Predicting Heating and Cooling Energy Use in New California Houses

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Our research team has examined the thermostat behavior, construction and location of ninety-six new California houses and correlated our findings with the heating and cooling energy used at each site. In the summer and fall of 1994, we examined houses in California inland valleys which had been constructed in 1992 and 1993 and were not participants in utility DSM programs.

At each site, we placed temperature sensors inside a supply air duct, near the thermostat, and outdoors. From the two-minute data collected by these sensors, we determined the average indoor temperature while heating or cooling and the fraction of time the house was conditioned during the monitoring period. We also performed a complete energy audit on each house and used the audit data to model the houses using the simulation program CALRES, which is used in the state of California to demonstrate compliance with the California energy code. These models predicted annual heating and cooling energy use given standard operating assumptions.

We then obtained utility billing data for each of these houses and used the Princeton Scorekeeping Method (PRISM) to estimate normalized annual heating and cooling energy use based on the energy bills and climate conditions during the period of billing data. We then correlated the measured thermostat set-points, the fractional on-time of the thermostat and the CALRES compliance results to the heating or cooling use predicted by PRISM. We have thus produced simple models for predicting heating and cooling energy use which account for occupant behavior as well as the energy efficiency characteristics of the building.

INTRODUCTION

Berkeley Solar Group and its project team carried out the 1993 Residential Field Data project for the California Energy Commission (CEC) and the California DSM Measurement Advisory Committee (CADMAC). The primary purpose of the project was to determine the conservation and occupancy characteristics of new single family homes built in hot valley climates. The houses studied complied with the Energy Efficiency Standards for New Low Rise Residential Buildings and were not participants in utility sponsored conservation programs. Over the course of seven months beginning in the summer of 1994, our team performed detailed field audits on ninety-six houses. Monitoring devices were left in a supply duct, near the thermostat, and outdoors to record temperatures at two-minute intervals. After one month, these devices were retrieved and the recorded data were analyzed to determine the thermostat setpoints and fractional thermostat ‘‘on’’ time for each house during the monitored period. We used the data obtained from the audit to create a standard input file for the energy program CALRES. CALRES is an hourly simulation program used by the State of California to demonstrate compliance with its energy code. We performed an annual hourly simulation using standard occupancy assumptions and standard regional climate data. The results of this simulation provided standardized measures of the heating and cooling energy efficiency of each house given its physical properties and the properties of its climate. In this way we determined three independent energy use variables for heating and cooling each house: thermostat setpoint, fractional thermostat ‘‘on’’ time and standard building energy use factor.

For the second phase of our project, we obtained monthly electric bills for eighty-six of the monitored houses and gas bills for fifty-five of the houses. Along with the energy bills, the participating utilities supplied several of years of daily average temperatures for each relevant climate region. We used this monthly data as input for the Princeton Scorekeeping Method (PRISM), which correlates heating degree days or cooling degree days per billing period with the energy use per billing period to generate a custom model of annual heating or cooling energy use for each house. Using heating and cooling degree days from standard California Climate Zone files, we used these customized PRISM models to obtain normalized annual consumption (NAC) values for heating gas use and cooling electricity use for each house.

As a validity check, we also used these PRISM models to predict the heating and cooling energy consumed during the month-long monitoring period and compared our predictions to the measured heating or cooling energy used during this period. This check showed that, on average, our PRISM models predicted heating gas use with great accuracy, while possibly slightly overpredicting cooling electricity use.

We then sought to correlate the measured thermostat behavior and the measured thermal properties of the buildings to the annual heating and cooling energy as predicted by PRISM. The mathematical model we produced may be used to predict the sensitivity of the heating and cooling energy of a particular house to changes in thermostat behavior as well as to changes in the energy efficiency of the house itself.

METHODOLOGY

We gathered and analyzed our data according to the methodology described below.

Thermostat Setpoints and Fractional On-Times

At each site, BSG installed a set of three free-standing, battery-powered, non-intrusive dataloggers to record temperatures for a period of four weeks. The dataloggers (ACR Systems, various models) recorded temperature readings every eight seconds, averaged the readings, and stored the data every two minutes. Each of the dataloggers was individually calibrated to agree with a highly accurate thermocouple to within 0.2° F. One datalogger was used to record indoor ambient air temperature in the living/dining area. It was placed vertically between one and two meters from the floor to record temperatures representative of the elevation in the zone where the thermostat was found. The second datalogger was placed behind a register close to the air handler to record supply air temperature. The third datalogger was placed outside the house to measure outdoor ambient air temperature. It was placed on the north side of the house, where it remained in shade all day and where reflected heat from the ground, walls, or roof was minimized.

