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# END-USE LOAD AND CONSUMER ASSESSMENT PROGRAM:

# THERMOSTAT RELATED BEHAVIOR AND INTERNAL TEMPERATURES BASED ON MEASURED DATA IN RESIDENCES

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# **SUMMARY**

The Bonneville Power Administration (Bonneville) began the Fnd-Use Load and Consumer Assessment Program (ELCAP) in 1983. Prior to beginning ELCAP, there was an abundance of information regarding total power consumption for residential structures in the Pacific Northwest (such as that found on billing records) and limited information regarding power consumption by various end uses (such as hot water, heating, and cooling). The purpose of ELCAP is to collect actual end-use load data from both residential and commercial buildings in the region.

ELCAP has recorded hourly internal temperature data along with energy end-use data for over 400 single-family, electrically heated homes in the Northwest. This database allows determination of actual temperatures and temperature patterns and, therefore, a better understanding of occupant behavior related to thermostat control. The internal temperature maintained by the occupant is of major importance because of the impact on residential heating loads, which account for 10% of all Northwest electrical energy consumption (Northwest Power Planning Council 1986).

This paper examines the internal temperature of residences in two regards. First, the aggregate average temperatures and temperature profiles are presented, with an emphasis placed on the heating season. Second, the thermostat control behavior implied by the temperatures is examined. For this second stage, an hourly pattern recognition algorithm which detects significant temperature changes (i.e., setbacks, setups) was developed. This algorithm allowed each residential site to be classified based on its thermostat control behavior

The key findings in this report are as follows:

- The average winter temperature is  $20.2^{\circ}$ C (68.4°F) in the Northwest. Temperatures are significantly lower in the nighttime during the , winter period.
- There is strong evidence that residents keep different parts of their homes at different temperatures. Bedrooms appear to be about  $2^{\circ}$ C (3.8°F) colder than the main living space, basements about 6°C

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 $(10.8^{\circ}F)$  colder. This observation should be further investigated, but could have significant impact on assessments of conservation impacts. All other key findings are for temperatures in main living spaces.

Clock thermostats do not significantly increase the incidence of thermostat setback behavior. They do make the behavior more regular. Residences with clock thermostats do have lower average temperatures; however, they averaged only about  $1/2^{\circ}C$  (39.2°F) less than those with manual thermostats. The conservation impact of clock thermostats will be significantly overestimated if the occupants' behavior is presumed to change from not setting back to setting back, with the installation of a clock thermostat.

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- Reported thermostat set points collected from a written survey are generally inaccurate. Reported nighttime setback temperatures are often much lower than the minimum temperatures actually achieved.
- Although there is a wide range of behavior, starts of thermostat setbacks are most common at 10 p.m. Starts of thermostat setups are most common at 6 a.m. The average setback is about  $4^{\circ}$ C (39.2°F).
- Behavior relating to thermostat control can often be seemingly erratic and may not conform to simplified assumptions. The thermostat control behavior of individual occupants varies significantly from day-to-day.
- The constant daily temperature pattern (no significant temperature change during the day) is the mostcommon pattern for ail heating season data and occurs about 40% of all days with heating. Night setbacks and morning setups are the second most common pattern.
- During the winter, daily thermostat setback and setup occurs about one-half of all days for residences in the aggregate.
- Occupants of residences are not easily categorized in terms of setback behavior but, instead, display a fairly constant distribution, from residences never setting back to always setting back thermostats. Actual thermostat set points vary over a considerable range from residence to residence. Because of the variation in behavior, both within and across residences, the measured temperature data are dissimilar to common assumptions about internal temperature patterns used in simulations.
- The daily temperature pattern analyses suggests three reasonable approaches varying in complexity for heating season temperature schedules in simulations.
	- 1. If a constant temperature is needed, 20°C (68°F) is recommended.

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- $2.$  IT the model allows a setback, a daytime temperature of  $20.5^{\circ}$ C (69°F) and a setbackto 19**°**C (66**°**F)from 10 p.m. to 6 a.m. is\_ recommended.
- 3. Take the average of a simulation with a constant  $20.5^{\circ}$ C (69°F) set point, and a simulation with a daytime temperature of  $20.5^{\circ}$ C (69**°**F) and a setbackto 160C (61°F)from 10 p.m. to 6 a.m.

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# **CONTENTS**



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# FIGURES



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# TABLES



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# 1.0 INTRODUCTI**O**N

Building interior temperature is one of the major driving forces of energy use. Steady'stateheat transferfor a buildingis a functionof the temperature difference between inside and outside air, along with the conductance of the building shell. Changes of only a few degrees in interior temperatures can significantly affect energy use in buildings. This report examines the internal temperatures collected from a large set of residences in the Pacific Northwest for the Bonneville Power Administration (Bonneville) by Pacific Northwest Laboratory (PNL)<sup>(a)</sup>.

While measurements of outdoor temperatures for metropolitan areas are commonly available, measurements of indoor temperature in a substantial number of residential (or commercial) buildings are generally not available. However, three large programs sponsored by Bonneville now provide a large dataset. The Residential Standards Demonstration Program (RSDP) (Drost et al. 1986) measured the interior temperatures of about 800 buildings at approximate weekly intervals. About 300 homes were end-use metered and data were collected at 15-min intervals in the Hood River Conservation Project (HRCP) (Dinan and Trumble 1989) in Hood River, Oregon. The End-Use Load and Consumer Assessment Program (ELCAP) measured interior temperatures in about 400 buildings, includinga subset of the RSDP buildings. The data analyzedin this report are principally data collected from the ELCAP project.

An important potential application of internal temperature data is in the use of building energy simulations, which are often used to project the consequences of proposed energy conservation measures. Accurate thermostat set points and/or schedules are needed in simulation models to obtain reasonable estimates of energy usage. Whether intended or not, the simulation models, either explicitly or implicitly, include a model of building occupant behavior. Simpler simulations often presume a constant thermostat set point (although not explicitly stated). More complex simulations assume interior

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temperature set points, which often include temperature setbacks. Because information on thermostat behavior is not generally available, the choices for these simulations are usually based on limited data from estimates especially where the definition of thermostat setback timing is concerned. Measured temperaturedata allowsdata supporteddefinitionsof typical thermostat schedules for interior temperatures. Several standard sets of thermostat schedule assumptions are suggested in Section 3.0.

