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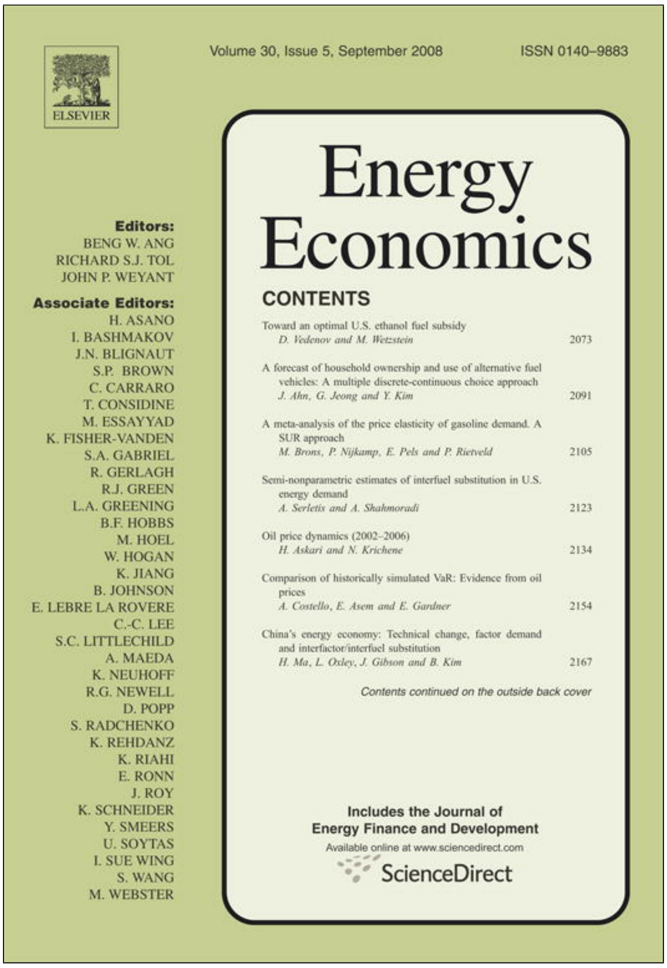

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An integrated engineering–econometric analysis of residential balance point temperatures ☆

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Abstract

This paper examines the theoretical and empirical properties of residential balance point temperatures. Heating-degree type measures in energy load temperature models are typically used because heating load should be zero when temperatures are larger than the base (balance point) level. Thermostat setting and the insulation properties of the residential shell determine the balance point temperature. Proper measurement of balance point temperatures is important in selecting the base temperature used in heating and cooling degree measures. I apply an engineering thermal load model to impute balance point temperatures for residential households in the Puget Sound Energy Washington service territory. The distribution of implied balance point temperatures suggests that heating degree measures base 65 °F inadequately capture the non-linear relationship between load and temperature due to prevalence of low balance point households.

JEL classification: Q41; Q54; L94; C14

Keywords: Heating degree; HDD; Temperature; Load; Econometrics

1. Introduction

Temperature is the 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

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affect peak usage, the load temperature 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.

However, while the relationship between load and temperature has been known to be highly non-linear, applied researchers and utilities continue to adopt simple linear relationships between load and temperature often relying on summary measures such as the heating degree days at an assumed base temperature (typically 65 °F).[1] Of course, the use of heating and cooling degree days to summarize weather effects has a venerable history in energy economics with examples including Lawrence and Aigner (1979) and Dubin and McFadden (1984).[2] More recently, semi-parametric models have been developed to estimate the non-linear relationship between load and temperature (Engle et al., 1986; Kissock et al., 2003). Alternatively, techniques such as Multivariate Adaptive Regression Splines (MARS) developed by Friedman (1991) are well suited to this task because the basis functions involving temperature are very similar to heating and cooling degree type measures. While semi-parametric and MARS methods are appropriate in some instances and specifically for some types of data (especially aggregate information measured hourly or daily), such techniques are ill-suited to individual level data where structural modeling can improve both the precision of the statistical models and fully utilize individual level household data.

The purpose of this paper is to examine the balance point temperature in residential households. The balance point temperature is defined as the point at which no additional heating is required when outdoor temperatures are higher than the balance point. The use of a heating degree type measure based at 65 is often used in energy demand models because heating load should be zero when temperatures are larger than the base (balance point) level. Thermostat setting and the insulation properties of the residential shell determine the balance point temperature.[3] This paper adopts an engineering approach based on thermal analysis to determine balance point temperatures. I combine engineering thermal analysis with survey information on thermostat levels in order to determine the distribution of likely balance point temperatures. I obtained the data used for this study from Puget Sound Energy (PSE) for their Washington service territory. As the principal source of information, I rely on a residential survey performed by PSE in 2004 matched with individual household billing and weather information for the prior 3 years. The use of billing data allows me to compare a conditional demand analysis for electricity that relies on heating degree days based 65 °F to a similar analysis that uses instead a varying base temperature derived from a engineering thermal model. The use of the latter is preferable on theoretical grounds and is found to provide a better correlate to energy demand. Additionally, a finding of this analysis is that the use of standard (based 65 °F) heating degree day measures is likely to understate the elasticity of demand between usage and temperature.

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[1] The concept of using 65 °F as a base temperature has been employed in the United States since the early 1930s. According to the American Society of Heating, Refrigerating, and Air-Conditioning (ASHRAE), ASHRAE Handbook, 1985 Fundamentals, this practice was founded on correlations between energy use and heating degree days (Chapter 28). While ASHRAE acknowledges that since 1930, gains from incidental internal heat sources and better insulation have resulted in lower balance point temperatures, the predominant empirical practice continues to utilize 65 °F in energy demand modeling and the National Climatic Data Center (NCDC) continues to report the 65 °F measure in most of its regional weather publications.

[2] For related analyses, see Hyde and Hodnett (1997) and Hor et al. (2005).

[3] For additional discussion of balance point temperatures and the use of engineering thermal models, see Fels (1986). Huang et al. (1987) report balance point temperatures from 56 °F to 65 °F depending on the thermal integrity of typical dwellings. Their analysis is similar to the analysis reported here and is based on the DOE-2 energy simulation program.