Thermostat Data Analysis

We analyzed the temperature data collected by these dataloggers to determine when the furnace or air conditioner was on and what the average indoor temperature at the thermostat was during furnace or air conditioner operation for each hour of the day. This temperature was assumed to be the effective thermostat setpoint for the purposes of calculating energy consumption. Using this measured setpoint, we then determined the ‘‘fractional on-time’’ (FOT) for the heating and cooling thermostats for each hour of the day during the monitoring period.

In order to determine the FOT for the cooling equipment, we identified the periods of time when the air conditioning would have been on to maintain the occupants’ desired setpoint but had been switched off by the occupant. This was done by summing all of the two-minute periods in which the indoor temperature was clearly above the effective setpoint for that house and the air conditioner was not running. The cumulative total of these periods was identified as time off above setpoint (TOAS). To avoid identifying periods when the room temperature rose due to normal compressor cycling as off periods, we used the thermostat setpoint plus 1° F as the criteria for determining time off above setpoint. The sum of that time and the time the air conditioning was running is assumed to be the period when the air conditioner would have run if the house was constantly conditioned (i.e. if the FOT were equal to 1.0). The fractional on-time can be calculated using the following equation:

$$\mathrm{FOT} = 1 - \frac{\mathrm{TOAS}}{\mathrm{Time\ on} + \mathrm{TOAS}} \qquad \text{Eq. 1}$$

The FOT equals one for a particular hour if the time off above setpoint is zero. The FOT equals zero if the air conditioning never ran during the hour and the room temperature was above the overall setpoint for the house for that entire hour. FOTs were calculated for each hour of the day, then the hourly FOTs were averaged for all hours to produce an average FOT characterizing each house. This number indicates the fraction of all the hours during the period when the occupants sought to mechanically control the air temperature. The heating FOT is calculated using an analogous procedure.

The FOT does not account for the time of day when the occupants tended to use their furnaces or air-conditioners. For instance, a house which is heated for exactly one hour every day will have a heating FOT of 1/24 or 0.042. A house which is constantly heated for exactly one day during a monitoring period of twenty-four days will likewise have an FOT of 0.042. Thus the FOT is by no means an full characterization of thermostat behavior, but it does offer an indication of whether a particular house is heavily or lightly conditioned. From the standpoint of energy use, the FOT is most revealing when viewed alongside the thermostat setpoint. In fact the FOT can be viewed as a mitigation factor in relating the thermostat setpoint to annual energy use. For instance if the cooling setpoint is found to be 72° F , one would expect that the house in question would use a great deal of energy for cooling. The effect of this low setpoint would be greatly mitigated however in the case of a house with a cooling FOT of 0.05 relative to one with a cooling FOT of 0.5.

Field Audits and CALRES Runs

The audits provided detailed information about energy consuming features of the houses including HVAC equipment, hot water heating equipment, appliances, lighting efficiency, envelope construction, fireplace data and window types. Enough information was also gathered to produce a CALRES file for each house. These input files were run as if to show Title 24 compliance. A standard set of assumptions about occupancy and schedules including thermostat set-points, internal gains, natural ventilation and window shade operation were used along with standard California Climate Zone weather data in performing an hourly simulation and obtaining heating and cooling energy use in source Btu/sf for each house. These heating and cooling use estimates therefore characterize the thermal performance of the house and its equipment given the assumed typical climate conditions for its particular location as well as the assumed standard occupant behavior. These estimates become the standard heating factor and the standard cooling factor (SHF and SCF) in our equations relating these factors to the predicted energy use.

PRISM Energy Bill Analysis

We performed PRISM analysis on eighty-six sets of electric billing data and fifty-five sets of gas billing data. The PRISM method assumes a linear relationship between heating degree days (HDD) or cooling degrees (CDD) and gas or electricity use. The PRISM program performs a fitting routine to determine what HDD or CDD base, heating or cooling coefficient, and baseline energy use produces a pattern most similar to the actual energy consumption.

Gas Data. The PRISM model for gas use in a billing cycle is:

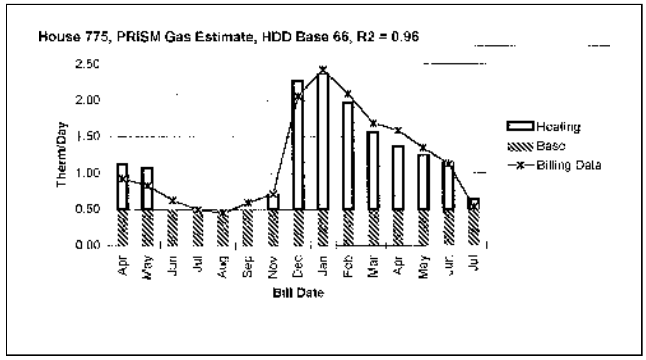
$$G = \alpha + \beta HDD(\tau_H) \qquad \text{Eq. 2}$$

where G is the gas used during the billing period and $HDD(\tau_H)$ is the average daily heating degree days based on reference temperature τ_H during the billing period. The parameters α and β as well as τ_H are determined by PRISM. The constant component α, plotted on the bottom of the chart is the basic minimum daily consumption in kWh per day. The heating component $\beta HDD(\tau_H)$ varies with the heating degree days in the billing period, and represents the amount of heating energy used during the period.

