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Approaches to Analyzing the Thermal Performance of Commercial Buildings

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PROJECT SUMMARY

Project Title:

Thermal Performance Monitoring for the Solar in Federal Buildings Program (SFBP)

Performing Institution:

Solar Energy Research Institute
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Project Manager:

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Project Objectives:

Building thermal performance is monitored for a variety of reasons, including retrofit analysis, comparison with design prediction, and determination of actual component savings. The latter is the direct object of the SFBP thermal monitoring program. For passive solar components integrated with a building savings cannot be inferred from directly measuring total fluxes through the component, even if feasible, because all the positive flux may not be useful, auxiliary may not offset negative flux, and the efficiency of other building thermal systems may be significantly changed by the component. Hence, the saved or displaced energy is inferred from the difference between annual consumption calculated with two models driven by standard weather. One model represents with actual building, and the other model is for the building with the solar aperture replaced by some reasonable alternative. The actual model parameters are determined by regression from the monitoring data, and the reference model parameters are calculated perturbations of the regressed values.

Project Status:

Techniques for thermal performance monitoring were intensively reviewed. The simplest techniques use time-integrated fuel usage over many months to normalize simple thermal models based on a long-term energy balance (e.g., degree-day models). These techniques are already developed to near full potential by industry energy consultants but are inherently ambiguous and subject to large error in analyzing buildings where base temperature approaches average ambient, such as in low-energy solar buildings. Macrodynamic models, such as equivalent thermal circuit or transfer function models, have great potential for analyzing dynamic system-level data from thermally complex buildings involving solar and mass storage were impressively successful in residential/test cell applications. These methods are targeted for minor development, testing, and application in the SFBP thermal task,

representing their first substantial application to commercial buildings. The solar aperture parameterization and its interpretation will receive major focus, and a general software upgrade for macrodynamic model radiation processing is underway.

Plans and Objectives for FY 1985

No matter how exotic the model, radiation-related parameters cannot be reliably regressed in many circumstances because of, for example, the natural correlation between ambient temperature and solar radiation, scaling problems in free-float buildings, or unknown efficiencies in HVAC equipment. Hence, the major objective in FY 1985 will be to define those tests that are needed to break radiation parameter degeneracy and reduce uncertainty to acceptable levels. This will be done mainly by using a microdynamic thermal tool (e.g., BLAST) to produce ersatz data for analysis with a macrodynamic regression model. Test cell and existing commercial building dynamic data bases may also be used to uncover flaws not detectable in idealized tests.

Relation to Industry:

The monitoring overview in this paper will be of interest to commercial building managers (for choosing an approach to retrofit analysis), utility and government program managers (for documenting performance of subsidized retrofits or components), and building energy designers (for determining causes of discrepancies between design and actual performance). The dynamic thermal monitoring techniques identified for further development in this task will ultimately be used in routine analysis of data commonly available in state-of-the-art building energy management and control systems (EMCS), giving on-line diagnosis of building skin and HVAC equipment performance.

Major Publications:

"An Overview of Building Thermal Performance Monitoring," peer-reviewed symposium paper at Ninth Passive Conference to be published in symposium proceedings.

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\$125K

APPROACHES TO ANALYZING THE THERMAL PERFORMANCE OF COMMERCIAL BUILDINGS*

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ABSTRACT

Building thermal performance monitoring involves acquiring appropriate data, adjusting a thermal model to that data, and using the adjusted thermal model to answer questions regarding actual or potential building thermal operation. A monitoring method is thus classified by data type, model used, and calculation procedures. Data types are based upon the aggregation level of inherent spatial and temporal variations. The two most useful thermal models are long-term energy balance and macrodynamic simulation. Calculations involve a choice of "reference building" to be assumed for savings or retrofit analyses and procedures for normalizing building size, occupancy, and weather. Using this framework, several examples are analyzed.

INTRODUCTION

Thermal evaluation of a building through performance monitoring is of interest to building owners, designers, scientists, and public officials, amongst others [1]. Building owners may want to know if there are retrofit measures that could significantly reduce rising energy costs, or if their building is performing as advertised by the design team. They may want to corroborate their cost/benefit analyses before planning similar buildings, or compare their building to others for advertising rental space. Innovative designers may want to know if the building or mechanical equipment system they designed is performing as it was designed and what the reasons are for any discrepancies [2]. Scientific interests include model testing and mechanism research. Building officials will want to unambiguously verify that subsidy of particular measures/designs is justified and equitable. There are, thus, multileveled interests which will require very different monitoring methods. As shown in Figure 1, a performance monitoring method has three stages: data acquisition, model normalization, and model analysis. In this paper, we introduce and apply a classification scheme based on these three elements.

* An expanded version of this paper to be presented at the 9th Passive Conference, entitled "An Overview of Building Thermal Performance Monitoring."

PERFORMANCE MONITORING DATA

Performance monitoring data are some indicator of the overall thermal response of the building, such as HVAC energy requirements. These data are like the "tip of the iceberg," the iceberg being the thermal problem for the building. The building thermal problem [3] is the thermodynamic response (all temperatures, T, and energy flows, Q) inside the building to given driving forces, which include schedules of usage and weather conditions. The energy fluxes which any thermal model must incorporate are shown schematically in Figure 2.

