data published by NOAA, which computes normal HDDs and CDDs for locations in the United States. HDD and CDD are indices designed to reflect the energy use of a home for heating and cooling. HDDs and CDDs are the number of degrees difference between ambient temperature and a base level temperature. The base level temperature is supposed to approximate the outside

temperature at which a person inside a house would need to turn on the heat or turn on a cooling system in order to remain comfortable inside. Historically, 65 degrees Fahrenheit has often been selected as that base level temperature. HDDs base 65 degrees are the number of days where the ambient temperature is colder than 65 degrees. CDDs base 65 degrees are the number of days where the ambient temperature is warmer than 65 degrees. Larger values of HDDs demonstrate colder temperatures for a given time period and larger values of CDDs demonstrate warmer temperatures for a given time period.<sup>4</sup>

Primarily, this paper concerns itself with measuring HDDs and CDDs in the test year and how resulting temperature differentials under alternative measurement methodologies impact the degree of weather normalization. There are three principal methods to define a degree day. The first method denoted,  $D$ , is based on actual hourly temperature readings and determines daily degree days from the average of the degree hours that occur during each hour of the day. The second method denoted,  $D^a$ , approximates  $D$  using the daily average temperature. The third method, denoted,  $D^m$ , uses the average of the minimum and maximum temperatures in a day as an estimate of the average temperature for the day. This is the method most commonly used by NOAA and one that necessitates the least amount of data. However, reliance on the  $D^m$  measure, published by NOAA, may introduce significant bias in estimated weather normalization.

Some discussion of our definition of bias here is warranted. As shown in Dubin (1985, Chapter 2), the theoretical relationship between energy used per hour for heating a dwelling is approximately quadratic in the difference between interior and exterior (hourly) temperatures for exterior temperatures below the “balance point temperature” of

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<sup>4</sup> Normal HDD and CDD are typically long-run averages for 30-year periods. Test year HDD and CDD are calculated using actual temperature data that occurred in the test year.

a dwelling.<sup>5</sup> Hence the hourly HDD measure,  $D$ , which averages hourly HDDs, most closely corresponds to the average daily load. We regard the other measures  $D^a$  or  $D^m$  as alternatives to  $D$  with inherent measurement error relative to the  $D$  measure.<sup>6</sup> This interpretation is not strictly necessary. Alternatively, our analysis demonstrates the magnitude of the differences among the various measures that analysts should expect in empirical applications. However, we also show below how NOAA's rounding in the process of calculating the  $D^m$  measure leads to a systematic bias in their published heating and cooling degree day estimates.

As an example, the top-of-the-hour (TOH) temperatures measured at Sea-Tac airport on August 1, 1998 were: 60, 60, 60, 60, 60, 60, 59, 59, 60, 61, 62, 63, 65, 67, 67, 70, 69, 71, 71, 69, 65, 63, 64, and 62.<sup>7</sup> The August 1998 data is summarized by the National Climatic Data Center (NCDC) in a monthly report. We reproduce the first page of this report in Figure 1.

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<sup>5</sup> Theoretically the relationship is quadratic due to air infiltration, which itself varies with the temperature differential between inside and outside temperatures. However, the departure from the linearity assumption in a given hour is usually small.

<sup>6</sup> While we refer to the departures of  $D^a$  and  $D^m$  from  $D$  as bias they are only biased estimates if  $D$  is the true parameter of interest. In empirical practice, it may be possible that  $D^a$  or  $D^m$  provides superior correlation to daily system load. However, the empirical evidence here is weak with all measures having close correlation to load when relying on aggregate data. Instead, we presume in this paper that  $D$  provides the theoretically correct measure of the temperature effect on weather sensitive load.

<sup>7</sup> The data for this example may be found in the hourly observation table for Sea-Tac Airport as reported by the National Climatic Data Center and is available from their website: <http://cdo.ncdc.noaa.gov/ulcd>. In reading these tables, it is important to note that hourly temperature readings are conducted at 56 minutes past the hour which we refer to as TOH readings. The first hour of a given day is the midnight reading from the prior day.

Figure 1



**AUGUST 1998**  
**LOCAL CLIMATOLOGICAL DATA**  
 NOAA, National Climatic Data Center

**SEATTLE SEA-TAC AP, WA**

SEATTLE-TACOMA AIRPORT (SEA)  
 Lat: 47° 27' N Long: 122° 18' W Elev (Ground): 400 Feet  
 Time Zone: PACIFIC WBAN: 24233 ISSN #: 0198-5450