The measured monthly gas use and the gas use predicted by PRISM using the above model are shown for a typical house in Figure 1.

As can be seen in the above plot, occupancy variations can cause poor PRISM fits for particular billing periods, but in general the PRISM heating models provide a very good fit to the data, with an average R^2 for all fifty-five houses of 0.91.

Figure 1. *PRISM Gas Use Analysis*



We calculated normalized annual gas heating use using annual heating degree days from the same California Climate Zone weather files as were used for the CALRES runs. Because gas hot water heating energy use increases in the winter, there is a seasonal component to non-heating gas use similar to that for non-cooling electricity use. In order to remove this component from annual consumption calculations, we apply an adjustment factor increasing the predicted annual base gas usage. This adjustment factor is approximately 1.2, depending on the climate zone and is based on the results of a study of summer consumption and average monthly temperatures from utility data for electric hot water heaters.

Electricity Data. The improved PRISM model we used to determine electricity use in a billing cycle is:

$$E = \alpha + \beta_1 HD + \beta_2 CDD(\tau_C) + \beta_3 HDD(\tau_H) \qquad \text{Eq. 3}$$

where E is the electricity used during the billing period, HD is the average daily number of hours of darkness during the billing period, $CDD(\tau_C)$ is the average daily cooling degree days based on reference temperature τ_C during the billing period, and $HDD(\tau_H)$ is the average daily heating degree days based on reference temperature τ_H during the billing period. The parameters α, β_1, β_2 and β_3 are determined by PRISM runs. The constant component α, plotted on the bottom of the chart, is the basic minimum daily consumption in kWh per day. The seasonal component $\beta_1 HD$ varies with the number of hours of darkness in each billing period, and represents the increased energy use in the wintertime due mainly to increased lighting use. The cooling component $\beta_2 CDD(\tau_C)$ varies with the cooling degree days in the billing period, and represents the amount of cooling energy used during the period. The heating component $\beta_3 HDD(\tau_H)$ varies with the heating degree days in the billing period, and represents the amount of electric heating energy used during the period.

For the electric bills, twenty different PRISM runs were performed, using both the ''robust'' cooling-only and the heating-cooling PRISM models with seasonal dependence varying from none to maximal. From these runs, the best valid model was chosen, with validity determined by positive cooling and/or heating coefficients and reasonable CDD/HDD bases. The electricity data tends to show much less dependence on climate than the gas bills, with many houses showing little or no clear cooling energy use. In addition, a surprising number of the houses show clear patterns of electric heating use, particularly those houses which use bottled gas for their main heating system.

The measured electricity use and the electricity use predicted by PRISM using the cooling only model is shown for a typical house in Figure 2.

The monthly electricity use and the electricity use predicted by PRISM using the heating/cooling model is shown for a typical house in Figure 3.

The PRISM models for electricity use tend to fit the billing data much more poorly than the gas use models, particularly when electric heating is evident, with an average R^2 of 0.75. This is because there are are many more possible end-uses for electricity than for gas, providing the opportunity for much more non-seasonal (i.e. apparently random) fluctuation in electricity use. Therefore, the PRISM models for electricity use are less predictive of individual electricity use than are the PRISM gas use models. After much inspection of the data however, we are convinced that the errors in the PRISM results are random rather than systematic, so that for a large set of houses, the average cooling energy use predicted by PRISM will be accurate.

We estimated normalized annual electric cooling use using annual cooling degree days from the same California Climate Zone weather files as were used for the CALRES runs.

Figure 2. PRISM Electricity Use Analysis, Cooling Only

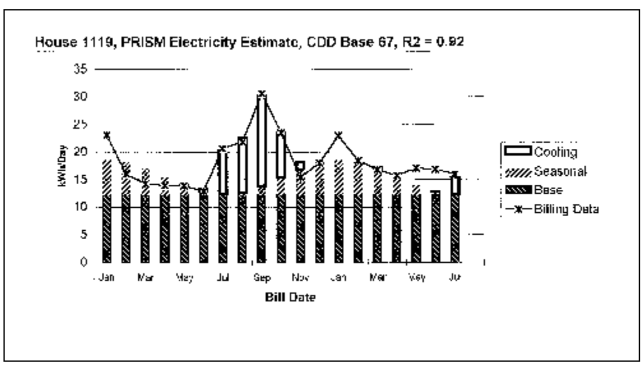
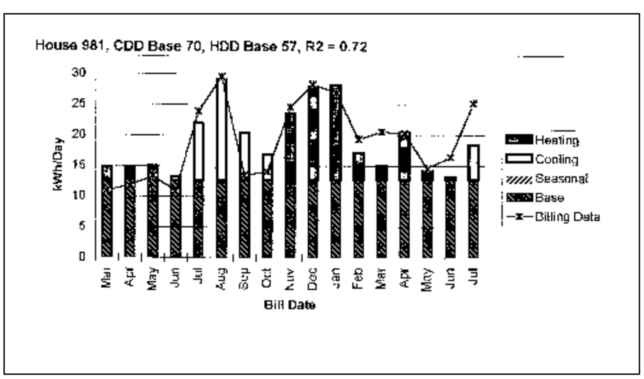


