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QUICK SAVINGS ESTIMATE WITH GSTEAM: THE GRASP SHORT TERM ENERGY ANALYSIS METHOD

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Background

PRISM Advantages and Disadvantages

The PRInceton Scorekeeping Method (PRISM) has gained widespread use in evaluating weatherization programs. PRISM's principal advantages include its physical basis, statistical reliability and insights into the causes of changes in usage (Fels, 1986). PRISM's primary disadvantage is its requirement for a full year of pre- and post-treatment fuel consumption data with a minimum of six (and preferably 10-12) fairly evenly distributed real meter readings for each period (Dunsworth and Hewett, 1985). The requirement for a full year of post-treatment data means that program managers cannot incorporate new, better methods or discard inferior ones any earlier than a year after completing a pilot program. The number of meter readings required can lead to many houses being dropped from the analysis. PRISM evaluations of Philadelphia's low-income programs typically have 80+% drop-out rates due to frequent utility shut-offs and few actual meter readings. Such large drop-out rates can introduce significant sample selection biases. Recent GRASP research found that houses which met a data screen for PRISM are 30% tighter, as measured by a blower door, than unscreened houses (Blasnik, 1988).

The Search for Short Term Alternatives

PRISM's post treatment data requirements have led researchers to seek out alternative methods for quicker program evaluation. The most promising alternatives include short-term submetering analysis (Nadel, 1987) and short term variations on PRISM (Nadel, 1987 and Dunsworth and Hewett, 1985). Submetering analysis has had excellent agreement with full year PRISM and clearly disaggregates heating consumption, but is expensive, labor intensive, and invasive. Short term variations on PRISM have taken two forms: attempts to use short term consumption data with the PRISM model, and substituting post-treatment weather data into pre-treatment PRISM equations to estimate percent savings (Nadel 1987 and Dunsworth & Hewett, 1985). The former method has proven unsatisfactory. The latter method has led to good preliminary results (Nadel, 1987), but has not been well explored in terms of data quality, post period selection, and statistical validity. Because this method seemed worthy of further exploration, GRASP developed and tested the GRASP Short-Term Energy Analysis Method (GSTEAM) outlined below.

GSTEAM

Description of the Method

GSTEAM is a short term variation on PRISM that substitutes post-treatment weather data into pre-treatment PRISM equations to project 'no-savings' usage. The difference between this projected usage and the actual usage is used to estimate a percent savings which is then applied to PRISM's pre-Normalized Annual Consumption (NAC) to estimate raw savings. GSTEAM minimizes the errors associated with this type of analysis by selecting the most statistically valid post period. This period is determined by when the post-period average degree days per day, using the pre-period reference temperature, equals the pre-period average degree days per day (i.e. DDpost(t-pre)=DDpre(t-pre)).

Theoretical Basis

A post period in which the DD(t)/day is equal to the pre period DD(t)/day is the most statistically valid period for short term analysis because the estimate of a regression is most certain at the mean of the x values, which in the case of PRISM, is the pre-period average degree days per day. In standard linear regression analysis, using this mean value eliminates errors associated with fitting the slope. With PRISM, using the mean value minimizes (but does not eliminate due to the non-linearity of the model) the errors associated with fitting the heating slope to just second order effects.

GSTEAM has several drawbacks. First, GSTEAM's estimate of savings is an estimate of actual post period savings, not of long-term average savings. Fortunately, these numbers tend to agree quite well if pre-period weather is not atypical. Second, GSTEAM determines its savings estimate on 5-7 months of data. Bias can be introduced if houses consume energy differently in the second half of the year due to factors which are not air-temperature dependent, e.g. solar gain, wind speed, ground temperature, thermostat management. This effect can be minimized by using a control group to account for systematic biases. Third, GSTEAM still requires a pre-period PRISM analysis and therefore still has large drop-out rates. Finally GSTEAM does not disaggregate the factors of NAC or provide any measure of the uncertainty in the savings estimate as PRISM would.

EVALUATION OF GSTEAM

Data Set

The data set used for this analysis is from a study of secondary condensing heat exchanger retrofits in public housing units in Philadelphia (Daspit and Roberts, 1987). This data was chosen because pre and post PRISM analysis for treatment and control groups was readily available. The data available for performing GSTEAM consisted of 165 units: 63 treatment and 102 control.

This group provided a strenuous test for GSTEAM as PRISM analysis showed both pre and post data to be low quality with median RxR=.967 and median CV(NAC)=4.9%. Depending upon the criteria used to screen for valid results, PRISM estimates the treatment group to have net control-adjusted savings ranging from -7.5% to +5%, none of which are statistically significant.

Data Analysis And Results

GRASP ran GSTEAM using a database program which utilized pre-treatment PRISM parameters and post-treatment weather data and meter readings. The resulting estimates of savings were compared to PRISM estimates. The wide variations in PRISM data quality for this particular data set (as measured by RxR and CV) allowed analysis of the sensitivity of GSTEAM estimates to PRISM data quality, parameter values and standard errors. GSTEAM was also run with later starting dates for the post period in order to analyze the sensitivity of the estimates to shorter evaluation periods.

GSTEAM can be considered a good estimator of energy savings if it yields similar mean savings to PRISM (i.e. the errors are normally distributed with a mean difference close to zero) with a small enough standard deviation to allow reasonable sample sizes to determine savings accurately. Table I compares PRISM and GSTEAM savings for all cases in the treatment and control groups.

