Mass-Market Demand Management Offerings: Evaluation Methods Assessment and Results

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ABSTRACT

This paper draws on impact evaluations of mass-market load management programs at three utilities — Louisville Gas & Electric Company, Kentucky Utilities, and the Sacramento Municipal Utility District. Mass-market programs can provide load reductions that are essentially dispatchable, i.e., available on five minutes or less notice since they involve the direct control of a large number of energy using appliances (e.g., air conditioners and water heaters). The large number of appliances makes these programs both dispatchable and reliable in terms of the load reduced for a given control strategy. This paper investigates cost-effective evaluation methods that combine data from run-time loggers with a small sample of data from more precise interval meters. The results from the analyses presented in this paper show that a nested sampling approach can provide estimates of load impacts using different control strategies at a relatively high level of precision. The different utility analyses also allowed for an investigation of comfort, i.e., change in indoor temperature and humidity during control periods (LGE/KU) and an investigation of a rebound effect where air conditioner consumption increases in the hours after the end of a control event.

Introduction and Background

Mass-market demand management (DM) and direct load control (DLC) programs are receiving increased emphasis across the country. This is due to the growing recognition of the benefits they provide in terms of hedges against price spikes, unforeseen outages, and demand growth that exceeded forecasts (both system-wide growth and local area growth for T&D infrastructure). These benefits stem unique program attributes that can be used to create a balanced resource portfolio that: (1) accommodates key synergies between dispatchable DM programs and energy efficiency (EE) programs that reduce overall peak demand, and (2) takes advantage of the lack of correlation between the availability and cost of DM and EE programs with drivers of generation costs (fuels, O&M, availability) and T&D costs (upgrades, congestion, and outages). The use of DM/EE as physical hedges against supply shortages, price spikes, and unforeseen rapid growth in demand requiring high cost resource acquisition is important given the limitations associated with financial and other supply-side hedges available to resource planners.

One key to the application of these programs within a portfolio of resources is the ability to accurately evaluate and verify curtailed loads at a reasonable cost. These approaches must provide resource planners with the level of confidence they need to rely upon these DM and EE programs as a portfolio resource. Some approaches to verifying load reductions to provide this level of confidence have required costly metering and monitoring that can make these programs uneconomic.

This paper makes an important contribution to the literature on cost-effective evaluation of mass market load management programs by presenting the methods and results from in-field verification

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projects for three utilities — Louisville Gas & Electric Company (LGE), Kentucky Utilities (KU), and the Sacramento Municipal Utility District (SMUD). Unique features of this work include:

1. The use of regression/statistical tools that make full use of all available data. The fixed-effects regression model to be discussed in this paper negates the need to explicitly develop baseline days for use in estimating the impacts of programs on control days.[2]
2. The use of less-expensive measurement methods that make use of a combination of interval data recorders and run-time recorders. The cost of interval data recorders can range from $1,400 to $2,000 per site, whereas run-time meters can range from $150 to $200 per site installation and collection.
3. The use of nested data and other procedures to calibrate and translate the percent on/off information from run-time meters.

This paper is presented in three sections with the first presenting the methods and results used for analyses at Louisville Gas & Electric and Kentucky utilities. In this application, run-time meters were installed on a sample of load management participants and a second sample was drawn for interval metering. In the second section, results from an analysis of a pilot thermostat program used for load control implemented by the Sacramento Municipal Utility District is presented. In this application, a sample of participants were selected with run-time meters placed on the compressors of air conditioning units to measure on/off times during control days which can be compared to non-control days. In this case, a nested sample of participants was selected for interval kW metering. These participants had both run-time meters and interval meters installed which allowed for more direct calibration and transformation of the of run-time data into kW impacts of the load management program. The third section provides a brief conclusion based on results from all three of the utilities' demand management program impact analyses.

Methods and Results — LGE/KU Demand Management Program

Data Collection — LGE/KU

The analysis is based on data collected during the summer cooling season of 2002 for the LGE/KU service territory. The data collected for the analysis included interval metered data, run-time hour data, spot power measurements and site characteristic data for a sample of homes (see the discussion below for more details). In addition to the metered data, basic site characteristic data (e.g., home type) were collected by the implementation contractor, Enertouch, on all homes where load control devices were installed. As of the date of this report, a total of 11,500 load control devices have been installed on air conditioner (AC) units and 105 on electric water heaters within LGE and KU service territories. Table 1 shows the number of AC units and water heaters controlled by each service territory.