Figure 3. PRISM Electricity Use Analysis, Heating and Cooling



RESULTS

The procedure outlined above yielded the following results:

Heating and Cooling Setpoints and Fractional On-Time

BSG monitored heating and cooling activity in each audited house for a period of one month and analyzed the data to infer the hourly thermostat set points and fraction of time the houses were conditioned. Figure 4 shows heating thermostats for the twenty-one houses monitored during the winter months. Figure 5 shows the average of the cooling setpoints for the sixty-three houses monitored during summer condi-

Figure 4. Measured Heating Setpoints vs. Standard California Assumptions

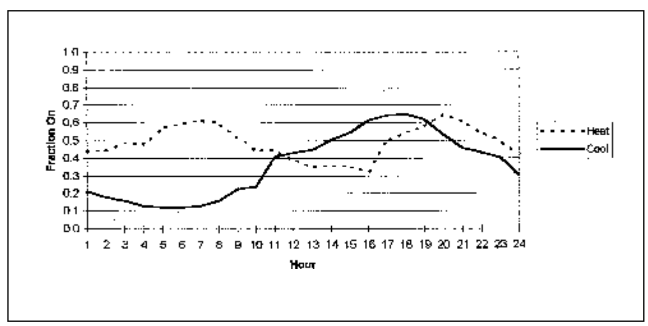
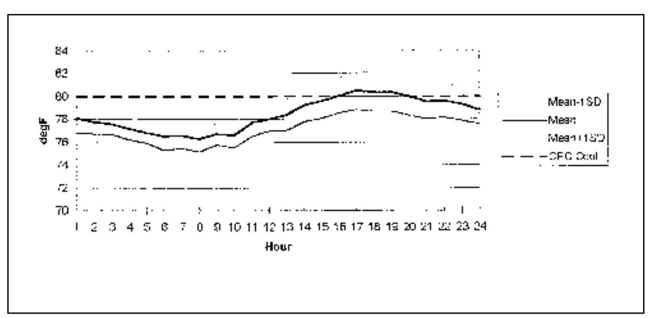


Figure 5. Measured Cooling Setpoints vs. Standard California Assumptions



tions. Figure 6 shows the fraction of the time the occupants operated their cooling and heating systems to maintain their chosen set points. This fraction represents the ratio of the time that the heating or cooling system was on to the sum of this ‘‘on-time’’ and the time that temperature in the house was outside of the set point and the system was off.

The above discrepancies between the measured thermostat settings and the standard assumptions illustrate the difference between the occupancies assumed in the standard California CALRES runs and those actually measured. These occupancy differences cause the energy use predicted by standard compliance energy runs to differ from actual energy use both on a house by house basis and for the entire set of houses.

PRISM Predictions vs. California Standard Simulation Predictions

Heating. The average PRISM NAC prediction for the heating energy of the fifty-five houses for which we obtained gas bills was 15.87 source kBtu per square foot of conditioned floor area, while the average simulation prediction was 15.59 source kBtu per square foot of conditioned floor area. This similarity in average values does not indicate that the standard simulation heating prediction is a good predictor of heating energy use on a house by house basis, although as is illustrated in Figure 7 below, there is a slight trend correlating PRISM heating with the standard heating estimate.

Cooling. The average PRISM NAC prediction for the cooling energy of the eighty-eight houses for which we obtained electricity bills was 9.65 source kBtu per square foot of conditioned floor area, while the average simulation prediction was 13.37 source kBtu per square foot of conditioned floor area. This overprediction by the simulation program is to be expected based on the difference between measured behavior and standard California assumptions illustrated above. As is illustrated in Figure 8 below, while there is a slight trend correlating PRISM cooling with standard simula-