Thermostat schedules are commonly assumed to be very simple and straightforward. However, the experience gained from the ELCAP project has highlighted the importance of the occupants, Occupants and their behavior are major determinates of energy use in buildings. As has been demonstrated by the ELCAP data, there is a major variation in the range of behavior seen for individual building occupants.

This report is divided into two parts. Section 2.0 explores the measured internal temperatures in residences, and Section 3.0 examines the thermostat control behavior that, in large part, determines the measured internal temperatures. Section 2.0 presents aggregate internal temperatures, including mean and mean diurnal temperature profiles. Section 3.0 explores the thermostat control behavior, which is deduced from a site-by-site, hourly analysis of the heating season temperature data. Recommended thermostat schedules for use in simulations are a product of the behavior analysis.

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# 2.0 INTERIOR TEMPERATURES

The ELCAP project has collected data for energy end uses, internal temperature, and meteorological variables from a large number of homes over , several heating seasons. A monitoring device, referred to as a logger, has been installed in each of the houses **W**ith data sent via telephone line to a computer at PNL. Data are collected and\_averaged to an hourly value. As part of this data collection, each ELCAP Base Sample house has one temperature sensor installed, with the RSDP sample homes having either two or three sensors. Each site has had a limited visual inspection of a few days worth of temperature data as a reasonableness check, and an automated range check of all data.

The data used in this report were collected within the period of August 1984 through June 1988. The data were collected from temperature sensors located in the main conditioned living area of each house. Temperature sensors are typically located in the living room but, depending on the configuration of the residence, can be in any of a number of rooms such as the dining room, kitchen, or hallway. The installers who put in the temperature sensors were instructed to put the sensors away from any major heat source.

The ELCAP Base Sample was chosen to represent a cross-section of singlefamily, detached, electrically heated residences in the Pacific Nouthwest. For this reason, the analysis used only the ELCAP Base Sample with one exception: the analysis of variations in temperatures within the house by room or zone. The RSDP sample was used because it had multiple temperature measurements for each home.

Depending on a number of factors, each ELCAPsite has a different amou**r**,t of data including when the metering was started. The required amount of data for inclusion in this study varied depending on the aggregation level in question, such as the monthly, yearly, or hourly profile. Typically, a minimum of 904 of the period is required to meet metering qualifications for the analysis. For example, the annual temperature averages for each site required a minimum of 904 of a year. Each of the graphics in this report contains the number of sites used in the caption below the figure.

There is a significant use of wood stoves for space heating in the Pacific Northwest. Sites with monitored wood stoves (LeBaron 1988) that are known  $\frac{1}{100}$  to have had significant wood stove use wene left out of the analysis. The to have had significant wood-stove use were left out of the analysis. The primary reason for eliminating sites using wood stoves is that the internal wood stove temperature is not easily controlled when the wood stove is in use and, therefore, may not reflect the desires of the occupants. As woou stoves are not governed by a thermostat, they may overheat the room in which they are located. Furthermore, wood stoves rely on natural convection to distribute heat, which is not as effective as the distribution of most heating, ventilating, and air conditioning (HVAC) systems and, therefore, may not be effective in heating many rooms in the house. Because of the difficulties and uniqueness of sites with wood-stove use, all monitored wood-stove sites that averaged more than 20 hours of use a month on a year-round basis were removed. This decreased the sample size from 289 to 206, or a total of about 400 site-years worth of data.

# 2.1 AVERAGE INTERIOR TEMPERATURES AND 24-HOUR PROFILES

Average interior temperatures are shown in Table 2.1 for annual, winter, and summer periods. Winter, or the heating season, is defined as November through March. Winter is presumed to be the range of months when most of the ELCAP-monitored homes are usually in the heating mode. Summer is defined as June through August. These averaged temperatures show a clear difference of about 3.2°C (5.8°F) between summer and winter periods.

The ELCAP-average winter temperatures were lower than HRCP-monitored temperatures (Dinan and Trumble 1989). For both the pre- and post-retrofit stages of HRCP, the temperatures averaged roughly 22 $^{\circ}$ C (71.6 $^{\circ}$ F) for November through February. For homes with electricityas the sole heating fuel, the

# TABLE 2.1. Average Interior Temperatures



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HRCP-averaged temperatures were lower, about 20.5**°**C (7**0**.5°F), but were above the ELCAP temperatures. It should be noted that the HRCP residences were not selected to represent the region, they were a sample selected from a large weatherization program primarily in one city (Hood River, Oregon).

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Figure 2,1 displays the monthly temperature distributions for ELCAPBase sites. The middle line of each box represent the median and the top and bottom of each box represents the upper and lower quartiles. The median . temperatures start at 20.3**°**C (68.5°F) in January, increase steadily to a peak in August, and drop off sharply in September and October. Ranges for the monthly temperatures from the upper to lower quartile, or the middle 50% of sites, are about 2°C to 3**°**C (3.6**°**F to 5.4**0**F). The range of the extreme high and low average temperatures by site vary significantly, about IO**°**C to 20**°**C (18**°**F to 36**°**F). This figure demonstrates the variation present in real data; in this case, a wide range of actual temperatures across sites. Note that in a sample of 148 residences, as displayed in Figure 2.1, there is a high likelihood that some of the outlying points may be caused by vacancies (with little or no heating or cooling) during the months.



FIGURE 2.1 Monthly Temperature Distributions of 148 ELCAP Sites

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Histograms of average winter and summer temperatures by site are displayed in Figures 2.2 and 2.3. The height of each bar represents the number of sites having average temperatures in the range specified on the horizontal line. In Figure 2.2 most winter average temperatures fall in the range of 18°C to 23°C (64.4°F to 73.4°F). As seen in Figure 2.3, summer temperatures are typically in the range of  $21^{\circ}$ C to  $26^{\circ}$ C (70°F to 78.8°F). These figures indicate that for both heating and cooling, the common range of average temperatures across sites appears to be about  $5^{\circ}C$  (9°F), though some sites fall beyond this range.