Table 1. Summary of Load Control Switches Installed

Controlled Device	LG&E	KU	Total
Central AC units	11,156	344	11,500
Electric water heaters	90	15	105

[2] See Violette, D. and F. Stern, "Cost-Effective Estimation of Load Impacts from Mass-Market Projects: Providing Value in Restructured Markets," Proceedings of the 2001 International Energy Program Evaluation Conference, Salt Lake City, Utah, August 21-24, 2002.

Demand savings estimates were generated for both AC and electric water heater direct load control. Savings estimates were produced with a multi-variate regression model, and engineering analyses of the data sets were employed to provide additional information on the performance characteristics of air conditioning units.

The research objectives were to:

1. estimate the total load reduction achieved over the evaluated control period, and the average load reduction per participant by controlled end use (i.e., AC, water heater); and
2. assess factors influencing the load reduction, including:
   - Load Factor. The average or typical actual load for each type of controlled device (i.e., AC unit, water heater) compared to the rated or nameplate value (see algorithm below).
   - Diversity Factor. The typical fraction of units actually operating during the control period.

Data collection to support this analysis encompassed the following activities:

- **Site and equipment characteristics data.** Basic site and equipment data were collected for each participant where a load control switch was installed. Additional data were collected at each site where a run-time data logger was installed, and a detailed audit was conducted at each site where an interval load recorder was installed.
- **Run-time hour data and spot measurements.** Run-time data loggers were used to collect run-time (AC state change) data for a sample of AC units. Spot measurements of AC electrical demand, kW and power factor, and outdoor air temperature were taken at the time that the loggers were installed and at each monthly data download.
- **Interval metered data.** End-use data loggers were used to collect 15-minute interval data on a sample of AC units and water heaters.

Run-Time Data. Air conditioner compressor state change data were collected from 82 participant sites using state change data loggers.[3] The state change loggers recorded a time stamp and the state of the AC compressor each time the state changed. In other words, each time the compressor went from on to off, or visa-versa, a time stamp was recorded. Data were downloaded from these loggers during site visits at intervals ranging from approximately 3 to 5 weeks.[4] Spot measurements of the air conditioner unit's demand were taken during each site visit. The spot measurement data were recorded on a standard form that also captured the date, time, and outside air temperature.

Interval Meter Data. Twenty additional sites were equipped with multi-channel interval meters that recorded the 15-minute average values of the following data: (1) whole house demand, (2) air handler unit electrical demand, (3) air conditioner compressor and condenser fan electrical demand (the

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[3] run-time data logger Motor on/off logger with AC-field sensor, part number H06-004-02, manufactured by the Onset Computer Corporation.

[4] Several in-field issues arose in the use of the data loggers that will be addressed in subsequent applications. The most significant involved the placement of the logger such that they would reliably sense the operating current of the compressor. This was often due to space limitations. Often the run-time loggers would appear to be recording properly when they were installed, but in fact were only sensing the momentary current surge produced when the compressor motors started. They didn't sense the steady state current of the unit. The result was that some data files recorded by the loggers would consist only, or predominately, of very short (on the order of 0.5 second) on cycles followed by relatively long off cycles. Another possible source of the problem is vibration. If the logger was installed such that it experienced excessive vibration, the magnet in the logger that was intended to move in response to an alternating current magnetic field would instead move as a result of the vibrations. This problem would also result in a series of very closely spaced on/off cycles of very short duration. Data that exhibited either of these problems clearly didn't reflect the operation of the AC units and were excluded from the analysis.

sum of the demands was recorded), (4) water heater electrical demand, and (5) indoor air temperature and relative humidity.

Analysis Method — LGE/KU

The fact that the run-time data and the interval-metered samples were not nested resulted in an analysis method that did not calibrate the run-time data to the metered data. As a result, the four steps in this analysis were:

Step 1: Interval metered data analysis. The interval-metered data were analyzed using a multi-variate regression model for AC and water heater control.

Step 2: Run-time logger data analysis. The run-time data logger run-time data were analyzed in a regression model for AC control.

Step 3: Analysis integration and reconciliation. The data collected for all participants and the results of the interval metering, run-time data logging, and on-site data collection were analyzed, integrated, and reconciled.

Step 4: Supplemental analysis. Supplemental engineering analyses of metered, run-time, and site data were conducted to examine equipment performance.

