Energy Signature Analysis: Radar for Energy Managers

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ABSTRACT

Energy Signature Analysis (ESA) acts as a noise filter, to enhance usefulness of energy data. It provides vital feedback on operating and maintenance (O&M) consistency and strategies, trends, and on conservation changes to facilities and equipment.

Energy and temperatures characterize building performance. Energy use "drivers" fall in one of two groups: (1) weather and inside temperatures, or (2) building characteristics, occupancy, and O&M practices. ESA weather-normalizes with delta T, and uses optimal smoothing to minimize weather, occupancy, and thermostat-driven scatter in energy use. The remaining variability arises from causes of great interest - changes in building characteristics, occupancy patterns, and O&M practices.

Energy use rate is plotted versus coincident delta T, for sequenced typical weeks. When nothing but weather changes, consistently managed buildings show low scatter; r^2 for regular occupancy is often 0.96 or better. Efficiency requires consistency; energy use should only change with weather and thermostat settings. Inconsistent management or equipment faults cause scatter, outliers, or an uptrend to alert management. Improved consistency reduces scatter. Worthwhile retrofits, HVAC tuning, and improved management strategies lower the curve. Important changes show merit in a week.

High scatter cripples purely statistical uses of building energy data. For ESA, outliers are chances to find inconsistency and behaviors to avoid (high outliers) or foster (low outliers). Area-normalized ESA permits comparing facilities with different size or weather. Model output for new buildings, recast in ESA format, can help track building commissioning or give modelers feedback.

Example ESAs use hourly total energy, outside and sampled inside temperatures. Problems found are investigated using hourly HVAC and baseload data. Baseload and HVAC loadshapes show peak-shaving, shut-down and tuning opportunities. New weekly data points show results of changes.

Introduction

The Energy Manager's Challenge

Energy managers sometimes need to know how and when energy is used, and get feedback on staff's conservation efforts, for best results. But utility bills don't show how or when energy is used. Effects of conservation efforts are often masked by weather and daily or weekly occupancy-driven fluctuations in energy use. Equipment maladjustments and failures can go unrecognized. Results of HVAC tuning efforts, and of interactive conservation measures, are particularly hard to gage.

Energy management and control systems (EMCS) don't normalize for weather, and some don't provide energy use profiles. Energy managers may face commissioning problems, and often have tiny budgets. Other facilities management duties may leave scant time for conservation. Worst of all, managers typically must try to save energy with woefully inadequate energy management information.

Wanted: MIS

The US spends roughly 2% of GDP on financial management information systems (MIS), to manage financial resources. We should spend as much - 2% or more of annual energy costs - on energy MIS, to manage energy wisely. A building's energy MIS should provide these basics:

* A permanent set of economical basic measurements.
* A flexible capability to measure items of temporary special interest.
* Low effort data processing and simple interpretation to minimize scatter from weather and occupancy-driven variations in energy use, and help identify and track problems.

Ideally, this MIS should pay for itself through enhanced O&M energy savings. Such savings might typically amount to 10%. In facilities with annual bills over $25,000 to $50,000, realizing such savings would swiftly pay for equipment[1]. The first two of these basics are straight-forward and inexpensive to achieve. But their usefulness is limited without effective data interpretation.

Currently, energy managers must choose between relatively simple methods - such as PRISM (Fels 1984) and EUI comparisons - or complex approaches such as energy management and control systems, hired experts, shared savings contracts, audits or "virtual buildings" (computer energy models) to understand building energy use. The simple methods are cheap but give little insight; the complex ones are expensive, time consuming, and often involve unproven assumptions. Energy managers need a simple, accurate, reality-based tool that doesn't require an engineering degree for use.

Useful information requires interpretation as well as measurement. Mandatory measurements should be kept low in cost; data processing and interpretation should be as nearly intuitive as possible. The MIS should empower managers to rely more on their own judgement, and less on consultants, to save energy. Meeting these conditions depends on how the data will be used.

Data Uses

The typical energy service company (ESCO) saves energy primarily by scheduling, tuning, or retrofitting. *Scheduling* is curtailing unneeded equipment operation -- making sure the lights aren't on all night, turning thermostats down or fans off at night and weekends, etc. *Tuning* is adjusting building systems, typically HVAC, for best efficiency.

Data must help to reveal problems and track corrections. For example, scheduling requires finding unneeded equipment operation, and verifying subsequent curtailments. Tuning implies a need to verify that adjustments reduce energy use. Retrofits may involve the need to verify that new or modified equipment operates correctly, or measure before and after energy use.

Data should anticipate human error and equipment failure, sometimes signalled only by higher total energy use. Finally, conservation measures can be interactive; e.g., reduced lighting increases space heat and reduces air conditioning. Interactive effects typically involve changes in HVAC energy.

These data uses imply continuously monitoring total and HVAC energy use, and temporarily monitoring other end-uses, as needed for commissioning, scheduling, retrofit commissioning, etc.

Barriers to Data Comprehension

Monitoring can produce lots of data, but routinely reviewing all time-series data takes too much time. Periodically reviewing baseload versus time makes sense to detect unneeded night or weekend uses. But interactions of thermostat and fan schedules, weather, and internal gains with HVAC can cause standard deviation of HVAC (or total) energy use to exceed its mean. This scatter constitutes noise that makes reviewing time-series HVAC or total energy use data difficult and less informative.