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Figure 2.4 displays the average daily profiles for 4 months of the year along with the yearly average profile. January, April, July, and October represent the four seasons. Temperatures for other months will fall between the extremes seen here. January is coldestwith the 2 swing months; April and October are very similar in temperature; and July is far warmer than the other months. The maximum daily temperature occurs at 8 p.m. for all months. The mirimum daily temperature is at 6 a.m. for all months except July, which has a low at 7 a.m. To allow the calculation of temperatures for any daily time period, the temperature data in Figure 2.4 for the annual, January, and July periods are reproduced in Table 2.2.



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Selected Monthly Temperature Profiles ( $n = 142$ ) FIGURE 2.4.

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				Average Temperature in °C (°F)			
	Hour of Day	Annual		<u>January</u>		July	
	1 a.m.		21.5(70.6)		19.9(67.9)		23.7(74.6)
	2 a.m.		21.1(70.1)		19.6(67.3)		23.4(74.1)
	3 a.m.		20.8(69.5)		19.4(66.9)	23.0	(73.5)
	4 a.m.		20.6(69.0)		19.2(66.5)	22.7	(72.9)
	5 a.m.		20.3(68.6)		18.9(66.1)		22.4(72.3)
	6 a.m.		20.1(68.2)		18.9(66.0)		22.1(71.7)
	7 a.m.		20.1(68.2)		19.1(66.4)		21.9(71.3)
	8 a.m.		20.3(68.5)		19.4(66.9)		21.9(71.4)
	9 a.m.		20.5(68.9)		19.6(67.3)		22.0(71.6)
	10 a.m.		20.7(69.2)		19.8(67.6)		22.2(71.9)
	11 a.m.		20.9(69.6)		20.0(68.0)		22.4(72.4)
Noon			21.1(70.0)		20.1(68.2)		22.7(72.9)
	$1$ p.m.		21.3(70.3)		20.2(68.4)		22.9(73.3)
	2 p.m.		21.5(70.7)		20.4(68.6)		23.3(74.0)
	3 p.m.		21.7(71.1)		20.4(68.7)		23.7(74.6)
	4 p.m.		22.0(71.5)		20.5(68.9)		24.0(75.3)
	5 p.m.		[22.1 (71.8)]		20.5(68.9)		24.3(75.8)
	6 p.m.		22.3(72.1)		20.6(69.1)		24.6(76.3)
	$7$ p.m.		22.4(72.4)		20.8(69.4)		24.8(76.6)
	8 p.m.		22.5(72.5)		20.9(69.6)		24.9(76.7)
	9 p.m.		22.4(72.3)		20.8(69.5)		24.6(76.3)
	10 p.m.		22.3(72.1)		20.8(69.5)		24.4 (75.9)
	11 p.m.		22.1(71.7)		20.6(69.1)		24.2(75.5)
	Midnight		21.8(71.2)		20.2(68.4)		23.9(75.0)

TABLE 2.2. Seasonal Temperature Profiles

To allow a direct comparison of the profile shapes, the curves have been replotted in Figure 2.5 with the mean temperature for each profile adjusted to O. The January profile is flatter than the other profiles, and the July

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# FIGURE 2.5. Selected Monthly Temperature Profiles (n = 144)

profile has the widest daily range. The flatness of the January temperature may indicate that temperatures typically do not rise above (or sink below) the heating set points. The aggregate daily profiles can be seen to be constantly changing from hour to hour, rather than changing in distinct steps.

#### TEMPERATURE VARIATION BY HVAC TYPE  $2.2$

The relation of internal temperature in the main living space to the type of heating equipment was examined. Figure 2.6 displays the average winter daily profiles for houses with five types of primary heating equipment. Sites with radiant heat, having a mean winter temperature of about 21.7°C (71°F), were seen to be higher in temperature than the other HVAC types. The average temperatures of radiant heat sites were statistically higher in temperature than both central electric furnace and heat pump sites, which were an average of about 19.4°C (67°F). No other statistically significant differences (at the level of 5% or higher) occurred between any other combination of HVAC



FIGURE 2.6. Winter 'emperature Profiles by HVAC Type

types, including baseboard heaters and wood stove. It is not clear why the radiant sites are so much warmer than the other HVAC types, or even if the difference is attributable to the occupant behavior. The radiated heat may be striking the shielded temperature sensor and warming it above the actual temperature of the room air. However, if that is the case, the radiated heat should also be striking the thermostat, causing it to react the same as the shielded temperature sensor, as they are very similar to one another.

Figure 2.7 displays the profiles normalized so the daily shapes can be compared. All profiles for sites with fuel or equipment types other than wood stoves are similar. The sites with wood stoves as the primary heating source tend to be much warmer from midnight to 7 a.m. and cooler during the day. This supports the reasoning presented in Section 2.0 for leaving wood-stove sites out of the general analysis.



# FIGURE 2.7. Winter Temperature Profiles by HVAC Type

#### TEMPERATURE VARIATION BY THERMOSTAT TYPE  $2.3$

Sites with clock thermostats were studied. These thermostats allow the occupant to automatically set a daily thermostat schedule. Twenty-five of the 206 ELCAP sites studied had clock thermostats. The average temperatures for winter data for sites with clock thermostats were lower than sites without clock thermostats, but this was not a statistically significant difference. However, Figure 2.8 displays a clear trend in the winter profiles for clock thermostat sites versus sites without clock thermostats. The clock thermostat sites were often a degree or more lower than the manual thermostat sites for each hour of the day except for the period of 7 a.m. to 11 a.m.

Figure 2.9 illustrates the normalized temperature profiles for the clock and manual thermostat sites. The profiles indicate that occupants in the clock thermostat sites tend to set the thermostat lower during the night. The rapid temperature rise in the morning for clock thermostat sites shows that these occupants use the clock schedule to set the thermostat in the morning, and









establish a daytime temperature at about the average for manual thermostat sites. The clock thermostats can be utilized to set the temperature before the occupantswake up, thereforewarming the house by the desired time. The behavior of the clock thermostat sites compared to the manual thermostat sites is examined in Section 3.5.