Interval Data Analysis — LGE/KU

The purpose of the analysis was to estimate the decrease in kW associated with the two service territory load control programs. The model developed for this analysis took the form of a fixed-effects panel analysis. For this analysis, data are available both across households (i.e., cross-sectional) and over time (i.e., time-series). With this type of data, known as "panel" data, it becomes possible to control at once for differences across homes, as well as differences across periods in time through the use of a "fixed-effects" panel model. The fixed-effect refers to the assumption that differences across houses can be explained in large part by house-specific intercept terms, as discussed below. Because the consumption data in the panel model include periods before and after the control period, the pre-control periods can act as a proxy for what consumption would have been without the intervention.

The fixed-effects model can be viewed as a type of differencing model in which all characteristics of the home, which (1) are independent of time and (2) determine the level of air conditioning and water heating use, are captured within the house-specific constant terms. In other words, differences in housing characteristics that cause variation in the level of energy consumption, such as building size and structure, are captured by constant terms representing each unique house.

The fixed-effect panel data model is characterized by $y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it}$ where:

y_{it} = energy consumption by end use (AC or water heat) for home *i* during hour *t*

α_i = constant term for site *i*

β = vector of coefficients

x = vector of variables that represent factors causing changes in AC or water heating consumption for home *i* during hour *t* (i.e., weather and control strategies)

ε = error term for home *i* during hour *t*.

In practice, rather than estimating a unique intercept term for each home, an equivalent approach is employed which expresses both the dependent and independent variables in terms of deviations from the time-series means for each home. The resulting estimated coefficients from this "deviation from the mean" approach is equal to the coefficients found by having house-specific intercept terms.

The panel data model estimated for the AC control analysis is presented in Table 2. This model performs well, with most variables being statistically significant. Thus, through this model we are able to effectively estimate the effects of the control strategy, as well as capture the relationship between weather and air conditioner usage.

Table 2. Fixed-effects Hourly Model for AC Control — Interval Data

Dependent variable: Hourly AC electricity use (kW)	
Independent variables	**Coefficient (t-value)**
Indicator indicating control hour times temperature squared	-0.0198 (-16.9)
Month which this hour is in (1 is January, 12 is December)	0.036 (4.4)
Relative humidity	0.0169 (6.4)
Relative humidity squared	-0.0001 (-7.1)
Outside dry-bulb temperature, current hour	-0.224 (-15.6)
Outside dry-bulb temperature squared	0.0013 (15.6)
Outside dry-bulb temperature, one hour ago	0.03 (5.5)
Outside dry-bulb temperature, two hours ago	0.03 (5.03)
Outside dry-bulb temperature, three hours ago	-0.0014 (-0.25)
Outside dry-bulb temperature, four hours ago	0.054 (15.0)
Full R-square R-square	.89 .41

Run-Time Data Analysis — LGE/KU

The statistical analysis of the run-time data was different than that used for the interval data because run-time data only provide information on whether the unit was on or off, and not the load at that time. A regression model was developed to estimate the percentage on time for each unit using the run-time data logger data. The large sample size (109,000 observations) prohibited the development of a panel model, thus the model had one constant term for all houses, rather than a constant term specific to each house. This had the result of reducing the over-all R-Square of the regression equation to a level more commonly found with cross-sectional models as opposed to panel-data models. The hourly model for the run-time data is presented in Table 3.

Integration and Reconciliation of Interval and Run-time Analyses

The data collected for all participants where switches were installed and the results of the interval metering, run-time data, and on-site data collection were integrated and reconciled. It was not possible to directly calibrate the run-time data with the interval metered data due to the fact that the samples were not nested sample for this season (Note: A nested sampling approach is used in the SMUD analysis described below). An integrated model was developed and used to extrapolate results to all participants. Specifically, the run-time data on the larger sample were combined with the on-site data and spot-power measurements. Metered percent-on run-time data (from the run-time data logger data

