A Tool for Efficient First Views of Commercial Building Energy Performance

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ABSTRACT

This paper describes a proof of concept for a method of operational benchmarking. This benchmarking can be done with only daily weather data and the monthly energy bill information required for an Energy Star rating calculation, but the result is overtly functional, directed at improving operating efficiency. Several derived building attributes are compared with reference values to identify the general nature of major building inefficiencies. This "first view" can direct further investigation of the problem and potentially result in energy saving corrections.

The underlying approach builds on past work on inverse modeling and energy signatures, discussed in detail herein, which shows useful performance insights proceeding from a monthly, temperature-correlated view of energy consumption. This process has produced promising anecdotal findings but has been difficult to scale up because it requires review by a reasonably experienced engineer or building operator. This new work standardizes and automates an enhanced regression process to support wide implementation, with pilot testing on a sample of 185 buildings across the country.

The results demonstrate the feasibility of automating an energy balance-based Equivalent Analog Building Model that reproduces a building's monthly energy usage in relation to outside temperature. For gas-heated office buildings, a relatively small set of eight key parameters has proved to produce robust and repeatable results. Automated messages based on indicators derived from the parameter values can suggest areas of particularly high efficiency or potential future improvement, categorized under broad areas of occupancy-related loads, facility structure and systems, and heating and cooling controls.

Introduction

To make dramatic progress toward very low-energy buildings, owners, designers and energy program managers need prompt and meaningful feedback on whole-building measured performance. Such high-level insights into performance can come from properly parsed information as basic as monthly billed usage by energy type. However, these high-level performance views are not customarily available, for either an owner/operator of a small, simple office or an operator of a large complex building with an energy management control system that provides a wealth of interval data and other detail. This paper describes the development of a proof-of-concept tool for providing useful first views in a way that could be automated to readily scale up to broad availability.

The approach here rests on the insights available from the monthly billing results, a level of information readily available to nearly all buildings but not fully utilized in simpler metrics based only on a normalized EUI. Given a building's physical and occupant characteristics, the dominant energy relationship throughout the year is between its energy use and the outside temperature. The actual observed patterns vary widely, and the interpretation of these patterns leads to the more useful conclusions than does simple comparison of annual totals.

Background

Patterns of energy use relative to outside air temperature, frequently referred to as energy signatures, are well known in the engineering community. These signatures can be derived from the data by a variety of curve-fitting techniques. Common approaches for monthly data include PRISM (Fels 1986) and the ASHRAE Inverse Modeling Toolkit (Kissock, Haberl & Claridge 2003). They utilize inverse models, which solve for the value of key parameters that reproduce an observed pattern of energy usage amounts in relation to outside temperature. Haberl and Culp (2007) summarize and compare a variety of inverse modeling approaches. Standard engineering and evaluation practice fits monthly energy use as a function of temperature, with the primary purpose of normalizing for weather differences to estimate achieved savings. To meet this purpose, it matters little what sort of model or energy units are used, as long as a good statistical fit is achieved.

Analysis of whole-building patterns has increasingly emphasized interpretation of slopes and change points in the resulting signatures. These graphic parameters are almost always indicative of building performance characteristics (Kissock & Mulqueen 2008; Turner & Reichmuth 2009; Koran 2010). These energy signatures have produced some promising findings, but they have been difficult to scale up because they require review and interpretation by a reasonably experienced engineer or building operator. Interpretations are complicated by the fact that the graphic parameters of most of these models do not provide a physical building model per se; they are simply slopes and change points that statistically describe the pattern of observed data points. In addition, the analyses are generally done separately for electricity and natural gas, obscuring the interplay between the two in total building energy use.

An Extension of Current Practice, the Equivalent Analog Building

The objective of this work is to define an alternate procedure that can automate both data-fitting and generation of basic interpretive messages, supporting broader implementation. A first view such as this could then easily be incorporated in any monthly bill review system - for example, EPA's Portfolio Manager (EPA 2007) or commercially available energy review software - to provide general understanding of not just the current performance level but also the general areas to investigate for possible savings. To accomplish the objective, a generalized whole building physical model (instead of a geometric model) is fit to the monthly data. This process solves for a set of physical parameters that define the "Equivalent Analog[1] Building." Turner and Reichmuth (2009) described the benefits of fitting the observed energy usage pattern to a physical energy balance model. Briefly, this approach incorporates the interplay of electricity and gas usage in the total energy balance, more directly identifies areas with likely improvement potential, highlights data questions when the observed patterns are not physically coherent and forms a basis for estimating the energy impact of various changes.

