

A Directed Weather Data Filter

Abstract: It is important to reduce the computational burden of energy-analysis computer programs (such as those that compute expected heating and cooling loads and the energy required to meet these loads) since the input may include, for example, hourly measurements of several weather variables over periods of time of up to ten years. It is possible to generate a small set of weather data to represent a larger, more comprehensive set by using computer programs called weather data filters. However, existing filters that are generally able to preserve statistical properties of the original data offer no *a priori* method for controlling or even estimating the errors they introduce in the output of the energy analysis programs. This problem exists because these filters deal only with weather data and do not utilize any information regarding the building to be analyzed, its occupancy schedule, its mechanical systems, or the energy analysis function itself. This paper describes a weather filter that preserves the "energy content" of the data; i.e., given a particular building design and usage schedule, this filter generates a small set of weather data which, when properly weighted, produces the same total heating and cooling loads as the original data. Because the error caused by using the filtered weather data falls well within acceptable bounds even when changes are made in the building design, the filter described allows the designer to test a large number of design or retrofit alternatives for energy efficiency at very low computational cost.

Introduction

In order to compute the expected heating and cooling thermal loads or energy requirements for a particular building design, it is necessary to know the weather variables to which the building will be subjected. The National Climatic Center in Asheville, North Carolina publishes magnetic tapes containing hourly values of the following weather factors over periods of one year for each associated weather station: dry-bulb temperature, wet-bulb temperature, dew-point temperature, barometric pressure, wind velocity, wind direction, cloud type, cloud amount, and cloud modifier. At a limited number of stations, direct solar radiation and diffuse solar radiation are also measured. At locations where solar measurements are not taken, direct and diffuse radiation intensities are approximated from the cloud modifier, the known position of the sun, and estimates of the clear-sky radiation intensities [1-3].

Several algorithms [1, 4-8] that use such weather data enable analysts to compute the thermal loads and the energy required to meet them for buildings in the design stage. We refer to all such algorithms by the generic term *E* (see Fig. 1). A partial list of the energy analysis programs appears in the Appendix. A few filtering algorithms [5, 9, 10] reduce computational costs by filtering the year's weather data to output a small set of weather data

for repetitive use by the designer in thermal load computations, but such weather data filters reflect only weather characteristics; they incorporate neither an energy function *E* nor any building or building usage data.

The relative scarcity of scientific journal articles concerning weather data filtering for the hour-by-hour energy analysis computer programs is worthy of comment. In the opinion of the author there are two primary reasons. First, most of the work in this area is by researchers in private industry, who have elected to keep their results confidential. Second, not until very recently has there existed an interest or a requirement for the *repeated* execution of these relatively sophisticated and time-consuming computer programs. There is increasing pressure from governments and public interest groups to mandate extensive energy analysis of building designs *before* building permits are issued. Thus, it is becoming advantageous (and in some cases, necessary) to analyze the energy consequences of design decisions as they are made throughout the design process, rather than simply to evaluate the final product of the design. Also, constrained optimization, with its demands for many (in some cases several hundred) program executions, is just beginning to be applied to energy conservation in buildings. The natural consequences of these factors are efforts, such as the

