5.0 SOFT MONITORING

A great deal has been learned regarding retrofit performance through analysis of monthly billing data collected from sample houses. While this type of data was insufficient for the objectives of the SWAP Program Hard Monitoring Plan, it may provide an estimate of energy saved by solar water heating. To test this hypothesis a soft monitoring project was conducted on a sample including 275 SWH systems. Soft monitoring included monthly electric bill analysis, site inspections and surveys. The instrumented (hard monitored) homes from the SWAP Program Field Monitoring Program were also part of this sample.

The soft monitored samples were chosen from the same geographical and climatic locations as the thirty-five hard monitored homes. Electric bills from homes meeting the selection criteria were obtained for the nine-to-twelve month period prior to installation of the solar system. The length of time was sufficient to include one summer and one winter season so the extremes in temperature were represented.

Local solar contractors installed solar water heating (SWH) systems in selected homes. Electric bills from these homes were collected for a second nine-to-twelve month post solar period. As before, this period included a summer and winter season. Each house served as its own control with monthly electricity costs being compared before and after installation of the solar water heating systems.

The soft monitoring phase of the SWAP program was instituted to evaluate if the use of utility bill data could be used as a simplified method for the evaluation of energy savings from the addition of the solar systems. Unlike the hard monitoring, there is no additional equipment that needs to be installed. This level of detail for monitoring is typically used for the evaluation of other types of weatherization options.

Unlike standard weatherization options, which are usually focused on reducing heating and cooling costs, the SWAP program will affect only the water heating energy use. This becomes an issue in evaluating the usefulness of utility bill analysis because the heating and cooling loads typically dominate the electricity bill, followed by water heating/refrigeration costs.   The evaluation of utility bills is a statistical method that predicts a "typical" normalized annual energy use for a specific residence given weather data and utility billing data before a retrofit is made.   Savings can then be calculated from the difference between the typical energy use before the retrofit and the normalized energy use after the retrofit. Normalization to typical weather is made assuming that the energy usage consists of a base load, a cooling component, and heating component.

A goal of 200 houses for the soft monitoring phase was established in order to give a precision of total electrical use of approximately +/- 1000 kWh/year at a 90% confidence interval. In order to obtain this figure, approximately 300 of the 801 installed sites were selected for utility bill analysis, assuming that approximately 1/3 of the sites would have unusable billing data for the following reasons: missing billing data, inadequate amount of billing data, occupancy changes, and problems with the solar system.

5.1 SOFT MONITORING: DATA COLLECTION

Unlike the process of electronically obtaining data for the hard monitoring, the soft monitoring energy data acquisition is all done through the various utility companies that serve the monitored systems. This entails getting the proper approvals for releasing utility company records prior to receiving any data. The procurement of the data receipt was timed so that both pre and post-solar data could be received. Because most utilities maintain data for a period of approximately 2 years, in many cases it was necessary to obtain data at several separate times, so that the required period before the solar installation and after the solar installation was satisfied. At least 9 months, and preferably one year's data is required for both periods, so that summer and winter electrical usage is measured.   The data of interest consists of two parts, the billing date and the measured electrical use in kWh.

The data were put into a spreadsheet form that was easily importable into the PRISM program (Fels et al., 1995) that was used for the data analysis. The month in which the retrofit occurred was excluded from the data so that partial days of retrofit and start up problems were resolved before the data were compared. Unlike the experimental data that can be flagged and cleaned up electronically, much of the

utility bill data were transcribed by hand in at least one step. Therefore, it is likely that some errors may have occurred in the recording of data. The first step in the data collection was to examine it visually, looking for obvious errors and missing data. Sites with missing or inadequate amounts of data were discarded at this stage. Obvious transcription errors were fixed. Other sites with known problems, including solar systems that had failed for extended periods of time and sites with no utility usage (e.g. power shutoff) were also discarded at this stage. At this stage in the process, no data were available regarding occupancy and/or HVAC changes. The remaining data cleanup was handled by using the PRISM program, which identified other problems using statistical methods.

In addition to obtaining utility billing data, daily temperature data for the sites of interest were also obtained. All of the selected sites were divided into three geographical regions: North, Central, and South, corresponding to their proximity to the following weather stations: Tallahassee, Tampa, and Miami. To obtain accurate estimates of the building response to climate, the PRISM program recommends that a minimum of 12 years worth of weather data be used for analysis, including the years during the experimental phase. The year 1984 was selected as the starting year, because the data format has been consistent since then. This selection yielded 13 years of data.

The weather data were obtained from the National Climactic Data Center (NCDC) in Asheville, NC. The first 12 years worth of data had been previously digitized and was contained on 2 CDs (data set TD3200). The parameters of interest were the daily maximum and minimum temperatures that are used by PRISM to determine an estimated number of heating and cooling degree-days as a function of the reference temperature. The reference temperature is assumed to be the outdoor temperature below which heating is needed (or above which cooling is required). In general, this temperature is related to the indoor temperature, but with an offset which implicitly includes internal loads, shading, and solar gain. A separate program was written to extract the digitized weather data in the required columnar format, because the available format of the data did not match the processing input in PRISM. The last year of data for the three sites was input manually.