The paper is organized as follows. Section 2 reviews the non-linear relationship between load and temperature. Section 3 develops the engineering approach to the determination of balance point temperatures and describes the PSE survey data upon which this analysis was based. Section 4 develops the thermal model and the balance point temperature distribution. Section 5 provides econometric evidence comparing the standard and varying balance point temperature methodologies while Section 6 provides conclusions.

2. Weather normalization and the non-linearity relationship between load and temperature

Electricity and natural gas usage are highly dependent on the weather. In Fig. 1, I show PSE's electric load versus heating and cooling degree days. Heating degree days and cooling degree days 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 or office would need to turn on the heat or turn on a cooling system in order to remain comfortable. Historically, 65 °F has often been selected as that base level temperature. Heating degree days base 65 °F are the number of degrees where the ambient temperature is colder than 65 °F. The PSE service territory comprises a 6000-mi^2 region in the State of Washington primarily in the Puget Sound region. Fig. 1 displays the average daily use per customer per month for residential electric customers for the period 2002 through 2004. The figure reveals a significant correlation between temperature and electric (or natural gas) demand on the PSE system. The positive correlation between heating degree days and load, holding other factors constant, is a measure of the weather sensitivity coefficient and describes how load changes as temperature changes.

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

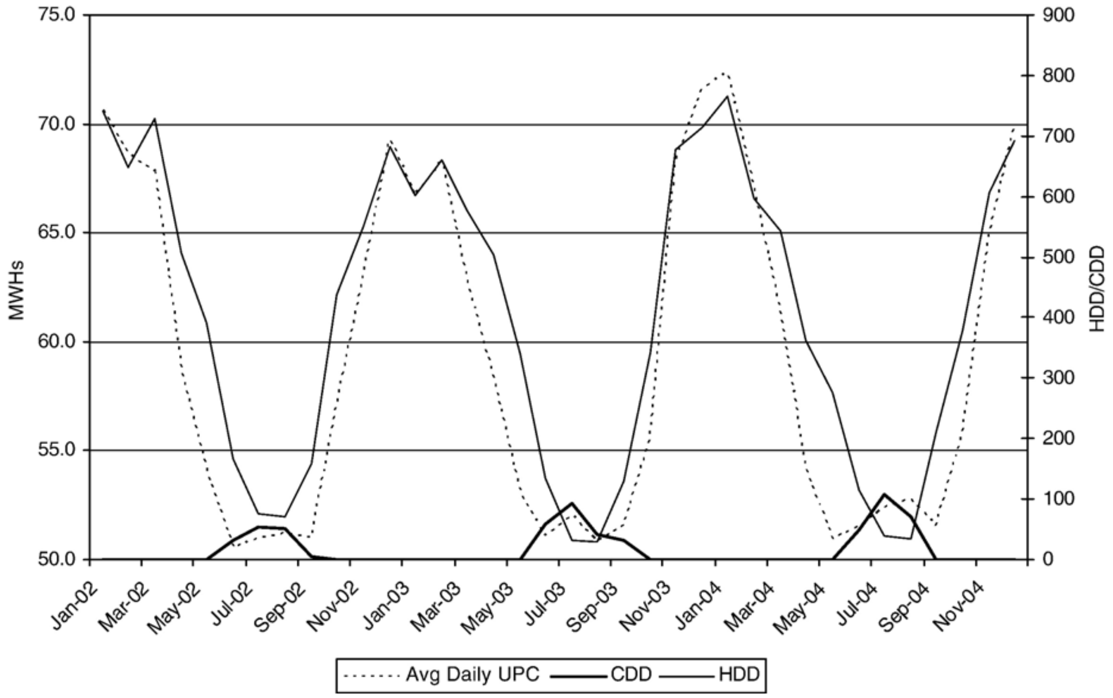

Fig. 1. Average daily use per Customer per month, monthly HDD/CDD.

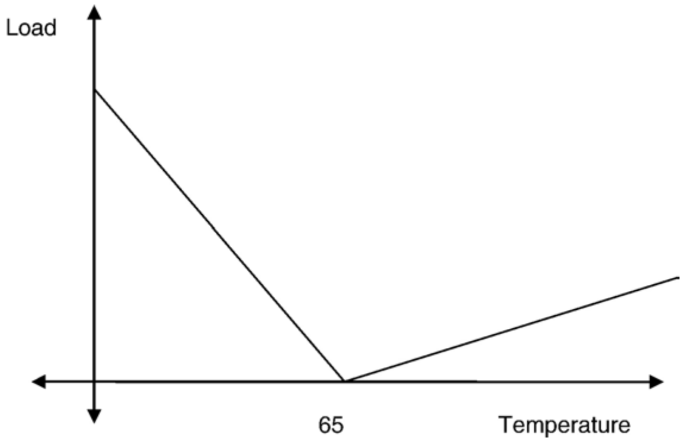

Fig. 2. V-shaped load response function.

load for residential customers). These models will usually include some form of heating and cooling degree day measure in order to control for the temperature sensitive portion of load or to ascertain the load–temperature relationship to facilitate load forecasting under normal conditions (weather normalization).[4] The method of using HDDs and CDDs based at 65 °F in the regression assumes that the load response is essentially V shaped. This V-shaped load response is shown in Fig. 2.

Recall that HDDs based on 65 °F are defined to be positive and decreasing in temperature for temperatures less than 65 °F (i.e., HDD falls when the temperature outside rises up to 65 °F), while CDDs based on 65 °F are positive and increasing for temperatures over 65 °F. Including these two measures in a load–temperature regression allows the slopes of the two segments of the V to be measured. The slopes (or weather sensitivity coefficients) determine the degree to which load is increased (for heating) when it is colder than 65 °F and the degree to which load is increased (for cooling) when it is warmer than 65 °F. In this formulation, the load–temperature relationship is assumed to be linear in each segment.