Table 3. Hourly model for the LG&E AC control – Run-time Data

Dependent variable: Percentage of the hour the AC is on (0 to 100%)	
Independent variables	**Coefficient (t-value)**
Constant	-6.55 (-19.5)
Name plate kW	-3.22 (-36.6)
Name plate times temperature	0.04 (41.0)
Control strategy	-7.60 (-2.4)
Control strategy times hour of day	0.38 (1.9)
Control strategy times house type	2.03 (4.34)
House type (1 is single family)	-0.41 (-15.1)
Outside dry-bulb temperature, one hours ago	-0.10 (-17.1)
Outside dry-bulb temperature, two hours ago	0.13 (27.4)
Relative humidity lagged an hour	0.009 (10.5)
Hour of the day	0.02 (15.3)
Weekend indicator	-0.22 (-7.7)
R-square	.15
Number of observations	109,181

set) was used in a multi-variate regression (MVR) to produce an equation that predicts the hourly percent on time for program participants. A separate MVR was performed using the spot power measurements taken from the AC units that had run-time data logger meters installed to produce a relationship describing average load factors. Finally, an engineering algorithm was developed which, informed by the two aforementioned MVRs and their underlying metered data, predicts the demand of participant AC units. The model is described as follows:

$$kW_{hr} = [0.00635(T) + 0.000413(RH) + 0.2203] \times [RLA \times V \times P^{0.5} \times 0.93/1000]_{np\ comp} \times \%On_{hr} \quad \text{(Eq. 2)}$$

Where:

- T = Outdoor air dry bulb temperature[5]
- RH = Outdoor air relative humidity
- RLA = Rated load current [amps] of the air conditioner compressor as read from the nameplate
- V = Voltage of the air conditioner's compressor as read from the nameplate
- P = The number of phases listed on the nameplate for the air conditioner's compressor
- 0.93 = The average of the AC compressor power factor measurements taken in this study
- $\%On_{hr}$ = The percent-on factor derived from the run-time data logger data set using a MVR.

The expression in the first set of brackets of Equation 2 above was developed by performing a MVR using the AC spot measurement and nameplate data gathered from the participant sample, as well as the weather data from the NCDC Louisville station. It predicts the ratio of the actual power consumed when the equipment operates to the demand calculated using data gathered from the unit's

[5] All of the outdoor temperature and relative humidity data used in this work were downloaded from the National Climactic Data Center website at http://ols.ncdn.noaa.gov/onlinestore.html.

nameplate. The calculation of the unit's nameplate demand is given in the second set of brackets of Equation 2.

The percent-on factor used in Equation 2 was developed using the run-time logger data set and other metering participant data in an MVR. The hourly percent-on of the AC equipment was the dependent variable. The independent variables in this regression included: (1) Weekday (i.e. Monday, Tuesday); (2) Hour; (3) Outside dry bulb temperature; (4) Outside relative humidity; and (5) Home type.

This model is used as a powerful predictive tool for residential air conditioner direct load control programs. Equation 2 was developed specifically so that it could be applied using data available for the entire program participant population. This allows a unique calculation of each program participant AC's demand contribution to the demand reduction to be made. As the participant population changes over the program's life (i.e. different sizes and types of AC units for instance) the evaluation will continue to accurately predict the savings produced in a variety of conditions and control schemes. Furthermore, Equation 2 can be incorporated into a database containing the characteristics of the participant population to provide real-time impact estimates. This predictive result can in turn be used as a planning aid for the program's managers.

Air Conditioning Demand Savings Estimate Based on Run-Time Data Logger Site Data

The demand savings estimate prepared with the run-time logger data and the equipment nameplate data are presented in Tables 4 and 5.

Table 4. AC Impact Estimates Per Unit Based on Run-Time Data

Outdoor Temperature Bin	Impact Estimates (KW per AC Unit)					
	Cycling Strategy					
	33%	40%	50%	66%	75%	100%
<90 F	0.56	0.66	0.80	0.94	1.07	1.44
90 <95 F	0.59	0.70	0.87	1.02	1.21	1.75
>95 F	0.60	0.73	0.91	1.07	1.35	2.04

Table 5. AC Impact Estimates Per Ton Based on Run-time Metered Data

Outdoor Temperature Bin	Impact Estimates (KW per Ton)					
	Cycling Strategy					
	33%	40%	50%	66%	75%	100%
<90 F	0.25	0.29	0.35	0.41	0.47	0.64
90 <95 F	0.26	0.31	0.38	0.45	0.53	0.77
>95 F	0.27	0.32	0.40	0.47	0.60	0.90

Air Conditioning Demand Savings Based on Interval Data

Demand savings results were estimated from the interval data for AC and water heating using the interval metered data. The results for AC are presented below in Tables 6 and 7.[6]

[6] Water heater results are available from the full report available from the authors.