Because the digitized data from the NCDC had been previously cleaned up, there was no need to further clean up these data. The data entered manually were re-examined and cleaned up to remove transcription errors.

5.2 SOFT MONITORING: DATA ANALYSIS

As previously indicated, the analysis of the data was conducted with the PRISM program. This program uses statistical methods to predict the building energy response as a function of outdoor temperature. Because the program can normalize electrical heating/cooling energy use to weather, the baseline energy use (which includes water heating) can then be compared before and after the solar system has been installed to evaluate savings, independent of the weather. There is one primary formula that describes the PRISM evaluation method:

$$\text{NAC} = 365\alpha + \gamma_H B_H \text{Ho}(\tau_h) + \gamma_c B_c \text{Co}(\tau_c)$$

Where $\gamma_{H,C}$ are model selection parameters and are equal to zero or one. $B_{H,C}$ are the slopes of the cooling and heating load as fitted by the regression. The $\text{Ho}(\tau)$ and $\text{Co}(\tau)$ functions are the approximate reference temperature equations and are based upon a least squares fit of a building's utility billing data to the weather data (or they can be fixed). α is the baseline energy load that consists of all loads except the heating and cooling (the second term is the heating expression and the last is the cooling expression). The result of this equation, the NAC (Net Annualized Consumption) is used for the computation of energy usage before and after the solar has been installed.

The primary assumptions of the PRISM method are:

1. Building heating/cooling loads can be expressed as a direct function of the dry bulb temperature difference (in degree-days) between the building space and the outdoor temperature. This assumption is that other effects including radiation, wind speed, and humidity are all proportional to this term, even though they are not explicitly calculated.
2. Building temperature is constant during the heating/cooling season (although PRISM predicts the reference temperature to create the best fit from the data).
3. Efficiency of the heating/cooling equipment is inversely proportional with respect to the driving force in #2.
4. The baseline energy load is independent of weather effects and is relatively constant throughout the year.
5. Heating/cooling systems are run in accordance with the dry bulb temperature difference in #2.
6. Occupancy and use of the building is relatively constant.

The first step of the PRISM analysis is the processing of the weather data. In the first stage, the columnar format data are converted into a format PRISM uses for further analysis. At this stage, PRISM will also indicate if there are any problems that it detects with the data, aiding the manual clean-up process. In the next step, all of the weather data for a location are read in and two normalization files are generated. Each of these expresses the number of degree-days (heating and cooling) as a function of the optimized reference point. This point is used to minimize R^2 after the base energy use and heating/cooling slopes have been determined from a regression of the data.

Processing of the utility billing data also occurs in a multi-step process; the data are converted from a columnar format to a format that PRISM uses (the meter file). In this process, obvious errors are flagged and reported.

When the final processing is ready to begin, the user selects a weather site, a meter file, and run parameters to process. The run parameters are used to refine the model used for each specific building to predict energy usage. Among the refinements to this process are if cooling and/or heating are to be considered, and if outliers are to be weighted less. An option (used for this study) is to let PRISM automatically select these parameters. PRISM does the automated selection by evaluating the fit generated with several operational modes and selects the one that most appropriately fits the data.

The first step of this process was repeated several times to clean up errors not found previously in visual inspections or in the original file conversion. PRISM uses several methods to identify common problems with utility billing data:

1. Identification of estimated readings. The identification is done by flagging consecutive data that has a high and low deviation with respect to the normalized monthly energy consumption.
2. Identification of mis-ordered data. This usually entails flagging data with incorrect date stamps.
3. Identification of outliers. PRISM flags this value by noting a high deviation from the expected monthly energy usage.

Even after correcting errors, the PRISM program still detected errors that fell into categories #1 and #3. The recommendations from the PRISM program were used to run the program with the corrected estimated readings and the robust calculations for the outliers. In general, outliers reflect occupancy changes that have a large impact on energy usage. Estimated readings are as indicated, even if the utility does not flag them as such (Marean, 1998). After the determination of the NAC for each site, the PRISM program calculates several statistics for each site, including both the pre- and post-solar cases:

R^2: this parameter identifies how good the overall fit is. A value near 1.0 is desired.
CV (NAC): this is the relative standard error in %. This is the standard error. A low value for this parameter is desired.
FI: this is the flatness index. This value indicates how well the building's response is to temperature difference. A low value of the FI, combined with a low CV can indicate a building with a good NAC, even if the R^2 value is low (the fit is poor because the heating and/or cooling is not too temperature dependent).

The calculated savings are based upon the cutoffs selected by the three criteria listed above. The default values are : R^2 > 0.7, CV <= 7 %, and FI<0.12 with CV<0.57* CV cutoff. Acceptance of these values is used for calculation of energy savings. Energy savings is simply the difference in NAC before and after the installation of the solar system for the systems that meet the reliability criteria.

5.3 SOFT MONITORING: RESULTS

A preliminary analysis of the data is included in Appendix 11. This analysis was performed because the early indications were that the data were not well predicted by the PRISM model as indicated by the three performance indices for all three regions. Although the data did not agree well with the listed criteria, the distribution of the data appeared to be in a bell shape, indicating that there was not a particular bias in the data. This is reaffirmed by the generally good agreement between the mean and median values. In order to address possible shortcomings in the data, the stability of the population used for generating the data, and the model used to evaluate the data, a series of runs were made with the PRISM program.