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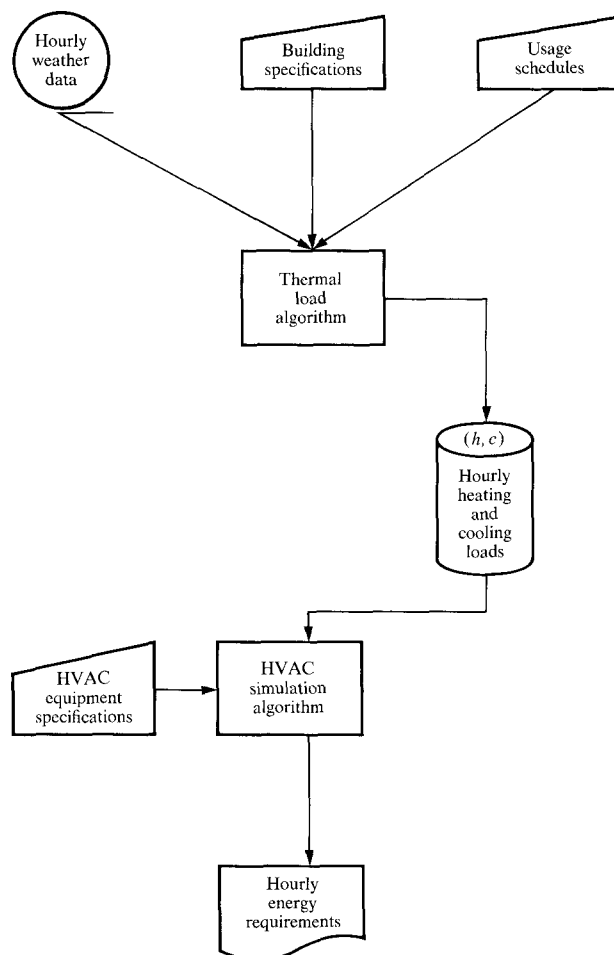


Figure 1 Schematic of typical energy analysis computer program (referred to in the text generically as *E*). Heating and cooling loads are given in energy units and represent deficiencies and excesses of heat, respectively. Energy requirements are the amounts of fuel energy (gas, oil, electricity, etc.) necessary to operate the heating, ventilating, and air-conditioning (HVAC) equipment so that the loads are satisfied.

work presented here, to reduce the cost of using these programs, augmented by attempts to simplify the programs themselves.

This paper describes a weather data filter that substantially reduces computational requirements for the class of thermal load and energy consumption algorithms (and the computer programs that implement them) which require periodic samplings of many weather factors. Because the filter also reflects the impact of building design and building usage on the heating and cooling loads generated by the weather, the weather data filter described here enables the designer to test the consequences (for energy consumption) of a large number of design or retrofit alternatives within very small error tolerances. As a result, the

designer is able to discover economically which of the many aesthetically and functionally acceptable designs is the most energy efficient.

Weather data filtering

To the energy analyst, the process of designing a building can be viewed as a sequence of designs $B_1, B_2, B_3, \dots, B_n$, the last representing the final design. Associated with each design is an energy-related computation E (thermal loads or energy consumption). If the energy computation is to be meaningful, it must reflect information concerning the building usage U (schedule of internal loads and mechanical system control strategy) and the weather W to which the building will be subjected. Each design B_i includes, if appropriate, specifications for the mechanical systems as well as architectural and structural parameters. Output from the computation includes hourly values of heating and cooling loads (or energy requirements) (h, c) .

In order to reliably estimate annual energy consumption, many different combinations of weather factors must be simulated. To ensure that all realistic weather situations will be encountered by the energy program, from one to as many as ten years of actual hourly weather measurements are regularly used. Since considerable computation is required for each hour of simulated data, it is natural to investigate the possibility that the thermal loads (or energy requirements) for a year might be reasonably approximated from a carefully constructed smaller set of weather data. A computer program F that can reduce weather data W to a shorter sequence of data W' that accurately reflects W can be called a weather data filter. The use of such a filter greatly reduces the computational time required for performing energy calculations throughout a building design process.

Such filters generally preserve one or more statistical properties of the original weather data, such as means and extremes. The filter selects or constructs a small number of "weather days" to represent, e.g., each month of weather data. The shortened weather data are then input to an energy function in order to compute the thermal loads for each of these "weather days." The output is then scaled to predict anticipated annual thermal loads for the building. Unfortunately, it is impossible to estimate the error in energy requirements induced by such filters. Thus, there is a recognized need [4] for the development of a rational methodology for the selection of typical days for each month or group of months in order to reduce the number of calculations (e.g., $365 \times 24 = 8760$ for a year's worth of hourly weather data).

We present a filter that does provide such a methodology for reducing the cost of energy function calculations, while at the same time maintaining very small error tolerances.