Table 6. AC Impact Estimates Per Unit Based on Interval Metered Data

Outdoor Temperature Bin	Impact Estimates (KW per AC Unit)					
	Cycling Strategy					
	33%	40%	50%	66%	75%	100%
<90 F	0.45	0.55	0.68	0.90	1.03	1.37
90 <95 F	0.52	0.63	0.78	1.03	1.17	1.56
>95 F	0.56	0.68	0.85	1.12	1.28	1.70

Table 7. AC Impact Estimates Per Ton Based on Interval Metered Data

Outdoor Temperature Bin	Impact Estimates (KW per AC Unit)					
	Cycling Strategy					
	33%	40%	50%	66%	75%	100%
<90 F	0.13	0.16	0.19	0.26	0.29	0.39
90 <95 F	0.15	0.18	0.22	0.29	0.33	0.44
>95 F	0.16	0.19	0.24	0.32	0.36	0.48

Indoor Comfort Impacts

Indoor temperature and humidity were monitored at the interval metered sites to assess the indoor comfort impacts (if any) due to the AC control. In short, the program participants experienced negligibly small impacts on their comfort at least at the 33% and 40% control strategies employed during the monitoring period. It would be useful to revisit this analysis next summer under more aggressive control strategies (50% and higher). Tables 8 and 9 show relative humidity levels and the indoor air conditions of the metered participants stayed well within the bounds of a reasonable comfort zone. The average temperature rise during control periods was less than one degree Fahrenheit and the relative humidity increase was less than 5%. Both parameters stayed well within commonly accepted comfort ranges.[7,8]

Methods and Results — SMUD Demand Management Program

This section presents results from an impact analysis of SMUD's PowerStat℠ residential load control pilot program. In 2002, SMUD and the California Energy Commission (CEC) embarked on a joint pilot project, called PowerStat℠, to test the market potential, load savings potential and operational feasibility of new air conditioning load management technology. The new technology allows SMUD to radio dispatch a signal to a "smart thermostat" that cycles the air conditioner off for a programmed percent of time with hour to hour variations within a 4-hour control period. Unlike more traditional controllers, the thermostat can detect if and when the air conditioner is running. The analysis is based on data collected during the summer cooling season of 2002. The data collected for the analysis included interval metered data, run-time data, spot power measurements, characteristic data for a sample of homes, and survey data on all participants. Demand savings estimates were generated for the AC direct loads controlled. These savings estimates were produced using a regression model.

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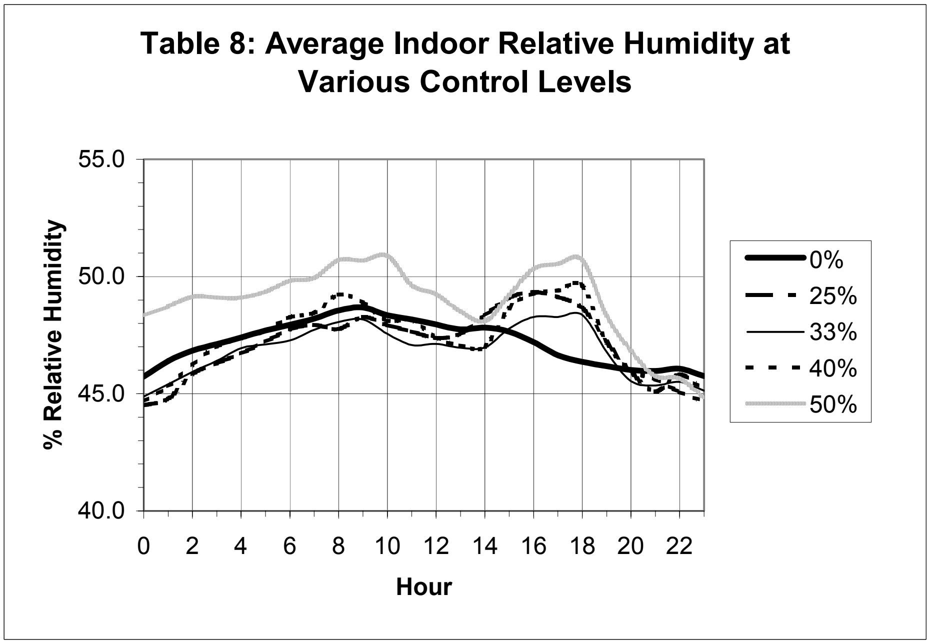
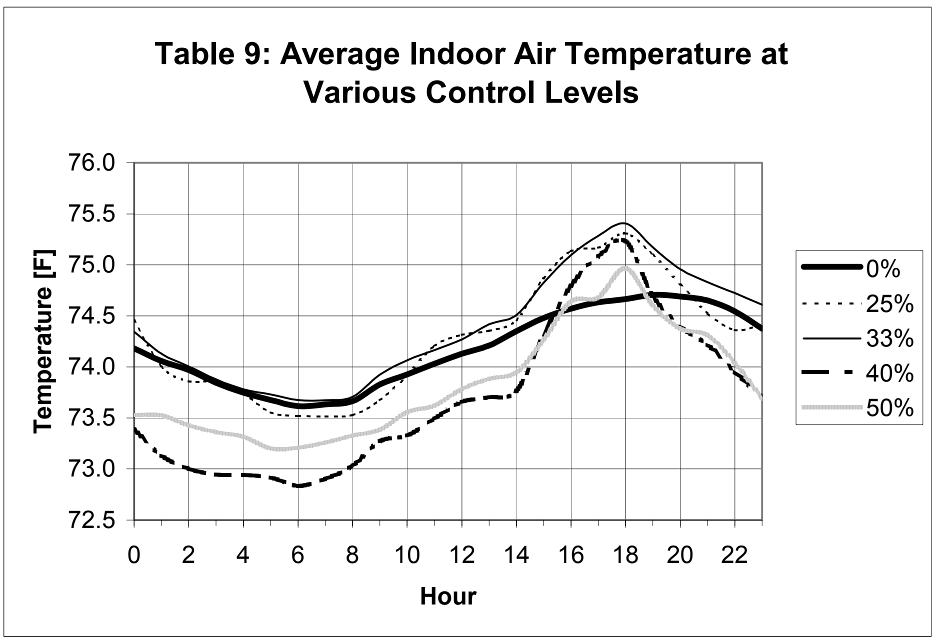
[7] A coefficient of variation analysis on Indoor Air Temperature was also conducted which showed little variability in the indoor air temperature which provides further evidence that there is little likelihood that participants would experience adverse comfort impacts under these control regimes.