# 2.4 TEMPERATURE VARIATION BY DEMOGRAPHICS

A brief examination of the internal temperature of the sites has been done on various subsets of demographic variables. The variables are climate zones (degree day based), number of occupants, income level, utility type (public or private), house size, and vintage of house. No statistically significant differences, or even visible trends, were seen in any of these demographics. This displays evidence that temperature cannot be correlated with commonly used demographics. This conclusion is supported by the findings of other studies, summarizedin Vine (19B6),which did not show consistent relationships between temperature settings and income, house size, or house age.

### 2.5 TEMPERATURE VARIATION BY ROOM

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The temperatures from room to room in a house may vary, either by occupants choice, from internal or solar gains, or as a result of the HVAC distribution system. The occupant may intentionally maintain a temperature difference by closing ducts and doors, or by turning off baseboard heat (referred to as zoning). Internal gains caused by factors such as stoves, lighting, and people may heat rooms above the temperatures of other rooms. The same is true for solar gains through windows. Finally, the ducting system may not evenly distribute heat to all rooms, causing temperature differences.

i lighting,and people may heat rooms above the temperaturesof other rooms. A comparison of temperatures in the different areas (or zones) in houses has been done. Data for this zoning analysis were taken from the RSDP study, which include control homes built to current practice, and Model Conservation Standard (MCS) homes built to high conservation levels. Only the RSDP homes were monitored with multiple temperature sensors, which allows the study of zoning. A box plot containing the distribution of winter temperatures for

living spaces<sup>(a)</sup>, bedrooms, and basements is illustrated in Figure 2.10. There is a statistically significant difference in temperatures between each of the three room types. Comparison of individual rooms in the living spaces did not produce statistically significant differences. Each site used on this plot has a monitored temperature for the living spaces and bedroom zones. About one-half of the sites have baseboard heat, one-quarter use central forced air, and one-eighth have heat pumps. The RSDP data indicates the possible use of zoning, with bedrooms and basements being maintained at lower temperatures. Inspection of nighttime data shows the temperature difference between bedrooms and main living space decreases (i.e., the temperature reduction from day to night is less for bedrooms than it is for the living space). This indicates that temperature control varies both by zone and by time-of-day within zones.





Living spaces is defined as the combination of living rooms, dining  $(a)$ rooms, hallways, family rooms, and general living areas.

# 2.6 ACCURACY OF TEMPERATURE SET POINTS FROM SURVEY DATA

Survey data with occupant-reported thermostat settings is more common and easily obtained than measured temperature data. The ELCAP-measured temperature data has been supplemented by resident surveys, thereby allowing an assessment to be made of how accurately occupants tend to report their thermostat settings. Two previous studies by Kempton and Krabacher (1987) and Gladhart, Weihl, and Krabacher (1988) indicated that the reported settings were typically one to three degrees lower than the true settings, although the number of sites in each study were low ( $n = 7$  and  $n = 10$ , respectively).

The accuracy of survey results was tested by comparing the ELCAP-measured temperature data to the occupant-reported temperature settings from the ELCAP 1987 residential survey. This written survey asked for the approximate thermostat settings of the main living area during waking and sleeping hours. In comparing the metered measured data to the written survey, the waking hours were averaged between 9 a.m. and  $10$  p.m. To obtain the lowest temperature for setback sites, the 5-a.m. period was selected. Figure 2.11 displays the real versus perceived set points for the waking hours or daytime hours. Figure 2.12 displays the real versus perceived set points for the sleeping hours or nighttime hours. The diagonal lines represent agreement between the reported and average measured temperatures.

Visual inspection shows that the occupants were poor predictors of their internal temperatures. Note that measured temperatures may have varied slightly from the actual thermostat settings because of the location and sensitivity of the thermostat. The nighttime estimates appeared to have an upward trend to match the sorted real data but were clearly lower than the real data. The trend of reported nighttime temperatures that are lower than those actually achieved may be partly because of temperatures not decaying quickly enough to reach the nighttime setback temperature. Out of the 18 sites with reported nighttime temperatures of 15°C (59°F) or less, none actually achieve the reported temperature.

The R<sup>2</sup> statistic for the daytime prediction of temperature by occupant was 0.06, indicating very little correlation. The R<sup>2</sup> for the nighttime period was 0.19, which was also a low correlation. The mean estimate for daytime

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temperatures was 20.9°C (69.6°F), an overprediction of the true average by only 0.2°C (0.4°F). The occupants predictions were close to the actual data. For the nighttime period, the mean-estimated temperature was 17.3°C (63.1°F), which was 1.9**°**C (3.4**°**F)below the actualmean temperaturesat 5 a.m. Even in the aggregate, reported nighttime thermostat setback temperatures were low.

The results display evidence that survey information on thermostat setting is inaccurate, though the overall average for the large group ( $n = 149$ ) is close to the real average in the daytime. Reported winter daytime temperatures from a United States Department of Energy (DOE) national survey (DOE 1987), support the finding that on an average, reported temperatures are fairly accurate. Survey data of residences with electrical heating in the west census zone with 4000 heating-degree days or more (generally the Pacific Northwest and rocky mountain states) gives an average reported temperature of 20.7°C (69.3°F). This compares to the averagewinter temperature20.2**°**C (68.4**°**F) for the ELCAP Base Sample.

# 3.0 THERMOSTAT CONTROL BEHAVIOR AT INDIVIDUAL SITES

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This section infers thermostat control behavior from the temperature data. To extract the apparent thermostat control behavior, the data was examined on a site-by-site, day-by-day basis. An hourly pattern recognition algorithm was developed specifically for this purpose. Each day was classified for each site according to the apparent thermostat control pattern. Each site's aggregate behavior was then categorized by its predominant daily patterns.

The hourly pattern recognition and classification algorithm included a number of steps, which are documented in detail in the Appendix. During the initial step, all hours where temperatures were either rising or falling were identified, based on a temperature change above or below the threshold value. If the change over the period examined around each hour was greater than the threshold, the hour was classified as changing either up or down. Temperature changes for several periods, up to 8 hours around every hour, were checked. The longer periods were needed to identify the slower, more gradual changes (see Appendix). The threshold values for significant temperature changes were chosen by visual inspection of results and were intended to catch meaningful temperature fluctuations. Results for all data indicate that 99% of the periods that were classified as changing had temperature changes greater than 1.7°C (3**°**F) and 874 had changes greater than 2.2°C (4°F).