Directed filter concept

The central thesis of this paper is that the energy function E , incorporating building design B and building usage U , should direct the weather filter as it reduces W to W' . Consequently, the reduced set of weather data W' reflects not only the weather W , but also generates precisely the same heating and cooling loads generated by W in a specific building B used in a specific way U . This property is called the "zero baseline error" property.

In the directed filter $F_{B,U,E}$, hourly weather data W , hourly usage data U , and building data B are input to the energy function E , which then outputs hourly heating and cooling loads (h, c) in BTUs (or joules). The generalized weather filter $\bar{F}$, which forms part of the directed filter $F_{B,U,E}$, first aggregates and sums the hourly heating and cooling loads into appropriate time periods (here, one week). The aggregates, representing weeks of weather, are then grouped (as described in the next section) and these groups are input to a weather data synthesis function. This function constructs hourly weather data that produce the precise mean heating and cooling loads of each group. In this illustration the synthesis function produces for each group one "week" of hourly weather data for each weather variable. Hence, if the heating and cooling loads that were aggregated into 52 thermal load weeks are combined into 15 groups, the filter function reduces the year's weather W to 15 "weeks" of weather W' . If the thermal loads are further condensed into three groups, the filter produces three "weeks" of W' that reflect the full year's weather.

Grouping function

Since the internal heating and cooling loads often follow a weekly cycle, we use seven days as the fundamental period, although larger or smaller periods could have been used. The hourly heating and cooling loads generated by the energy function for the building as it is used are aggregated by weeks and simply summed so that 52 pairs of non-negative numbers (h, c) represent the weekly heating and cooling loads or energy requirements for the year. These pairs of numbers are plotted on a graph (see Fig. 2) where the abscissa represents heating (h) and the ordinate represents cooling (c).

Each of the 52 dots represents the sum of the thermal loads generated by hourly weather data over seven days. We can now group the weeks of thermal load, using proximity as a criterion, by reducing the 52 weeks of thermal load data to, say, 15 "weeks," each represented by its computed center of mass (arithmetic average). In all cases tested, grouping by obvious proximity has served quite well, but any *valid* grouping (defined in the next section) would transmit the zero baseline error property to the associated reduced weather W' . Thus, questions can arise, such as which weather "weeks" should be included

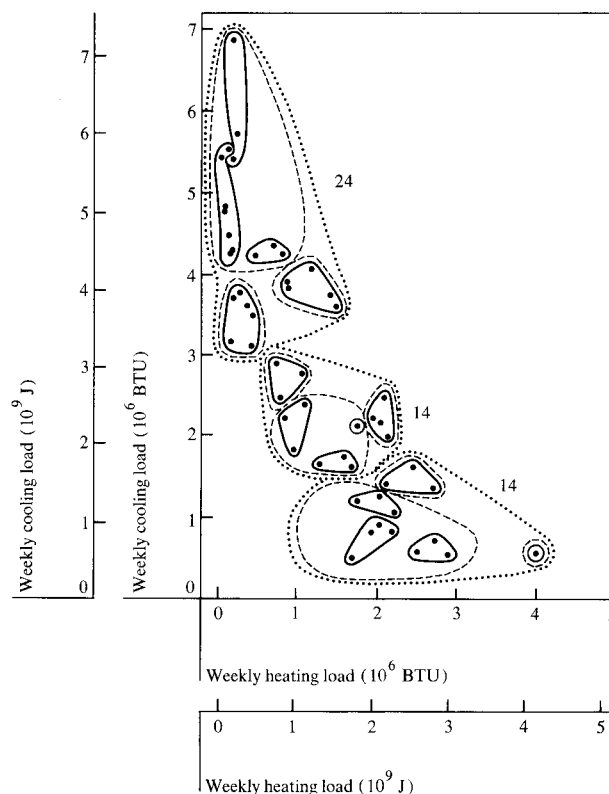
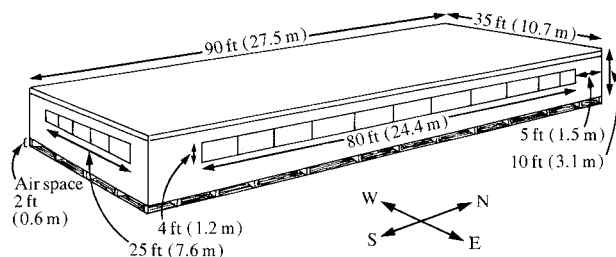