High noise impairs data usefulness. Aggregating data into longer periods reduces but doesn't necessarily eliminate noise. Weather and occupancy-driven variations from period to period can still impair comparability of either weather-dependent or baseload energy data.

[1] For example, a 32 channel energy data logger with CTs and temp sensors recently cost as little as $3100.

The facility manager's challenges - low budget, limited time, and impracticality of becoming an energy specialist to the detriment of other duties - must be recognized. Unless energy data are quickly and easily comprehensible, and inexpensive to put to use, they may be ignored.

Requirements

Data reviews should be quick, easy, and infrequent. Time-series data should be collected for problem solving - commissioning, investigating new problems, or policing schedules - but are too time-consuming for routine management use. Avoiding unneeded data proliferation and gauging interactive effects suggests limited separation of end-uses and aggregating small time intervals into larger ones.

Time-wise aggregation must recognize occupancy variations. Saturday, Sunday and Monday aren't comparable (different day types), nor are February and March (28 vs 31 days, and an unequal mix of week and week-end days). *Weekly* time aggregations provide *optimal smoothing* of occupancy variations, maximizing comparability of one period to another.

Effective weather normalization is imperative. Measuring small differences in energy use due to non-weather factors means that weather and the masking it introduces must be effectively removed from comparisons. Inside temperatures make significant swings in response to outdoor conditions. Therefore, accurate weather normalization implicitly requires accounting for indoor temperature variations.

Previous Efforts

Others have partially addressed time aggregation (e.g. MacDonald 1988) and weather normalization (e.g. Fels 1984, Hill et. al. 1981). Short-term measurements of loss coefficients and/or heating efficiencies (McKinstry and Frey 1981, Modera and Sonderegger 1980, Subbarao 1988) meticulously account for inside temperature. Dependency of inside temperature on outside temperature has been recognized (Nordman and Meier 1988). Long-term monitoring is becoming recognized as a part of building energy conservation (Claridge et. al. 1996). Others have called their works (some not at all like those discussed here) "Energy Signatures". But the author is not aware of systematic choice of aggregation intervals to minimize occupancy-driven energy use scatter by others. This, combined with long-term energy and inside and outside temperature monitoring, "tagged" data points, and area and weather normalization, distinguish the current "Energy Signatures" from prior work. The author first used this strategy in 1985 (Lambert and Robison 1989).

Enhancing the Energy Signature Concept

Reviews of billing data show that facility energy use is weather dependent, but the correlation is sometimes poor. For a statistician, poor correlation limits data usefulness.

From an engineering standpoint, devising a conceptual model that accounts for scatter, or better yet reduces scatter, is preferable. Here's the basic conceptual model for energy signatures:

> *With constant building physical condition, occupancy, operation and maintenance, variations in energy use rate depend solely on weather.*

At first, this seems of limited use - few buildings operate "steady state"; temperatures and occupancy often change. But AC power measurement and thermodynamic principals rescue the concept.

When measuring AC power at 60 Hertz, one must measure over a full line cycle (16.66 milliseconds) to get a representative value. Measuring for only a couple of milliseconds, apparent power might be unrepresentatively high, zero, or even negative. Indeed, measuring over *any* small non-integer number of cycles gives an unrepresentative result - a type of sampling error.

Applied to a commercial building, this means energy use rates won't be representative (or equal) on Monday morning or on Monday night or Friday afternoon or Sunday. Each of these times represents a different part of one **occupancy cycle**. In a building, getting a representative value, unaffected by sampling error, requires measurement over one or more integer cycles. For a building with cyclic weekly occupancy, energy use rates measured for a day or a month (except February) will be unrepresentative to some extent. This is partly why weekly time aggregation provides "optimal smoothing", mentioned earlier; but there's more.

In thermodynamics, a cycle is completed when conditions have gone through their full range of variations and *returned to their starting point*. For a building, this usually means going through a full week (exactly 168 hours), with similar inside temperatures at the start and end points of the 168 hour period. For most occupancies, Wednesday noon to next Wednesday 11 AM works well. Near-identical end-point temperatures minimize variations in stored thermal energy from one cycle to the next, important in massive structures. To see the effects we seek, we want to compare cycles. When comparing cycles, we must recognize that energy use rates for dissimilar cycles will be different; for example, a week with a holiday is dissimilar to a regular five-day work week.

Now the conceptual model can be restated and expanded:

(1) With constant building physical condition, consistent occupancy, operation and maintenance and consistent process energy use ("consistent conditions"), variations in total energy use rate from one cycle to the next depend only on weather and inside temperature.

(2) Of weather variations, outside temperature is the dominant driver of energy use rate; variations in humidity, wind, and insolation tend to be randomly distributed or second order effects.

(3) Under consistent conditions, a plot of cycle-average energy use rate versus mean coincident delta-T, over a sufficient number of cycles, will form a characteristic curve. With consistent conditions, all future cycles will fall on this same curve.

(4) Significant scatter in such a curve will be due to inconsistent operation, or to changes in building physical condition, maintenance, or occupancy.

A few terms need elaboration. "Consistent process energy use" applies to non-internal-gain energy uses such as outside lighting, cooking in a restaurant, or hot water and drying in a laundry. If such uses are totally consistent from cycle to cycle, the theory still works; but such uses can be so dominant, consistency should be verified by measurements.