1 DATE	TEMPERATURE F							DEG DAYS BASE 65°		WEATHER	SNOWICE ON GND (IN)		PRECIPITATION (INCHES)		PRESSURE (INCHES OF HG)		WIND SPEED - MPH DIR - TENS OF DEGREES						24 DATE				
	2 MAXIMUM	3 MINIMUM	4 AVERAGE	5 DEP FROM NORMAL	6 AVERAGE DEW PT	7 AVERAGE WET BULB	8 HEATING	9 COOLING	11 DEPTH		12 WATER EQUIV	13 SNOW- FALL	14 WATER EQUIV	15 AVERAGE STATION	16 AVERAGE SEA LEVEL	17 RESULTANT SPEED	18 RES DIR	19 AVERAGE SPEED	MAXIMUM								
																			20 5 - SEC	21 2 - MIN							
01	72	58	65	-2	55	59	0	0	BR				0.00	29.77	30.25	2.6	22	13	21	10	19	01					
02	83	56	70	4	57	62	0	0	BCFC BR HZ				0.00	29.73	30.21	2.6	33	4	19	35	10	01					
03	85	59	72	6	57	63	0	0					0.00	29.67	30.14	2.8	31	4	13	30	9	01					
04	84	60	72	6	48	58	0	0					0.00	29.60	30.07	5.1	01	6	18	36	15	03					
05	78	58	68	2	55	59	0	0					0.00	29.62	30.10	4.4	24	6	16	23	14	05					
06	76	59	68	2	55	58	0	0	RA			T	0.00	29.66	30.14	4.4	01	7	18	03	16	03					
07	72	53	63	-3	53	56	0	0					0.00	29.62	30.10	1.7	29	4	14	23	11	02					
08	78	54	66	0	53	56	0	1					0.00	29.56	30.04	2.7	34	4	15	04	13	04					
09	79	55	66	0	55	60	0	1					0.00	29.64	30.12	3.8	22	4	15	21	11	23					
10	79	55	67	1	55	60	0	2					0.00	29.67	30.16	1.4	28	4	14	04	11	04					
11	83	62	73	7	57	63	0	0					0.00	29.72	30.20	5.4	36	7	16	03	13	03					
12	84	61	73	8	55	62	0	0					0.00	29.77	30.25	8.9	02	9	18	35	15	04					
13	88*	59	74*	8	55	62	0	0					0.00	29.68	30.16	3.6	36	5	16	03	14	02					
14	80	59	70	0	55	58	0	0					0.00	29.56	30.04	3.5	23	4	17	20	13	19					
15	70	57	64	-2	55	58	1	0	DZ BR				0.14	29.53	30.01	2.9	20	5	16	05	14	06					
16	67	55	61	-5	53	56	4	0	TSRA RA BR				0.20	29.56	30.04	1.5	10	5	29*	34	20*	04					
17	69	53	61*	-5	56	56	4	0	FC BR				0.00	29.60	30.08	1.5	36	5	14	01	10	01					
18	68	56	62	-4	55	56	0	0					0.00	29.62	30.11	2.5	03	5	11	04	10	04					
19	75	52	64	2	55	60	0	0					0.00	29.58	30.06	5.0	02	6	15	35	10	01					
20	81	54	68	2	55	60	0	0					0.00	29.53	30.01	1.9	27	4	13	23	10	23					
21	74	57	66	1	54	58	0	1					0.00	29.63	30.11	4.8	21	6	16	11	13	20					
22	74	57	66	1	53	58	0	1					0.00	29.60	30.08	3.1	30	4	13	03	11	03					
23	68	56	62	-3	55	57	0	0	RA				0.01	29.59	30.08	4.5	20	4	15	20	11	20					
24	73	53	63	-2	54	57	0	0					0.00	29.55	30.03	2.1	35	4	14	04	11	04					
25	75	52*	64	-1	54	56	1	0	BR HZ				0.00	29.48	29.96	1.3	31	3	13	03	11	03					
26	72	57	65	0	56	59	0	0					0.00	29.57	30.05	1.2	25	3	0	13	24	9					
27	76	56	66	1	53	58	0	1					0.00	29.62	30.10	5.8	01	7	18	03	15	02					
28	82	56	69	5	53	60	0	4					0.00	29.56	30.04	5.7	01	6	21	03	16	02					
29	83	56	70	6	55	61	0	5					0.00	29.61	30.09	1.3	33	5	18	04	16	03					
30	82	53	68	4	56	61	0	3	BR HZ FU				0.00	29.62	30.10	3.8	34	4	20	01	15	01					
31	87	56	72	8	58	64	0	0					0.00	29.51	29.99	3.6	35	4	14	36	11	02					
77.3											56.2	66.8	■ ■ ■	54.4	59.3	0.7	2.7	< MONTHLY AVERAGES	TOTALS->		0.35	29.61	30.09	1.1	33	5.4	< MONTHLY AVERAGES
2.1											0.5	1.3	■ ■ ■	<----- DEPARTURE FROM NORMAL ----->											- .79	SUNSHINE, CLOUD, & VISIBILITY TABLES ON PAGE 3	
DEGREE DAYS											GREATEST 24-HR PRECIPITATION: 0.20 DATE: 16		GREATEST 24-HR SNOWFALL: DATE:		GREATEST SNOW DEPTH: DATE:		SEA LEVEL PRESSURE		DATE		TIME						
MONTHLY											TOTAL DEPARTURE		SEASON TO DATE		TOTAL DEPARTURE		MAXIMUM		DATE		TIME						
HEATING: 21											-44		42		-81		: 30.30		12		0917						
COOLING: 84											3		201		35		MINIMUM		31		2338						
											NUMBER OF DAYS WITH		MAXIMUM TEMP ≥ 90: 0		MINIMUM TEMP ≤ 32: 0		PRECIPITATION ≥ 0.01 INCH: 3										
													THUNDERSTORMS: 1		HEAVY FOG: 0		PRECIPITATION ≥ 0.10 INCH: 2										
																	SNOWFALL ≥ 1.0 INCH: 0										

**AUGUST 1998**  
**SEATTLE SEA-TAC AP, WA**

The average hourly temperature was 63.6 degrees while the mid-range temperature i.e. the average of the minimum (59) and maximum (71) temperatures was 65 degrees.<sup>8</sup> The NOAA method concludes that on this day there were zero HDDs (i.e.  $D^m = 65 - 65 = 0$ ). The degree days based on the actual average are  $D^a = 65 - 63.6 = 1.4$  degree days. Meanwhile, using hourly temperatures produces 24 heating degree hours for the day, or  $D = 2.58$  degree days.<sup>9</sup> As we show below, the difference between the  $D^m$  and  $D$  measures depends on the empirical temperature distribution which is dependent on geographic location and time of year.

As a second example, consider the TOH readings for August 7, 1998. These were 61, 59, 58, 56, 54, 54, 55, 56, 57, 57, 58, 61, 62, 64, 67, 68, 70, 71, 70, 66, 64, 62, 59, and 59. The minimum TOH temperature was 54 degrees while the maximum TOH temperature was 71 degrees. The absolute minimum temperature reported by NOAA was 72 degrees while the absolute minimum temperature was 53. Note in this case that the mid-range temperature is 62.5 degrees. NOAA reports the “average” temperature for this day at 63 degrees, which is 62.5 rounded up to the nearest whole number. The actual average of TOH temperatures was 61.2 degrees. NOAA reports that there were  $65 - 63 = 2$  degree days on this day rather than  $65 - 62.5 = 2.5$ . These rounding errors accumulate over the course of the month and for the year. For instance, NOAA reports 21 heating degree days for the month of August 1998 but, without rounding, the mid-range estimate

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<sup>8</sup> In reality, temperature information changes continuously. At present, NOAA weather stations record absolute daily minimum and maximum temperatures as well as TOH temperatures. According to NOAA, on this day, the absolute minimum temperature was 58 degrees while the absolute maximum temperature was 72 degrees. These differ little from the minimum TOH temperature of 59 degrees or the maximum TOH temperature of 71degrees. The use of the TOH temperatures in our analysis introduces only small measurement error when we recalculate NOAA heating degrees days in the test year period. We note that hourly skewness in this example is positive 0.55.

of heating degree days (based on the reported minimum and maximum daily temperatures) would be 23.5.

Temperature sensitivity coefficients are determined using historical data and econometric analysis. In order to compute temperature sensitivity coefficients, a utility will first compare actual residential system daily load per capita for a multi-year time period to actual daily temperatures for the same multi-year period. This permits the utility to develop coefficients that describe the relationship between temperature and load. Multivariate regression analysis is used to isolate the incremental weather effects from other factors such as weekdays versus weekends or lower energy loads on holidays, seasonality, trends in energy efficiency, or factors not related to temperature such as the number of customers.<sup>10</sup> The estimated weather effects on load are termed “weather sensitivity coefficients.” The utility then uses the weather sensitivity coefficients and “normal” weather data to convert the actual test year loads to “normal” loads. The weather sensitivity coefficients are multiplied by the difference between test year and normal degree days and the number of customers.