Engle et al. and others have observed that the temperature–load relationship is non-linear. They attribute this to basic laws of thermodynamics and limitations on existing heating and cooling equipment. The non-linearity of the load response to temperature has been noted by researchers for years. For instance, the theoretical relationship between load and temperature was discussed in Dubin (1985, Chapter 2). The empirical evidence has also recently been discussed and summarized by Moral-Carcedo and Vicens-Otero (2005). Non-linearity in the temperature–load relationship is clearly present in the PSE system. Fig. 3 shows the average daily temperature versus electric use per customers. Here I display the average daily electric usage per residential customer and the average daily temperature for the period 2002 through 2004. Clearly evident is the balance point temperature at or near 60 °F. Less evident in the figure but demonstrably present

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[4] Some analysts have relied on weather variables other than temperature or heating and cooling degree days in load regression models. See e.g. Hyde and Hodnett (1997) who consider humidity, wind speed, and sunshine but did not find that they were important determinants of electric load in Ireland and Dubin (1985) and Dubin and Henson (1988) who utilize predicted engineering load (from an engineering thermal analysis that combines dwelling characteristics with observed temperature data) directly in the regression analysis in place of typical heating degree type measures.

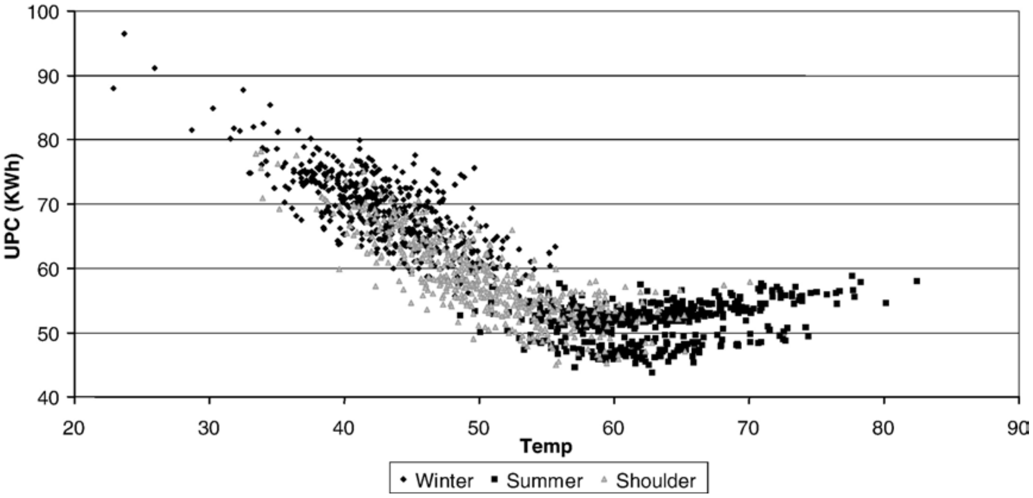

Fig. 3. Average daily temperature versus electric use per Customer.

via econometric analysis is further non-linearity in the load–temperature relationship at lower temperatures.[5]

While non-linear parametric and semi-parametric solutions to the non-linear load–temperature phenomenon have been developed, the deviations from non-linearity are usually small enough to be adequately captured by adding additional heating and cooling degree day measures at base temperatures other than base 65 to the regression model. In essence, this allows the leading and trailing edges of the V shape to reflect break points in the load response to temperature. Fig. 4 shows how these adjustments affect the V shape I discussed above. In this figure, a breakpoint is introduced at 45 °F so that the leading edge up to the 65 °F apex point is segmented into two sections. The two linear segments account for the non-linearity in the temperature–load relationship. Purely statistical methods may determine the base (balance point) temperatures at which the structural breaks occur. However, household specific data can also be used to determine balance point temperatures. This technique is pursued in the next section.

3. Engineering determination of balance point temperature

The balance point temperature is a temperature such that no additional heating is required when outdoor temperatures are higher than the balance point. Thermostat setting and the insulation properties of the residential shell determine the balance point temperature. The heat gain from occupants and appliances in a well-insulated dwelling may lower the balance point temperature significantly below the thermostat set point. If, for instance, customers set their thermostats at 65 °F in the winter, then it is possible that no extra energy (electricity or natural gas,

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[5] I performed a daily system load regression for residential electric customers on the PSE system for the period 2002 through 2004. The regression included monthly dummy variables, indicators for weekends and holidays and heating and cooling degree day measures. Specifically, for the Winter and Shoulder periods, heating degree days base 65 °F were included for each of the months September through May while heating degree days base 45 °F were included for each of the months October through April. The regression equation explained over 97% of the residential system load variation and in each case the additional heating degree day measures (at base 45 °F) were statistically significant. While the exact break point was difficult to discern (models using 50 °F as a secondary breakpoint fit equally well), the general pattern was greater implied weather sensitivity using the full set of regression effects. The complete details are available from the author upon request.

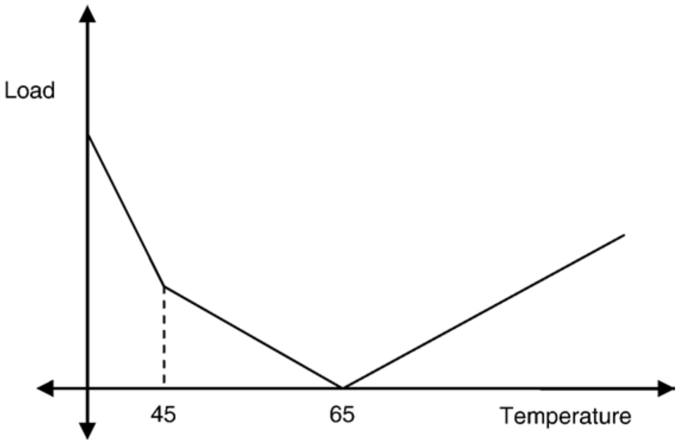

Fig. 4. Load temperature relationship using multiple base temperature figures.

etc.) will be required to achieve the 65 °F thermostat setting until outside temperatures drop to 45 to 55 °F depending on the dwelling and its occupants. A base temperature of 65 °F used for heating degree day measurement would tend to over-estimate the amount of likely energy requirement for heating in such a situation. In this section, I illustrate the use of an engineering thermal analysis applied to household level survey data to determine balance point temperatures.