Daily patterns at each site were classified as combinations of up, down, and/or even periods; this clearly allows for a large number of potential daily patterns. To summarize the results in a logical and simple method, each day has been split into three periods: 7 p.m. to 3 a.m. (night), 4 a.m. to 11 a.m. (morning), and 12 a.m. to 6 p.m. (afternoon). The beginning and end of the day has been defined at 7 p.m. The boundaries for the parts of the day were chosen as times of day when the least setback or setup activity occurred. . In other words, the day was divided to place times with high thermostat activity (e.g., evening setbacks) squarely within one of the three defined periods.

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Figures A.1 and A.2 (see Appendix) illustrate examples of the typical fluctuationsin measured heating season temperaturedata. Note that the temperature data variation seen in Figure A.2 is more common than that found in Figure A.1. The erratic nature of the real temperature data is worth noting; it greatly complicated the problem of accurate classification.

# 3.1 TIMING OF THERMOSTAT CHANGES

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To classify behavior, the timing of thermostat changes must be inferred from the temperature data. The time at which temperature changes start is of particular interest as this indicates thermostat setting changes. The setup start is defined as the beginning of a temperature rise period (see Appendix). The setback start is defined in a likewise manner. In reality, these temperature-change starts may not become apparent until sufficient time has passed since the occupant has changed the thermostat temperature. This is particularly true for temperature setbacks.

The start of both setbacks and setups was identified by time-of-day across all sites. Figure 3.1 displays the frequency with which setbacks have started during each hour of the day for all sites combined. Each bar



# FIGURE 3.1. Setback Starts  $(n = 145)$

represents the fraction of setbacks that start during that hour relative to all hours combined. Note that the temperature for each hour is the average of the preceding 60 min; for example, 1 a.m. is the average temperature from midnight to 1 a.m. Setbacks may not become evident immediately after the thermostat is lowered; the hour identified as the setback start could actually be the hour after the thermostat changes. The large majority of the setback starts are between 7 p.m. and 1 a.m., peaking in the 10 p.m. to 11 p.m. hour. The actual time when thermostat setbacks peak is estimated to be 10 p.m., this accounts for the delay between the time when the setback is made and when the temperature change becomes apparent. This is also likely to be the • time when occupantsare guing to bed. There is a small peak in set**b**acks between 8 a.m. and 9 a.m. in the mornings. This is probably because of setbacks occurring as occupants leave for work at around 8 a.m.

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Figure 3.2 displays the starting hour for setups across all sites. Each bar represents the fraction of setups that begin during that hour relative to all hours combined. The starts of the setups are much more bimodal than the



FIGURE 3.2. Setup Starts (n = 145)

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starts of the setbacks, The greatest numb**e**rof setup starts occur in the morning, peaking betweeen 6 a.m. and 7 a.m.. These can primarily be attributed to setups in response to nighttime setbacks. A second group of setups occur in the late afternoon, peaking between 4 p.m. and 5 p.m., or the time many occupants will be returning from work. Many of these afternoon setups can be coupled directly to nighttime setbacks with the occupants forgoing raising the thermostat in the morning.

Figure 3.3 displays the fraction of all combined setbacks and setups that start during each hour. The combined totals give justification to the choices of using 3 a.m., 12 a.m., and 7 p.m. for dividing the day into three parts (night, morning, and afternoon). These are clearly the periods of lowest thermostat activity.





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# 3.2 CLASSIFICATION OF THERMOSTAT BEHAVIOR BY DAILY STRATEGY

Each day having 3 or more hours of heating for all sites has been classified into a specific pattern based on the number of setups and setbacks that start in each of the three periods. Recall that the start of a period indicates the time-of-day which the temperature first changes. There was a total of 87 daily patterns observed in the ELCAP data. A large majority of the data fall into only a few unique patterns. The less common patterns tend . to be more complex, such as multiples and uneven numbers of ups and downs. (Isolated, single changes in the temperature without corresponding subsequent changes in the opposite direction will be referred to as ups and downs.) The possibility of two ups or two downs within one of the three daily periods was accounted for but rarely observed.

Figure 3.4 displays the number of occurrences of the 10 most common daily patterns. These 10 patterns account for 91% of all days with 3 or more hours of heating. Table 3.1 describes each of these 10 patterns, listed in order of descending frequency.





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TABLE 3.1. The 10 Most Common Daily Patterns (in Descending Frequency)



Constant days are by far the most common pattern, with the night setback morning setup pattern about half as common. Constant days are days where the temperature does not vary by enough magnitude in a short enough time to be flagged as having a period of up or down (see Appendix).

The next two most common patterns are night downs and morning ups. These will be referred to as single patterns because there is no associated up-todown or down-to-up pattern. Single patterns are quite common and can be attributed to a number of causes, both from the limitations of the classification algorithm and from occupant behavior.

For all temperature changes, either up or down, there must eventually be a change in the opposite direction, to keep the temperature in the occupantestablished comfort range. However, a temperature change in one direction may be large enough to be flagged as an up or down, but a temperature change in the opposite direction may not be substantial enough to be flagged.

Inspection of the average magnitudes of all the temperature changes reveals that the single changes are generally smaller than other daily patterns. Table 3.2 displays the average temperature change during the peric<sup>4</sup>s classified as up and down. The average change is about  $4^{\circ}$ C (7.2 $^{\circ}$ F). The classic night setback, morning setup has an average change of about 0.4°C (O.7°F) more than the overall mean, indicating this pattern has more depth. The daily patterns with single ups and downs have an average change of 0.6°C (1.1°F) less than the overall mean. This indicates that the single changes are less substantial, sometimes barely sizeable enough to be flagged.

. The average temperature change down is greater in magnitude than the average temperature change up. However, there were 10% more temperature changes defined as ups than downs. The higher frequency of temperature rises can be attributed to the driving factors for the ups and downs which affect the rate of temperature change. The duration of the ups is principal**l**y dependent on the capacity of the heating equipment and the size of the building. The duration of the downs is influenced by the inside-outside temperature difference and the thermal integrity of the building. Overall, temperature increases are more likely to be categorized as ups because they tend to occur more quickly than temperature decreases. A final reason for the single ups and single downs is from the grouping of patterns into a daily period coupled with the occupants inconsistent behavior**;** some of the ups and down have an associated change in the opposite direction in the previous or following days. For example, the occupant may make a nighttime setback and may not setup until a day or two later.