Several different criteria were evaluated to assess the model results:

> Model selection
> Savings criteria cutoff
> Use of a data set with no occupancy change
> Variances by region
> Correlation of predicted models with surveyed air-conditioning usage

The likely causes for the poor fits are:

> Large changes in occupancy
> Intermittent usage of air-conditioning
> Air conditioning usage is not constantly proportional to cooling degree-days. This might be caused by change in wet bulb temperatures that do not have a large impact on the dry bulb temperature.
> All baseline loads are not weather independent (seasonality of non-heating/air conditioning loads).
> Change/addition of heating and cooling during the analysis period.

To evaluate the impact of model selection, a series of three models were run for all three regions. The following models were used:

> Automated Selection (cannot select temperature bounds for models)
> Heating and Cooling (reference point from 70-85° F in summer and 60-75° F in winter)
> Cooling Only (reference from 70-85° F)

Where appropriate, all flagged estimated readings were combined and all outliers were evaluated with the "robust" version that de-weights the outlier points for making the analysis. For the south and central regions, the impact upon predicted energy usage averaged 30% or less, although one case varied from 533 kWh to 1,886 median savings. In the north, the results were poor, in particular, the use of the Cooling Only model generated a negative mean energy savings of –864 kWh, while the use of the automated model generated a mean energy savings of up to 2,068 kWh. In context, these results make sense because they indicate that the cooling only model does not work well in the north. This is expected from the climate.   Therefore, for the final analysis, the automated model selection, which screens the various models for cooling/heating trends in utility bill usage was used.

In addition to the selection of the modeling criteria, the selection of the savings criteria can have a significant impact on the results. Although the savings criteria affect the final results, this selection does not affect how the models fits the weather data, as this step occurs prior to the calculation of savings. For all of the runs, four combinations of criteria were used:

Accept all sites
$R^2 > 0.7$, CV<7%
$R^2 > 0.7$, CV<7%, FI (Recommended method)
$R^2 > 0.6$, CV<10%, FI

For the most part, the results from this process were fairly predictable. The first option, which excludes all criteria, has the poorest fit but the lowest standard error (because the most sites were used). In general, this approach has little merit due to normal errors/problems with the data.

The second criteria proved to be too stringent for this data set. In most cases, only about 10% of the data would have been used. Consequently, the R^2 values are the highest of the group, but the magnitude of the standard error is often the same as the predicted savings. This indicates that many of the buildings' temperatures/energy use have a low dependence on ambient temperature. This method was also rejected.

The third criteria is the default method and is intended to catch buildings that are not particularly climate sensitive ("flat"). This method yielded approximately twice the number of data points as the second method, with correspondingly lower R^2 values and lower standard errors.

A fourth set of criteria was modeled after the third, but with larger ranges to accommodate more of the data. Sharp (1994) also modified these values for their cooling data, which showed many of the same problems as this data set does. In particular, their cooling data showed R^2 values on the order of 0.1. His conclusion was that the air-conditioning usage was driven by factors other than just outdoor temperature. Although the aim of these data is to examine hot water heating savings from the solar system, the impact and understanding of the usage of the air-conditioning becomes critical as it typically is a larger electrical load than the water heating. The use of these criteria improves the size of the "acceptable" data for savings, but also reduces the overall R^2 value. For all of the criteria, the point at which the error becomes large, or larger than the predicted savings, indicates that an inadequate number of data points exists and/or the fit is poor. This is the case which exists with the north set when the criteria are applied. This criterion was selected for projecting savings.

The third objective to evaluate was if a better-conditioned data set, that had no reported occupancy changes (from the surveys), would yield better fits and a smaller proportion of "unacceptable" data points than the entire set had. To do this, the surveyed sites with no reported occupancy changes and appropriate billing data were re-run in the south and central regions. Only about 25% of the original data sets fell into this category. Note that this does not imply that 75% had occupancy changes, because only about 37% of the surveys were returned. These sites were run using the automated model selection and the various savings criteria described previously. When these results were compared with the full sets, the R^2 values were similar (+/- 0.1), and the percentage of buildings found "acceptable" by the various savings criteria was similar (+/-10%). If the reported occupancy changes were accurate, this finding would imply that the poor model agreement was not primarily due to occupancy changes. Another source of discrepancy in occupancy could be the "Friend Factor." This factor is a non-documentable change in occupancy that may occur on a regular or irregular basis. A follow-up survey was performed to answer this and other questions. Of the 39 respondents, 56% indicated that they have friends/relatives over for at least 4 hours/day. This occupancy could have a major impact if it does not occur as a regular pattern and involves significant energy use.

Another area of model evaluation is the geographical location of the sites. In general, all three areas show similar problems with disagreement. The northern region shows problems with higher relative errors, but this problem can be explained by the relatively few number of sites located in the North (approximately 40% of the other two regions). The previous discussion regarding modeling differences explains only the climate sensitive effect (cooling model not appropriate in the North). It is expected that the actual savings could vary by region.