The engineering approach is applied to survey data collected through PSE's Residential Appliance Saturation (RAS). The RAS survey samples individual gas and electric customers on the Puget system and contains detailed information on over 5000 households. The RAS sample was designed to be representative of the PSE service territory which comprises a 6000-mi^2 portion of the State of Washington primarily in the Puget Sound Region.[6] PSE performed a mail survey of its residential electric and gas customers in 2004. This survey is the most recent of several previous surveys conducted of PSE's residential customers (1981, 1983, 1986, 1989, 1992, and 1998). The RAS survey was designed to collect detailed and representative data on appliance holdings and customer characteristics. Using a mail survey instrument, the survey provides information on whether the customer is a gas, electric, or combined customer of PSE. It also provides basic information on housing tenure (owning or renting the dwelling and its type), as well as structural characteristics of the dwelling. These physical traits include: square footage, number of floors, and the presence of weatherization (ceiling insulation, wall insulation, duct insulation, weather strip doors, and glazed or storm windows). The survey also provides information on the use of fuels for heating and cooking, type of heating system (gas, electric, oil), and presence of air-conditioning. The RAS also captures information on water heat fuel types and the number of electricity using appliances (stove-top cooking, ovens, clothes dryers and so on). Finally, the survey collects and reports various socio-demographic characteristics, such as education levels, income levels, employment status, and number of household members.

The target population for the survey was all Puget Sound Energy residential customers. Billing records established the sampling frame, which was then sampled based on systematic sampling. Following this method, PSE achieved a sample that was proportionately stratified by dwelling type and billing schedule. My review of previously conducted RAS surveys suggested that a large

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[6] The RAS sample has coverage in each of PSE's eleven service counties (Island 4.6%, Jefferson 5.0%, King 23.2%, Kitsap 12.6%, Kittitas 5.0%, Lewis 4.6%, Pierce 15.9%, Skagit 4.1%, Snohomis 12.1%, Thurston 8.89%, and Whatcom 4.2%).

Table 1
PSE 2004 survey respondents

	2004 Survey	2004 Customers
Electric customers	2657	552,795
Gas customers	1373	259,205
Electric and gas customers	1286	260,400
Total	5316	1,072,400

enough initial population was sampled in 2004 to achieve a high degree of reliability[7]. The final survey results represent the responses of 5316 households. The 2004 survey sampled roughly a half percent of all customers. The sample and population counts are presented in Table 1.

Over 78% of PSE residential customers lived in single-family dwellings. I ultimately selected the single-family electric customers for further analysis. These customers constitute 3089 sampled households (78.3% * (2657 + 1286)).[8]

The Dubin–McFadden engineering thermal model (Dubin, 1985) was adapted to work with the PSE survey. I used information on single-family residence square footage, presence or absence of insulation, the types of storm or glazed windows in the home, and other factors available in the survey as inputs to the thermal model. These factors and matched weather information permit an engineering prediction of space heating load for each month that would likely occur for each household. The energy load model quantifies the differences between energy used for houses of different sizes. As discussed in the next section, I used this information to calculate the implied balance point temperatures for each dwelling.[9]

Several factors were necessary inputs to the Dubin–McFadden thermal model. They included: (i) house square footage, (ii) number of storm windows, (iii) number of non-storm windows, (iv) presence of wall insulation, (v) inches of attic insulation, (vi) number of rooms, (vii) number of floors, (viii) weather conditions for system design (summer outdoor daily temperature range, summer degree dry bulb and winter degree design temperature), (ix) 30-year normal heating and cooling degree days for estimated system coefficients of performance and (x) monthly heating and cooling degree days for the period 2001 through 2003.[10] To calculate some of these, it was necessary to recode the RAS survey information for data consistency. The thermal model also post-processed the information to check the values of all key factors.

For instance, I combined household members by age group to create a total number of household members. I further assumed that households with greater than 7 members had exactly seven members to "top-code" the small number of cases of implausibly large households. In

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[7] The survey response rate for 2004 is not known. However, as the sampling frame remained unchanged from previous years the response rate is likely to be very high. For instance, detailed information from the 1992 PSE RAS survey showed that nearly 70% of customers responded to the survey. This response rate is exceptionally high for a mail survey.

[8] PSE does not have access to electricity billing information for its non-electric (natural gas) residential customers. Roughly 3943 of 5316 households had electric load information while the remainder were only provided natural gas by PSE. Of the 3943 households, the sample was further restricted to 3089 households who reside in single-family detached dwellings so that the Dubin–McFadden thermal model could be applied. This engineering model was not designed to be used on multiple attached or detached dwellings nor was it designed for application to apartments or condominiums.

[9] Balance point temperatures also depend on thermostat settings as I discuss below.

[10] Design temperatures are regionally specific temperatures that represent design conditions, i.e., temperature extremes or ranges that are likely to occur all but 97 or 99% of the time. Engineers will typically determine heating and air-conditioning system capacities based on design conditions. In the present context, the likely heating or cooling system size affects the expected efficiency of the heating/cooling plant and thus the required energy to maintain a given indoor–outdoor temperature differential.

addition to this assumption, average values were given to households with missing data or non-response on this and other factors.[11] I explore the consequences of this imputation method for the determination of balance point temperature differentials in the next section. In order to determine the number of rooms in the residence, information on the number of heated rooms and the number of bathrooms was combined; heated rooms were top-coded above ten to ten.[12] After recoding missing data, there were, on average, approximately 6.96 heated rooms in the dwellings and 2.26 bathrooms. Mean values were assigned to houses with missing square footage using the continuously reported square footage variable, the categorical square footage when available, or alternatively statistical imputation.