Cycle means the *regular* occupancy cycle; it might be one day for a nursing home, prison or hospital, but more typically is one week. Cycle *does not* include irregular situations such as weeks with holidays, plant shut-downs for maintenance, etc. Anything that changes loads or changes HVAC efficiency compared to regular occupancy should be considered as possibly irregular.

"Significant scatter" has a working definition of r^2 less than 0.96, for heating. Different limits (or substitution of "delta h" - enthalpy - for delta T) might be necessary for some cooling-dominated situations. But plots of data for virtual buildings, generated by DOE-2 with consistent simulated occupancy schedules, setpoints, etc., are likely to show high r^2.

Example Energy Signatures

Energy Signatures preferably use: (1) total energy intensity in Watts or Watts/unit area; (2) coincident delta-T (or outside temperature as a last resort); (3) *identified* (usually by time-coding) weekly intervals. The examples show different features and uses of ESA, as noted in headings.

O&M Improvement Shown by Monthly Data. Monthly data forms a sort of energy signature. Billing intervals introduce scatter (non-integer number of weekly cycles), take four times as long to get a useful plot, and don't normalize for inside temperature. Even so, plotted as energy per unit time, versus outside temperature, with data points identified in time sequence, it can tell a story.

Figure 1 shows electrical energy use rate for a shopping mall common area in Bend, OR for 13 months (6/82...6/83). Outside temperatures are averages of daily highs and lows at a station four miles away. Points M and J (5/83 and 6/83) are outliers, below the previous cooling trend of points 6,7,8,9,O,3 and 4 (N, D, 1, 2 are heating). They show that over 350 kWh/day (over 10%) was saved by improved HVAC maintenance; loose air handler fan belts were tightened in rooftop A/C units.

Virtual and Monitored Data Comparisons. Figure 2 shows monthly data for an office building in Portland, OR, with outside but no inside temperatures. Alpha-numeric points are "virtual data" from a DOE-2 model of the building (Kaplan 1989). Asterisks show 15 months of monitored data. The model had been "tuned" with monitored weather to match monitored total energy. The model used one set of schedules (i.e. ultra-consistent virtual people) to represent the multiple real-world schedules used.

Figure 2 helps make several points. First, less-consistent occupancy contributed to more scatter in the real data; virtual data show higher r^2 for heating than the real data (0.97 vs 0.85). Second, tuning the model with monitored weather wasn't necessary for the comparison shown. ESA can weather-normalize comparisons of virtual and real data. Third, ESA enables model output to be inexpensively compared to real data. This is useful for model-based assessment of real buildings (White and Reichmuth 1996), and could be used to improve modelling accuracy. Fourth, if model output provided weekly intervals and delta T, such ESA-based comparisons would be more convenient and accurate.

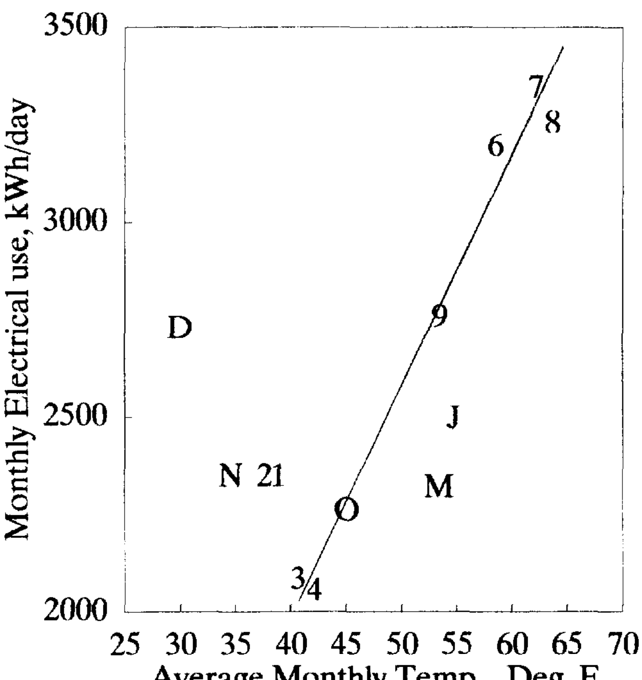

Figure 1. Mountain View Mall Commons Monthly Energy Use and Outside Temperature

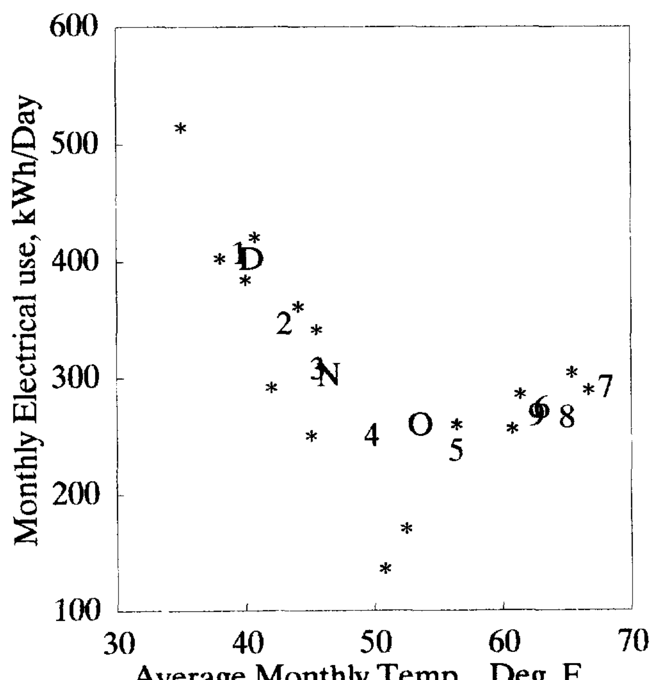

Figure 2. Portland, OR Office Building Monthly Energy Use and Outside Temperature