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TABLE 3.2. Mean Temperature Changes for Setups and Setbacks



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# 3.3 CLASSIFICATION OF SITES BY SETBACK AND SETUP FREQUENCY

The previous section examined the absolute frequency of daily winter temperature patterns. This section splits the typical winter thermostat control behavior for each site by assigning an index to each site, based on the frequency of setbacks and/or setups for all heating days. An index of zero represents sites with a constant set point (i.e., no setbacks or setups). An index of one represents sites with setbacks and setups during every day in the heating season. In the averaging of all days for a site, days with single ups or single downs have been assigned an index of one-half. A histogram of the setback index is displayed in Figure 3.5. The distribution of the indexes is fairly flat from zero to 0.8. The average setback index is 0.49. The mean is in general agreement with the results of the DOE national survey data (DOE 1987). In the survey, 48.1% of occupants responded that they turned the thermostat back 1.7°C (3.0°F) or more at night, and 44.4% of the occupants reported either keeping the same temperature or turning the thermostat up at night.



FIGURE 3.5. Winter Setback Frequency Index Histogram

The wide index distribution in Figure 3.5 indicates that the residences do not neatly fall into groupings of setback sites and nonsetback sites. It is important to emphasize that there are real people controlling the temperatures, people whose behavior may not be consistent or explainable. Many sites may have occupants that can be called fiddlers, who change the thermostat settings on some days but not on others.

The occupants who usually set back were compared to those who do not. For the purposes of this comparison, it was assumed that sites with setback indexes in the lowest third were essentially constant temperature sites. Correspondingly, the sites with indexes in the highest third were sites that normally utilize a nighttime setback. Winter temperature profiles for sites with indexes in the lowest third and the highest third are displayed in Figure 3.6. These two groups roughly correspond to sites with indexes less than 0.35 and sites with indexes greater than 0.65.





The average winter temperature for the constant sites is about 20.5<sup>°</sup>C (69°F). The setback sites also have an averageof about 20.5**°**C (69**°**F)for the daytime period. The average setback thermostat setting of the setback sites is likely to be lower than the minimum setback displayed in Figure 3.6 for two reasons. First, all the setback sites had some days that were not detected as having setbacks (i.e., none had an index of one). Second, the lowest temperature achieved before a morning setup begins may be above the thermostat setting. The rate of temperature decay is largely dependent on the inside/outside temperature difference and the thermal integrity of the house. Section 2.5 displays the measured early morning temperatures well above the occupant-reported setback temperatures. The effect of the decay rate, particularly during mild winter days, may be the reason that no sites are classified as setting back every day. A reasonable estimate of the average setback setting can be obtained using the average temperature drop of  $4.4\degree$ C (7.9<sup>o</sup>F) for the night-setback/morning-setup pattern. Based on the daytime temperatureand this setback drop, the setback temperatureis 16**°**C (61**°**F).

The hours at which the setback starts and ends are defined as 10 p.m. and 6 a.m**o** These hours were chosen from Figure 3.6 for the setbacksites, where the temperature can been seen to begin a rapid decay starting at 10 p.m., and begin to setup at 6 a.m. These hours actually occur 1 hour before the peaks of the setback starts and setups displayed in Figures 3.2 and 3.3. However, as discussed in Section 3.0, the starting hours established from the flagging procedure will begin only after a significant temperature change has occurred. The actual thermostat adjustment will occur some time before the temperature begins to change.

The results of the thermostat control analysis provide empirical data that can be used to establish realistic thermostat settings and schedules in simulations of residential buildings. There is a wide range of behavior not categorized in any distinct behavioral group. However, the results do suggest some reasonable approximations of thermostat schedules for use in simulations. Three approaches which vary by level of detail are presented in Table 3.3. The simplest but possibly least accurate approach is to use a constant temperature. The second approach is to use a single-thermostat schedule with all days having  $\alpha$  small setback. The most detailed and probably most accurate



TABLE 3.3. Recommended Thermostat Schedules for Simulations

approach is to use two schedules: one with a constant thermostat setting, and one with a large nighttime setback. This third approach could be implemeted as two schedules, each having one-half of all days or by doing tivo simulations (i.e., one with the constant temperature and one with the setback) and averaging the results. Note that simulations of residence thermal energy use that include either an assumption of a constant thermostat set point at the daytime set point 20.5°C (6g**°**F)or assume a uniform setback strategy of 20.5°C (69°F) in the daytime with a 16°C (61°F) nighttime setback may introduce errors into the conclusions.

# 3.4 THERMOSTAT CONTROL BY DEMOGRAPHICS

A brief examination of the correlation of setback behavior with various demographic variables was done. The variables studied were climate, number of occupants, income level, utility type (public or private), house size, and house vintage. Only two inconclusive trends were apparent: the number of setbacks shows a general decrease with increasing numbers of occupants, and the setback index is higher for occupants with a low income.

## 3.5 THERMOSTAT CONTROL BY WEEKDAYS AND WEEKENDS

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The daily patterns were studied to determine how thermostat behavior changes with respect to weekdays and weekends. Figure 3.7 displays the histograms of the most common daily patterns for weekdays and weekends. This figure can be compared to Figure 3.4, which contains the overall totals.



FIGURE 3.7. The 10 Most Common Daily Temperature Patterns Split by Weekday/Weekend

The total number of constant days is about equal for weekdays and weekends. However, for the days with thermostat activity, the distributions of the patterns are different. The weekends have 14% more of the night setback, morning setup pattern than the weekdays, but have 36% less of the night setback, afternoon setup pattern. The weekends have 12% fewer downs without any setup the next day, and have about 25% more morning ups without any other activity. All of these results indicate that occupants typically adjust their thermostat up on weekend mornings when compared to weekday mornings.