An important factor missing from the RAS survey was the number of windows. Using a sample of homes from the American Society of Heating, Refrigerating, and Air-Conditioning Engineers (ASHRAE) Fundamentals (1982), a regression analysis was conducted for the number of windows and floors, square footage, and number of rooms.[13] This analysis revealed a high correlation (R^2 81%) for a simple regression where the number of floors and the home's square footage determine the number of windows. The result was then used to impute the number of windows for RAS respondents. Next, the observed information on percent of double-pane and stormed windows was used to calculate a percentage of stormed or double-paned windows. The combination of percentage and total number of windows was used to impute a value for the number of stormed and non-stormed windows. Because the thermal model requires a distribution of small, medium and large windows, all windows were assumed to be medium sized.

Summer design weather conditions and winter design weather were taken from ASHRAE (2005) for Washington State based on the closest weather station for each recorded county of residence. Finally, a winter thermostat setting of 70 °F and a summer thermostat setting of 75 °F were additional assumptions made. As discussed below, these values do not affect the balance point temperature differential. However, they do affect the predicted space and cooling heat load.

Finally, the sample was restricted to the 2875 households for which PSE could ascertain the monthly heating and cooling degree information for the period 2001 through 2003. This time period matches the period of time for which billing data was available. The conditional demand analysis (reported below) is consequently based on 103,500 observations (36 months for each of 2875 households). Summary statistics for the inputs to the thermal model are given in Table 2.

4. Thermal model analysis

The approach used in the Dubin–McFadden model was to construct an engineering thermal model that is simple enough to use with typical residential survey data. Such data is often much less complete than one would obtain using a detailed energy audit. For the reason mentioned above, the thermal model makes simplifying assumptions when some data is not available. The

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[11] I assumed 12 in. of ceiling insulation for homes with ceiling insulation. Because dwelling vintage or information about the date of insulation upgrade to determine the likely amount of attic insulation was not available, neither piece of information became part of the analysis. Instead, I used the presence of insulation whether it had been added to the dwelling either before or after the current resident had moved.

[12] The number of rooms in the dwelling (number of heated rooms plus number of bathrooms) is only used to determine heating system transmission losses related to the length of piping or ducting used in the heating system. It does not affect the balance system point temperature differential.

[13] I relied on seven typical dwellings following Dubin (1985) and based on the information provided in the ASHRAE Fundamentals (1982). I then used a larger sample of households based on the ASHRAE Fundamentals (2005) but the results for the imputation regression were very similar.

Table 2
Variables used in thermal model[a]

Variable	Description	Mean	Min	Max	Standard deviation
sodr	Summer outdoor daily range	21.20	14.40	31.30	4.29
sddb	Summer design dry bulb	84.53	72.10	95.40	4.67
w99t	Winter design dry bulb	25.03	10.70	28.40	4.28
nhsldmem	Number of household members	2.63	1.00	7.00	1.24
hinwall	Presence of wall insulation	0.75	0.00	1.00	0.43
insat1	Inches of attic insulation	9.94	0.00	12.00	4.52
nrooms	Number of room	9.23	2.00	16.00	2.40
floors	Number of floors	1.62	1.00	3.00	0.61
sfe	Square footage in dwelling	1884.00	252.00	8975.00	829.07
mwinds	Number of windows	16.40	9.00	35.00	4.86
nmwind	Number of storm windows	13.30	0.00	35.00	7.33
2875 Households RAS (2004)					

[a] Not shown are monthly normal and actual heating and coolong degree days.

model assumes operating characteristics of dwellings that are not coded in typical survey data. The model has been successfully applied in several contexts. For example, the thermal model was adapted in Dubin (1985) for analyzing the Pacific Northwest Survey administered under the Bonneville Power Administration. The Dubin–McFadden model also uses summary weather measures, such as temperature means and extremes or heating and cooling degree days measured as alternative base temperatures to fit empirical temperature distributions. These measures are then used to forecast loads.

The basic approach follows ASHRAE engineering principles and conceptualizes the residence as a box with walls of varying thermal resistances to heat conduction. One insight of the modeling analysis is that the temperature load relationship is non-linear. As outside temperature declines, the marginal energy load necessary to maintain an interior temperature is non-constant. This fundamental observation is due to air-infiltration. As the difference between indoor and outdoor temperatures increases, the rate of exchange of the air volume in the house due to infiltration also increases. Each air exchange brings unheated air into the dwelling that must be heated to maintain the indoor temperature. This mechanism creates a multiplicative effect where the energy required for maintaining a given indoor temperature increases as measured by the product of air infiltration and temperature differential. Because indoor and outdoor temperatures are proportional to temperature differential, a quadratic relationship exists between indoor and outdoor temperatures and temperature differential. The quadratic approximation that Dubin–McFadden derived was:

$$Q(t_\mathrm{o}) = w_0 + w_1 * (t_\mathrm{i} - t_\mathrm{o}) + w_2 * (t_\mathrm{i} - t_\mathrm{o})^2$$

where t_o is the outdoor temperature and t_i is the interior temperature. The constants, w_0, w_1, and w_2, are functions of the dwelling's thermal characteristics. They are dependent on the size of the dwelling and its insulation levels, among other factors. The formula provides an estimate of BTU's lost per hour due to the temperature differential.

The presence of sensible heat gain due to occupants and appliances causes the constant, w_0, to be negative in the above expression. Provided that w_0 is negative, there is a balance temperature, t_b. Heat is not required for temperature above this level. After all, the load function $Q(t_\mathrm{o})$ is quadratic in t_o, negative at the point t_i, zero at the point t_b, and decreasing in the range $[t_\mathrm{b}, t_\mathrm{i}]$.