To address the final question, the ability of the model to predict reported air conditioning use, the final analysis is used. Figures 5.3-1 to 5.3-3. indicate the normalized energy savings for all of the sites with

utility billing data by region that passed the savings criteria. Note that the saving site numbers are not the same numbers used to identify these sites elsewhere.
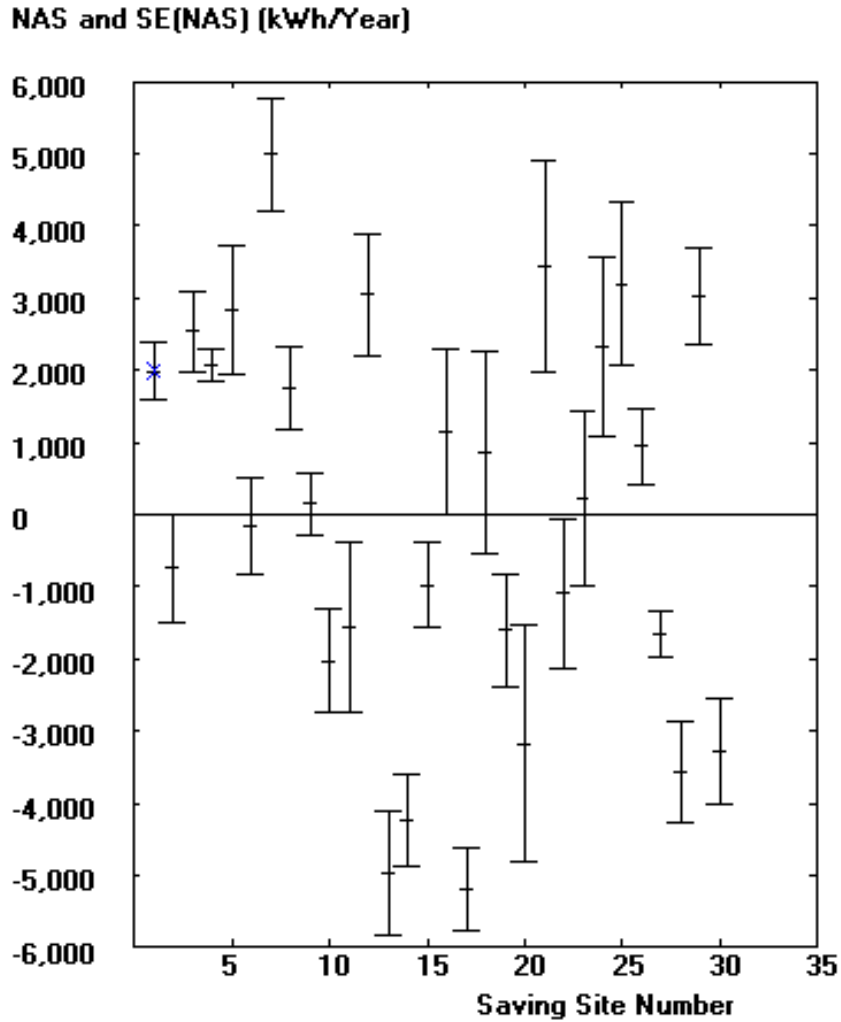
NAS and SE(NAS) (kWh/Year)

Figure 5.3-1. Normalized Annual Savings by Site for North Florida
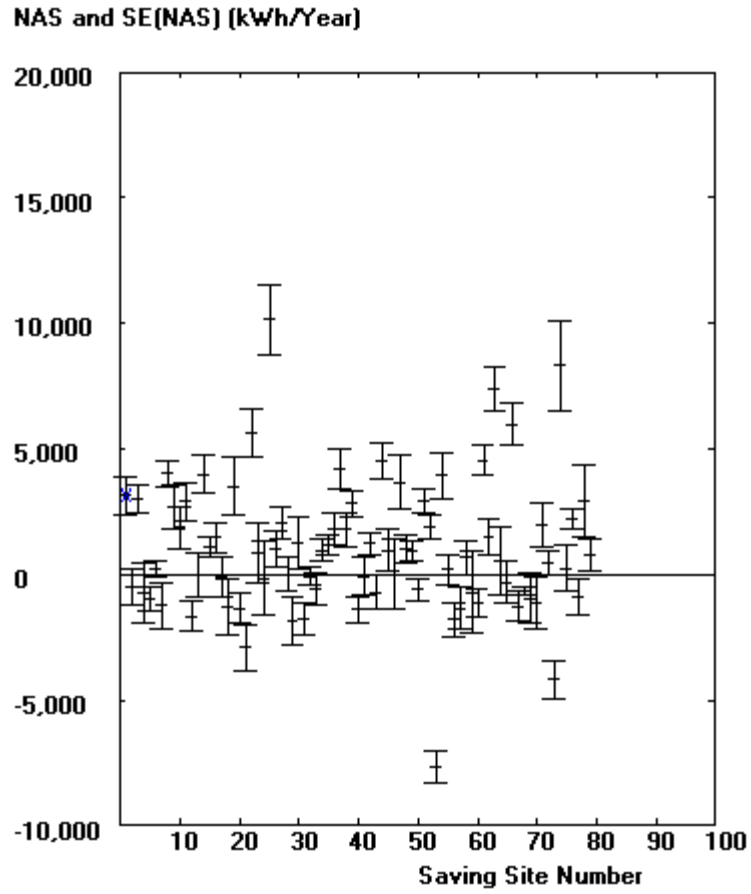
NAS and SE(NAS) (kWh/Year)