In almost all cases, utilities rely on a load regression specification in which HDDs and CDDs are defined using a constant base level temperature of 65 degrees and are compared to daily electric (or natural gas) loads. However, departures from this simple specification are sometimes required. For instance, Engle, Granger, Rice, and Weiss

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<sup>10</sup> Load sensitivity with weather is typically analyzed in a regression analysis that relies on individual level data (conditional demand approach) or aggregate data (daily or monthly system load per capita for residential customers). These models will usually include some form of heating and cooling degree day measures in order to control for the temperature sensitive portion of load. The most common measurement of heating and cooling degrees occurs at a base temperature of 65 degrees F. See e.g. Lawrence and Aigner (1979) and Dubin and McFadden (1984). Dubin (1985) replaces HDD and CDD estimates with engineering predictions from a thermal load model applied to individual dwelling data for each household.

(1986) have observed that the temperature-load relationship is non-linear. The non-linear relationship between load and temperature was also discussed in Dubin (1985, Chapter 2). The empirical evidence has recently been discussed and summarized by Moral-Carcedo and Vicens-Otero (2005). Non-linearities in the temperature-load relationship are handled either with non-linear parametric or semi-parametric solutions but are generally small enough that they can be adequately captured by adding additional heating and cooling degree measures to the regression equation.<sup>11</sup>

### **III. Heating Degree Days – Theory and Measurement**

The number of degree hours accumulated in a day is a measure of the energy load to maintain a dwelling at a base temperature. In empirical practice, there is a significant correlation between HDDs and thermal energy load. The purpose of this section is to rigorously define the various degree-day measures and demonstrate their mathematical relationships. There are several methods in practice to define the concept of HDDs. Our discussion begins with the concept of a degree hour.<sup>12</sup> Degree-hours are defined as:

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<sup>11</sup> For instance, to capture non-linearities in temperature-load relationship, a heating degree measure at base 45 degree F may be included in the regression model in addition to the usual 65 degree F measure of HDD. This adjustment might be appropriate for a utility with a mixture of well insulated dwellings and other less energy efficient dwelling where heating is triggered at higher exterior temperatures. An alternative to assuming particular alternative HDD measures at other base temperatures is to employ a MARS regression procedure. MARS is a semi-parametric statistical technique that determines the "best" relationship between a dependent variable and independent explanatory variables by locating "cut-points" in the explanatory variables and generating new explanatory factors based on these cut-points. For instance, when temperature is the explanatory variable, a MARS analysis will determine a cut-point and generate an explanatory variable called a "basis" function that measures the difference between temperature and the cut-point for instances where the temperature is lower than the cut-point. If temperature is higher than the cut-point, the generated variable is set to zero. MARS uses the explanatory factors to create basis functions based on the cut-points that it determines have the greatest empirical relevance. MARS basis functions for temperature factors are in the same form as HDD and CDD measures.

<sup>12</sup> This discussion generalizes the model presented in Guttman and Lehman (1992).

$$Z_h = |b - U_h|_+ = \max(b - U_h, 0) = \begin{cases} b - U_h & U_h < b \\ 0 & \text{otherwise} \end{cases}$$

where  $b$  = base temperature and  $U_h$  = temperature at hour  $h$ ,  $Z_h$  = degree hours for hour  $h$ .

Therefore, a degree hour is the number of degrees during a given hour when temperatures are lower than the base level.

The temperature  $U_h$  may be thought of as a random variable distributed with cumulative distribution function:  $F_h^*(U) = \text{Prob}[U_h \leq U]$ . We assume that this distribution has expectation  $\mu_h$  and variance  $\sigma_h^2$  that depend on the hour  $h$ .

In terms of standardized variables, we have:

$$\begin{aligned} F_h^*(U) &= \text{Prob}[U_h \leq U] = \text{Prob}\left[\frac{U_h - \mu_h}{\sigma_h} \leq \frac{U - \mu_h}{\sigma_h}\right] \\ &= F\left(\frac{U - \mu_h}{\sigma_h}\right) = F_h(t) \quad \text{where} \quad t = \frac{U - \mu_h}{\sigma_h} \end{aligned}$$

where  $F$  denotes the cumulative distribution function for standardized temperature. The expected number of heating degree hours in hour  $h$  is given by:

$$\mu_{z_h} = E[Z_h] = \text{Prob}[U_h \leq b] \cdot E[b - U_h | U_h \leq b] + \text{Prob}[U_h > b] \cdot 0$$

$$= \text{Prob}\left[\frac{U_h - \mu_h}{\sigma_h} \leq \frac{b - \mu_h}{\sigma_h}\right] \cdot \sigma_h \cdot E\left[\frac{b - U_h}{\sigma_h} \mid \frac{U_h - \mu_h}{\sigma_h} \leq \frac{b - \mu_h}{\sigma_h}\right]$$

Next, define  $\tau_h$  as the expectation of standardized temperature given that it is truncated from above at the standardized base temperature  $X_h$  i.e.  $\tau_h = E(t_h | t_h < X_h)$ . Then:

$$\mu_{z_h} = F(X_h) \cdot \sigma_h \cdot E[X_h - t_h | t_h < X_h]$$

$$\text{where } X_h = \frac{b - \mu_h}{\sigma_h} \text{ and } t_h = \frac{U_h - \mu_h}{\sigma_h}.$$

Hence:

$$\begin{aligned}\mu_{z_h} &= F(X_h) \cdot \sigma_h \cdot X_h - F(X_h) \cdot \sigma_h \cdot E(t_h | t_h < X_h) \\ &= \sigma_h \cdot F(X_h) \cdot (X_h - \tau_h).\end{aligned}$$

The conditional mean may be evaluated analytically in some cases. For instance, if temperatures are normally distributed, then (Maddala (1983, pp.365))

$$\tau_h = -\phi(X_h) / \Phi(X_h)$$

where  $\phi(\cdot)$  and  $\Phi(\cdot)$  are the standard normal density and standard normal cumulative distribution function, respectively. In this case<sup>13</sup>:

$$\begin{aligned}\mu_{z_h} &= \sigma_h \cdot \Phi(X_h) \cdot [X_h + \phi(X_h) / \Phi(X_h)] \\ &= \Phi(X_h) \cdot [b - \mu_h] + \sigma_h \cdot \phi(X_h)\end{aligned}$$

Note that when the average temperature for the hour is much lower than the base temperature  $b$ ,  $X_h$  will be large,  $\Phi(X_h)$  will be close to one, and  $\phi(X_h)$  will be close to zero, in which case  $\mu_{z_h} \approx b - \mu_h$ .