The physical model approach has been used successfully by a few experienced engineers and building operators, "tuning" results to a model of roughly 30 physical and systems parameters (Robison 2009; Robison & Reichmuth, 1999). However, that approach does not scale up well to broad application.

For automated solutions, the Analog Building Model must necessarily be based on a small set of parameters, and it thus reflects many idealized or typical characteristics. The result is

[1] Simplified hypothetical building *analogous* to the actual building in its monthly energy use.

not meant to be a complete definition of the real building or to contain parameter values with a high degree of precision. However, the solution set of key aggregate physical parameters that reproduce the actual building's response to temperature does provide a solid basis for the first view of translating observed energy use to useful operational insights. This paper summarizes the development and structure of this new approach. A more detailed description of the model definition and calculations is contained in the full project report to EPA. (Reichmuth & Turner, forthcoming 2010)

Approach

Automating the process of fitting a physical model to the observed energy billing data included the following steps.

- Compiling a test bed of real data to use in developing and evaluating the prototype.
- Defining the model, determining the limited set of aggregate physical variables to use and automating the calibration process to simultaneously fit these key physical parameters into the overall energy balance of the building.
- Identifying the practical interpretations associated with various result categories to meet the overall objective of imparting greater operational insights.

Test Data Set

The testing data set contained 185 cases, including 37 from earlier New Buildings Institute (NBI) performance review projects, for which knowledge of building systems and occupancy characteristics helped in validating results, and 148 from EPA's Portfolio Manager database of Energy Star-labeled office buildings, which provided third-party verified data for a broadened range of climate, vintage and size. For the initial proof of concept for automated solutions, we focused on a coherent subset of 155 of these 185 cases, all of which were offices with no other major activity type in the building, with natural gas for nearly all space heating, and with Energy Star ratings of at least 75. Future work could extend the approach to other situations, as described in the Discussion section below.

Analog Building Model Definition

The model operates with monthly average temperature as the primary independent variable. At this monthly level of energy aggregation, short-term thermal transients are averaged out, leaving seasonal temperature changes as the primary driver. A monthly building model that can reasonably fit the observed data becomes an algebraically simple linear model for each end use. The model reduces in essence to a set of simultaneous equations in several unknowns. Those unknowns are referred to here as the key building parameters, factors related to the physics of a building heat balance that can reproduce the observed data.

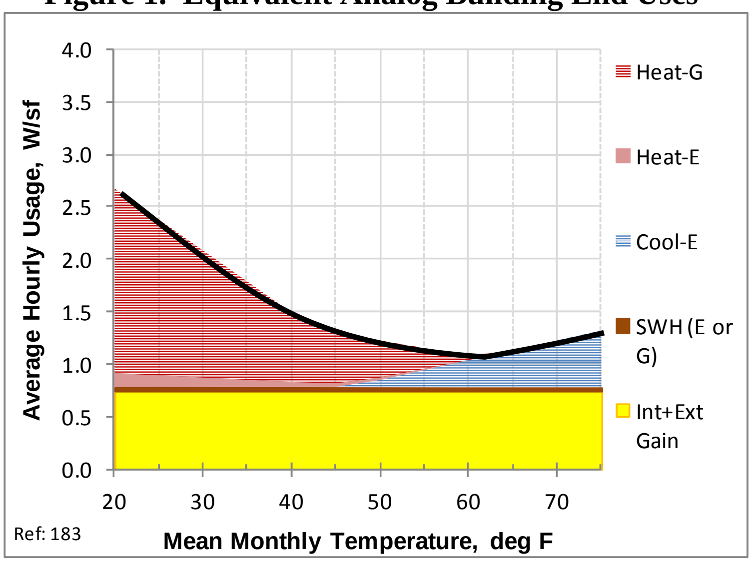
The system of equations is not readily solved by conventional linear regression and is instead solved by means of an iterative steepest descent algorithm (Fletcher & Powell 1963). Briefly, the approach relies on numerically calculated partial derivatives of a goodness-of-fit function with respect to each of the modeled parameters. The choice of the parameters and the structuring of the convergence path are critical to obtaining physically accurate results. A successful model requires a small number of fairly orthogonal variables that are reasonably robust with respect to data noise. Ideally, we want the best physically plausible fit to be associated with a unique combination of model parameters, and we want to avoid cases in which the fit is achieved with wide and physically implausible variations in the solved parameters.