[8] A number of supplemental analyses were also conducted examining the power factor for the AC units which had run-time loggers installed, the average load factor for different sizes of AC units under different temperature regimes, the AC percent hourly "on" factor for different AC units at different temperatures, and control effectiveness (i.e., the fraction of units actually receiving the control signal which was in excess of 99%).





Data collection to support this analysis encompassed the following activities[9]:

- Site and equipment characteristics data. Basic site and equipment data were collected for each participant.
- Run-time hour data and spot measurements. Run-time data loggers were used to collect run-time (AC state change) data for a sample of AC units. Spot measurements of AC electrical

[9] A web-based survey of all study households that address program satisfaction, demographics, air conditioner usage patterns, and house characteristics. The survey responses were used to address program satisfaction and assess program features. A web-based survey approach was deemed feasible since all participants had Internet access which they used to program the thermostat. Over 90% of the participants responded electronically, with about 10% follow-up via telephone interview to obtain results for approximately the entire population of participants in SMUD's PowerStat℠ Pilot program.

demand, kW and power factor, and outdoor air temperature were taken at the time that the run-time loggers were installed.

- Interval metered data. End-use data loggers were used to collect 15-minute interval data on a sample of AC units. All of these customers also received a run-time data logger.

Analysis Method — SMUD

The major steps in this analysis included:

- **Step 1: Interval metered data analysis.** The interval-metered data were analyzed using a multivariate regression model for a sample of 14 participants.
- **Step 2: Determine kW usage from run-time data.** Through the interval-metered sample which was nested in a larger sample of participants on which run-time data were available (n=50), we were able to compute the kW associated with each run-time measurement.
- **Step 3: Run-time logger data analysis.** A regression model was used to estimate the kW impacts for both the nested sample and the larger sample of participants on which run-time logger data were available.
- **Step 4: Analysis integration and reconciliation.** By comparing the run-time data logger results to the interval metered results, we refined the run-time data logger results to obtain a more accurate estimate of the kW impacts for the run-time data logger sample.
- **Step 5: Investigate Snapback.** By looking at kW usage during and after the control period, we were able to estimate snapback associated with a load control event. This gives some indication whether or not there are any energy savings associated with this program.

Given the in-depth discussion of the installation of run-time loggers combined with spot-power measurements when data-downloads were made in the prior section, this section focuses on the results from the nested interval data/run-time logger data.