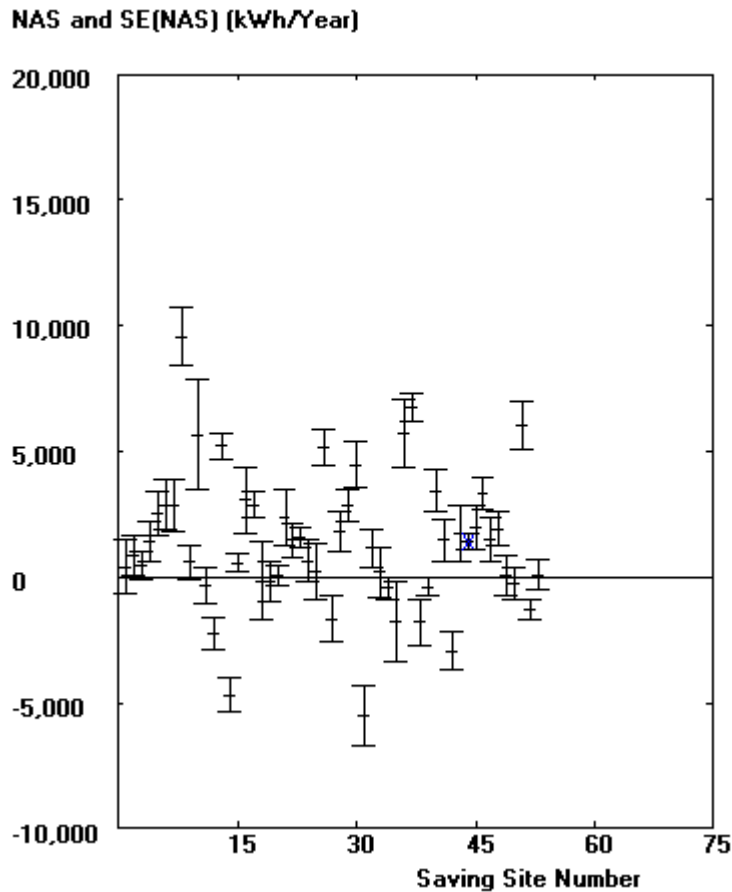Figure 5.3-2. Normalized Annual Savings by Site for Central Florida

Figure 5.3-3. Normalized Annual Savings by Site for South Florida

These figures indicate many cases with unrealistically high savings and/or negative savings that cannot be attributed to the solar system operation. Appendix 12 indicates more detailed information for all of the utility billing data (by location) as modeled with the PRISM program. The appendix tables indicate the following information for the three zones:

Site: Site Number (different from the diagrams!)
Period: Pre/Post Solar
Model: Modeling used (C = cooling, H = heat, O = Only, R = robust, MVD = Automated selection, with outlier detection)
Data: # of data points used
FI: Flatness index. A low value indicates a temperature-independent electric load.
R^2: Least squares fit quality
T(heat/cool): Calculated reference temperature in degrees F
SE (heat/cool/base/NAC): Standard error of portion of parameter in kWh.
Base: Base load, which includes water heating in kWh.
NAC: Normalized annual energy consumption, which is the predicted energy use in kWh.
A/C and Heat: Yes/No survey result of air conditioning/heat in the home
A/C Use: Survey result of standard usage of air conditioning/heat
Occupancy Change: Reported occupancy change during monitoring period. Reported in %, only reported for whole period.
Friends: Yes/No question indicating if friends/relatives are in house more than 4 hours/day.

Blank survey information indicates that no information was available, blank PRISM indicates that a particular model type was de-selected. One item of particular interest in these tables is the determination of the reference temperature at which heating and/or cooling is used for calculating the normalized heating and cooling loads. Blocks shaded in light gray indicate physically unlikely values. Although the manual model selection allows for the selection of a reasonable range for these values, the automated model does not allow for unrealistic values to be eliminated. Although many of these cases result in correspondingly low R^2 values, there are many that have high fits, indicating that PRISM will use these for savings calculations. However, in many cases, these errors are small because the problems leading to these low values indicate poor correlation with either heating or cooling (and consequently a small load). This limitation of the automated model selection leads to some of the errors observed.

These data also indicate discrepancies with houses moving from HO (Heating only model) to CO (Cooling only model) in one year. Corresponding values of Tau Heat and Tau Cool also vary significantly. Although this may yield a "best" statistical fit, it is unlikely that this is physically occurring. One of the survey questions was to determine changes in heating/cooling equipment during the monitoring period. As indicated in the darker gray bands, a few cases of this did occur, although this does not explain the bulk number of modeling changes. This leads to the thought that some of the modeling problems may be caused by the improper assumption of heating and/or cooling model(s). Ideally, this type of data is useful for making utility bill comparisons. However, getting the equipment change information for all of the sites is not always feasible. Overall, the impacts of these data points were thought to be minor and were not deleted from the data set.