Convergence path. The convergence path was structured by observing the pattern over a varied data set, carefully refining the initial conditions and controlling the iteration steps as necessary. At this proof-of-concept stage, the goal is to define a core set of conditions under which the approach can work and to begin to identify possible areas for further expansion. The current building model has proved to be stable and repeatable for buildings with electric and gas energy, as described under Results below.

Key parameters. The choice of parameters was informed by a combination of the basic physics of an energy balance, engineering experience in the interplay of building energy use factors, and experimentation with several alternative variable sets. In a real building, a purely orthogonal set of parameters is not achievable because all are somewhat linked in the total energy balance. Nevertheless, this work has led to a small set of minimally correlated variables (the key parameters) that has produced robust and repeatable results for gas-heated buildings.

These key parameters can determine estimates of the building energy end uses. Thus the total energy signature for the full Analog Building can be depicted as the sum of the end-use components, as shown in Figure 1. This example shows simple linear descriptions of end uses that rest on more complex underlying relationships. For example, the gas heating depends in part on the electric internal gain, as does the electric cooling. The heating and cooling also depend on the building's shell and ventilation characteristics, which are usually revealed most clearly in the temperature slope of the gas heating. The building parameters that determine these end uses are thus constrained with respect to one another by the engineering relationships that prevail in the aggregate energy use of a building.

Figure 1. Equivalent Analog Building End Uses



Example derived from a medium-sized Chicago office with an Energy Star rating of 94

The fundamental parameters used in this model are listed in Table 1 and discussed below. Note that six of the eight listed here are solved for, while two are held constant at this development stage for all solutions.

Table 1. Equivalent Analog Building Parameters

Parameter, symbol	**Units**	**Notes**
Internal Gain, **Qin**	W/ft2	Solved
External Energy, **Qext**	W/ft2	Fixed ratio of internal gain
Aggregate Normalized UA, **UAn**	BTU/deg F-hr-ft2	Solved
Heating Efficiency, **Eh**	No units	Assumed to be 0.75
Cooling Efficiency, **COP**	No units	Solved
Service Water Heating, **SWH**	Gal/day/ft2	Solved
Heat Intercept, **Ht**	T deg F	Solved
Cool intercept, **Ct**	T deg F	Solved

Internal gain (Qin) and external energy (Qext). Qin is the portion of the base load, i.e. the level energy use that is not dependent on temperature, that plays a role in the net load affecting the heating and cooling end uses. The external energy Qext (outdoor lights and external processes) is a part of the base load that plays no role in the heating and cooling loads. In this initial model, Qext is assumed to be a small fixed fraction of the Internal Gain, Qin. Later refinements may vary the ratio of internal to external gain on the basis of observed results and/or additional input information on the building. The end use calculations use both Qin and Qext directly. The model incorporates an idealized treatment of the portion of the internal gain that is retained in the heating and cooling balance (White & Reichmuth 1996).

Aggregate normalized UA (UAn). This is the aggregate heat loss parameter of the building. In this discussion, the aggregate normalized UA includes the building thermal losses/gains and the ventilation losses/gains, which are also temperature sensitive, all normalized per square foot of floor area. Such an aggregate value would be very difficult to calculate directly by combinations of individual measurements. But in the context of the inverse model, the aggregate effect of all these thermal and ventilation factors is relatively straightforward to determine and, as will be seen under Results, is useful in characterizing results. This floor-area-normalized temperature slope differs from the visible slope in the energy signature because it does not incorporate the efficiency of the heating and cooling equipment. UAn plays a role in estimating both the heating and cooling end uses.