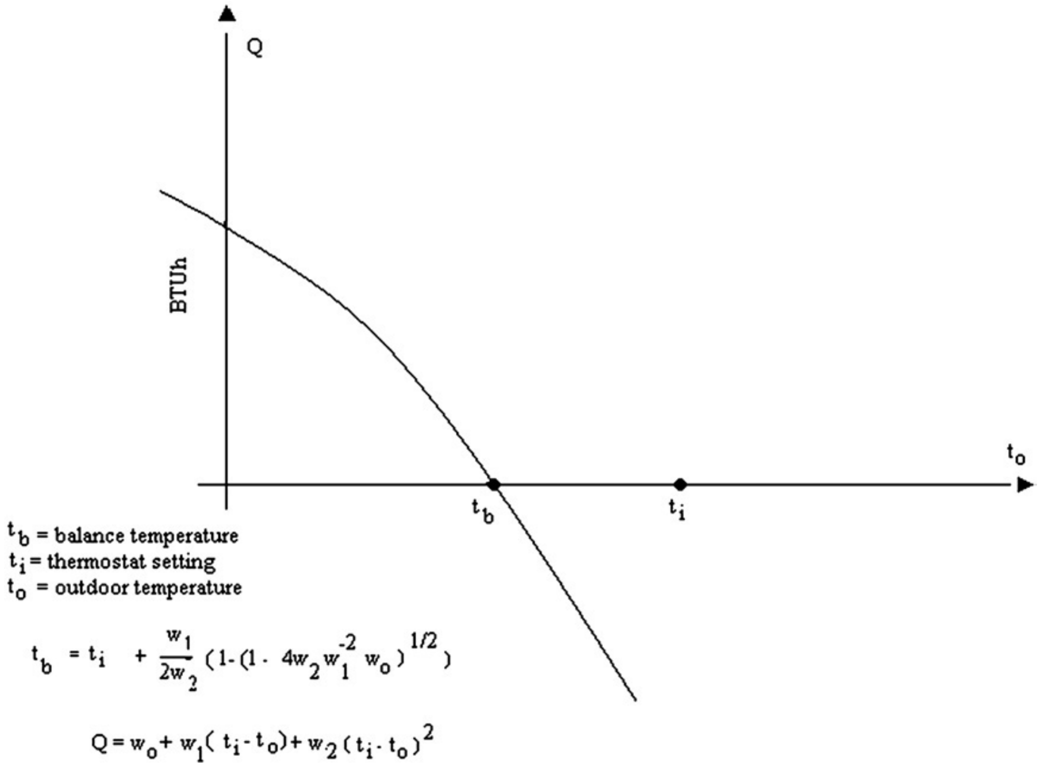

Fig. 5. Thermal load function.

Heating is not required until temperatures fall below the balance temperature, t_b. For further discussion see Dubin (1985, p. 52, Eq. (43)). The thermal load function is illustrated in Fig. 5.[14]

As described above, the inputs to the thermal load model consist of the design temperature information, monthly normal heating and cooling degree days, heating and cooling degree days by location of residence for the 3 years 2001–2003 on a monthly basis and the factors taken from the RAS survey described above.[15] The model processes data inputs for each of the 2875 households for every month from 2001 through 2003. The output from the model consists of an estimated balance point temperature differential (the difference between the estimated balance point temperature and the assumed indoor thermostat setting). The results also contain the estimated space heat energy loads for each of the 36 months, assuming that space heat is produced using the efficiency of an all electric space heating system.

To illustrate the methodology, detailed characteristics for two households from the survey are shown below.[16] They include the first and fifth households from the subset 2875 under analysis using the thermal model. Both households reside in King County, where the summer outdoor daily temperature range is 18.2 °F. The summer design dry bulb temperature is 84.9 °F, and the

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[14] Inspection of the formula for the balance point temperature differential shows that it is unchanged up to multiplicative scale changes in the thermal load function. Thus inaccuracies in the thermal load function, if present, do not affect the calculation of balance point temperature differentials reported below.

[15] Normal heating and cooling degree days pertain to averages for the most recent 30-year historical period and are used to determine typical load or to determine expected system performance. Actual monthly heating and cooling degree information on a monthly basis was also collected for the period 2001 though 2003.

[16] These households are selected to illustrate a range of dwelling sizes and are not meant to be representative of all households in the survey.

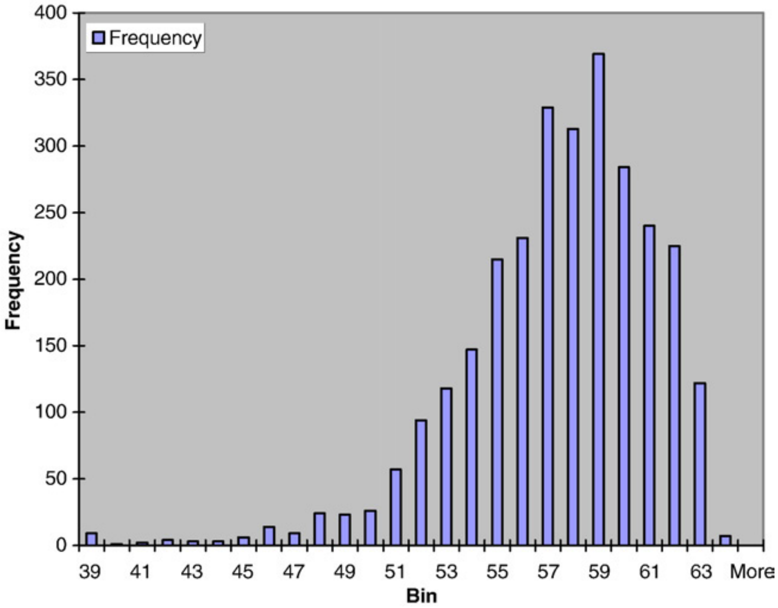

Fig. 6. Histogram of balance point temperature (assumes 65 °F thermostat setting).

winter design temperature is 28.4 °F.[17] Each household has two family members. Neither has wall insulation. Both households have stormed or double-paned windows. The first household has 8 heated rooms, 1 floor, 1290 ft^2, and 11 windows. The second household has 5 heated rooms, 2 floors, 322 ft^2, and 15 windows. The first house does not have attic insulation, while the second house does have attic insulation (assumed to be 12 in.). The thermal coefficients (w_0, w_1, and w_2) are estimated to be −3719.0, 682.4, and 1.291 for house number 1 and −3719.0, 312.3, and 0.329 for house number 5, respectively. The estimated balance temperature differentials are −5.39 and −11.76 °F for the households respectively.