Building thermal data can be taken on widely differing space and time levels. The spatial levels, shown in Figure 3, include mechanism, component, zone, sub-meter, or the master-meter. This hierarchy of spatial detail ascends like a pyramid from essentially unfathomable detail to simplicity of the readings on a meter dial. The building thermal problem also exists on different time levels, instantaneous or time-integrated, as in Figure 4. Integrated quantities present desired "bottomline" summary. Dynamic data are rich in "cause-effect" information, containing the fingerprints for many types of thermal processes. Data on either mechanism or component level are much too "fine-grained" for inclusion in overall building performance monitoring, and their uses are considered elsewhere [3].

The highest three levels of Figure 3 spatially integrate the effect of all components/mechanisms and are what are normally called "performance monitoring" data. The thermal zone data include, for example, zonal air temperatures, radiant or

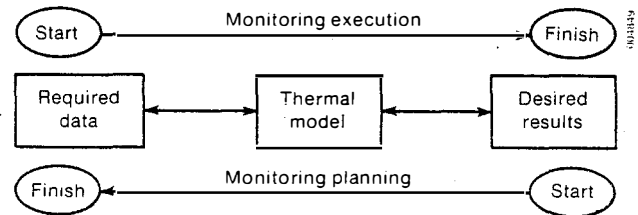


Figure 1. Steps in Performance Monitoring. Desired results must be clearly formulated to properly plan analysis, models, and data.

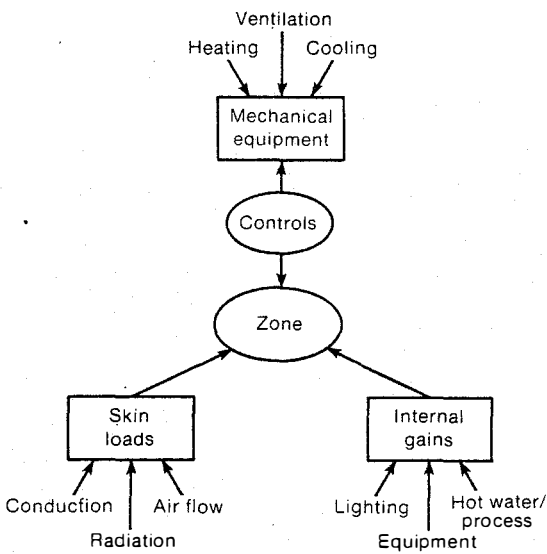


Figure 2. The Building Thermal Problem. Any thermal model must consider skin loads, internal gains, and mechanical equipment in the analysis.

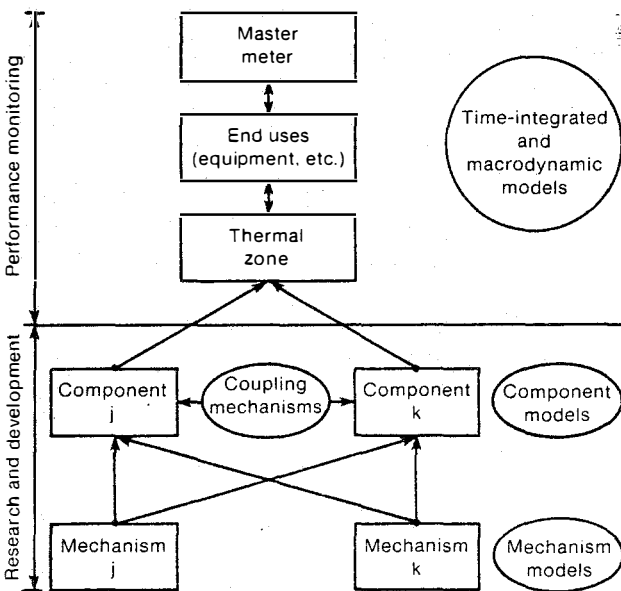


Figure 3. Monitoring Spatial Levels. Performance data spatially summarize the affect of many components and mechanisms of energy transport.

globe temperature, interior humidity, and/or delivered thermal from auxiliary. The sub-meter level means that fuel inputs to each major equipment type and other major end use, such as lighting, fans, etc., are measured. Although specifics always vary from building to building, common submetered categories used are: heating