Heating efficiency (He). This is the assumed heating efficiency, which at this stage has been fixed at 75% for all cases. In principal it could be a solved-for instead of an assumed variable. However it is close to co-linear with the aggregate normalized UA (UAn), and separating it lends some instability to the overall regression. While actual heating efficiency may vary from building to building, it will typically be in the range of 70-85%, and variations in this range would not generally produce material differences in the general conclusions from the aggregate model. In the relatively rare cases where actual efficiency is considerably less than assumed, the current model will produce an unusually large temperature slope (UAn) and an unreasonably high cooling efficiency (COP).

Cooling efficiency (COP). This is the apparent COP of cooling energy. It assumes that the UAn for cooling is the same as for heating. In practice this may not be the case. For example, there may be more ventilation during cooling season from economizer use, or some other thermal characteristic may change seasonally. Therefore, the model's solved COP value reflects both the actual COP of the primary cooling and the effects of seasonal changes in the thermal characteristics.

Service water heating (SWH). For buildings with summer gas use, this is the average of the non-space-heat gas energy use in July, expressed in units of heated gallons of water/day. Those units allow scrutiny of this variable relative to a plausible hot water use for the building. For most commercial offices reviewed, this summer gas use is a nominal portion of the total building energy. If there is no summer gas use, electric SWH is assumed to be 0.002 gallons/day/ft2, based on engineering judgment. Estimates of the SWH end use are based on a seasonally varying inlet water temperature and thus have a very slight seasonal variation. In the cases where the solved parameter is much larger than is plausible for typical service water heating uses alone, it indicates other process uses or significant summer gas usage such as for distribution loops or excessive reheat.

Heating intercept (Ht). This is the highest temperature at which heating is actually observed, and the end-use equations assume the heat load will linearly increase at temperatures below this. While this temperature is related to and influenced by the interior set temperature (including the net effect of temperature set backs during unoccupied hours), it is also affected by the internal gain and control errors. In general, Ht will be lower than the interior set temperature when internal gain is contributing to the heating, but many cases have also been observed where Ht is higher than the interior set temperature. These cases suggest excess heating or excessive re-heat. It should be noted that reheat is often a viable control scheme for particular system types or locations, but it is usually difficult to detect excess reheat because reheat manifests as very comfortable space conditions. This variable is sensitive to the level of reheat, and in cases where this variable is much larger than the interior set temperature, the heating intercept temperature is a strong indicator of potential design or control errors.

Cooling intercept (Ct). This is the lowest temperature at which cooling is observed, and the end-use equations assume the cooling load will linearly increase at temperatures above this. While this temperature is influenced by the interior set temperature (including the net effect of temperature set ups during unoccupied periods), it also is affected by the internal gain and the control errors. In general, Ct will be lower than the interior set temperature when internal gain is contributing to the cooling load.

The model uses this parameter to partition the electric energy between internal gain and cooling. In mild, cooling-dominated climates such as Southern California, there is often no visible balance point temperature on the electricity signature indicating when cooling begins; cooling appears to increase linearly above the lowest observed temperature. In these ambiguous cases, the cooling intercept is not well defined, and Ct is constrained to be no lower than 1 degree F less than the minimum observed monthly temperature. This constraint allows the reasonable maximum internal gain to be applied to the ambiguous cases.

Defining Useful Indicators

It would be possible to compare each of the solved parameters to a benchmark, but the interpretation of such relationships could be obscure and detract from a holistic view of building operation. Therefore, the solved parameters are assembled into three primary performance areas. These areas provide useful indications for largely separate aspects of performance, and together they form a comprehensive view of all end-use categories. These indicators are described briefly here. The Results section contains examples and further discussion of indicator interpretation.

Occupant energy intensity. Empirically this is the internal gain in the Analog Building as solved from the data. This is often very close to the apparent base load of an energy signature. But the base load may also include heating and cooling energy. The internal gain indicator is useful because the lighting schedule, plug loads and process loads pertain largely to occupant activity, an area typically considered outside the control of building designers or facility operators. High intensities here may indicate the specific requirements of the occupants' business and schedule or significant savings opportunities in better management of lights and plug loads. The internal gain is also usually the largest single portion of office building energy use, and managing it is fundamental to any comprehensive energy efficiency scheme.