Next, daily degree hours are the sum of hourly degree hours. Dividing daily degree hours by 24 hours yields the concept of degree days:

$$D = \sum_h |b - U_h|_+ / 24 \text{ with } \mu_D = E(D) = \sum_h \sigma_h \cdot (X_h - \tau_h) \cdot F(X_h) / 24$$

Again, if the average temperature for an individual hour is significantly lower than the base temperature  $b$ , then we have as an approximation:

$$\mu_D \approx \sum_h (b - \mu_h) / 24 = (b - \bar{\mu}_D)$$

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<sup>13</sup> This result is originally due to Thom (1954) and was generalized to non-normal distributions by Guttman and Lehman (1992).

*i.e.*, degree days are approximately the difference between the base temperature  $b$  and the

average daily temperature  $\bar{\mu}_D = \frac{1}{24} \sum_h \mu_h$ . This approximation motivates the usual

definition of daily degree days,  $D^a$  :

$$D^a = |b - \bar{U}_D|$$

where  $\bar{U}_D = \frac{1}{24} \sum_h U_h$ .

If hourly temperatures are randomly distributed, then average daily temperature is also random with mean  $\bar{\mu}_D$  and variance that depends on the hourly variances  $\sigma_h^2$  and the diurnal correlation of hourly temperatures. Next, we demonstrate a mathematical relationship between  $D$  and  $D^a$  that is independent of the random distribution of hourly temperatures. Recall that daily degree days,  $D$ , are the average of the hourly values in a day:

$$D = \frac{1}{24} \sum_h |b - U_h|_+$$

The function  $|b - U|_+$  is convex. Since, the average of a convex function is greater than or equal to the function evaluated at the average (Jensen's Inequality), we have<sup>14</sup>:

$$\frac{1}{24} \sum_h |b - U_h|_+ \geq |b - \bar{U}_D|_+$$

It follows that<sup>15</sup>:

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<sup>14</sup> Hardy, G. H.; Littlewood, J. E.; and Pólya, G. *Inequalities, 2nd ed.*, Cambridge, England: Cambridge University Press, pp. 83-84, 1988.

$$D \geq |b - \bar{U}_D|_+ = D^a$$

In practice, the empirical difference between  $D$  and  $D^a$  may be non-negligible, as has been noted by Guttman and Lehman (1992), Lehman (1987) and Huang *et. al.* (1987). Other things equal, we should expect the hourly degree day measure to provide a more accurate indicator of daily energy load as it averages the energy load for each hour rather than relying on a calculation based on the daily average temperature. This difference is likely to be particularly acute in “shoulder” months where average temperature differs from base temperature to a lesser degree, or in heating months when HDDs are computed at base temperatures lower than 65 degrees. Intuitively, using average temperature may miss events in some hours where temperatures are cold enough to generate HDDs, even though these events are not counted when the average temperature for the day exceeds the base temperature.

We next examine the HDD measure used most often in utility rate making.

Traditionally, the daily average temperature was estimated by the average of the minimum and maximum daily temperature. This is the procedure most commonly used by NOAA when calculating HDDs.<sup>16</sup> We denote a daily HDD measure based on this estimate by:

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<sup>15</sup> This result is also true under expectation by the inequality theorem. Hence,  $E(D) \geq E(D^a)$ .

Guttman and Lehman (1992) were able to demonstrate this result under the restrictive assumption that daily average temperatures come from a distribution with the same variability as hourly temperature.

<sup>16</sup> Until recently, NOAA’s method to calculate HDD daily normals did not calculate daily values from daily data. Instead, NOAA’s method first focused on monthly normal HDDs. Specifically, sequential monthly degree days were derived using procedures developed by Thom (1954). This technique utilized the historical monthly average temperature and its corresponding standard deviation to compute monthly degree days. Then, NOAA daily normals were derived by statistically fitting smooth curves through monthly values; daily data were *not* used to compute daily normals. NOAA has modified this procedure for the recent 1971-2000 normal period: “For first-order stations, where daily data sets are largely devoid

$$D^m = |b - t^m|_+$$

where  $t^m = (\min t + \max t)/2$ .

Here  $\min t$  and  $\max t$  denote the minimum and maximum temperatures for each day.

The concept of taking the average between the minimum and maximum temperature is known as the “mid-range” estimate in statistics. The mid-range is known to be an unbiased estimate of the center of a symmetric distribution where the mean, median, and mode all coincide. However, it is neither efficient nor is it even robust when the underlying distribution is symmetric. For asymmetrical distributions, the sample mid-range does not correspond to any fixed parameter of the population. Therefore, what it estimates cannot be stated (Gumbel (1958) pp. 108).<sup>17</sup> Hence, as a theoretical matter the mid-range has very little to recommend it. It is clear, however, that skewness in the temperature distribution can have an effect on the mid-range estimate of mean temperature and, therefore, a significant effect on estimated HDDs.<sup>18</sup> However, an

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of missing values, monthly degree day totals were derived directly from daily values.” See e.g. <http://lwf.ncdc.noaa.gov/oa/climate/normal/usnormalsprods.html#CLIM85> and <http://www.ncdc.noaa.gov/oa/climate/normal/usnormals.html#Overview>.

<sup>17</sup> The following properties of the midrange are known: (i) The sample midrange is an unbiased estimate of the center of a symmetric distribution; (ii) The sample midrange is the maximum likelihood estimator of the center of a rectangular (uniform) distribution and is more efficient than the sample average in this case (super-efficiency); (iii) The mid-range is generally much less efficient than the mean for symmetric distributions, and is inconsistent for some symmetric distributions; (iv) The mid-range exhibits an extreme lack of robustness, so that small changes in the underlying distribution lead to large changes in the behavior of the mid-range. The mid-range is very sensitive to errors and its accuracy does not increase with large sample sizes; (v) For large number of observations, the midrange is not as efficient as the sample average for members of the power distribution family; (vi) Theoretical properties of the mid-range have been established for non symmetric random variables where it is demonstrated that the mid-range becomes less accurate as the sample size increases; (vii) With large samples, the asymmetric distribution of the mid-range is dominated by one-tail and especially.

<sup>18</sup> By way of illustration, we selected the one-parameter gamma distribution (following Lehman (1987)) for the temperature distribution and simulated hourly temperatures by repeated random draws from this distribution. Introducing skewness into the gamma distribution, we found that the mid-range exceeds the mean for increasing levels of positive skewness. Huang *et. al.* (1987), Guttman and Lehman (1992) and

empirical comparison of the mid-range and average based HDD calculation has not appeared in the literature. We perform this comparison in the next section.

### **Hourly Temperature Skewness in the United States**

Skewness in the hourly temperature distribution varies by time of year and by geographic location within the United States. To illustrate the degree of hourly skewness we rely on typical meteorological years (TMY). TMYs provide hourly values of solar radiation and meteorological elements such as hourly temperature for a “typical” year period. These datasets were assembled by the U.S. Department of Energy’s Office of Solar Energy Conservation.<sup>19</sup> The data represents typical, rather than extreme, conditions at over 200 locations in the U.S.