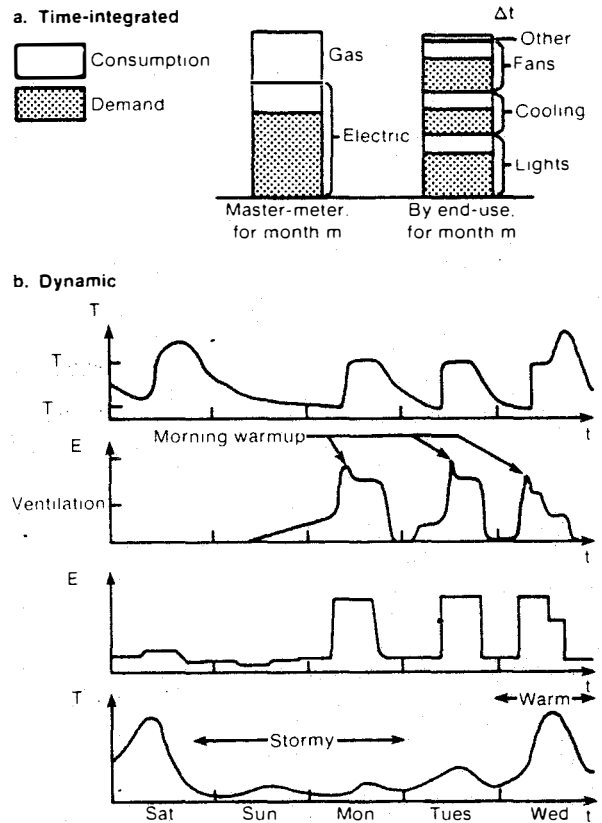


Figure 4. Monitoring Temporal Levels. Monitoring data can be either time-integrated or dynamic.

equipment, cooling equipment, air handling fans, lights, hot water, and other equipment [4]. The last and most aggregated spatial level of the thermal problem, the **master meter**, measures only the total building fuel input, by fuel type. The commercial building electric meter data must include totals and peaks, corresponding to utility charges. In several commercial building studies detailed in Ternoey et al. [4], demand charges average about 75% of the total annual utility bill.

Utility bills are "time-integrated master-meter data," and are the data commonly used by energy auditors. Dynamic data are rapidly becoming available, because for example, 1) dynamic electric master meter data are often recorded for demand calculation later; 2) dynamic temperature and sub-metered fuel/status data are already potentially available from Energy Management Control Systems; and 3) suitable data acquisition systems can be obtained for as little as \$2K. Master-meter data are a problem if weather-dependent heating/cooling/ventilation energy is aggregated with other, nonmetered uses, as for all-electric buildings, or where gas supplies hot water and cooking in addition to heating. In such cases, a disaggregation model will also be used to separate thermal and nonthermal uses. Disaggregation models are discussed in Wright [5] and Train et al. [6].

THERMAL MODELS

Methods for modeling the energy process in buildings can be ordered according to the form of the basic thermal model equations.

- A. Mechanism level: coupled partial differential equations, three-dimensional in space. A dynamic simulation based upon direct application of fundamental heat transfer laws, such as the Fourier law of conduction in three-dimensional solids [7], or the Navier-Stokes fluid equations [8]. Used only by researchers to generate/validate simpler models useful for practical design or monitoring analysis.
- B. Component level: coupled nonlinear ordinary differential equations in time, one-dimensional components and zones in space. A simulation based upon solving the coupled equations resulting from applying heat transfer algorithms on a simplified component-by-component basis (e.g., OOE/BLAST/SERIRES/DEROB [9-12]). A voluminous building thermal description is required for a whole building.
- C. Macrodynamic level: coupled, constrained linear differential equations or convolution integrals in time, zonal spatial resolution. A simulation based upon modeling that describes each thermal zone of the building with a few, summarizing "system level" parameters [13-23], which can be regressed from data.
- D. Time-integrated level: algebraic linear forms, long-term summary in time, with usually no zonal spatial resolution. An expression providing highly simplified, long-term (monthly or seasonal) summary estimates of bottomline consumed energy, based upon long-term energy balance, with a variety of possible ad hoc upgrades to allow for the average impact of various processes [24-39].

These models can be used in two "directions," as shown in Figure 5. The "forward problem" is the

prediction of the building thermal behavior from the building description only; i.e., input parameters derived from plans (design problem); the "backward problem" refers to regressing model parameters from data (performance monitoring problem). Although all models discussed here solve the backward problem, the most useful models also solve the forward problem as needed for retrofit or component savings calculations and design collaboration.

Note that each level of simulation directly calculates thermal values corresponding to specific levels of the thermal problem data, shown in Figures 2 and 3. In analyzing data from buildings, it is difficult to use the model with data that doesn't directly correspond to the primal quantities calculated directly by the model, although there have been attempts to do so. Only the macrodynamic and time-integrated models appear widely useful for performance monitoring. For these methods, the building thermal zone performance depends upon only a few "equivalent" parameters, which allow the possibility of these parameters being regressed from performance data.

Macrodynamic Simulation

Macrodynamic simulations predict the dynamic overall building performance (temperature for and auxiliary into each defined thermal zone). The methods referenced here treat explicitly the skin loads aspects of the problem only. There are two ways to derive models: 1) postulating a simple thermal circuit, that effectively corresponds to aggregated building components [13-18] or [2] postulating some form of transfer functions for the response of the thermal zone to relevant driving forces for the problem [18-23].