Figure 6. Average Fraction of Time Heating and Cooling are On

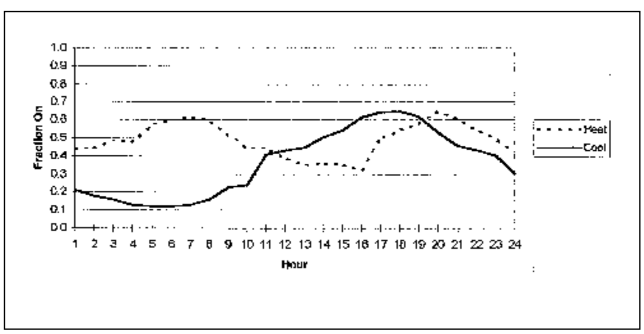


Figure 7. California Standard Heating Predictions vs. PRISM Estimates

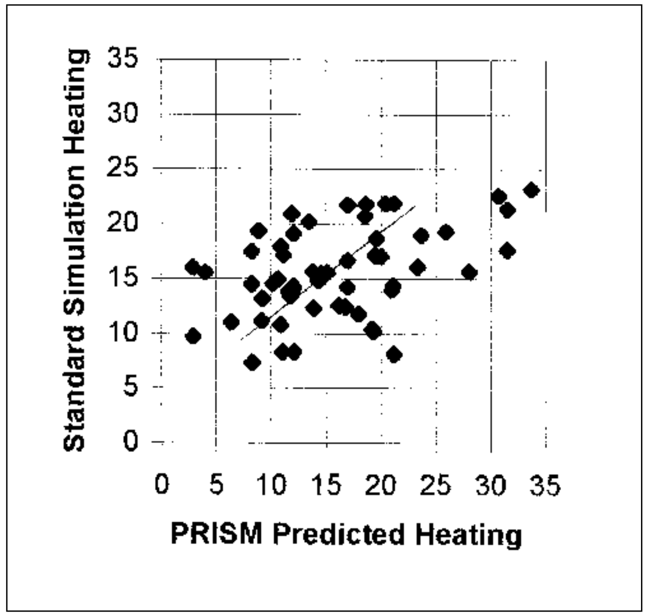
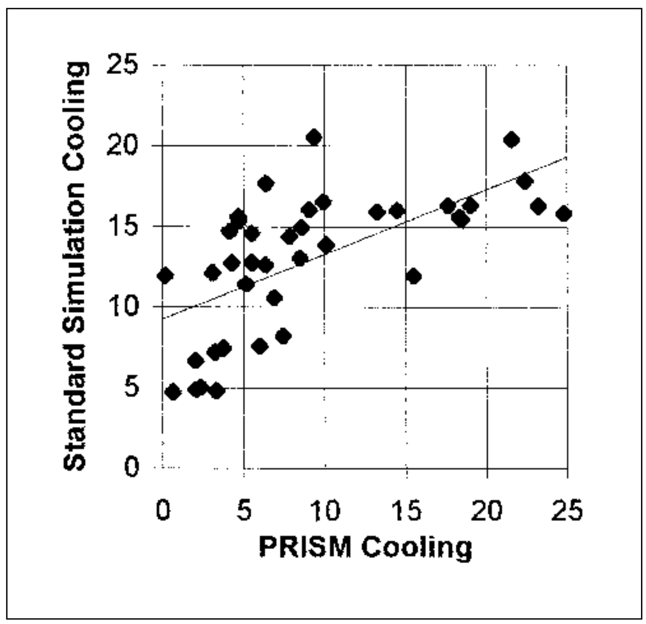


Figure 8. California Standard Cooling Predictions vs. PRISM Estimates



tion cooling, the simulated cooling alone is a very poor predictor for individual cooling energy use.

PRISM Predictions vs. Thermostat Behavior

Heating. Of the fifty-five houses for which we obtained gas bills, twenty-four showed evidence of heating during their monitoring period. Of these houses, twelve were monitored during the winter, which we defined as September 15 through May 15. We compared the measured heating setpoints (SP) and fractional on-times (FOT) for houses measured during the winter and for houses showing some heating behavior during warmer times of the year. As shown in Table 1 below, houses monitored during the winter showed an average SP of 70° F and an average FOT of 0.18 while houses monitored during warmer times showed an average SP of 74° F and an average FOT of 0.02. The average normalized annual consumption (NAC) predicted by PRISM for the houses measured in the winter was very close to average NAC of the houses measured in the summer, indicating that the average year-round thermostat behavior of the two groups was much more similar than the measured behavior during the monitoring period would imply.

We conclude from this that people tend to use their heating systems differently in the winter, and therefore that the thermostat behavior measured in the summer is not a good indication of overall annual heating energy use. Because of this, we narrowed our sample of measured gas heating use to the twelve houses measured in the winter.

Cooling. Of the eighty-six houses for which we obtained electric bills, thirty-nine showed evidence of cooling during their monitoring period. When we divided these houses into groups by season as we did for the house with measured heating, we found very little difference in the measured thermostat behavior in the two groups. The seventeen houses showing air-conditioning use before May fifteenth or after September thirtieth had setpoints and fractional on-times very close to those measured in the summer, as shown in Table 2.

We conclude from this that people tend to use their cooling systems consistently throughout the year and therefore that the thermostat behavior measured in the winter is a good indication of overall annual cooling energy use. Because of this, we used all thirty-nine houses in our analysis.