Table I. GSTEAM and PRISM savings comparison - all cases. (+/- 95% confidence intervals in parentheses)

	PRISM SAVINGS	GSTEAM SAVINGS	DIFFERENCE	NACPRE
63 TREATED: MEAN	-12.0% (7.9%)	-10.9% (7.0%)	-1.1% (2.8%)	1764
MEDIAN	- 6.8	- 6.2	-0.7	
102 CONTROL: MEAN	-10.1% (5.5%)	-10.1% (5.2%)	0.0% (1.6%)	1688
MEDIAN	- 7.9	- 8.6	+0.7	
SAVINGS: MEAN adj	- 1.9% (9.1%)	- 0.8% (8.3%)	-1.1% (3.2%)	
MEDIAN	+ 1.1	+ 2.4	-1.4	

The results are quite encouraging, with a statistically insignificant 1.1% difference in the treatment group and perfect agreement in the control group. The mean difference between GSTEAM and PRISM estimates for all 165 cases combined is 0.4% (with std.dev. 8.7%). The difference between GSTEAM and PRISM estimates for each house are within one standard error of PRISM's NAC savings estimates in 95% of the cases.

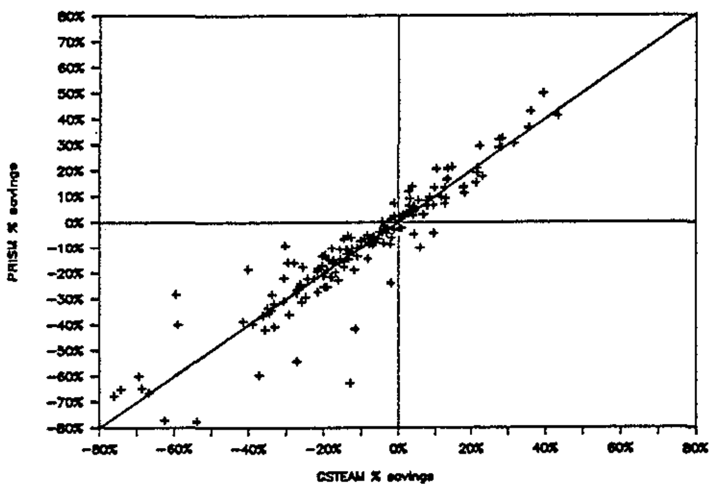

Figure 1 shows PRISM and GSTEAM estimates of savings for all houses (except 6 cases which extend beyond the scales). A line is drawn to represent perfect agreement. A linear regression of GSTEAM against PRISM savings estimates shows excellent correlation (PRISM savings = 1 ccf + 1.04 * GSTEAM savings with RxR=.91) with both parameters statistically indiscernible from a perfect fit.

Figure 1. GSTEAM vs. PRISM savings estimates - 159 cases.

Screening houses for the quality of their PRISM analysis by setting maximum CV and minimum RxR requirements led to fluctuating but comparably small mean differences with significantly smaller standard deviations as the screen is tightened (std. dev.=3.3% at .95/.05 screen N=42). In other words, the correlation of GSTEAM and PRISM was best for houses with the best PRISM estimates, encouraging news for future users who may have better quality data.

Because net savings were small and statistically insignificant, the data set was artificially partitioned into winners and losers to see if GSTEAM accuracy would hold for samples with large savings. This analysis gave excellent results with net savings estimates of 33.3% (+/-5.0%) from PRISM and 32.5% (+/-5.0%) from GSTEAM. An analysis of GSTEAM savings estimates for later post-period starting dates showed that late December through January is the optimal starting time, but after mid-February significant errors appear.

CONCLUSIONS

GSTEAM appears to be an excellent short term estimator of energy savings, with savings estimates within 2% (absolute) of PRISM's. Its correlation to PRISM is best for houses in which the PRISM model is well determined. GSTEAM is inexpensive, requiring a pre-period PRISM analysis, only two post-period meter readings and no special equipment. It is not invasive and provides results in 5-7 months. GSTEAM can also evaluate houses where poor data quality makes post-PRISM analysis unusable. It is ideal for quick evaluation of pilot weatherization programs completed before late winter.

Further statistical analysis is needed to determine sample size requirements to achieve a specified level of accuracy for a given quality of pre-period data. Further research is also needed to compare GSTEAM to PRISM for larger, high quality data sets, and data sets with different climates, years, and starting times.

REFERENCES

M. Blasnik, Sample Selection Bias From Using PRISM In Evaluating Low-Income Energy Conservation Programs, GRASP, 1988.

C. Daspit and R. Roberts, High Efficiency Gas Furnace Modification in Low-Income Housing, Energy Task Force of the Urban Consortium for Technology Initiatives, 1987.

T.S. Dunsworth and M.J. Hewett, Data Quality Considerations In Using The "PRISM" Program, Minneapolis Energy Office technical report #85-4-AM, 1985.

M. Fels, "PRISM: An Introduction", in Energy and Buildings, 9 (1986) Elsevier Sequoia, p.5-18.

S. Nadel, "Timely Evaluations: A Discussion Of Methods Used By The Massachusetts Audubon Society To Evaluate Fuel Savings In Under One Year", in Energy Conservation Program Evaluation: Practical Methods, Useful Results, Volume 2, pp.73-83. (Argonne National Laboratory: Argonne, Ill.) 1987.