Figure 2 Cross plot of weekly heating-cooling load pairs (individual points) for the building and usage illustrated in Fig. 3 for Los Angeles weather in 1973 (see Fig. 6). The solid lines indicate an initial grouping of the heating-cooling load pairs into 15 "weeks" of data, where each "week" (a) is constructible by convex combination from the actual weather weeks in the group, and (b) produces, for the same building B and usage U , a heating-cooling load pair equal to the center of mass of the load pairs in the group. The dashed lines show a further grouping into nine "weeks," while the dotted lines show the final grouping into three "weeks."

in a particular group, or which "week" is to be constructed as the group representative. It is understood that the error between W and W' can be minimized only if one knows the sensitivity of building energy loads to particular weather variables. Work is continuing in this area.

The weather data synthesis function within the filter $\bar{F}$ constructs a "week" of hourly weather variables for each of the 15 centers of mass presented to it. The 15 groups ("weeks" of W') reflect one of several possible grouping decisions; see solid lines in Fig. 2. Such "weeks" of W' may be used by designers in their search for optimal designs in terms of energy consumption within the design constraints [11]. There are specific advantages to designers in using either a small or a large number of groups. A small number of groups permits computation of preliminary estimates of the consequences of design changes at low cost in computational time, while a larger number of groups results in more refined estimates.



BUILDING OPERATION

Thermostat: 64.4°F (18°C), constant

Room relative humidity = 50 percent, constant

Weekly schedule = Five workdays, two-day weekend.

Workday schedule = Full occupancy (20 persons)

from 8:00 to 17:00

Full lighting (2000 BTU/hr)

from 7:00 to 18:00

Weekend schedule = Half occupancy (10 persons)

from 8:00 to 17:00

Half lighting (1000 BTU/hr)

from 7:00 to 18:00

DESCRIPTION

Ceiling:

Wood, 7/8 in. (inside)

Building paper

Green slate, 1/2 in. (outside)

Floor:

Asphalt tile, 1/8 in. (inside)

Wood floor, 3/4 in.

Wood subfloor, 2 in. (outside)

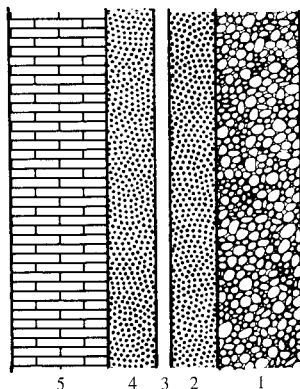
over 2 ft air space

Windows:

All windows regular plate glass,

1/4 in., four sides

symmetric as shown



KEY

1 = Gypsum board, 0.0312 ft

2 = Insulation, 0.15 ft

3 = Air layer, 0.0625 ft

4 = Insulation, 0.15 ft

5 = Brick, 0.28 ft

Figure 3 Description of the test building and its usage schedule. The five-layer wall cross section is shown at the bottom.

Constructing a representative weather period

Once the center of mass $(\bar{h}, \bar{c})_i$ has been determined for each group i , one must construct a single "week" w_i^* of weather (hourly values for each weather variable over the length of a period) with the following property:

$$(\bar{h}, \bar{c})_i = E(B, U, w_i^*). \quad (1)$$

Table 1 Glossary of mathematical symbols.