Table 1. *Seasonal Comparison of Heating Thermostat Use*

	Thermostat Setpoint	Fractional On-Time	PRISM Heating NAC
Winter	70	0.18	17.2
Summer	74	0.02	16.3

Table 2. *Seasonal Comparison of Cooling Thermostat Use*

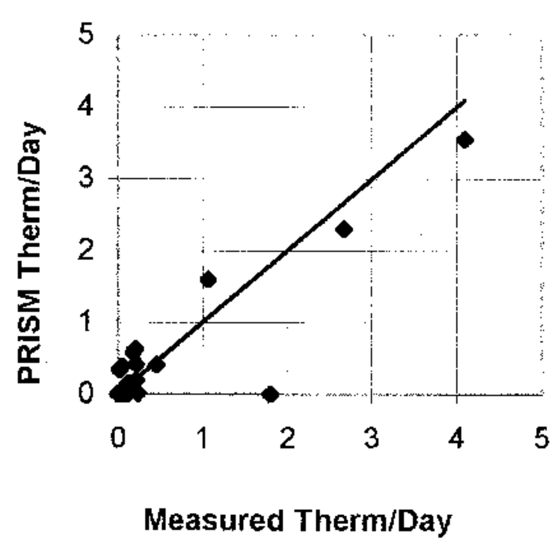
	Thermostat Setpoint	Fractional On-Time	PRISM Cooling NAC
Summer	79	0.24	9.4
Winter	79	0.22	12.1

Validation of PRISM Models

As a validity check, we used the PRISM models to predict the heating and cooling energy used during the month-long monitoring period and compared our predictions to the measured heating or cooling energy used during this period. This check showed that, on average, our PRISM models predicted heating use quite accurately, with an average PRISM heating prediction of 0.46 Therm per day versus a measured heat use of 0.41 Therm per day, with an R^2 value of 0.60. This is illustrated in Figure 9 below.

We repeated this analysis for the cooling data. When cooling energy use is estimated based on the rated seasonal efficiency (SEER) of the compressor this estimated energy use tends to be less than that predicted by the PRISM model, with the estimate predicting an average of 6.62 kWh of cooling electricity use per day versus the 8.89 kWh per day predicted

Figure 9. *PRISM Predicted Heating vs. Measured Heating*



by PRISM, with an R^2 value of 0.60. This is shown in Figure 10 below. This discrepancy may be due to optimistic rated equipment SEERs, standard equipment oversizing causing excessive cycling losses, or equipment aging. We repeated this analysis using the rated load amps (RLA) of the compressor as a proxy for the average input amps (including fans). Using this approach, our cooling energy estimate predicts an average of 8.88 kWh of cooling electricity use per day versus the 8.89 kWh per day predicted by PRISM, with an R^2 value of 0.72. This is shown in Figure 11. We interpret these tests to indicate that our PRISM estimates may slightly overpredict cooling energy use.

Figure 10. *PRISM Predicted Cooling vs. Cooling Estimated Using SEER*

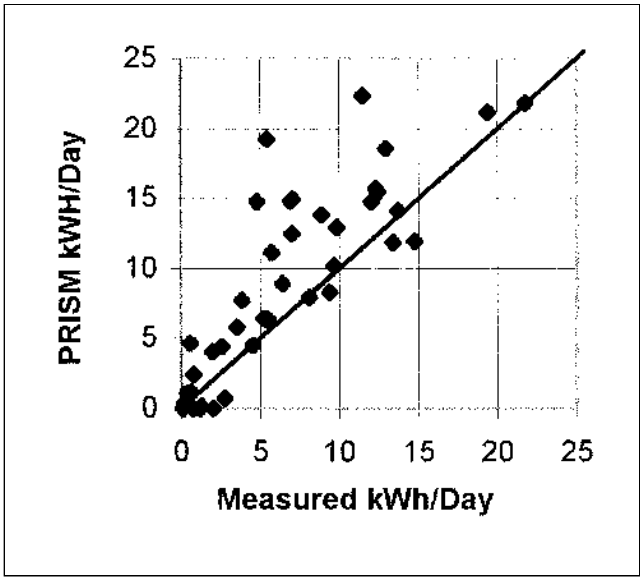
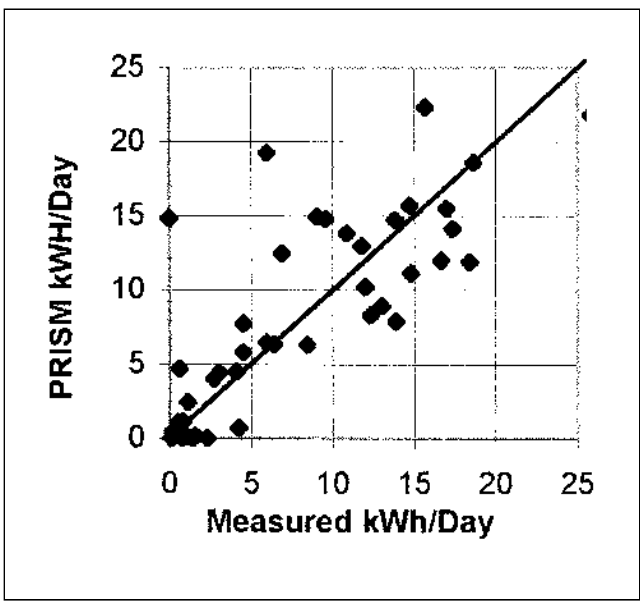