# 3.6 THERMOSTAT CONTROL BY THERMOSTAT TYPE

A similar comparison of daily patterns was made for sites with and without clock thermostats. Figure 3.8 displys a comparison of the common daily patterns for manual and clock thermostat sites. The clock thermostat sites have about the same number of constant days as the non-clock sites. The major difference between these two subsets of sites is that the clock sites have



The 10 Most Common Daily Temperature Patterns Split FIGURE 3.8. by Manual/Clock Thermostat

about 32% more of the night setback, morning setup pattern than the non-clock sites. The other difference is that the clock sites tend to have less single ups in the mornings and afternoons than the non-clock sites. As expected, clock thermostat sites have more uniform behavior than manual thermostat sites, with the night setback, morning setup much more common. This verifies the use of the morning setup for clock thermostat sites.

# 4,0 CONCLUSIONS

The ELCAP monitoring project has enabled the study of a large number of internal temperature sensors in Northwest residences for multiple years at an hourly level of data collection. This report summarized the results of examining measured temperature data for aggregate temperature behavior and implied thermostat control behavior. The development of a patternrecognition algorithm has allowed sites to be grouped based on their described temperature patterns.

The key findings in this report are as follows:

- The average winter temperature is 20.2<sup>o</sup>C (68.4<sup>o</sup>F) in the Northwest. Temperatures are significantly lower in the nighttime during the wlnter period.
- There is strong evidence that residences keep different parts of their homes at different temperatures. Bedrooms appear to be about 2°C (3.8**°**F)colder than the main living space, basementsabout 6°C (10.8°F) colder. This observation should be further investigated, but could have significant impact on assessments of conservation impacts. All other key findings are for temperatures in main living spaces.
- Clock thermostats do not significantly increase the incidence of thermostat setback behavior. They do make the behavior more regular. Residences with clock thermostats do have lower average temperatures; however,they averagedonly about I/2**°**C (32.g°F)less than those with manual thermostats. The conservation impact of clock thermostatswi**l**l be significantlyoverestimatedif the occupants' behavior is presumed to change from not setting back to setting back, with the installation of a clock thermostat.
- Reported thermostat set points collected from a written survey are generally inaccurate. Reported nighttime setback temperatures are often much lower than the minimum temperatures actually achieved.
- Although there is a wide range of behavior, starts of thermostat setbacks are most common at 10 p.m. Starts of thermostat setups are most common at 6 a.m. The average setback is about 4°C (39.2°F).
- Behavior relating to thermostat control can often be seemingly erratic and may not conform to simplified assumptions. The thermostat control behavior of individual occupants varies significantly from day to day.

The constant daily temperature pattern (no significant temperature change during the day) is the most common pattern for all heating season data and occurs about 40% of all days with heating. Night setbacks and morning setups are the second most common pattern.

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- During the winter, daily thermostat setbacks and setups occur about one-halfof all days for residencesin the aggregate.
- Occupants of residences are not easily categorized in terms of setback behavior but, instead, display a fairly constant distribution, from residences never setting back to always setting back thermostats. Actual thermostat set points vary over a considerable range from residence to residence. Because of the variation in behavior, both within and across residences, the measured temperature data are dissimilar to common assumptions about internal temperature patterns used in simulations.
- The daily temperature pattern analyses suggests three reasonable approaches varying in complexity for heating season temperature schedules in simulations.
	- 1) If a constant temperature is needed, 20<sup>°</sup>C (68<sup>°</sup>F) is recommended.
	- 2) If the model allows a setback, a daytime temperature of  $20.5^{\circ}$ C (69°F) and a setback to 19**°**C i66**°**F)from 10 p.m. to 6 a.m. is recommended.
	- 3) Take the average of a simulationwith a constant20.5**°**C (6g**°**F) (69°F), and a setback to 16°C (61°F) from 10 p.m. to 6 a.m.

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APPENDIX

# METHODOLOGY USED IN DATA CLASSIFICATION ALGORITHMS

# APPENDIX

# METHODOLOGY USED IN DATA CLASSIFICATION ALGORITHMS

This Appendix provides information on the methodology used in the data classificationa**l**gorithms. Internalair temperaturein residenceshas been studied to attempt to classify each day's appa ent behavior in terms of setbacks, setups, and thermostat set points. The process developed here was highly empirical. We experimented with several methods before developing the method defined below. The major qualification of the algorithm chosen was that it produced results that approximated the results obtained by visual inspection.

Because real, measured data was used for this work, based on our judgement, we made a significant number of empirical choices. For example, when classifying the temperature as falling or rising, we had to select a threshold for the required temperature change. In reality, the data does not display distinct boundaries and the selection of a specific threshold creates a somewhat arbitrary boundary. In many cases, there were apparent trends which aided the selection of parameters, such as the clear prevalence of setbacks in certain hours at night.

### DATA CLASSIFICATION PROCESS

The following steps outline the data classification process used in Section  $3.0^{(a)}$ .

#### Eliminate Short Periods of Missing Data

There were numerous reasons for short-term missing data. One common cause was power outages to the residences. The most common lengthof time for a period of missing data was 1 hour. One-, two-, and three-hour periods

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<sup>(</sup>a) This classification algorithm was automated using a series of S macros. S is a statistical graphics software package oriented toward interactive display and analysis of data (Becker and Chambers 1984).

of missing data were eliminated from the temperature data by replacing these periods with a linear average of the previous and following hour's measured temperature. Data filling using linear averages increases the amount of available data and provides a reasonable data approximation, even though the peaks or valleys of setups or setbacks may be inadvertently eliminated in some cases. Because the algorithm evaluates a 9-hour period, classifying the falling and rising temperature around each hour, the possible minor inaccuracy of estimating short-term missing data was considered insignificant. The amount of data replaced by this averaging process was only one-half of 1% of the combined hourly data. Periods of missing data longer than 3 hours were not altered.

# Smoothing Out Short-Term Data

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Short-term irregularities were found to be a problem in determining regular data patterns. The data were smoothed out or normalized somewhat by replacing each hour of data by a weighted average of that hour's temperature along with the previous and following hour's temperature:

 $T(i) = 0.5 \cdot T(i) + 0.25 \cdot T(i-1) + 0.25 \cdot T(i+1)$  (A.1)

where  $T(i)$  = temperature of the current hour

 $T(i-1)$  = temperature of the previous hour

 $T(i+1)$  = temperature of the following hour.

Temperature averaging has the effect of eliminating some of the noise, including sawtooth temperature patterns that occur because of the resolution of the temperature sensor.