References 13-18 contain simple thermal circuit models with some examples as in Table 1. In each reference the model parameters were regressed from data and fits seemed reasonable. These models should match performance well unless there are significant processes that are not accounted for by

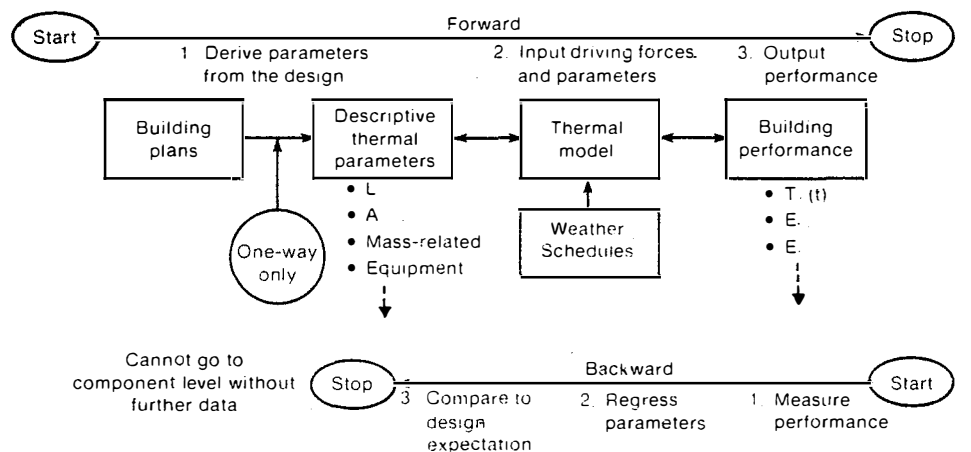


Figure 5. Thermal Problem Directions. The thermal model can be used in either a forward direction (for design) or a backward direction (mainly for monitoring).

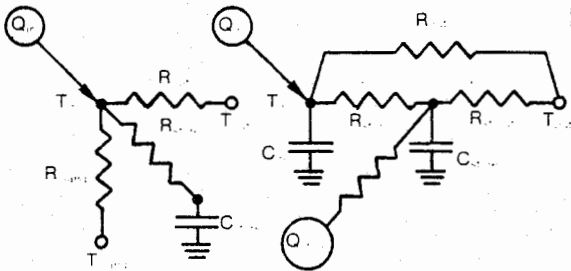
Table 1. Dynamic Models

Thermal Circuit

i^{th} Nodal energy balance \rightarrow

$$C_i \frac{dT_i}{dt} = \sum_j (T_j - T_i) R_{ji}^{-1} + Q_i$$

Examples:



Transfer Function

Zonal energy balance \rightarrow

$$\sum_i Q_{in,i} = 0 = \sum_i \int_{t'=-\infty}^t h_i(t-t') F_i(t') dt'$$

where $F_i =$ forcing function, as T_{out} , I_{sun} , Q_{aux} , T_{in} , ...

Examples:

Explicit formulation

$$h_i = h_0 \delta(t-t') + h_1 \left\{ \delta(t-t') - \frac{1}{\tau_i} \exp\left[-\frac{(t-t')}{\tau_i}\right] \right\}$$

[18]

Response factor

$$Q_{in,i}(t_n) = \sum_0^{Nt} b_j T_{out}(t_{n-j}) + \sum_1^{Nq} C_j Q_{in,j}(t_{n-j})$$

[19a]

the models, such as: internal zone temperature gradients, earth coupling, and nonisothermal mass. The less closely the models correspond to the basic physics of the building, the more the regressed capacitances and couplings are "effective values" that must be regressed and become very difficult or impossible to relate to the building thermal properties. For example, the internal mass depends upon penetration of "thermal waves," which introduces dependence on the capricious data frequency spectrum into the effective capacitance representing that internal storage. Another difficulty with any such thermal circuit approach is "cross-talk" between the parameters [18]; i.e., parameters in the response to a given force (e.g., outdoor temperature) affect the model response for other driving forces (e.g., solar radiation), although these responses are actually independent functions.

Transfer function methods avoid cross-talk by simply postulating an independent form for the

response to each significant driving function present in the thermal problem. Another advantage of transfer function methods is that one can easily add more transfer functions as the thermal problem increases in complexity [18,22,23]. For example, the lights can be dominant load in a large building. If significant mass is irradiated by these lights, the thermal model must account for the consequent time-phasing of the thermal load. The transfer function in response to the forcing function of electricity input is postulated, and parameters would be obtained by a short, one-time test.

Response factor methods, which postulate a single time series for each zone, have not developed a means for calculating the series coefficients from plans [20-22]. Rather, the coefficients have been determined by regression of the parameters from ersatz data generated by a mainframe component model (e.g., TRNSYS [22] or NBSLD [20]). This process unfortunately forces one to still use the more complex component model as an intermediate step, even though the actual hourly calculations are done with the simpler macrodynamic model. Further, the parameters have no clear physical interpretation and even with idealized data show unphysical behavior (e.g., not monotonically decreasing in value), indicating potentially serious sensitivity to noise in the problem. One of the transfer function methods [18] has solved these dilemmas by posing explicit forms whose parameters uniquely relate to building response at given frequencies. Typically zero and diurnal frequencies would be chosen for skin-loss transfer functions, although other choices may be appropriate for unusual buildings or processes. A very massive wall section having zero diurnal response would be described at some frequency close to its characteristic frequency. A chemical reactor cycling hourly would be characterized at hourly frequency. The framework allows both regression (backward) and perturbative calculation for savings (forward) analysis.