Aggregate shell and systems efficiency. This indicator pertains to the efficiency of the structure and its HVAC components. It incorporates the model solutions for heating and cooling efficiency (Eh and COP) as well as aggregate normalized UAn, which reflects the building thermal losses and air change rates. These characteristics all merge into the aggregate temperature slope of the data.

Aggregate control effectiveness. This indicator is the least directly derived of the three but is a very useful pointer to control issues, distinct from the impact of basic systems efficiencies and thermal characteristics. The calculation first uses the slope UAn and the internal gain Qin to construct a *reference* heating and cooling expectation assuming a 65^{o} F neutral temperature. Note that the heating and cooling end use estimates for the Analog Building are not dependent on this fixed neutral temperature, but are instead derived from the heating and cooling intercepts, Ht and Ct, as solved from the data. Thus the Analog Building's heating and cooling end uses may be significantly above the reference heating and cooling expectations (which are based on the 65^{o} F neutral temperature). Such an excess suggests performance areas warranting further investigation. A control effectiveness metric, expressed as the sum of the excess Heating and Cooling energy as a percent of the total building energy, is discussed further under Control Analysis Plots below.

Results

The automated process created Equivalent Analog Buildings for the entire dataset, continuing the convergence iteration for each until the best fit was found to the monthly energy use data (12 pairs of monthly energy use and average temperature for each of gas and electricity). The results stored for each case included the Analog Building's key parameters, normalized EUI and other intermediate results. Several items of descriptive information were also retained for each building, including personal computer and occupancy counts per thousand square feet of floor area, operating hours per week and Energy Star rating. This additional information played no role in deriving the building model, but may support subsequent analysis of results. For each building, a brief summary categorizes comments under the three performance areas described above: occupant energy intensity, shell and systems efficiency, and control effectiveness.

Validation of the model included reviewing parameter distributions for reasonability and other consistency checks, discussed in the following two sections.

Parameter Distribution

The validity review of results began by creating and examining a wide variety of histograms and scatter plots to confirm that logical relationships among variables were emerging and that each of the solved-for variables showed a reasonable distribution of values. The distributions for the key parameters of UAn, internal gain and COP are presented in below.

Figure 2. Distribution of UAn Parameter Values

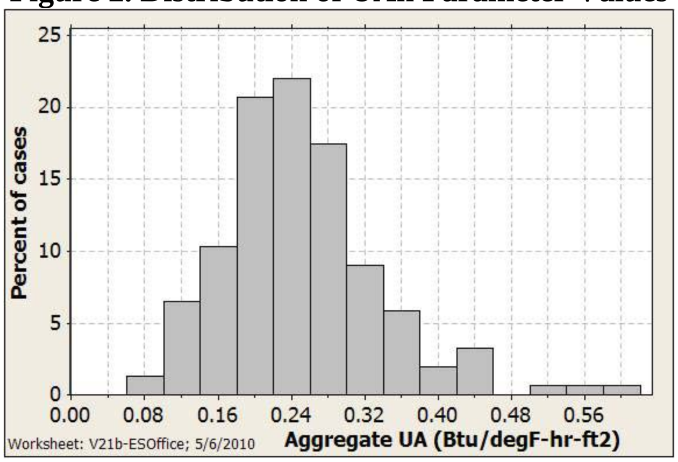


Figure 2 shows nearly 60% of the buildings with an aggregate UAn between 0.18 and 0.28 Btu/deg F-hr-ft2. To put this in context, in most large buildings the energy associated with conditioning the ventilation air is the largest component of the aggregate UA. Expressed in the normalized units of UAn in Figure 2, an average of one air change/hour equates to a normalized aggregate UAn slope of about 0.17 BTU/ deg F-hr-ft2.