We assembled over 2 million hourly temperatures for 237 locations and calculated hourly temperature skewness for each month and day at each locations.<sup>20</sup> Our calculations of hourly temperature skewness (hourly temperature skewness within the day) for each of the 365 typical days in the year resulted in 86,505 measures of skewness (365 days \* 237 locations). Average national hourly skewness was measured to be roughly zero (0.038 with a standard deviation of 0.44). We display the hourly temperature

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Lehman (1987) also considered the shape of the empirical temperature distribution *for daily average temperatures*. These authors found that temperature distributions are not normally distributed and instead are asymmetric with the degree and direction of skewness varying by region of the country.

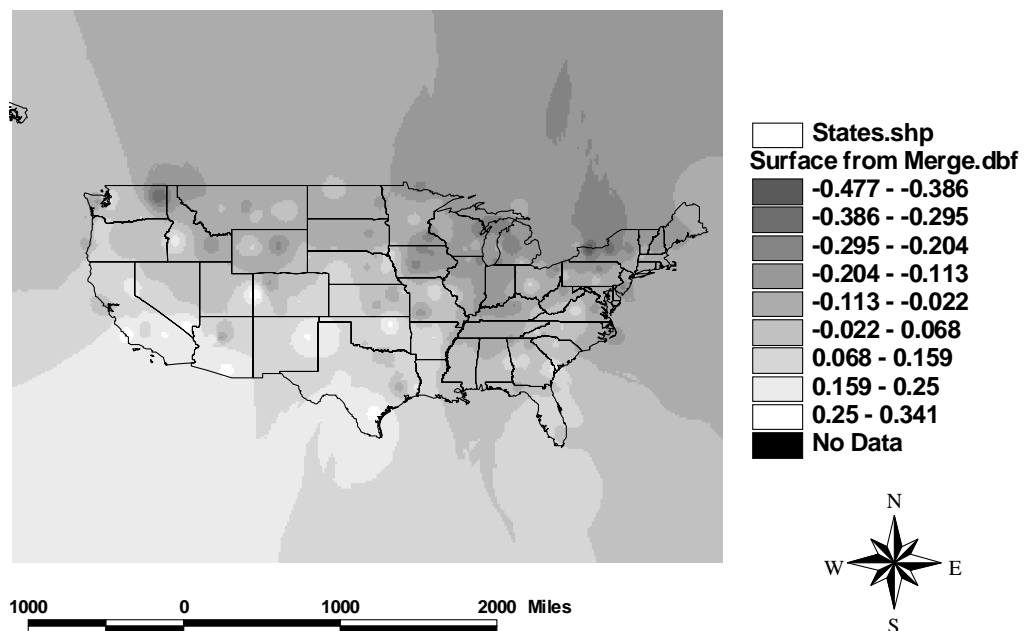
<sup>19</sup> These data were produced by the National Renewable Energy Laboratory's (NREL's) Analytic Studies Division under the Resource Assessment Program, which is funded and monitored by the U.S. Department of Energy's Office of Solar Energy Conversion. See e.g. <http://rredc.nrel.gov/solar>. We used the TMY2 available from [www.doe2.com](http://www.doe2.com). For each location, statistical procedures were employed to select a representative year using data from the period 1961 through 1990.

<sup>20</sup> Skewness is measured by the third-central moment of a distribution divided by the cube of the standard deviation.

skewness in Figure 2. Evidently more negative hourly temperature skewness is found in the Eastern U.S. as compared to the West and skewness tends to be somewhat smaller in the Southern U.S.<sup>21</sup>

Figure 1

## Hourly Temp Skewness



Following our discussion of alternative measures of HDDs, we expect that greater skewness will lead to greater differences in the measurement of HDDs between the NOAA mid-range based estimate  $D^m$  and the average based measurement  $D^a$ . We calculated these two measures for each of the 86,505 location/days. The average value of the difference ( $D^a - D^m$ ) was roughly zero at the national level. In other words, we find

<sup>21</sup> The shading in Figure 1 extends beyond the U.S. border due to interpolation algorithm used to draw the graphic. As temperature data outside the continental U.S. was not part of the analysis, this region may be ignored in the Figure.

no difference between these estimates at the national level. This does not, however, rule out important regional differences between the measures. We next compared the heating degree difference ( $D^a - D^m$ ) to the degree of skewness while controlling for seasonality with monthly dummy variables. The resulting regression determined that a unit change in skewness leads to a 2.06 degree day difference per day (752 degree days per annum).<sup>22</sup> Similarly, we compared the HDD difference ( $D - D^a$ ) between the hourly measure of heating degree days and the average based measure and found that it was positive (0.531 degree days per day with standard error of 0.0036) in the National sample but not correlated with hourly temperature skewness. According to our empirical analysis, there are systematic differences in the alternative HDD measures. However, these differences are of a type that would tend to cancel one another in a given region and time period. This is important for weather normalization as it is the difference in HDDs between normal and test-year periods that comprise the weather adjustment.

Based on these results, we see that the difference between the NOAA mid-range measure of HDDs and the average based measure is most negative in the Eastern U.S. and most positive in the Southern and Western U.S. Generally, the mid-range estimate of heating requirements is larger (as compared to the hourly measure) in the Eastern U.S. where the diurnal temperature skewness is more negative and is smaller in the Southern and Western U.S. where the opposite pattern appears. Across locations, and for this TMY, the hourly estimate of HDDs was 5,854 using the hourly definition, 5,660 degree days using the average based measure, and 5,660 degree days using the NOAA mid-

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<sup>22</sup> Omitting the seasonal dummy variables, we find  $(D^a - D^m) = -0.078 + 2.06 * \text{Skewness}$ . Detailed regression results showing the affect of seasonality are available upon request. The standard-error of the slope coefficient is 0.0066 degree days per day.

range.<sup>23</sup> Both the mid-range measure and the average method understate the hourly heating degrees by 194 degree days. However, hourly temperature skewness affects the mid-range estimate but not the average based method implying regional differences between the  $D$  or  $D^a$  and the  $D^m$  methods resulting from the use of NOAA's mid-range method. These results have important implications for weather normalization as we discuss in the next section.

#### **IV. Heating Degree Days and Weather Normalization**

To illustrate the consequences of using alternative measures of HDDs in weather normalization, we present the results for a typical Northwest utility operating in the Pacific Northwest. To begin, we assembled hourly temperatures from 1971 through 2005, measured at Washington's Sea-Tac Airport.<sup>24</sup> There were 306,816 such hourly temperatures. Our results utilize hourly temperatures for a 30-year period in order to calculate heating degree normals under the  $D$ ,  $D^a$ , and  $D^m$  methods. However, we do not suggest that such an undertaking be performed in every rate case. Indeed, our results demonstrate that practitioners would only require such extensive data if it was necessary to calculate the  $D$  or  $D^a$  measures of normal degree days. Using published NOAA normals should suffice, provided degree-days are properly calculated in the test-year period.