Detecting Variations in Operation. Figure 3 shows monitored 1990-91 weekly heating data for a 200,000 ft^2 middle school (Plymouth-Carver Intermediate School, PCIS) in Massachusetts (Lambert 1991). First cut analysis, a linear fit of all points, had r^2 of 0.87; the scatter suggested inconsistent operation. We found that for holiday weekends (Veteran's day, Thanksgiving, Christmas, New year's & Martin Luther King day) rooftop HVAC was shut down for three days instead of two.

Re-evaluated as two data sets for two distinct occupancy cycles, the fits improved to 0.95 (two-day weekends) and 0.925 (three-day weekends). Delta-T explicitly accounts for temperature setback, so the difference in fits had to be another factor -- large ventilation loads. (Eventually we established that rooftop HVAC mixed air temperatures had been revised from 65 to 60, coincident with a lighting retrofit, making the retrofit appear to fail.) Also, the energy signature slopes showed the school could save $1500 per month for each degree winter-time inside average temperatures were reduced.

Comparing O&M Differences between Buildings. Area-normalized energy signatures enabled comparing PCIS to four nearby elementary schools. Figure 4 shows heating fits, for regular five-day weeks, for PCIS plus Federal, Indian Brook, South and West Elementaries (P,F,I,S,W). Since all four elementaries were built from the same plans, one might expect identical energy signatures. Instead, there are significant O&M differences; different ventilation controls and settings were used.

Checking Staff Efficiency, Detecting Interactive Effects and Breakdowns. Figures 5 and 6 show weekly data for two of the elementaries. As with PCIS, regular and holiday weeks differed. Figure 5 shows longer fan shut-downs for holiday weeks at Federal; figure 6 shows no holiday shutdowns at West. West's custodian either forgot to program holidays, or had equipment problems.

Also, Thanksgiving and Christmas weeks (T & C) are visibly higher at West. Internal gains from lights, etc. were lower during the holidays, requiring more heat from the rooftop HVAC. Resistance heat - because of ventilation losses - had less than 100% efficiency, requiring higher total energy input to maintain the same delta-T. This shows interactive effects between lights (100% efficiency) and HVAC (less than 100% efficiency).