Methods based upon dynamic models may require some change from "normal operation" during the period used for parameter determination, to disentangle the parameter space degeneracies which can confound the regression procedure [23]. There are three separate cases to consider: free-floating only, thermal equipment of known efficiency, and equipment of unknown efficiency. If temperatures only are measured, as in a free-floating building, then only scale-independent ratios of physically-related parameters can be obtained. This is most obvious from the form of the equations in Table 1A. A known heat flow must be introduced to break this scaling degeneracy. A portable electric heater with known input can be used for smaller buildings. Another option is to treat the solar flux as known, if the aperture system is sufficiently simple. In this case, the "known flux" is the "solar computed" [3,18].

If the installed building thermal equipment has known efficiency, then a normal run of data of order one week will most likely be sufficient. System efficiencies are known if: 1) the system is electric heating (implying $\eta = 1.0$); or 2) direct measurement is made of system delivered thermal

energy, once or continuously. If the installed building systems do not have known operating efficiency (e.g., almost all natural gas or oil systems whose output is not measured directly), then one must either perform one-time equipment tests or do sequential system-crippled tests. In the latter case the analysis would be constrained by fixing the skin-related parameters at values obtained during testing with the systems of unknown efficiency being turned off. Then the thermal loads (calculated from the skin loads model using the parameters regressed from the one-time, systems-crippled tests) can be treated as knowns, and the instantaneous efficiency of the unknown systems is computed as the ratio of calculated load to measured fuel input.

Time-Integrated Methods

Time-integrated methods are based upon long-term energy balance assuming negligible change in storage, with various simple expressions used for the additive terms in the energy balance. Three related classes of models are: 1) degree day; 2) bin; or 3) semiempirical. Mathematical forms of these thermal models are shown in Table 2. Degree-day and bin models are widely used in performance monitoring analysis [24-33]. Simple degree or bin models with the base or balance temperature (outside temperature at which auxiliary is needed) equal to a standard set-point (65°F, as in Ref. 24) will be inadequate; variable base degree day (VBDD) adjusts the base to account for solar and internal gain [33]. Hence, as in Refs. 25-28, the base temperature (T_b) for the degree-day calculation is treated as a variable extracted from utility billing data, along with the load coefficient, L . Variable base bin (VBB) methods predict comparably to VBDD models. VBB are able to accurately consider some time-dependent aspects not easily done with VBDD such as thermostat setback in lightweight buildings, variable ventilation rates, economizer cycles, nighttime insulation, and coincident latent loads. Rudy's [32] system accounts for lags introduced by solar-loaded massive skin walls and will accurately predict savings for a wide range of HVAC system changes. None of the VBB referenced here account for mass affects with night-setback of the thermostat, although it could be done, such as in Kusuda and Saitoh [30] for VBDD models.

Semiempirical models used for data analysis postulate the energy balance terms in the form shown in Table 2 with constants of proportionality obtained by fitting the postulated expressions to performance data, such as from utility bills [35] or from ersatz data produced by component simulations [34,37]. Hence, these models will tend to reproduce results of the data base used to find K_i . It is not demonstrated nor clear what biases will be introduced in using these expressions to compute retrofit savings, particularly as the models admit more and more parameters, such as correspond to coincidence between solar and temperature [34]. Again, these models should do well for extrapolating to other climates or internal gain schedules, as the forcing functions have been somewhat separated from the less-interpretible building parameters. Well-known correlation models based on fitting ersatz data

Table 2. Time-Integrated Models

$$Q_{aux} = \sum a_i Q_i(B_j, \overline{F_k}), i = \text{skin loads, internal gains, etc.}$$

Degree-Day Models

$$Q_{skin} = L \int_{\Delta t} (T_{base} - T_{out})^+ dt$$

$$\text{Simplistic: } T_{base} = T_{set} - \text{constant}$$

$$\text{Variable base: } T_{base} = T_{set} - \frac{Q_{int}}{L}$$

Enhanced:

$$L = L_0 + L_{inf}(\overline{\Delta T}, \overline{v_{wind}}; \overline{pair})$$

$$T_{base} = T_{base}(t)$$

Mass correction

Bin Models

$$Q_{skin,b} = \sum_{\text{hours } h \text{ in bin } b} L_h \sum_{\text{days}} (T_{base} - T_{out})_h$$

$$\text{Simplistic: } T_{base} = T_{set,h} - \text{constant}$$

$$\text{Variable base: } T_{base,h} = T_{set} - \frac{Q_h}{L_h}$$

Enhanced:

$$L_{out,h} = L_{0,h} + L_{inf}(\Delta T_h, v_{wind,h}; pair,h);$$

Coincident humidity

Semiempirical Models

$$Q_i = K_i(B_j \overline{F_k}), \quad K_i = \text{"best fit" constant}$$

$$B_j = \text{building parameter}$$

$$\overline{F_k} = \text{average driving force}$$

bases [42,43] are in a similar vein, but are not discussed further here, as they are design-oriented tools.