## Eliminate Temperature Float

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On warm days, temperatures floating above and returning to the heating set point can be falsely classified as a setup and setback. For example, on a sunny and mild winter day, the temperature in a house may reach 24°C (75°F) even though the thermestat is set to heat up to  $21^{\circ}C$  (70°F). Without an adjustment, the classification algorithm would indicate that the thermostat

set point temperature was 24°C (75°F). Because the emphasis of this analysis is placed on estimating the true thermostat set point, the float periods were ,i eliminated.

Low HVAC energy usage, in periods when the temperature was rising, was used to indicate that the temperature was floating. The method of eliminating temperature float was to compare each hour to the previous hour. If the temperature went up and the HVAC was below a threshold of 200 W, the hour was considered a float hour and the temperature was set to the previous hour's temperature. This process was repeated up to 24 times until every float hour that was above the temperature before the float started was set equal to the initial temperature. This process flattened out periods of float by setting the period temperature equal to the temperature of the hour prior to the float. An examination of data indicated that almost all periods of float in the heating season lasted only a fraction of the day; 24 cycles were established to regulate computation requirements.

# Categorize Hourly Temperatures

To determine when the setbacks of setups occur, each hour was classified as up, down, or constant. Each hourly temperature was assigned to one of three categories: temperature going up, temperature going down, or constant temperature. This was accomplished by summing the averages of the temperature changes for  $2-$ ,  $4-$ ,  $6-$ , and  $8-$ hour periods around the hour of interest, (i):

> $[T(i-2) - T(i+2)]$  $\boldsymbol{+}$ + [T(i-3) - T(i+3)]<br>+ [T(i-4) - T(i+4)] > 3.3°C (6°F) or < -3.3°C (-6°F) (A.2)

The last two periods in the equation were included to capture slower, long-term setbacks. The initial method of testing placed greater emphasis on short-term changes, but that algorithm was not sensitive enough to detect the slower decays. The threshold criteria of an absolute temperature change greater than  $3.3^{\circ}$ C (6°F) was chosen based on the visual inspection of data. The process of selecting both the temperature change algorithm and the threshold value involved many iterations. These iterations were needed to

develop an algorithm that was in agreement with the concept of hourly temperature classifications. Another criterion for an up hour was that the temperature must increase during either the previous or following hour and, conversely for the down hour, the temperature must decrease during either the previous or following hour. Additionally, each up and down period, which lasted only a single hour, was set according to the constant criteria.

No matter which test is used, the situation where a temperature rise or fall is just large enough to be classifiedas a setback or setup will occur. Correspondingly, a subsequent temperature fall or rise later on may not be large enough to be flagged by the test. This situation contributed to a significant number of days with ups or downs unmatched by a corresponding change in the opposite direction. This is typical of the nature of real data.

The test described above was generally effective in catching the middle hours in the periods of setting back and setting up. However, to flag additional hours in setback or setup periods, an additional test was used. The following conditions had to apply to flag the additional up and down hours:

- The hour had to be initially classified as constant.
- The hour had to have a temperature change from either the previous or following hour.
- The temperature change had to be in the same direction as a flagged change in the corresponding previous or following hour.

If these conditions applied, the hour initially classified as constant was flagged like its neighbor. For example, if the temperature went up 0.5°C  $(0.9°F)$  during an hour initially classified as constant, and in the following hour the temperature was classified as an up hour, then the constant hour was changed to an up hour.

Figures A.1 and A.2 illustrate two examples of the pattern recognition results. Two weeks of data are shown for each of two sites with vertical lines separating the days at midnight. Small vertical lines, or hairs, on the temperature curve represent the classification of an hour as changing. The periods with hairs indicate periods the empirically developed algorithm considered to be significant temperature changes. The hairs above the

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temperature curve represent hours in which the temperature is classified as increasing, hairs below the curve represent hours with decreasing temperature. The first example depicts a clear nighttime setback site with daily temperature fluctuations of 5°C to 8°C (9°F to 14.4°F). The second example displays a muchmore erratic behavior where it is difficult to define the thermostat control clearly. In Figure A.2, it is not always clear which temperature changes reflect a thermostat change by the occupant and which changes are just used again. The temperature data for the site in Figure A.2 are more typical of the day-to-day variation displayed in real data than the relatively consistant data displayed in Figure A.1.

## Eliminate Insignificant Heating Behavior Days

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The primary interest in thermostat behavior is in what occurs in the depth of the heating season. Days in the swing seasonoftendid not have sufficient HVAC use to determine temperature setting. Days that had missing data, insignificant heating loads, or possible cooling loads with less than 3 hours of heating were removed. In addition, any day with periods of 4 or more hours of missing data was eliminated(periodsof 3 hours or less had already been filled).

To ensure that the analysis was limited to the heating season, an additional step became necessary. Some of the ELCAP loggers monitor both heating and cooling on the same channel. The presence of cooling loads can cause difficulties in the elimination of the float periods. When a cooling load started, the float elimination algorithm would stop, and the modified temperature pattern typically increased. This increase would then be falsely classifiedas a setup. To remove this problem,all days with average outside temperatures above 18.3°C (65°F) were designated as missing. The choice of 18.3°C (65°F) was selected based on the inspection of HVAC loads versus outside temperatures for sites with mixed heating and cooling data. This temperature  $\blacksquare$  indicates the transition range from heating to cooling. was typically near the range where the HVAC is at a minimum and, therefore,

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# Classify Days by Behavior

The categorization of hours as up, down, or constant was used to classify daily patterns. Each day was split into three parts: 7 p.m. through 3 a.m. (night), 4 a.m. through 11 a.m. (morning), and 12 a.m, through 6 p.m. (afternoon). The beginning and end of the day was defined at 7 p.m. to allow night setbacks and the corresponding morning setups to be classified together. Daily thermostat control patterns were determined based on the starting hour for up and down periods. For example, if a temperature drop was first flagged at 9 p.m. and a temperature rise was first flagged at 8 a.m. the next day, the daily pattern was night setback, morning setup. Most of the days in Figure A.I display the night setback, morning setup pattern. Figure A.2 displays an assortment of daily patterns, including constant days (days with no hairs at all). The 10 most common daily patterns are given in Section 3, Table 3.1.

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