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<sup>23</sup> Importantly, these mid-range estimates are not subject to the rounding that NOAA applies to its mid-range temperature estimates employed in NOAA published heating and cooling degree-days. This will be discussed in further detail below.

<sup>24</sup> Sea-Tac Airport is a "first-order" weather station with largely complete and accurate historical temperature information. Temperatures at Sea-Tac are highly correlated with temperatures in the Northwest region.

We calculated the skewness for each day in this period (hourly temperature skewness), as well as the mean daily temperature and the mid-range temperature.<sup>25</sup> Using the Sea-Tac data, we found that the hourly temperature distribution was positively skewed with a greater likelihood of warmer extreme temperatures than colder extreme temperatures. Across the period 1971 through 2005, the skewness coefficient averaged 0.15. Positive skewness in the hourly temperature distribution caused the average daily temperature to be underestimated by 0.40 degrees using the mid-range estimate as compared to the simple average. As the mid-range is larger than the average temperature, the base temperature less the mid-range estimate is typically smaller than the difference between the base temperature and the average temperature. For the period 1971 through 2000, the estimate of HDDs based on the mid-range is 4,817 on an annual basis. This is 125 degree days lower than the estimate based on the mean average temperature.

We next examined actual hourly temperatures to compute the  $D$ ,  $D^a$ , and  $D^m$  HDD measures. We found that for the period 1971 through 2000, there were 5,093 HDDs on an annual basis (method  $D$ ). Using the daily average of such hourly temperatures lowers the estimate to 4,942 HDDs (method  $D^a$ ). Using the mid-range estimate of the mean degree temperature lowers the estimate to 4,817 HDDs (method  $D^m$ ). There is a further difference of 20 degree days to get to the published normal of 4,797 due to NOAA errors, spline adjustments, and rounding.<sup>26</sup> Hence, HDDs are

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<sup>25</sup> All temperatures were recorded at the top-of-the-hour by NOAA.

<sup>26</sup> It is interesting to compare this number to that published by NOAA. The NOAA published HDD value for the 1971-2000 period is 4,797. We have analyzed the difference between 4,817 and 4,797 by reviewing NOAA's calculations as provided to us by NOAA. There is a 17 degree day difference due to the TOH approximation (*e.g.* using absolute daily maximum temperature versus the maximum of the twenty-four TOH temperatures), a 8 degree day difference to spline adjustments, and an -5 degree difference due to erroneously including February leap days when NOAA calculated the 30 year normal (an error acknowledged by NOAA in personal communication):  $4817 = 17 + 8 - 5 + 4797$ .

underestimated by 0.4 percent due to miscellaneous adjustments, 2.6 percent due to the difference between mid-range and daily average temperature and a further 3.1 percent due to the difference between daily average temperatures and hourly based estimates. The NOAA method relying on the mid-range produces an estimate of HDDs that is significantly lower than hourly degree days. These results are summarized in Table 1 under the column 1971-200 Normal HDD.

With respect to weather normalization and rate making, we find that a smaller HDD weather adjustment may be expected between normal periods and test year periods when relying on NOAA published heating degree-day data. The reason is that the published HDDs (for “actual” periods as opposed to “normal” periods) are downwardly biased because NOAA rounds their mid-range estimate of average temperature to the nearest whole number before calculating actual HDDs.<sup>27</sup> This rounding step is not followed when NOAA reports HDD normals.<sup>28</sup> Using the period of 1971 through 2000 as the normal and October 2004 through September 2005 as the test-year period, we found that the adjustment between the published NOAA normal and test year period is 344 degree days, but is only 267 degree days using the average temperature or the weather adjustment implied by the *D* method. Correcting the rounding error in NOAA’s calculation of actual HDDs increases the test year published value from 4,453 to 4,531

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<sup>27</sup> The direction of the bias is clear. If the minimum and maximum temperatures during the day are recorded as whole numbers then roughly half of the mid-range estimates of average temperature will be whole numbers while the rest (even and odd temperature pairs) will have exact remainders of 0.5. As NOAA rounds to the nearest whole number, the first half will be unchanged by rounding while the second half will increase by 0.5 degrees. In this case the mid-range estimates will be too large (roughly half of the time) and HDDs will be too small as a consequence of the rounding.

<sup>28</sup> We requested NOAA’s worksheets that back-up their calculation of the Sea-Tac 1971-2000 normal. We verified that NOAA does not round its mid-range daily temperature estimate when calculating the daily degree days that are ultimately averaged to form the 30 year normal.

degree days and implies a nearly identical weather adjustment as that derived from the hourly data (the HDD adjustment is 4,797 - 4,531 = 266 degree days). These results are summarized in Table 1.

**Table 1**  
**Comparison of Calculated HDD Base 65° F Using Different Methods – Sea-Tac Airport Data**

Method	1971-2000 Normal HDD	Difference Across Methods	Actual HDD Test Year (10/04 – 09/05)	HDD Adjustment
<i>D</i> - average of 24 hrly heating degree days	5093		4826	<b>267</b>
<i>D<sup>a</sup></i> - average of 24 hr TOH temps	4942	151	4675	<b>267</b>
<i>D<sup>m</sup></i> - average of min/max 24 hr TOH temps	4817	125	4553	<b>264</b>
<i>D<sup>m</sup></i> - as published by NOAA	4797	20	4453	<b>344</b>

TOH – top of the hour readings

Based on these observations, we see that degree of weather normalization is nearly identical between normal and test-year periods as long as the same methodology is applied in both periods. However, using published NOAA data for test-year HDDs is problematic as NOAA published figures employ a rounding methodology that is present in the monthly data that comprise the test-year but not present in the published normals. Moreover, in most rate proceedings, it is very unlikely that normals will be recalculated.<sup>29</sup> Hence, in practice, the degree of weather adjustment is strongly influenced by the choice of HDD measurement methodology applied to the test-year period. We discuss this further below.

Differences in degree days translate into weather normalized load adjustments once the degree day difference is multiplied by the estimated weather sensitivity coefficient. Weather sensitivity is calculated using an energy demand regression

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<sup>29</sup> There are occasional exceptions to this. For instance, some utilities will argue that normal heating and cooling degree-days should be recalculated for the most recent 30 year time-period as opposed to the decennial periods used by NOAA. While hourly data is readily available for recent periods and for many locations, this is unlikely to be the case for historical data necessary to recalculate normals.

analysis. In our analysis, we use data from a Northwest utility for the period January 1, 2002 through January 31, 2004 for a January equation, and data from February 1, 2002 through February 29, 2004 for the February equation, and so forth. The energy demand equations, by month, are assumed to be of the form:

$$Q_t^e = \alpha + \beta^1 X_t + HDD_t \sigma + \varepsilon_t$$

where:

$Q_t^e$  = energy demand (system load per capita) on day  $t$  measured in KWH;

$X_t$  = vector of explanatory variables including price, income, day of week, holidays, trend, conservation programs, etc;

$HDD_t$  = heating-degree days measured on day  $t$  according to method;  $D$ ,  $D^a$ , or  $D^m$ ;

$\alpha$ ,  $\beta$ , and  $\sigma$  are unknown coefficients.