In general, the time-integrated methods should be accurate when the base temperature is much larger than the maximum outdoor temperature, implying that time-integrated conduction and infiltration fluxes (which will dominate the problem) are linearly related to average temperature differences. When the base temperature approaches the outdoor temperature, requiring consideration of storage and flux time-phasing for acceptably accurate modeling, the long-term models can become very inaccurate [23]. Table 3 indicates where simpler versions of long-term methods have potential modeling problems needed to reasonably predict savings for various building configurations. VBDD models must be upgraded to treat most time-dependent strategies, such as in Kusuda and Saitoh [30] for residences. Both VBDD

Table 3. Modeling Issues

Rigor of forward problem solution for savings prediction
Modeling for
multizoning
HVAC equipment
latent heat
air flow
solar gains
ground coupling
Error analysis
Macrodynamic Models
Interpretation of regressed parameters
Seasonal extrapolation of solar parameters (shading, transmission, etc.)
Time-Integrated Models
Variable base temperature used?
Potentially inaccurate accounting for
massive building (e.g., with night setback)
solar-driven buildings, multiple apertures
low energy buildings ($T_{base} = T_{out}$)
night ventilation
economizer cycle

and VBB models have good basis in theory, and should reasonably predict retrofit savings when they are not extended beyond limits of the basic modeling incorporated. For a number of retrofit measures, especially in harsher climates, these models appear to have close correspondence to savings predicted from DOE2.1 component-level simulations (i.e., same change between cases), even if the individual absolute values for the two cases were considerably more in error [33]. It is unclear what effect the adjustment procedure will have on savings predictions made with semiempirical methods.

CALCULATIONS

Analyses done with the normalized thermal model depend upon the intent of the monitoring, as in Table 4. Three general types of analyses, cross-comparison, savings, and design verification, are discussed here.

Cross-comparison is done to identify general potential for retrofit and involves comparing a given building's performance to a statistical base of similar building types in the same area, possibly differentiated into "typical" and "energy-conserving" classes [25,46]. Utility bills are usually the only monitored data used, and an effective load coefficient (L), base temperature (T_{base}), and seasonally-constant weather-independent energy usage (E_o) are regressed. Building size is usually normalized by dividing annual consumption (total or for heating/cooling only) by floor area, although volume or number of occupants may be better normalizers [44]. Consumption is weather-normalized by recomputing the weather-dependent loads from the regressed L, T_{base} , using a "standard" degree-days profile. The base temperature is usually not adjusted for "standard" solar gains, though it could be. It makes little sense to normalize across climates by dividing total energy by degree-days, since for commercial buildings the thermal problem is most often strongly driven by internal-gains, and, hence, loads are not proportional to degree-days.

Savings calculations are done for retrofit analysis and for determining displaced energy from a component. Generally, as in Figure 6, one defines saved or displaced energy Q_{saved} as the difference between annual consumption calculated using two models, one for the actual and one for the reference building. Some standard weather data drives the two models. This quantity then is used in economic equations for cost/benefit evaluation. For determining the savings due to a component in an actual building, the reference will be the same building with the component replaced by some other section/measure. Obvious choices for a solar aperture are an adiabatic wall, or the opaque wall section used elsewhere in the building. In either case, the reference is an "imagined" building whose

Table 4. Reference Choices

Monitoring Purpose	Retrofit Potential	Predict Retrofit Savings	Checking System Controls or Schedules	Diagnose Envelope Behavior	Diagnose HVAC Operation
Appropriate Reference	Statistical Average: all buildings of type energy-efficient buildings of that type	Actual building as modified by imagined retrofit	Building as designed, from as-built plans	Building as designed	Systems as designed/ specified by manufacturer
Comparison Parameters	Normalized Performance Factors: $Q_{end-use}/A_{floor}$	$Q_{end-use}$	$Q_{use}(t), T_z(t)$ compared to expected	B_i^{design} compared to B_i^{actual}	$\eta = \frac{Q_{delivered}}{E_{input}}$

thermal model parameters have to be calculated, implying the thermal model must solve the forward problem (Figure 5). The best method appears to be relying on forward calculation of only the changes in parameters due to changes from actual to reference building. Thus, the "rest of the building" is fixed by the experiment, and only the imagined features are calculated, as in Figure 6.

Design corroboration is done by comparing the building's thermal parameters, calculated from the building plans, with those regressed from the monitoring data. For time-integrated data, one in principle might determine if E_{base} , L , T_{base} are as designed. However, a very broad least-squares trough will exist in (L, T_{base}) space, because increases in base temperature are compensated by decreases in the load coefficient [27]. Similar parameter space degeneracies exist for dynamic methods also. With dynamic methods the parameter space degeneracies can be reduced by controlling one or more forcing functions to some extent. Careful error analysis must be done to avoid misleading inferences.