Figure 3. Distribution of Internal Gain Parameter Values

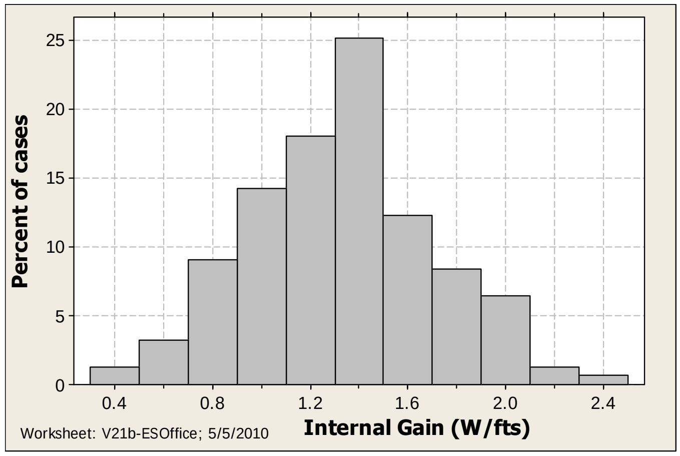


Figure 3 shows the distribution of internal gain, expressed in the floor-area-normalized average energy/hour units of W/ft2. The highest incidence of internal gain, 25% of the sample, was about 1.4 W/ft2, and over half the results fall between 1.0 and 1.6 W/ft2. These results are consistent with our general experience of the magnitude and range of average internal gain in commercial buildings. (While many models assume a higher total connected load for lights and plugs, the higher loads apply only for occupied periods.) As noted, the initial model assumes external energy at a fixed percentage of internal gain for all cases. Future refinements to separately set the external energy factor could result in some shift in the internal gain distribution.

Figure 4. Distribution of Building Cooling COP

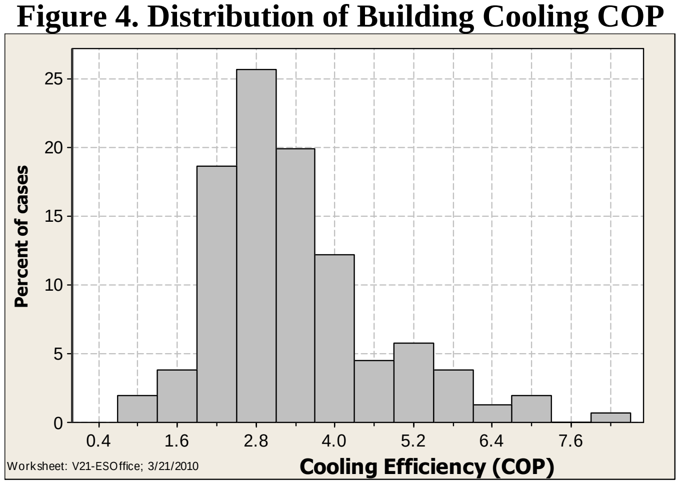


Figure 4 shows the most prevalent cooling COP results clustering around 2.8, with the majority falling in a reasonable range between 1.9 and 3.7. Extreme values in this COP (or other solved parameters) may suggest areas to investigate in either the building or reported data. For example, the COP above 8 in the above distribution was an office building from Portfolio Manager with minimal increase in summer energy use, which could reflect extremely efficient cooling or low summer usage of the building. In other cases, extreme values may suggest classification errors in the automated solving. For example, several of the higher COPs are accompanied by a steep slope (UAn), a combination that suggests the possibility of a misclassified external load.