Each monthly equation was estimated by generalized least squares using a low-order ARMA process. The estimation is based on roughly 100 daily observations for a two year period (2002 and 2003) prior to a “test year” period, which we selected to be October 2004 through September 2005. In principal, the selection of variables  $X_t$  will influence the weather sensitivity coefficients  $\sigma$  but alternative specifications lead to similar results in our analysis. Similarly, we could have pooled the data to estimate a single equation with some constraints among the monthly parameter, but we found that monthly equations provide a better empirical fit to the data. Finally, the energy demand equation is estimated on a per capita basis both to control for changes in population size over time and to allow for comparability of our results across utilities. Our specifications

include an intercept, weekend dummy variable and the *HDD* measure. Our regression models are displayed in Table 2.

**Table 2. Energy Demand Models For Northwest Utility**

	VARIABLE	JAN	FEB	MAR	APR	MAY	JUN	JUL	AUG	SEP	OCT	NOV	DEC
MODEL A (D)	Constant	51.87 (39.944)	54.18 (33.701)	53.31 (38.78)	52.10 (56.187)	50.89 (54.397)	51.75 (324.126)	51.16 (117.535)	52.54 (177.774)	52.56 (176.362)	53.52 (31.412)	52.62 (37.944)	57.36 (39.228)
	HDD (Avg 24 Hrs)	0.851 (15.64)	0.677 (9.75)	0.571 (10.931)	0.402 (7.334)	0.239 (5.085)	0.208 (10.635)	0.313 (8.308)	0.295 (7.85)	0.467 (4.443)	0.430 (7.815)	0.684 (11.027)	0.630 (10.066)
	Weekend Dummy	-4.492 (-9.779)	-5.144 (-11.863)	-4.398 (-11.497)	-4.827 (-11.825)	-4.444 (-14.701)	-4.783 (-28.566)	-4.811 (-15.515)	-5.128 (-27.797)	-4.488 (-19.805)	-4.417 (-13.087)	-3.833 (-8.255)	-4.567 (-9.399)
	Nobs	93	85	93	90	93	90	93	93	90	93	90	93
	R-Squared	0.915	0.846	0.900	0.827	0.866	0.935	0.867	0.932	0.862	0.876	0.844	0.771
	MODEL C (D <sup>a</sup> )	Constant	51.80 (40.889)	54.40 (34.587)	52.16 (38.7)	50.20 (53.736)	49.37 (63.382)	51.76 (340.401)	51.53 (107.938)	51.92 (161.529)	52.43 (157.998)	53.13 (30.601)	52.21 (38.527)
HDD (Avg 24 HD)		0.854 (16.131)	0.668 (9.832)	0.629 (12.121)	0.525 (9.206)	0.384 (7.244)	0.299 (10.676)	0.396 (7.687)	0.346 (8.908)	0.327 (3.583)	0.459 (8.484)	0.707 (11.58)	0.636 (10.008)
Weekend Dummy		-4.486 (-10.126)	-5.150 (-11.779)	-4.278 (-11.919)	-4.890 (-12.497)	-4.348 (-15.057)	-4.818 (-28.442)	-4.687 (-15.221)	-5.134 (-29.82)	-4.429 (-18.892)	-4.351 (-13.46)	-3.898 (-8.567)	-4.612 (-9.431)
Nobs		93	85	93	90	93	90	93	93	90	93	90	93
R-squared		0.920	0.845	0.912	0.847	0.886	0.934	0.864	0.940	0.851	0.885	0.852	0.769
MODEL C (D <sup>m</sup> )		Constant	53.52 (39.047)	54.78 (34.859)	54.21 (40.169)	51.40 (56.968)	51.02 (58.187)	52.05 (367.421)	51.98 (115.128)	52.42 (175.303)	52.56 (176.441)	54.39 (26.636)	53.42 (39.822)
	HDD (Avg MinMax)	0.793 (13.888)	0.663 (9.609)	0.540 (10.525)	0.469 (8.213)	0.252 (4.972)	0.288 (10.068)	0.364 (8.093)	0.290 (8.401)	0.380 (4.503)	0.401 (7.966)	0.667 (10.822)	0.640 (10.618)
	Weekend Dummy	-4.502 (-9.899)	-5.201 (-12.144)	-4.475 (-11.456)	-4.697 (-11.472)	-4.488 (-14.644)	-4.896 (-27.524)	-4.697 (-15.724)	-5.092 (-28.499)	-4.554 (-20.062)	-4.325 (-13.208)	-3.923 (-8.312)	-4.660 (-10.078)
	Nobs	93	85	93	90	93	90	93	93	90	93	90	93
	R-Squared	0.913	0.847	0.896	0.833	0.864	0.928	0.870	0.936	0.862	0.880	0.839	0.786

Note: t-statistics in parentheses

The regression models produce similar degrees of explanatory power, with roughly 90 percent of the variation in daily system load explained. Similar to the degree day measures themselves, the models showed the most similarity between the average and hourly methods for calculating weather sensitivity.<sup>30</sup> For instance, the January weather sensitivity coefficient was roughly 0.9 kwh per customer-day per degree day for these two measures of degree days. The NOAA measure of HDDs attenuated the weather sensitivity coefficient toward zero and implies a lower weather sensitivity coefficient of 0.87 for January. However, the degree of difference (relative to the *D* measure) for the January weather sensitivity coefficient was not statistically significant.

<sup>30</sup> If the *D<sup>m</sup>* measure is in fact a noisy estimate of the *D* measure then we might expect some attenuation of the estimated coefficients toward zero in the *D<sup>m</sup>* regression models. To develop this point would require load/temperature data from a broader geographic region than we present in this paper.

Weather sensitivity coefficients were statistically similar (based on the alternative definitions of HDDs) for all months, excluding the shoulder period from May through June.<sup>31</sup>

The units for the weather sensitivity coefficients  $\sigma$  are in kilowatt hours per person per degree day. To provide some sense of the magnitude of the effects, the dependent variable in our analysis for January has a mean value of roughly 70 KWH per person per day, yielding a typical monthly bill for January of about \$100 for a Northwest customer paying \$0.05 per KWH. The January equation estimates that the weather sensitivity coefficient is roughly 0.85 KWH per customer per degree day or roughly 850 MWH per degree day for a utility with 1 million customers.