Figure 11. *PRISM Predicted Cooling vs. Cooling Estimated Using RLA*



CONCLUSIONS

Using the above results, we correlated thermostat behavior and the standard energy efficiency ratings to the heating and cooling energy use derived by PRISM from the energy bills.

Correlation of Thermostat Behavior and Standard Simulation Results to Energy Use

Thermostat behavior and standard simulation results each contribute independently to energy use. We further refined our quantification of thermostat behavior to create predictive models for annual energy use based both on behavior and house construction. Although these models display a good general correlation between energy use and our measured factors, they also display a high degree of apparently random fluctuation, suggesting that they neglect a number of other factors which affect energy use. These factors, which are relatively difficult to measure and quantify, may include the use of natural ventilation, internal gains, space heater operation, window shade operation and the time of day that heating or cooling occurs.

Heating. In order to quantify the impact of our measured thermostat behavior on the heating predicted by the energy standards, we defined our two thermostat behavior variables in relation to the behavior assumed by the standards. From our measured thermostat setpoint we calculated the variable ''delta T'' (DT) by subtracting the 68° F setpoint assumed in the simulation from the measured setpoint. Houses with DT less than zero are expected on average to use less energy than that predicted by CALRES, while those with DT greater than zero are expected to use more. From our measured fractional on-time we calculated the factor ''weighted on-time'' (WOT) by multiplying FOT by the difference between the heating setpoint and the average outdoor winter temperature for the given climate. WOT thus accounts for both the amount of time that heating is desired and the amount of heating needed to maintain the desired setpoint. A higher WOT is expected to indicate, on average, more energy use.

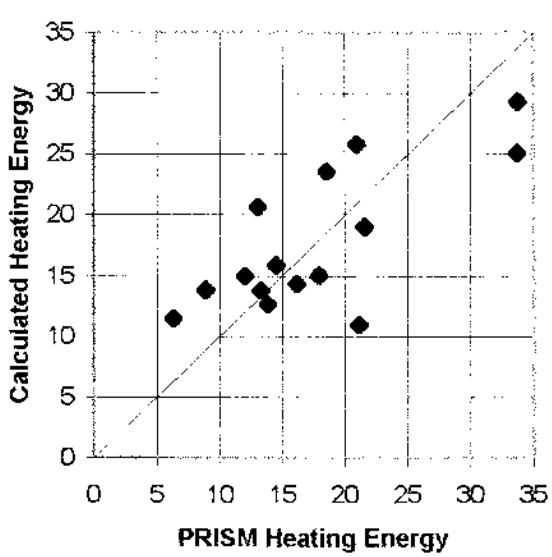
We used the heating DT and WOT along with the standard heating factor from the California energy code (SHF) as independent variables to generate a linear model predicting PRISM normalized annual heating consumption (NAC). This model fits the PRISM data with an R^2 error of 0.52. This model can be applied to a specific house to give an indication of the sensitivity of annual heating energy to thermostat setpoint or run-time given a particular standard prediction. Likewise, it gives an indication of sensitivity of annual heating energy use to building construction and climate given a particular thermostat behavior. This equation is:

$$0.69*SHF + 0.54*WOT + 0.63*DT + 3.08 = NAC \quad \text{Eq. 4}$$

The results of applying this equation to the data are illustrated in Figure 12.

To illustrate the extent that heating energy use is correlated to thermostat behavior in the above equation, we apply the equation to a house with slightly higher than average heating use and examine the results. Assume a given house has the average measured heating energy use of 15.9 Btu/sf in a climate with an average winter temperature of 50° F. According to the above equation, if the occupants were to increase their thermostat setpoint to 72° F from the average of 70° F and increase their fractional on time to 30% from the average of 17%, their measured annual heating energy use would be expected to increase 16% to 18.4 Btu/sf. To understand the magnitude of this increase in energy use, we ran increased the window area in a standardized test house simulation until the predicted heating energy showed a similar 16% increase. For this 2094 square foot house in Sacramento with double glazing, the window area increased 53% from 566 sf to 864 sf before a similar percent energy change was noted. If the setpoint were increased to 75° F and the fractional on time to 60%, the measured annual heating energy use would be expected to increase 52% to 24.2 Btu/sf.