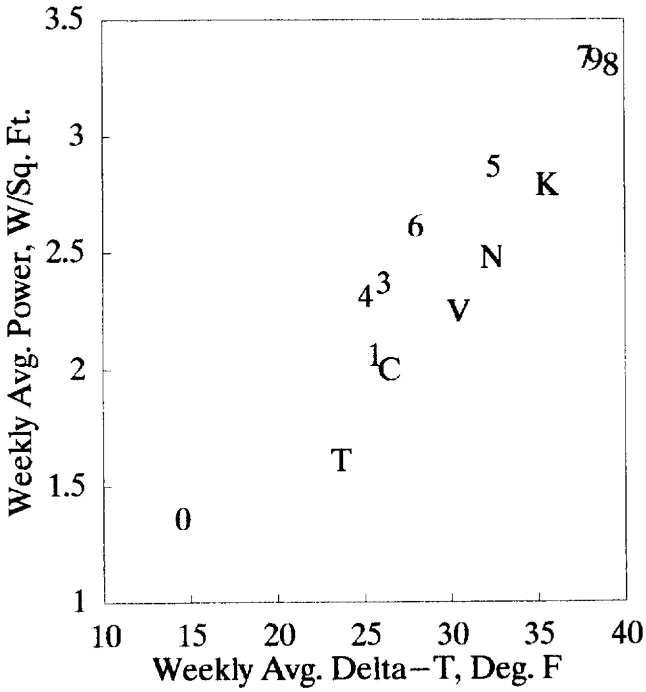

Figure 3. Plymouth-Carver Intermediate School Weekly Average Power and Delta-T

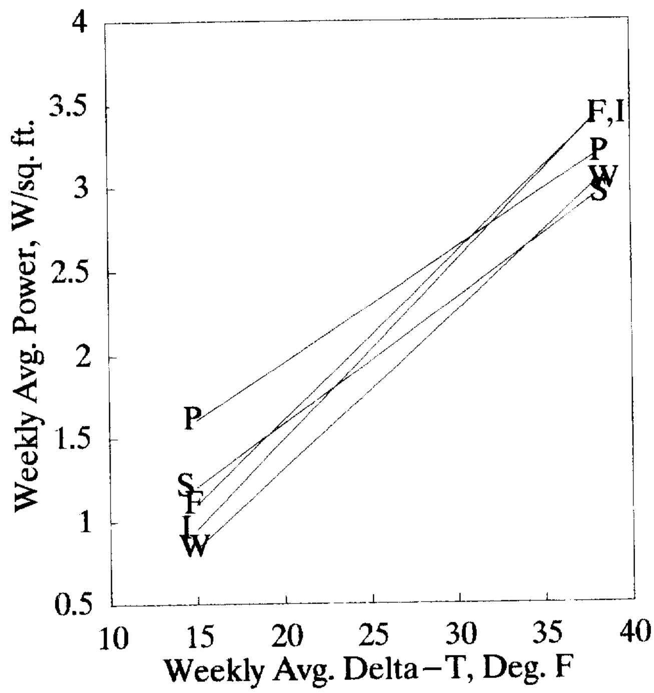

Figure 4. Comparison of Curve Fits for Two-day Weekends, PCIS vs Elementaries

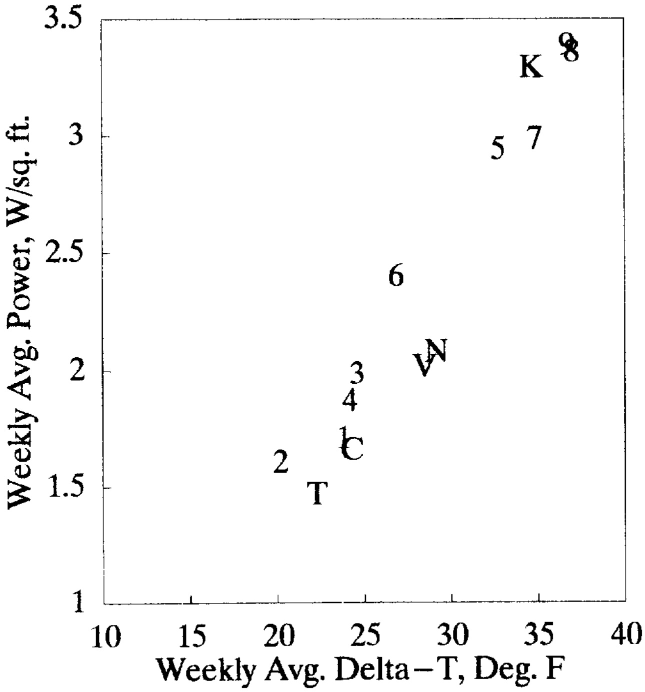

Figure 5. Federal Furnace Elementary School
Weekly Average Power and Delta-T

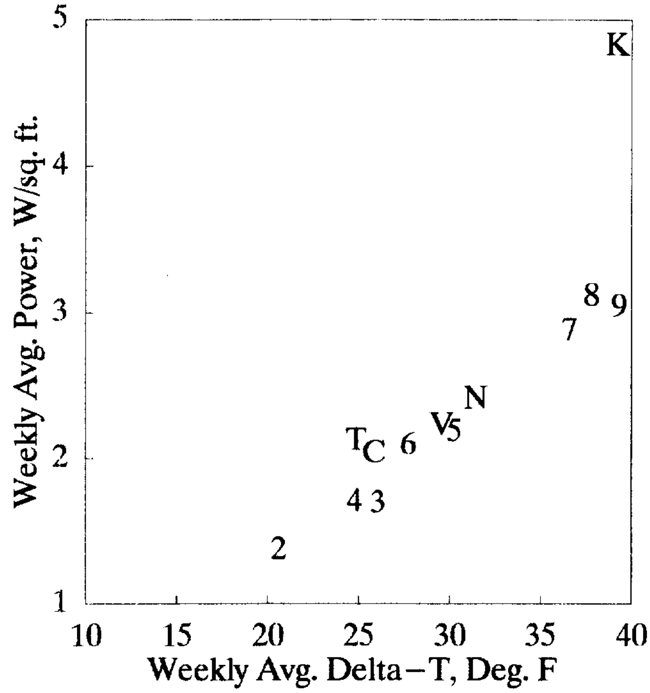

Figure 6. West Elementary School
Weekly Average Power and Delta-T

Figure 6 shows a striking O&M problem. The outlier (K) includes a three day week-end, M. L. King day. Saturday setback had started, when a power outage disrupted the EMCS. It reverted to its occupied temperature and ventilation settings, day and night, for the week-end, just after passage of a cold front. Extra cost of this O&M mishap was $2600, all because the EMCS needed new back-up batteries.

MIS for Commissioning and O&M. Figures 7...9 show monitoring and ESA used in concert for commissioning and energy management. Figure 7 shows baseline data for six modular classrooms in Bend, OR during 2/98...3/98. Three weeks of pre-commissioning data are shown for buildings A...F. Of these, five are identical in envelope, size and HVAC units. (Modular A is half the size of B...F and has one HVAC unit instead of two.) The plot is revealing.

First, modular D uses about 150% more energy than the others. Second, although A, B, C, E and F are more closely grouped, they still differ by nearly 50% in energy intensity. Third, there is a ten degree F range in delta T values. All of these observations warranted follow-up.