The actual weather adjustment using the energy demand equation is straightforward enough. A prediction of energy using monthly test-year HDDs is calculated and a corresponding calculation is done using normal HDDs. The difference in the forecasts is simply the weather sensitivity coefficient (in a given month) multiplied by the degree day difference between test-year and normal for that month. Differences in weather adjustments occur due to differences in the estimated weather sensitivity coefficients and differences in the estimated degree of HDD adjustment. For instance, the weather adjustment under method  $D$  for a given month is:

$$\sigma^D (D_{normal} - D_{test-year}).$$

Similarly, the weather adjustment under method  $D^m$  is:

$$\sigma^m (D_{normal}^m - D_{test-year}^m).$$

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<sup>31</sup> Differences in estimated weather sensitivity coefficients were statistically different from zero at conventional levels between methods  $D$  and  $D^a$  in May and June, methods  $D$  and  $D^m$  in June, and methods  $D^a$  and  $D^m$  in May.

The difference between these two methods is:

$$\text{Weather Adjustment Difference} = \sigma^D (D_{\text{normal}} - D_{\text{test-year}}) - \sigma^m (D_{\text{normal}}^m - D_{\text{test-year}}^m).$$

The difference in weather adjustment arises from differences in coefficients of weather adjustment and from differences in the measurements of HDDs. As discussed above, we find that the coefficients of weather adjustment are similar so that:

$$\text{Weather Adjustment Difference} = \sigma[(D_{\text{normal}} - D_{\text{normal}}^m) - (D_{\text{test-year}} - D_{\text{test-year}}^m)].$$

In situations where only one measurement of normal HDDs is at issue (such as the “official” level published by NOAA) the weather adjustment becomes:

$$\text{Weather Adjustment Difference} = \sigma[D_{\text{test-year}}^m - D_{\text{test-year}}].$$

With a revenue requirement of \$50/MWh to \$90/MWh and weather sensitivity coefficients on the order of 500 MWh to 900 MWh per degree day, a one-million customer utility would expect revenues to rise by roughly \$50,000 for each additional HDD experienced per annum (\$0.05 per customer per degree day). The degree of weather adjustments, of course, varies by month. For instance, the test-year (October 2004 – September 2005) was warmer than normal for January by 25 heating degree-days. Consequently, loads would be expected to be larger under “normal” conditions.<sup>32</sup> The weather sensitivity for January is roughly 850 MWH per degree day, leading to a weather adjustment of  $850 * 25 = 21,250$  MWHs. Using a revenue requirement of roughly \$70/MWH implies a \$1.5 million revenue adjustment for January during the test-year. As we previously observed, the amount of weather adjustment is roughly constant, provided the same HDD methodology is consistently employed to measure normal and

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<sup>32</sup> The test-year was approximately 3.5 percent warmer than normal. The weather adjustment causes an approximate 1 percent increase in expected load.

test-year degree days. As may be seen in Table 1, our Northwest utility requires a 264 to 267 degree-day weather adjustment between the test-year and normal conditions independent of method. However, relying on the published NOAA data would result in too large a weather adjustment (344 degree-days versus 264) purely as a consequence of the rounding employed by NOAA in calculating the monthly degree-days that comprise the test-year period. Comparing the normal period and the test year, our Northwest utility would experience a revenue shortfall of nearly \$4 million (based on a weather normalization difference that is approximately 77 degrees too high using the NOAA published statistics). Projected sales would be adjusted by too large an amount and rates would be set too low for a given level of cost of service. In this case, the weather normalization is roughly 30 percent too high, with rates set too low by similar magnitudes.

If the reference point in a given rate case is the normal HDD level as published by NOAA, then the degree of weather adjustment varies among the methods as the  $D$ ,  $D^a$ , and  $D^m$  methods produce significantly different estimates of test-year degree days. These differences are likely to vary from one region of the country to another due to regional differences in hourly temperature skewness as we discussed above.

#### **IV. Conclusions**

Accurate weather adjustment in the rate making context requires accurate estimates of HDDs and CDDs. It is reasonable to use more precise techniques to calculate degree days because hourly temperature data is now widely disseminated. We have seen that rote reliance on published NOAA statistics can lead to excessively large

weather adjustments in some situations. Further, the NOAA mid-range estimate is likely to overstate heating load in the Eastern as compared to the Southern and Western U.S. as a consequence of evident hourly temperature skewness. While further research would be useful to determine whether our results for the Northwest extend to other regions, our results suggest that most of the biases in weather adjustment can be avoided by using consistent methods for determining HDDs and CDDs. Method D for determining daily HDDs from hourly temperature measurements has much to recommend it on a theoretical basis but a complete weather normalization analysis requires that normal and test-year estimates of HDDs both be calculated using Method *D*. However, it must be recognized that the data requirements necessary to calculate historical normals using Method *D* are far from trivial. If the effort to recalculate historical normals in a particular rate case is deemed to be prohibitive, we instead recommend that NOAA normals be compared to  $D^m$  degree-days calculated for the test-year period without rounding. In our examples, this procedure appears to be the most economical while providing an unbiased estimate of the appropriate weather adjustment.

## References

- Dubin, Jeffrey A., *Consumer Durable Choice and the Demand for Electricity*. New York-Amsterdam:North-Holland Publishing Company, 1985.
- Dubin, Jeffrey A. and D. L. McFadden, "An Econometric Analysis of Residential Electric Appliance Holdings and Consumption," *Econometrica*, Volume 52, No. 2, pp. 345-362, 1984.
- Gumbel, E.J. 1958. *Statistics of Extremes*. New York: Princeton University Press.
- Guttman, Nathaniel B., Lehman, Richard L. 1992. Estimation of Daily Degree-Hours. *Journal of Applied Meteorology* 31: pp. 797-810.
- Hardy, G. H.; Littlewood, J. E.; and Pólya, G. *Inequalities*, 2nd ed., Cambridge, England: Cambridge University Press, pp. 83-84, 1988.
- Huang, J.; Ritschard, R.L.; Bull, J.C., and L. Chang. 1987. Climatic Indicators for Estimating Residential Heating and Cooling Loads. *ASHRAE* 93: pp. 72-111.
- Lawrence, Anthony and D. J. Aigner (eds.), Modelling and Forecasting Time-of-Day and Seasonal Electricity Demands," *Journal of Econometrics*, Volume 9, 1979.
- Lehman, Richard L. 1987. Probability Distributions of Monthly Degree Day Variables at U.S. Stations. Part I: Estimating the Mean Value and Variance from Temperature Data. *Journal of Climate and Applied Meteorology* 26 (3): pp. 329-340.
- Madalla, G.S. *Limited-Dependent and Qualitative Variables Econometrics*, New York: Cambridge University Press, 1983.
- Thom, H.C.S. 1954. The Rational Relationship Between Heating Degree Days and Temperature. *Monthly Weather Review* 82 (1): pp. 1-6.