One item that could impact the results significantly is the intermittent use of heating and cooling. As part of the follow-up survey, this question was raised. Contrary to common thought, most residences indicate that they use their air conditioning continually during the summer (64%). Twenty-three percent used it on only hot days, and the rest used it at night (3%), during the day (5%) or never use/don't have air conditioning (5%). For heating, the results were more evenly distributed, with 26% using it continually, 37% using it only on cold days, 8% using it at night, and 24% did not use or have any heating. Clearly, the heating, if used, was used more intermittently than the air conditioning. This could result in some impact on the results. However, because the heating is a lesser load than the cooling, the heating results affect the NAC by a lesser amount.

Another potential source of error is the ability of a degree day model to accurately model cooling energy in a humid climate. This issue has been explored previously for Houston (Fels and Reynolds 1993). Their analysis indicates that the daily average comfort index can be reasonably correlated to the dry bulb temperature in Houston. A corresponding relationship can also be found between wet and dry bulb temperatures. By comparing the fit with dry bulb temperature and comfort index, they showed that the NAC in Houston is similar for both methods, although the R^2 is always higher when the dry bulb temperature is used. Although they used the heat index as a relative comparison of performance, it should be noted that this value indicates the effect of heat on the body (primarily though limiting perspiration) rather than the effect of heat on a building, which entails both latent and sensible loads and cooling methods. It appears that the reliability of fitting Houston's data should also apply to Florida's climate, indicating that this issue is not the primary problem factor.

Another potential source of variance in the data is the assumption that all non-heating/cooling loads are constant throughout the year. The monitored data clearly indicate that the water-heating load varies by approximately 30% between August and January. A study by Fels et al. (1985) addressed this very issue, including a variance in the water-heating load of 41%. As applied to PRISM, their results indicate that the errors in the seasonality of loads were not significant enough in comparison with the standard error to affect the NAC for individual homes. However, it should be noted that their analysis was with heating in Denver. Some of the seasonality effects evaluated in this study may tend to cancel themselves out in a cooler climate than Florida (Lights vs. Refrigeration). Consequently the effect of the seasonality would be reduced.

An additional possibility is the effect the seasonality has on the summer/winter fits. In the winter, the seasonality (5% above mean in the Denver study) is reflected as an additional heating load (reducing the

reference temperature) and in the summer, the seasonality (12% below the mean in the Denver study) is reflected as a lowered cooling load (increasing the reference temperature). However, in the "swing" seasons, there is no way of attributing seasonal loads to heating and/or cooling, although they are presumably at their minimum during these times. This swing season lasts approximately 4-6 months and may be significant enough to affect the baseline load and consequently the NAC, especially if there is a seasonal bias.

Table 5.3-1 indicates an overall summary of the PRISM results by zone. A comparison with the monitored sites has also been included. Although the relative distribution of system types is similar for both the monitored and PRISM sites, the monitored sites represented are not a large population sample, so it is possible that other effects other than the aforementioned modeling issues may have impacted the discrepancy in the results. The overall results for the state (weighted by # of buildings per zone for PRISM), indicate no agreement within the limits of error.

Table 5.3-1. Zonal Comparison of Prism and Monitored Sites

Climate	Measured		PRISM				
Zone	Savings (kWh +/- 60	# Buildings Used	R^2 Pre Solar	R^2 Post Solar	# Total Buildings	# Buildings Used	Mean Savings (kWh)
North	1,700	6	.754	.779	44	30	185 +/- 752
Central	1,500	13	.804	.790	117	79	766 +/- 386
South	1,850	13	.643	.796	114	53	1437 +/- 416
State	1,700	32	N/A	N/A	275	162	878 +/ - 464

It is unclear why the results between the monitored sites and utility bill monitored sites disagree. It is also unclear as to why many of the sites did not fit well with the PRISM data. The following list indicates some of the likely possibilities for these discrepancies:

      Undocumented occupancy changes
      Intermittent heating use
      Summer biased seasonality effects
      Mis-selection of models/reference temperatures in automated PRISM
      Undocumented change of heating and/or cooling equipment