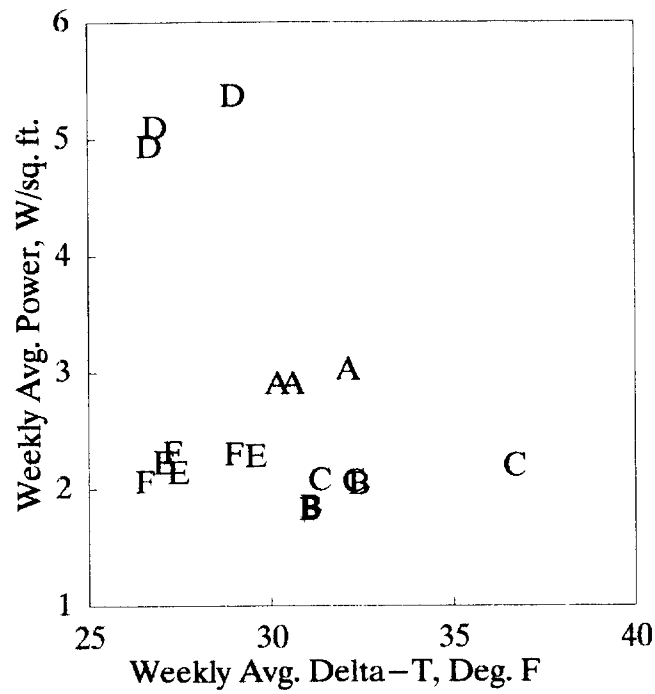

Figure 7. Sunriver Preparatory School
Weekly Baseline Data for Modulars A...F

Total and HVAC energy use, and inside temperature, were monitored for each modular. Diagnostic channels (Lambert 1988, 1992) were used for all HVAC units. Diagnostics for modular D showed simultaneous cooling and heating by one HVAC unit. The diagnostics helped guide warranty service, which succeeded after three attempts. The first stopped unwanted cooling, but the unit's fan still ran continuously. Continuous fan use, explicitly shown by diagnostics, was also eliminated.

Why weren't these modulars, from the same production line, all alike? The differences weren't just different inside temperature preferences. Had this been the only difference, all would have plotted on the same line, perhaps to the right or left of each other. Modular A (a single-wide) has a higher surface-to-volume ratio than the others, but E and F were higher than B and C, despite identical sizes, envelopes and HVAC units. Ventilation differences were suspected. Review of diagnostics showed a variety of fan modes, from "fan-on" to "fan-auto". Different amounts of ventilation appeared to cause the differences. We decided to try using fan-auto mode as much as possible, with staff able to temporarily select fan-on mode for more fresh air (early results are discussed below).

Finally, the wide delta-T range showed inconsistent temperature settings or inconsistent setbacks. The data review that disclosed a variety of fan modes also showed variations in temperature patterns. Only a few of the staff understood how to program their thermostats; many thermostats were used as manual temperature controls. The manual operation was also causing exaggerated demand peaks at morning warm-up, confirmed by monitored data. Subsequently, all thermostats were reprogrammed for aggressive night and weekend setbacks, and for a staggered morning recovery.

Estimating Savings. Figure 8 is an early energy signature for modular C, constructed from four weeks data. The only change for modular C had been setback temperatures, so this represents a condition that should be achievable for all the modulars except possibly A. Using this to quantify three of the four problems identified by Figure 7, the O&M savings potential for six modulars was estimated as follows:

* 25% energy savings from correcting the simultaneous cooling/heating problem.
* 10 to 15% additional energy savings from consistent, aggressive setbacks.
* 10 to 15% additional energy savings from systematic ventilation control.
* 40% reduction in peak demand from a staggered start sequence for morning warm-up.

Figure 8 differs from previous examples; it shows a continuous curve instead of discrete data points. The curve shows weekly rolling average energy intensity, advancing in one hour time steps, plotted against weekly rolling average delta-T. Contrasted to 100% or greater standard deviation in hourly energy data, the regularity of this curve shows ESA's "optimal smoothing" benefits.

Measuring Savings. Figure 9 shows before-and-after data for two corrections. The plot on the left shows modular D. The portion above 5 Watts/square ft. represents baseline data. The sequence of "T"s from 5 down to nearly 1, shows transitional values. The lower trace shows fully corrected operation for D (numbers show weeks after correction; $r^2 = 0.97$). The right-hand plot shows baseline (A= "fan-on") and later "fan auto" operation for modular A, connected by a transition trace. In both cases, post-correction values have moved closer to modular C (figure 8) than in baseline data.

Seven weeks after first round O&M adjustments, about 30% difference in signatures remains between the most and least efficient modulars. We suspect differences in ventilation damper settings and/or duct losses. We'll test these ideas next fall, with a variation of a coheating test, delivering heat without fan operation, and hope to measure improvement from retrofit of heat pumps. So far, NAC calculations (Fels 1984) of commissioning and O&M savings show approximately $2600, or 31%.

Results

The examples demonstrate useful capabilities and facts. ESA can also be inferred to apply to other situations not covered in the examples. The example Energy Signatures show that:

* Energy signatures did an excellent job of normalizing for weather and inside temperature preferences, and of smoothing out cyclic effects of consistent occupancy patterns.