The mean balance point temperature differential was −8.1 °F for all electric households. The weighted average value (extrapolating to the full sample) is −7.86 °F. The standard deviation of this differential was 3.8 °F. The data imputation described in the previous section has a minor consequence on the determination of the balance point differential. For instance, square footage was imputed in 311 households but the implied balance point differential for the 2564 households for which square footage was not imputed was −8.21.[18]

Balance point temperatures corresponding to different thermostat settings are easily derived. The mathematics show that the balance point estimate decline one degree for each one degree change in the thermostat setting. Hence, at a thermostat setting of 60 °F for the interior temperature, the balance point temperature would be roughly 52 °F. At a thermostat setting of 65 °F the balance point temperature would be 57 °F on average.

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[17] Design temperatures are from American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2005 Fundamentals, Chapter F28, Climatic Design Information. Design temperatures affect system design capacities but do not affect the estimated balance point temperature differential.

[18] Similarly, the number of household members was imputed in 155 cases but eliminating these households produces an estimated balance point temperature of −8.1. The number of heated rooms was imputed in 781 cases but eliminating these households leaves 2094 households for which the average balance point differential was −8.49. Finally, if one were to eliminate the households for which imputation was necessary in either square footage, number of household members, of heated rooms, the resulting sample of 1984 households has an implied temperature differential of −8.48. Further detail regarding the imputation procedures is available from the author upon request.

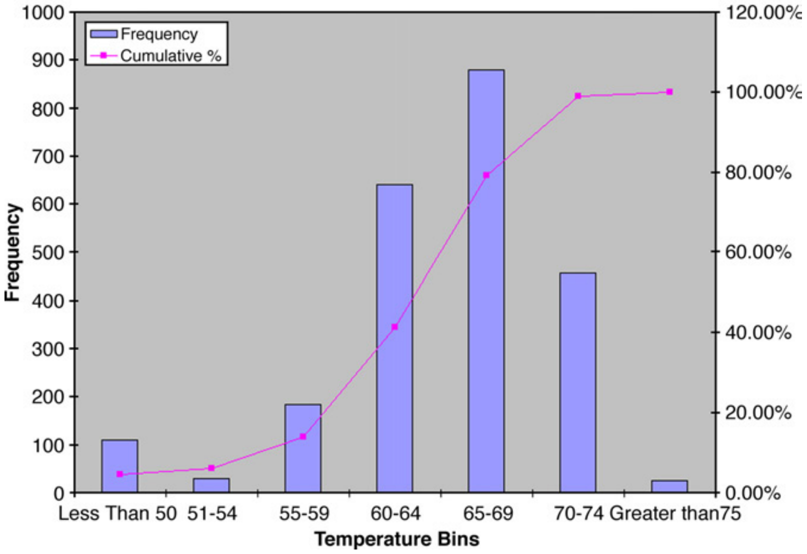

Fig. 7. Puget sound thermostat settings histogram.

Fig. 6 shows the histogram of balance point temperatures assuming a 65 °F thermostat setting. This distribution has a “fat tail” with many values below the average. Assuming that the thermostat is set at 65 °F (a 15 °F balance point temperature differential), about 5% of the sample has a balance point of 50 °F or less. However, analysis of thermostat settings on the PSE system reveals that many customers set their thermostat at levels lower than 65 °F. Monthly self-reported thermostat information is available by month for each month from April 2005 through March 2006. Analysis of survey data taken from roughly 400 PSE residential customers during the last 12 months reveals a seasonal pattern in average thermostat settings wherein lower thermostat levels are set during summer months.[19] The survey also collected thermostat settings for living and sleeping areas in the home and for three time periods: day, evening, and night. Clear variation in thermostat settings by time of day and somewhat less variation in the sleeping versus living area of the home were evident in the data. For instance, average evening thermostat settings were 64.9 °F in the sleeping area and 66.6 °F in the living area. By contrast, average nightly thermostat settings were closer to 63.3 °F. Over 40% of the sample had winter thermostat settings lower than 65 °F, while over 10% of the sample reported thermostat settings less than 55 °F.[20] Fig. 7 shows the histogram of thermostat settings.

As the RAS survey and the web thermostat surveys are independent and as thermostat settings and balance point temperature differentials may reasonably be assumed to be independent, there are a significant number of customers whose true balance point temperature is quite low.[21] In

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[19] PSE devotes a significant portion of its web page (www.pse.com) to energy efficiency. PSE customers can conduct a free energy self-audit through an online survey. This produces a report with specific and customized energy efficiency recommendations. The thermostat data was collected as part of the online survey process.

[20] These results are similar to those obtained from the EIA 2001 Residential Energy Consumption Survey (RECS). The public use micro data file: http://www.eia.doe.gov/emeu/recs/recs2001/publicuse2001.html contains 481 survey respondents in the Pacific region, which includes Washington State. I find that thermostat settings range from 45 to 80 °F with an average of 64 °F. Roughly 4% of respondents set their thermostats lower than 50 and roughly one-third set their thermostats lower than 60 °F.

[21] For instance, roughly 5% of customers have balance point temperature differentials of 15 °F or more, while roughly one third of customers set their thermostats under 60 °F. Thus, there are at least 1.5% of customers whose balance point temperature is 45 °F or lower.

these households, energy load for heating would not be triggered until the outdoor temperature becomes fairly cold. The relevant measure on a daily basis of such events is based on heating degree days for bases lower than 65 °F. A single measurement of heating degree days base 65 °F does not capture this information. Aggregate load–temperature analysis demonstrates that non-linearity between load and temperature is adequately captured using a measurement at base 45 °F in conjunction with a measurement of heating degree days at 65 °F. In the next section, I combine the estimated balance point temperatures for individual households with observed billing information to compare the heating degree day base 65 °F versus an engineering derived heating degree day measure.