5.4 SOFT MONITORING: RESULTS COMPARISON WITH INDIVIDUAL HARD MONITORING DATA

As indicated in Figure 5.4-1. The utility-bill-predicted energy savings agree poorly with the measured energy savings from the solar systems. Thirty-one of the thirty-two monitored sites were used for this comparison. Site # 17 was dropped due to missing utility bill data. Of the remaining sites, only 1 site (#21) (3%) is predicted within the range of experimental and statistical errors and passes PRISM's criteria for "good" data. Two of the sites (#24 and #28) fell into the category of having air conditioning added, but they did not indicate large discrepancies with the measured data. A rough estimate would have been more useful than this one "good" prediction. Only 45 % of the hard monitoring sites passed PRISM's criteria for "good" data. However, 32% of the sites fell within the range of experimental and statistical error, but did not pass PRISM's criteria for "good" data. It is clear from some of the sites that magnitudes of energy savings (positive and negative) were larger than the total potential of water heating. It is expected that some noise will occur in a single sample, but these results show that the data and analysis used with the existing PRISM model were inadequate to accurately predict energy savings from the individual solar water heating systems in Florida.
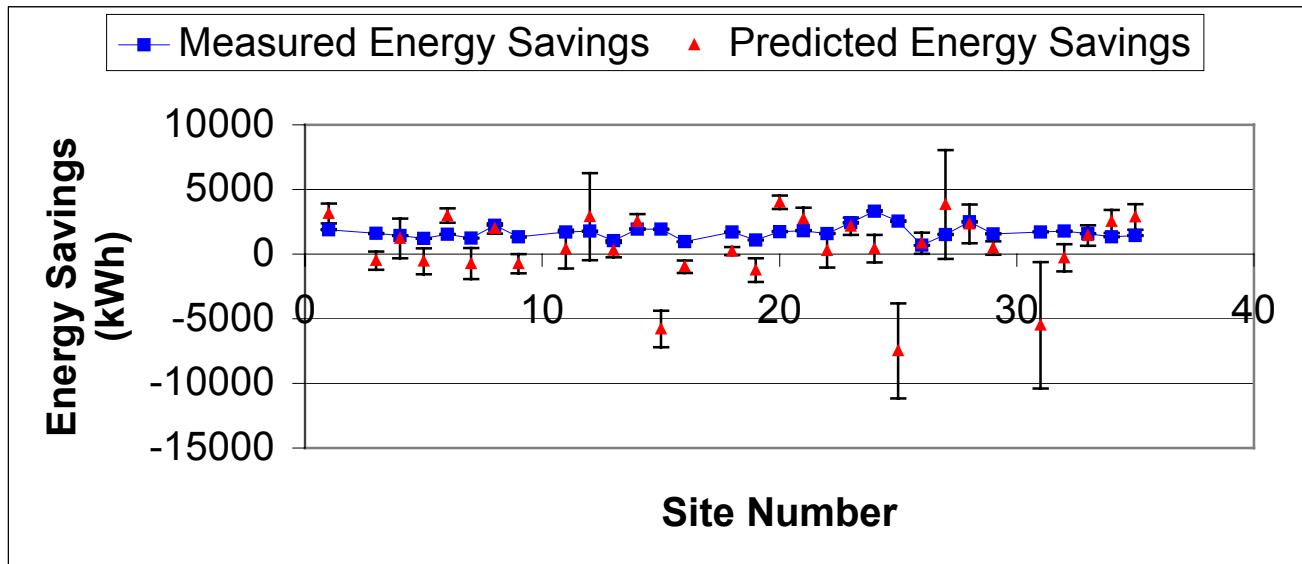
Figure 5.4-1. Comparison of Measured and Utility Bill Predicted Energy Savings

5.5 SOFT MONITORING: DETERMINATION OF WATER HEATING PERCENTAGES FROM UTILITY BILLS

For the hard monitored sites with adequate utility billing data and stable operation of the monitoring equipment/solar system, additional analysis was done to compare water-heating percentages of the electrical bill. Sites #7,#17, #26, and #31 were not evaluated in this comparison. For this analysis, the actual utility bills and actual monitored data were compared. No adjustments were required for weather, so the PRISM analysis was not used. Figures 5.5-1. and 5.5-2. indicate the percent of the electrical bill devoted to water heating both before and after the addition of the solar system.
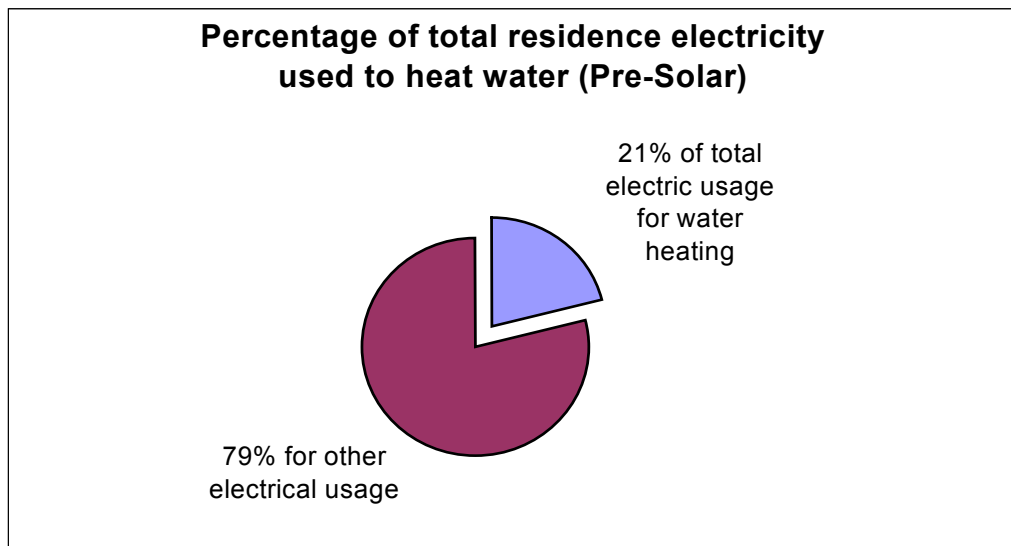