The run-time loggers provide information only on the time the unit was on/off and not on the load during that period of time. Therefore, this run-time information must be converted into kW usage. We investigated several approaches to do this, including estimating the kW demand based upon the in-field spot metered results and the unit's nameplate demand. However, this would introduce significant additional error into the statistical model. Therefore, the approach we used took advantage of the nested sample, where we had both kW measurement and run-time information. The analysis involved normalizing kW usage by the unit's size (tons) and relating that (via a regression) to the measure percentage on during that period. The results are presented in Table 10. The high R-square and t-value indicates that this model very well defines the relationship.

Table 10. kW Usage from On Time Measurements

Dependent variable: Hourly AC electricity use (kW) divided by AC ton	
Independent variables	**Coefficient (t-value)**
Percentage on during that hour from run-time data logger	37.864 (339.20)
R-square	.92
Number of observations	16,861

This information on the relationship between kW usage and percentage on was then used to develop kW impact estimates from the run-time logger data in the nested sample. Unlike the use of run-time data in the LGE/KU analysis discussed above, a fixed-effects model based on the calibrated run-time data for the larger sample could be estimated. The results are shown in Table 11. Note the higher

Table 11. Fixed-effects hourly model for AC control Run-Time Meters

Dependent variable: Hourly AC electricity use (kW)	
Independent variables	**Coefficient (t-value)**
Indicator indicating control hour times temperature squared	-0.0256 (-19.6)
Relative humidity	-0.023 (-5.8)
Relative humidity previous hour	0.004 (0.76)
Relative humidity two hours ago	0.056 (13.8)
Outside dry-bulb temperature, current hour	0.088 (2.5)
Outside dry-bulb temperature squared	-0.127 (-6.14)
Outside dry-bulb temperature, one hour ago	0.273 (4.93)
Outside dry-bulb temperature, two hours ago	-0.516 (-14.7)
Outside dry-bulb temperature, one hour ago squared	-0.002 (-6.4)
Outside dry-bulb temperature, two hours ago squared	0.0058 (28.00)
R-square	.97
Number of observations	48,405

R-Square produced by this model compared to the run-time model estimated for LGE/KU and the higher t-value on the control variable.

The resulting impact estimates are presented in Table 12. In this step of the analysis, the sample model and the nested run-time data logger sample are used to estimate the kW impacts from the full run-time data logger sample. The relationship described above was used to estimate kW and from the percentage "on" data. Then, using the same fixed-effects model as before, the kW impacts are estimated from the run-time logger data.

Table 12. Reconciled Impact Estimates

Outdoor Temperature Bin	Impact Estimates (kW per AC Unit)							
	Cycling Strategy							
	25%	33%	37%	50%	66%	75%	87%	100%
<=90F	0.46	0.60	0.68	0.91	1.21	1.37	1.59	1.83
91-95	0.49	0.64	0.72	0.98	1.29	1.46	1.70	1.95
96-100	0.54	0.71	0.80	1.08	1.43	1.62	1.88	2.17
101-105	0.60	0.80	0.89	1.21	1.59	1.81	2.10	2.42

An analysis of snapback was also conducted by looking at AC kW and run-time for the participants in the sample for two hours after the control period. In three hours subsequent to a control period (which always ended at 6 PM), there was a rebound effect with the AC unit showing greater kWh use for up to three hours after the control period. However, this statistical analysis was preliminary and did not address the influence of alternative cycling strategies, yet there was substantive evidence of a rebound effect occurring in the hours subsequent to a control period. Additional work is needed to dimension the magnitude of this rebound, but it seemed to roughly off-set any energy savings (kWh) that might be attributed to the load management program.

Conclusions

The analyses of the LGE/KU load management efforts and the SMUD program both showed reductions in load at high levels of significance. The use of the fixed-effects model proved to be a powerful tool in terms of making full use of available data, and produced estimates with high levels of statistical precision. For example, the control variable in the SMUD regression model had a t-value of 19.6 indicating that the impacts are estimated with a precision in excess of plus/minus 5% using a 90% level of confidence. In addition, these results illustrate the usefulness of run-time data in impact evaluations of load management programs when combined with a small sample of interval meters in a nested sample that can be used to directly calibrate the on/off run-time data to provide kW estimates. This is important since collection of run-time data costs approximately $150 per site for a summer season, whereas interval metering can cost more. As a result, run-time data can be an important component of cost-effective evaluation of mass-market load management program impacts.