5. Conditional load estimation and alternative measures of base temperature

I perform a conditional demand analysis to explain observed electric load on a monthly basis from appliance characteristics and weather information observed on a monthly basis for the period from 2001 through 2003. There are two steps in this procedure. First, I acquired additional data from the RAS survey on a full complement of individual household appliance and space heating characteristics. These characteristics include the presence of electric water heating, electric stove-top cooking, electric oven, and the number of various other appliances including refrigerators, freezers, televisions, and so on. These variables are used in a traditional conditional demand analysis where the monthly electric usage is explained by these explanatory factors. Socio-economic variables were limited but included observed cross-sectional variation for the 2875 households. Price of electricity variable was not included given the lack of either temporal or cross-sectional variation for this variable in the 3-year period 2001 through 2003. Each household presents 36 months of billing information yielding 103,500 observations for the conditional demand analysis.

I compare two measures of heating degree days as explanatory factors. The first is based on heating degree days base 65 °F measured at the Seattle-Tacoma airport. Using a single geographic location simplifies the data collection process and is unlikely to affect the results as aggregate analysis showed that weather sensitivity coefficients do not vary significantly by county.[22] The second measure of heating degree days uses a variable base temperature. For this variable I calculated a predicted base temperature for each household assuming that the thermostat setting was 65 °F and using the balance point temperature differential estimated from the thermal model. I then created five balance point temperature ranges (greater than 62.5 °F between 57.5 and 62.5 °F, between 50.0 and 57.5 °F, between 40.0 and 50.0 °F, and balance points less than 40 °F). For each of these ranges I assigned the heating degree measure using the base temperature at the mid-point of the corresponding interval. For instance, I used heating degree days base 55 for households with implied balance points between 50 and 60 °F. The groups were selected based on the alternative heating day measures reported by the NCDC. The estimated electricity conditional demand model is reported in Table 3 below.

The appliance explanatory variables are generally significant and correctly signed with plausible magnitudes in comparison to prior studies (see e.g. Dubin, 1985). The adjusted *R*-squared for this regression is roughly 20% and is not atypical for cross-sectional analyses with limited time dimension. Comparing the heating degree day measures, we see that each measure has similar statistical significance and while the *R*-squared of Model 2 (varying balance point

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[22] Similarly, Hyde and Hodnett (1997) used four weather stations for the entire country of Ireland but ultimately concluded that only one weather reading was required for temperature normalization.

Table 3
Conditioned demand analysis

Variable	Description	Model 1 Coefficient	Model 1 *t*-Statistic	Model 2 Coefficient	Model 2 *t*-Statistic
one	Constant	−65.41	−6.5	45.78	4.8
whfuel	Electric water heat fuel	222.83	42.8	222.92	42.9
ckrntyp	Electric stove-top	1.79	0.3	7.27	1.1
ckovtyp	Electric oven	82.78	12.4	76.98	11.5
drytyp	Electric dryer	62.86	11.0	62.44	10.9
sphtf	Electric hot tub	179.86	29.5	177.43	29.1
pltyp	Electric heated pool	360.07	14.1	367.19	14.3
dishwn	Num dishwasher	26.21	4.3	25.99	4.3
micowvn	Num microwave oven	27.16	3.9	15.98	2.3
refrn	Num refrigerator	59.75	12.8	59.98	12.8
freezern	Num freezers	126.25	34.5	127.89	35.0
hwdispn	Num hot water dispenser	59.71	9.6	51.26	8.2
roomacn	Num room air conditioner	84.57	11.2	79.00	10.5
elblnktn	Num electric blankets	−6.91	−1.8	−7.10	−1.8
tvn	Num televisions	32.16	15.6	29.73	14.4
vcrdvdn	Num VCR or DVD players	−0.29	−0.1	0.50	0.2
pcn	Num personal computers	26.78	9.6	26.95	9.6
offeqpn	Num of Office equipment	39.77	12.8	36.33	11.7
stereon	Num home stereos	13.89	4.3	14.98	4.7
homeoffc	Home office at residence	34.82	5.3	34.62	5.2
prihtsys	Electric primary heat	333.47	58.0	337.30	58.7
income	Annual income	0.00	8.7	0.00	8.5
hdd[a]	Heating degree days	0.72	85.5	0.89	86.5

Dependent variable is monthly kWh for each customer. There are 103,500 observations in the regression analysis.

[a] HDD is based on 65 °F in Model 1 and is based on engineering derived varying balance point temperature in Model 2.

model) exceeds that for Model 1 (constant base 65 balance point measure), the explanatory power is similar. More importantly, the weather sensitivity coefficient rises from 0.72 (monthly kWh per degree day) to 0.89 as we move from Model 1 to Model 2. This difference is statistically significant (*t*-statistic = 16.6) and implies greater weather sensitivity than would be estimated using the constant degree day formulation. These results parallel the findings using an aggregate (system-wide) regression with daily data. In practice this difference would, for instance, imply greater weather normalization. If electric rates are set based on normalized weather, this adjustment helps keep rates from being set too high and thus benefits residential electric customers.

6. Conclusions

The engineering thermal modeling approach to electric loads in the PSE service territory shows that balance point temperatures may be as low as 45 to 50 °F for some households. This finding demonstrates that base temperatures of 65 °F used in weather normalization regression models are not likely to capture the load temperature relationship for a significant number of dwellings. Regression techniques using MARS splines or other non-parametric methods exploring curvature in the load–temperature relationship should rely on multiple base temperature measures of degree days. The Dubin–McFadden engineering thermal model shows considerable promise in forecasting space heating load. Applied to the RAS data, the model yields practical implications and demonstrates that the energy load on the PSE system is not best measured using heating degree days base 65 °F. Balance point temperatures are significantly lower than comfort levels for a significant fraction of the PSE customer class. Thermal load analysis is particularly useful in micro econometric energy demand studies because balance point information may be imputed for individual households. As utilities collect and begin to analyze automatic metering data, the engineering–econometric approach should be considered a viable alternative to purely statistical methods. Importantly, unlike a non-parametric method, the structural engineering–econometric approach permits detailed policy simulations for proposed changes in insulation levels or other changes that potentially affect balance point temperature differentials. Meanwhile, the approach presented in this paper yields more accurate weather normalized rates that should benefit residential electric customers.

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