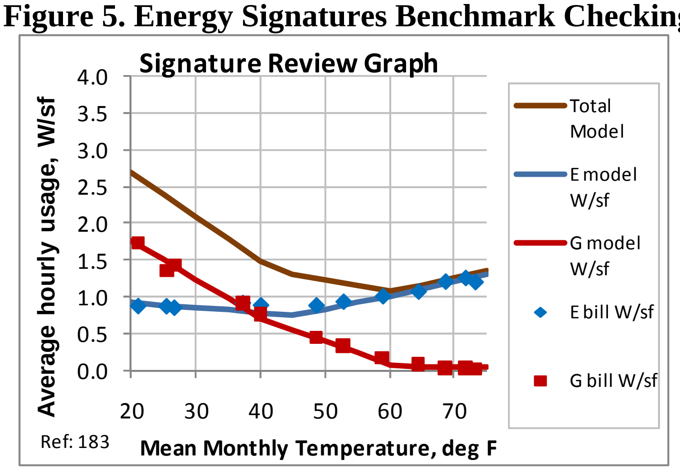
Other Validity Checkpoints

There is an inherent challenge to determining the validity of any analytical tool purporting to assess building performance, so several checkpoints were used in the development of this project. The bulk of the cases used in this work came from the Energy Star Portfolio Manager, and the only information available beyond the monthly energy usage was from the few characteristics required for an Energy Star rating (such as operating hours, staff counts and PC counts). However, about 20% of the total cases were from NBI projects in which more was known about the actual building operation and occupancy. In these cases, the indicators generated for the Analog Building were not inconsistent with information gathered from building owner/operator interviews. Some interviews with owners highlighted changes in building operation or structure that were directly aligned with the analysis results. In others, the owner was not aware of current operation details. These latter situations failed to confirm or refute the Analog Building results but did clearly point out the need for a tool such as this that points an owner to the need for further investigation and suggests broad areas in which to begin.

Another validity test was provided by sites with multiple years of data and stable EUIs from year to year. These provided a check on the repeatability of the solution for building parameters given a different set of energy consumption numbers and temperatures. The solution algorithm solved for similar, but not identical, parameter values for the years tested.

A different type of check involved applying the Analog Building Model approach to monthly performance generated by a well-specified Energy Plus building model. The U.S. Department of Energy (DOE) medium office new construction prototype model was used (DOE, 2009), which reflects a basic 50,000 square foot office modeled to ASHRAE 90.1-2004 standards. In this test of the Analog Building Model, the Energy-Plus modeled monthly electric and gas usage and associated TMY2 temperatures were treated as if a case of actual performance data. Figure 5 shows that the Analog Model fits the more detailed Energy Plus model well, as would be expected. This test case is further discussed under Control Analysis Plots.

Figure 5. Energy Signatures Benchmark Checking



Data Review Flags

The review of the full set of results included the use of flags to identify individual cases and clusters with unusual circumstances, or other combinations of values that bore further analysis. Table 2 gives the primary flags used, grouped by performance area. These flags form the basis of custom messages summarizing the analytical findings for each case. A fourth category, "Other Factors," shows a few situations where the results are more likely to suggest a case that is not well-handled by the current model.

Table 2. Data Review Flags

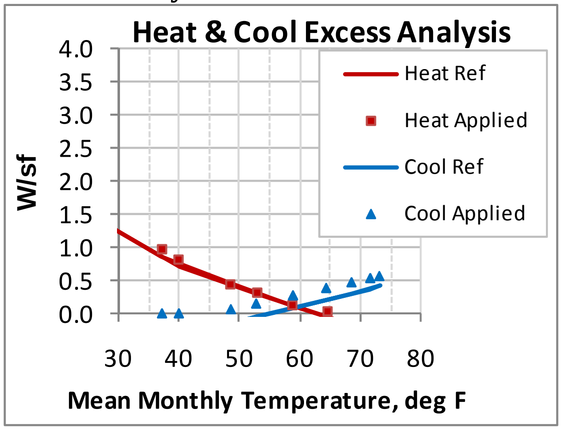
Flag	Possible Causes	Count*
Occupant Energy Intensity		
High occupant loads	Lights, plug/process loads, schedule. Misclassified external load fraction.	54
Low occupant loads		27
Building and Systems Efficiency		
Inefficient shell and ventilation	Ventilation rate, heating efficiency, thermal conductivity of shell, glazing ratio	34
Efficient shell and ventilation		38
Inefficient cooling (COP)	Poor cooling performance, higher summer ventilation rate than winter	11
Control Effectiveness		
Main control inefficiency from heating	High summer gas use or gas process load; hysteresis or erratic usage; faulty heat distribution	54
Main control inefficiency from cooling	Large internal loads such as solar or metabolic, aggressive cooling set point	14
Possible solar gain Influence	Less heat than expected and more cooling than expected are usually associated with inefficient shell or high glazing	22
High summer gas use	Other gas uses (kitchen, etc); excess circulation losses; excessive reheat (if high cooling also indicated)	44
Excessive reheat	Excess cooling that balances for excess heating	11
Other Factors		
High COP + High slope	Heating efficiency lower than the assumed 0.75; misclassified external load; solar impact in the heating slope	17
Poor fit to monthly data (R^2 < 0.9)	Estimated bills or bill data entry problems; Control problems; Monthly changes in occupant schedule	18

* Occurrence count for the flag out of the 155 case set.