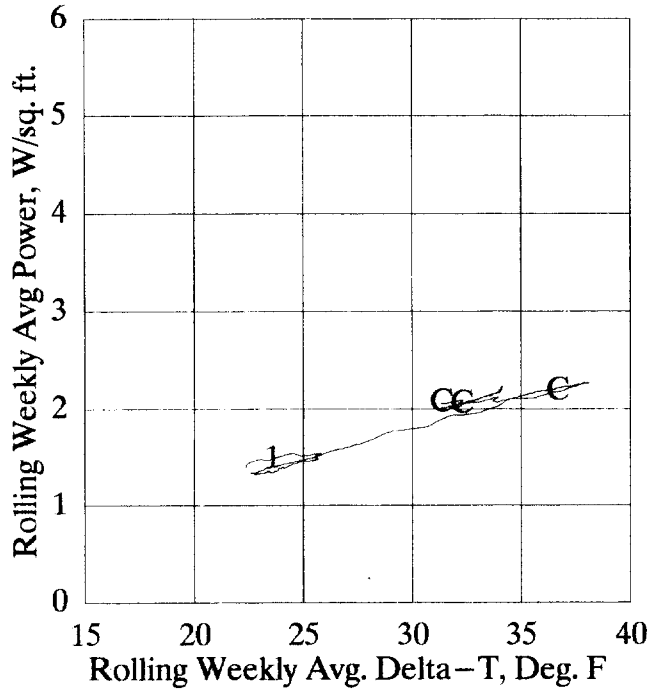

Figure 8. Sunriver Preparatory School
Modular C Continuous Energy Signature

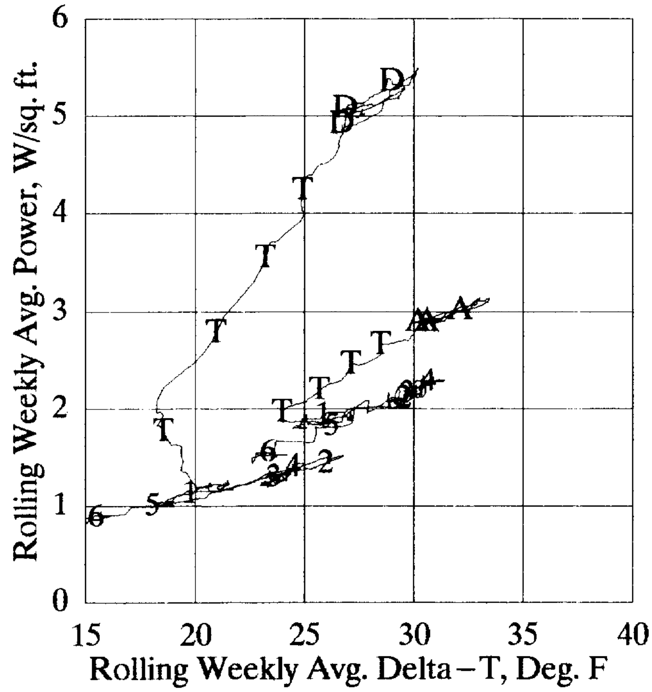

Figure 9. Sunriver Preparatory School
Improved Management Results, Bldgs A & D

- Changes or inconsistencies in occupancy, O&M and controls use were the primary causes of variability in these ESA data sets. High scatter was *not* inherent to these buildings, as shown by high values of r^2 during consistent operation.
- Meaningful comparisons between operating modes or between buildings (using area normalization) and to computer models of buildings can be made.
- Failures of energy-critical equipment can be detected, and their cost assessed.
- High energy use, scatter, or a pattern change (without evident reasons such as holidays or breakdowns) gives a warning to review equipment and operations for problems.
- *Absence* of scatter can show staff are failing to take advantage of holiday shut-downs.
- For a consistently occupied and operated building, ESA provides clear indications if operational changes result in savings.
- Effects of thermostat management strategies can be readily assessed.
- ESA is quite effective for detecting and measuring ventilation impacts on energy use.
- ESA can be useful as a commissioning tool.
- Cheaply remediable O&M factors can seriously inflate facility energy use.
- Modest-sized facilities that haven't been commissioned can warrant substantial effort.
- Continuous energy signatures provide fast feedback regarding major changes.
- ESA could be used by ESCOs to prospect for savings opportunities.
- ESA could be used to evaluate or commission retrofits, especially pilot activities.
- ESA could be used for management feedback on staff effectiveness and consistency.

Discussion and Conclusions

ESA is an important addition to the energy manager's and researcher's toolkit, either by itself or in combination with other tools. The concept is sufficiently demonstrated for immediate use in numerous applications. For other uses, it shows good promise and a need for further trials.

Used alone, ESA is a model-based tool that reveals trends in facility total energy use despite occupant and weather-driven noise. ESA works with as few as three monitored channels, functioning as a low-cost energy management MIS. ESA provides an "energy label" to compare facilities against their peers, as context for conservation decisions. Inconsistent O&M is revealed by excessive scatter, and ESA provides a means to test ideas for efficiency improvement. After efficiency improvements, ESA indicates continued efficiency -- or warns of deterioration.

But ESA is more useful in conjunction with hourly data. Since hourly data's needed anyway for ESA, additional channels will often make sense. It's sometimes easiest to simply use ESA to test the effects of a readily implemented O&M change. But if the user is clueless as to which O&M changes may help, hourly data can provide ideas; then, some dis-aggregation is valuable.