Figure 12. *Heating Energy Predicted by Eq. 3 vs. PRISM Heating Energy*



Cooling. As in the case of heating, we defined our two cooling thermostat behavior variables in relation to the assumed behavior. From our measured thermostat setpoint we calculated the variable ‘‘delta T’’ (DT) by subtracting the measured cooling setpoint from the 78° F setpoint assumed in the simulation. Houses with DT less than zero are expected on average to use less cooling energy than that predicted by CALRES, while those with DT greater than zero are expected to use more. From our measured fractional on-time we calculated the variable ‘‘weighted on-time’’ (WOT) by multiplying FOT by 160 minus the cooling setpoint. The average outdoor temperature is not used because cooling depends much more on peak temperatures and on solar heat gain than on average temperature. Subtracting the setpoint from 160 effectively inverts it, so that a higher subtracted setpoint indicates a higher cooling energy use. WOT thus accounts for both the amount of time that cooling is desired and the amount of cooling needed to maintain the desired setpoint. A higher WOT is expected to indicate, on average, more energy use. In the two charts below, PRISM predicted cooling use is plotted against DT and WOT, and both charts show a slight positive trend.

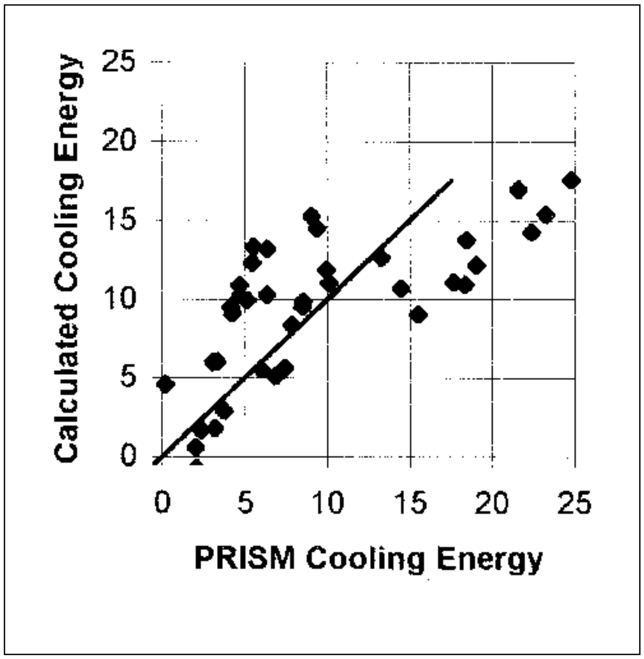
We used the cooling DT and WOT along with the standard cooling factor from the California energy code (SCF) as independent variables to generate a linear model predicting PRISM normalized annual cooling consumption (NAC). This model fits the PRISM data with an R^2 error of 0.51. This model can be applied to a specific house to give an indication of the sensitivity of annual cooling energy to thermostat setpoint or run-time given a particular California energy code prediction. Likewise, it gives an indication of sensitivity of annual cooling energy use to building construction and climate given a particular thermostat behavior. This equation is:

$$0.83*SCF + 0.23*WOT + 0.06*DT - 5.77 = NAC \quad \text{Eq. 5}$$

The results of applying this equation to the data are illustrated in Figure 13.

To illustrate the extent that cooling energy use is correlated to thermostat behavior in the above equation, we apply the equation to a house with slightly higher than average cooling use and examine the results. Assume a given house has the average measured cooling energy use of 9.7 Btu/sf. According to the above equation, if the occupants were to decrease their thermostat setpoint to 77° F from the average of 79.3° F and increase their fractional on time to 50% from the average of 39%, their measured annual cooling energy use would be expected to increase 45% to 14.0 Btu/sf. To understand the magnitude of this increase in energy use, we ran increased the window area in a standardized test house simulation until the predicted cooling energy showed a similar 45% increase. For this 2094 square foot house in Sacramento

Figure 13. *Cooling Energy Predicted by Eq. 4 vs. PRISM Cooling Energy*



with double glazing, the window area increased 41% from 566 sf to 800 sf before a 45% increase in cooling energy use was noted. If the setpoint were further decreased to 75° F and the fractional on time increased to 70%, the measured annual cooling energy use would be expected to increase 82% to 17.6 Btu/sf.

Recommendations

As the above examples show, even small fluctuations in thermostat behavior can affect energy use to as large an extent as major changes in a building's construction. Because thermostat settings determine the balance of cooling and heating consumption for each house, relying on an artificial set of assumptions about these settings to run a simulation program and then translating the annual energy use predicted by the simulation into a single energy efficiency rating for the house may yield misleading conclusions about the actual performance of the house if the eventual occupants deviate even slightly from the assumed standard behavior. More universally relevant approaches to residential energy analysis might involve separate ratings for heating and cooling performance, or an analysis of the thermal comfort of the unconditioned building under several different design conditions.