Once the errors have been carefully considered, then, if they are sufficiently small, regressed parameters can be compared to those expected from the design plans. Given no confusion with ground losses, an unexpectedly large steady state load coefficient (a parameter in all macrodynamic models) is easy to understand in the abstract: anomalous coupling(s) exist to outside air. However, it may be hard to locate the exact cause. Missing insulation, "leaky" construction, unmodeled thermal bridges, broken or open windows or door, or unscheduled night ventilation are examples of potential causes, and engineering acumen is clearly essential. A value for effective aperture area which is lower than expected from the design indicates not enough sun is being admitted into the

building. Some causes, for example, could be unmodeled shading, dirty glazings, high back losses from irradiation of drawn blinds or light-colored objects, or spatial isolation of thermalized energy, as in clerestories. Similarly, an anomalously large value for the solar aperture diurnal frequency transfer function [18] indicates that the sun admitted to the building is not well-coupled to mass. Potential causes for this could be rugs/furnishings blocking direct gain irradiation of the mass, low conductivity in exposed mass, convective uncoupling of mass (closets, partitions, etc.), or wrong colors on mass.

EXAMPLES

Performance of a 4000 m² multifamily apartment complex was monitored in DeCicco [27] using: 1) time-integrated, master-meter gas/electricity data; 2) VBDD model; and 3) calculation of weather normalization, retrofit savings, and design verification. Monthly data (letters) and VBDD fit (line) are shown in Figure 7. A DHW boiler retrofit was not clearly resolved from the uncertainty in normalized annual consumption, and the regressed load coefficient was 1.7 times the value calculated from the plans. Only partial explanation of the heightened load coefficient was obtained, confounded in part by the correlation between values for L and a strangely high T_{base} . Spot checks indicated very high zone temperatures in some of the senior citizen apartments with open windows in others. No effect due to a zone controls retrofit was noted. In general, the low information content, and high noise potential of time-integrated master-meter data clearly limits the inferences possible; in practice, only the condition of abnormality can be inferred, and the causes must be uncovered by site engineering.

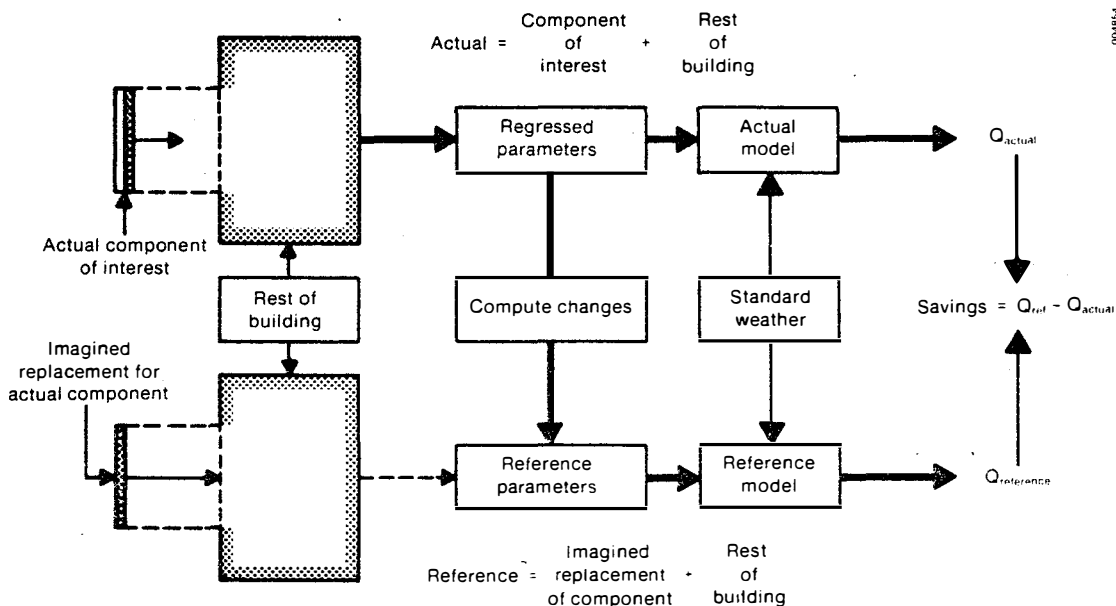


Figure 6. Component Savings Calculation. Component savings are determined by comparing the annual end-use consumption of two models, one for the actual building and one for the reference building.

This classification forces one to detect data-model mismatching, wherein the measured quantities do not correspond to primal calculations of the model used to analyze that data. One example is the "calibrated model" of Hill [41], where a few of the parameters of a component-level thermal model (BLAST) were adjusted to "fit" dynamic zonal performance data. It is clear that there are far more degrees of freedom in the input file than could ever be fixed by performance data alone. Hence, which parameters to adjust is somewhat arbitrary without much more detailed data, corresponding to the component calculations, as in Burch [3]. For example, assuming no ground losses are present, system level data-calculation comparison can clearly indicate that total steady state coupling to ambient air implied by the BLAST input file is incorrect. However, without further data on wall fluxes, infiltration rates, etc., any of (typically) dozens of inputs could be changed to adjust the file to match that load coefficient implied by the data. It cannot be stated in general what affect this arbitrariness would have on component savings calculations.