Percentage of total residence electricity used to heat water (Pre-Solar)

21% of total electric usage for water heating

79% for other electrical usage

Figure 5.5-1. Percentage of Electricity Used to Heat Water – Pre-Solar

**Percentage of total residence electricity
used to heat water (Post-Solar)**

11% of total
electrical usage
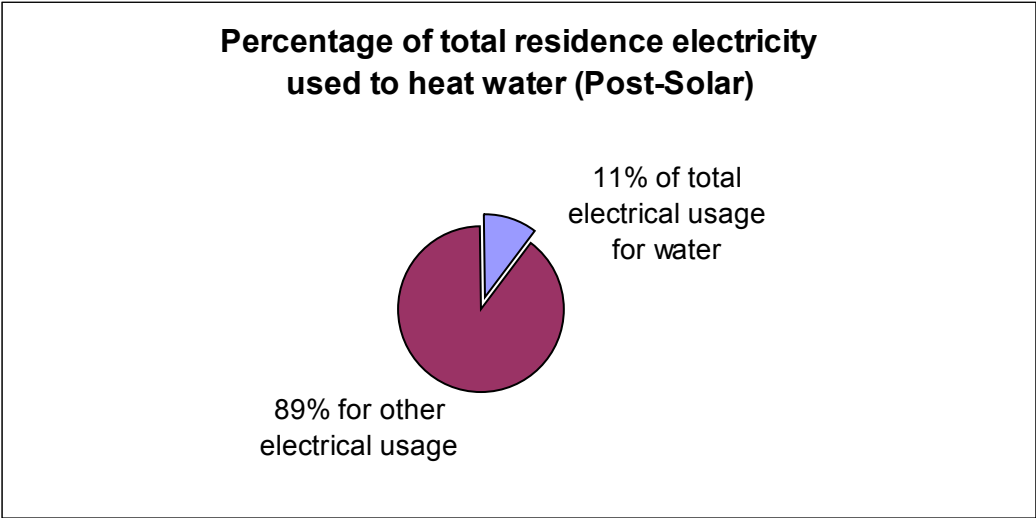for water

89% for other
electrical usage

Figure 5.5-2. Percentage of Electricity Used to Heat Water – Post-Solar

Figure 5.5-3. Provides a site-by-site breakdown of the percentage of electrical usage that is devoted to heating water. As this figure indicates, the amount varies by site and is typically a very substantial portion of the utility bill. The solar system installation reduces this percentage dramatically. Note that the 21% of total usage implies that most of the households use the air conditioning on a regular basis. Probably 75% of the homes fall into this category. Note that some of sites with high water heating percentages of the total electrical bill, had no air conditioning (#23), or added air conditioning during the study period (#24, #28). Other sites with high water usage (#8) and/or undocumented changes in air conditioning account for high relative water heating percentages of their electrical bills.
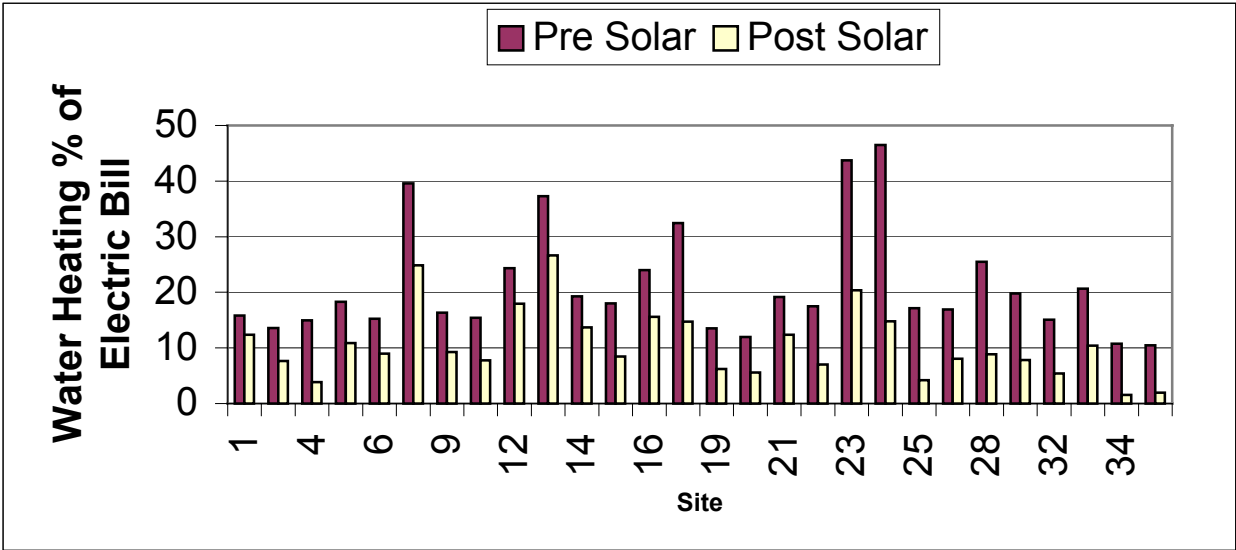
Figure 5.5-3. Percentage of Electricity Used to Heat Water – Pre- and Post-Solar by Site