Separate data for baseload and weather-dependent loads helps to find scheduling opportunities. Continuous or spot monitoring of discrete HVAC loads with computed diagnostic channels identified O&M savings opportunities in the later examples. It's especially useful to explicitly track ventilation, which may use little fan power but can have huge energy consequences for conditioning outside air.

Because ESA is model-based, unexpected outcomes can be weighed against the model's assumptions and predictions. Serendipitous scatter that would cripple usefulness of a purely statistical method may instead reveal useful information, leading to efficiency improvements.

Synergies of ESA, time-series data and computed HVAC diagnostics enable great time savings. Once commissioning and energy efficiency improvements are completed, hourly data details are only needed to diagnose or follow-up on new problems signalled by ESA.

ESA has limits. It reduces, but doesn't eliminate, the detective work needed for problem solving. ESA won't necessarily reveal non-optimum O&M practices, unless you make changes and observe effects. Peer comparisons or experimentation may be required.

Applications

ESA combined with computed diagnostic channels and hourly data provide an unrivaled combination that should be the basis of any energy management MIS. ESA offers substantial improvement to present and planned portions of the IPMVP. ESA can also aid in use of data captured from EMCS in large buildings (Olken et. al. 1998), if the EMCS data supports ESA.

Many facilities can benefit from ESA. The data suggest ESA is the tool of choice for institutional, governmental and office buildings, many retail establishments, and similar occupancies. Among those, most obvious candidates are those with no feedback other than the billing meter, those that lack staff inclined to deal with complex tasks, or that lack funds for retrofits.

Although ESA can be used in retrofit situations, the best use of ESA is to cheaply achieve increased O&M savings. ESA is likely to be less capital-intensive than aggressive pursuit of retrofits. Other than modest equipment expenditures, costs are low, especially compared to likely savings.

People can efficiently regulate equipment using local controls. EMCS use is often justified on the basis people are unreliable. Without management feedback, this can be correct. But dissatisfaction with inflexible EMCS schedules can result in abandonment. An EMCS can be a labor-saver. Enlightened management, ESA for feedback, and motivated staff can also be a winning combination.

ESA may be especially useful to developing countries. Foreign exchange and infrastructure to purchase, maintain, and operate building automation systems is sometimes lacking, and labor rates may be comparatively low. Building systems are often less sophisticated than those in developed countries. Systems that save energy primarily through the labor force, rather than costly automation, may be especially attractive and help implementation of the Kyoto Protocol.

ESA is most effective for detecting hidden problems. Most inefficiencies are in the HVAC realm, and the associated losses can be especially large. Detecting and correcting inefficient HVAC O&M practices is particularly rewarding, often providing large savings.

The example facilities exhibited at least some regularity in their occupancy, and were not dominated by intense "process energy use". Just how far the ESA concept can be extended to encompass less regular occupancies and those with more industrial character remains to be seen. Cooling-dominated climates may require use of enthalpy difference instead of temperature difference.

Future Directions

Fully exploiting the potential of ESA requires more experience, to answer questions such as:

* What are reasonable O&M savings levels to expect, by facility type?
* What preliminary energy intensity levels suggest good prospects for ESA?
* What are appropriate levels of monitoring for different facility types?
* What's the right mix of outside help and training to assist energy managers to use ESA?
* What are the savings expectations from using ESA in building commissioning?

Savings expectations and risks determine whether conservation is attempted. The author's hypothesis is that O&M savings of at least 10% should result from well-informed energy management using ESA. But too little data is available to say how reliable this expectation may be. The private school (figs. 7...9) was promised savings of 10%. But a wasteful commissioning problem and poor demand regulation resulted in over 30% savings. High scatter means lots more data is needed.

A cheap way to easily compare building efficiencies would be useful. Many utilities provide coincident outside temperature data with customer bills. Just one more data point, conditioned floor area, would enable screening-quality monthly energy signatures. These would give a rough indication which facilities are most likely to benefit from more intensive review of their conservation potential.

What's the right level of monitoring? Too little data may cause missed opportunities. Too much data can have a high first cost. Theoretically, ESA would work with very regular weekly billing meter readings and a pair of stick-on temperature loggers. For a "Mom & Pop" dry goods store, this could be the right choice. In a bigger facility, some hourly energy data is helpful to track down problems.

At the private school, we originally planned to monitor total energy at the service entrance. Utility quotes for pulses led us to monitor "other" loads in each modular; we finished with more channels, higher labor cost, and better data resolution. We also could have combined HVAC units, two on a channel. But we wanted to know what each three ton unit was doing in detail. Experience in a variety of situations will help find the best mix of standard and contingency measurements.

Energy managers may want outside help to install monitoring equipment, and some may want training in how to interpret the data. But deciding what's the right level of help, from training videos and website help to seminars to on-site help, needs more experience.

Commissioning could be the highest payback use of ESA. Commissioning facilitates better comfort, and warranty repair of defects, as "sweeteners" to accompany energy savings. For large or complex buildings, commissioning may be especially important. But experience to verify these assertions is lacking. Commissioning new facilities that have been modelled during design, using DOE-2 or similar, would be easier if model output were exactly comparable to ESA data. This requires weekly energy use and inside temperature summaries be added as model output options. Comparison of virtual data to real data could soon indicate if there were serious departures from design intentions.

The author would be grateful for any results or experiences other investigators or users of ESA are willing to share, to start answering questions posed above.

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