Another data-model "mismatch" is discussed in Swisher et al. [38] and Shea et al. [39] the DOE Class B program. Here, dynamic data were acquired but were generally simply time-integrated for application of a time-integrated thermal model. Clearly, there is much more information in the dynamic data that was not utilized in the analysis,

as will always be the case when dynamic data is analyzed via a time-integrated model. The Class B data was more fruitfully analyzed via a macrodynamic model [18]. Eight system level thermal parameters were extracted from the data, some of which were compared to values expected from a coheating experiment and from plans. Quality of the fit of model to data is shown in Figure 8. The regressed values were within error of expected values, although uncertainty was large, due to the aforementioned parameter degeneracy in the uncontrolled data.

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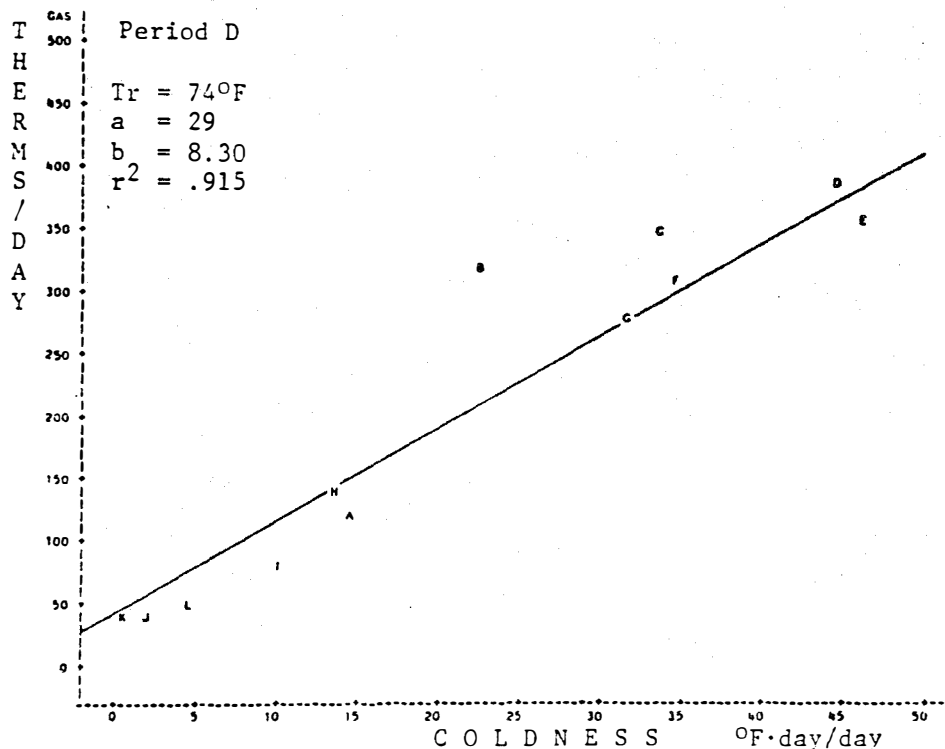


Figure 7. Time-Integrated Energy Use Versus Degree Days [27]. Monthly energy use (letters) is plotted versus actual degree days with the line being the variable base degree day thermal model best fitting the monthly data.

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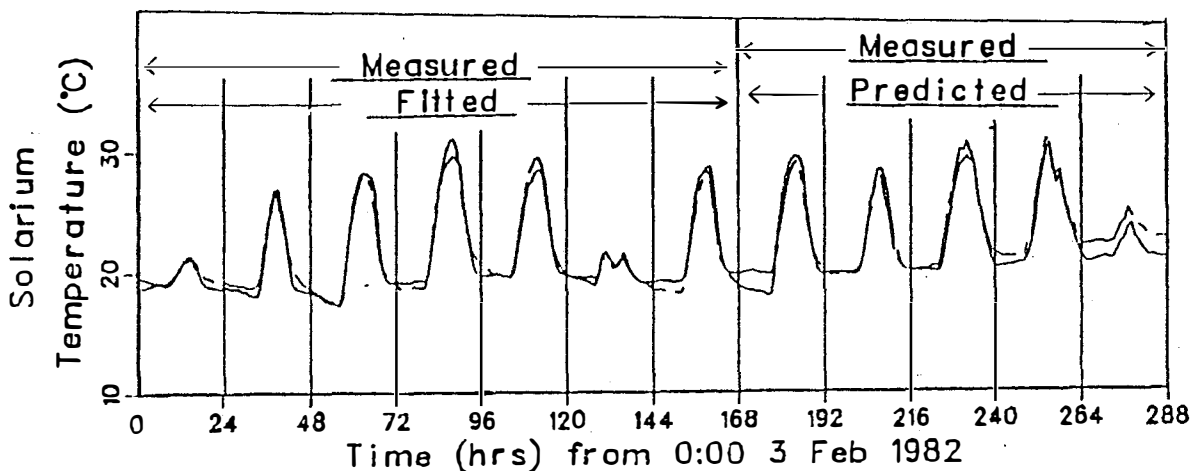


Figure 8. Dynamic Solarium Temperatures [18]. Temperature versus time in a residential sunspace, the solid line being measured and the dashed being the macrodynamic model predictions.

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