Control Analysis Plots

The DOE benchmark model was also used to check the reasonability of calculated heating and cooling excess indicators. The Control Analysis Plot in Figure 6 displays *lines* for the expected or reference heating and cooling by temperature, based as described earlier on the UAn, internal gain, and heating and cooling intercept parameters. The plotted *points* show the heating and cooling end use energy for the Analog Building. When the points and the lines match, the aggregate controls performance appears reasonable. As seen here, the Analog Building for the DOE benchmark check case does not detect excess heating or cooling, a desired result for a valid indicator.

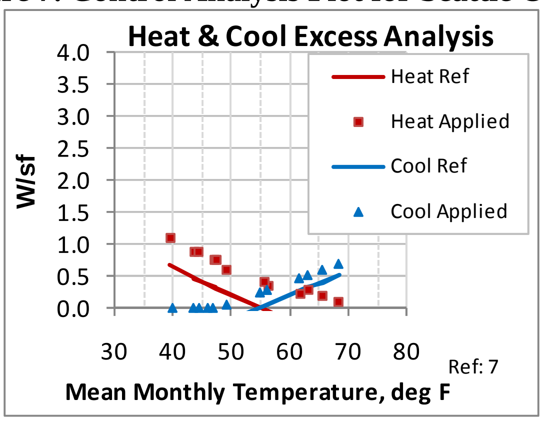
Figure 6. Control Analysis Plot for DOE Benchmark Building



The relative ease with which the Analog Building was created for the DOE benchmark suggests that other benchmark files may be very useful as calibration checks as the analysis approach is extended.

Often the control analysis plots on real buildings in the sample do not show such a precise match between applied heating and cooling and the reference lines. For example, Figure 7 displays a Seattle office in which the heating and cooling end use estimates are both above the reference lines. Interviews with the operator of this building confirmed that problems in control of the HVAC systems led them to request an energy audit.

Figure 7. Control Analysis Plot for Seattle Office



A review of the control analysis results for the whole sample shows the heating and cooling results falling into five major performance categories:

- Satisfactory controls performance, about 30% of sample.
- Excess reheat about 10% of sample, with heating and cooling points both well above the reference levels.

- High heating excess and no material cooling excess, about 35% of the cases. This may be caused by a relatively high gas base load, such as from the presence of commercial kitchens, or by unknown gas processes.
- High cooling excess and no material heating excess, about 10% of the cases. This may be caused by aggressive cooling set points or under-predicted cooling loads such as solar or metabolic loads.
- Apparent solar influence, about 15% of the cases. This is characterized by less heating use than expected and more cooling than expected, usually also with a higher than normal UA slope suggesting large glazing areas.

Discussion

This work has demonstrated the feasibility of automating an energy balance-based Analog Building Model that reproduces a building's monthly energy usage in relation to outside temperature. For gas-heated office buildings, a relatively small set of key parameters has proved to produce robust and repeatable results. Automated messages based on indicators derived from the parameter values can suggest areas of particularly high efficiency or potential future improvement, categorized in the broad performance areas of occupancy-related energy, facility structure and systems, and heating and cooling controls.

Automating this analysis leads to the potential for scaling the application up to provide this type of first-view insight for a large percentage of commercial building stock. Several additional steps can help accomplish that goal. First, additional field validation is essential to further confirm that the automated messages are reasonable and relevant to actions a building energy manager may take. This field phase of the project work is just beginning and will help refine the interpretation of model results and define the most useful format and wording for communicating those results. This experience can also inform future refinements in the area of optional additional input items, describing existing building or activity characteristics that could result in a significantly better model solution.

The prototype tool focused on office buildings with typical electricity use plus gas heat, one of the easiest situations for a controlled solution. A tool that applied only to these situations would find wide applicability. However, the work underlying this initial proof of concept has identified several extensions to other activity types and fuel mixes that would also be quite feasible, which will be further defined in future reports.

Acknowledgements

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