$\{x_1, x_2, \dots, x_n\}$	A set whose elements are $x_1, x_2, \dots, x_n$.
$(x_1, x_2, \dots, x_n)$	A vector whose components are $x_1, x_2, \dots, x_n$.
$\sum_{j=1}^n x_j$	The sum $x_1 + x_2 + \dots + x_n$.
$x \in A$	x is a member of the set A .
$A \subseteq B$	A is a subset of B .
$\emptyset$	The empty set.
$\cap$	Intersection ($x \in A \cap B$ if $x \in A$ and $x \in B$).
$\mathbb{R}^n$	The set of all vectors containing n real numbers.
$f: A \rightarrow B$	The function f with domain A and range B .
f^{-1}	An inverse function. If $f: A \rightarrow B$, then $f^{-1}: B \rightarrow A$; f is defined only if for each $b \in B$ there is only one $a \in A$ such that $f(a) = b$.

Then, by the additive property of the center of mass, we have

$$E(B, U, W) = \sum_{i=1}^n m_i E(B, U, w_i^*), \quad (2)$$

where n is the number of groups, and the sum of the weights m_i (m_i is simply the number of points in group i) equals the number M of periods in one year; i.e.,

$$M = \sum_{i=1}^n m_i. \quad (3)$$

A numeric example is given in order to clarify the process, but first a discussion of the method for constructing w_i^* , $i = 1, 2, \dots, n$ is given. (A glossary of mathematical symbols is included in Table 1.)

Since the heating and cooling loads computed by E for a given week are solutions to a system of partial differential equations, it is necessary to specify the conditions that apply at the beginning of the week. Because buildings have "thermal memories" that affect future energy requirements, nine days of weather were chosen to represent a week. The first two days were used solely for initialization purposes; i.e., the loads computed for these

two days were not added into the totals for the week. For all tests with the building described in Fig. 3, it was found that the use of two days for dynamic initialization gave results within 0.1 percent of the results obtained by using fifty days. A week's worth of weather data is represented by a matrix w of dimension 216 (i.e., 9 days $\times$ 24 hours per day) by 10 (ten weather variables). For the remainder of this section, we consider an arbitrary single group; for simplicity of notation, the group index i is suppressed.

When m points are grouped on a heating-cooling scatter plot (as in Fig. 2) there is also an implicit grouping of the associated m matrices of weather data; these matrices are numbered 1, 2, $\dots$, n . In order to ensure that the weather matrix w^* constructed for each group truly represents the weather for the weeks in the group, the search is constrained to matrices that are convex combinations of matrices within the group. That is, if w is to be a candidate for w^* , there must exist n non-negative numbers, $\beta_1, \beta_2, \dots, \beta_n$, such that

$$\sum_{j=1}^n \beta_j = 1 \text{ and } w = \sum_{j=1}^n \beta_j w_j. \quad (4)$$

Thus, the solution w^* represents the group of weeks in two important senses: 1) the heating and cooling loads obtained must equal the arithmetic mean of the heating and cooling loads in the group, and 2) w^* must be constructible by convex combination from the weather data that generated the thermal loads in the group. The first requirement allows one to use weighted sums of the thermal loads of the various groups; the second ensures that the constructed weather data are similar to the actual weather data in the group.

On the heating-cooling graph, the group center of mass $(\bar{h}, \bar{c})$ can be represented as a convex combination of the heating-cooling pairs in the group. For a given group of size n , define

$$A_n = \left\{ (a_1, \dots, a_n) \mid \sum_{j=1}^n a_j = 1; a_j \geq 0; j = 1, \dots, n \right\}. \quad (5)$$

Then, there exists a vector α^* of non-negative numbers $(\alpha_1^*, \dots, \alpha_n^*) \in A_n$ such that

$$(\bar{h}, \bar{c}) = \sum_{j=1}^n \alpha_j^* (\bar{h}_j, \bar{c}_j) \quad (6)$$

[an obvious choice is $\alpha^* = (1/n, \dots, 1/n)$].

We seek a w^* that is expressible as a convex combination of the elements of $\{w_1, w_2, \dots, w_n\}$ such that

$$(\bar{h}, \bar{c}) = E(B, U, w^*). \quad (7)$$

An alternate and more useful statement of this group-representative problem is as follows: Let α^* be given. Find a vector β^* of non-negative numbers $(\beta_1^*, \dots, \beta_n^*) \in A_n$ such that

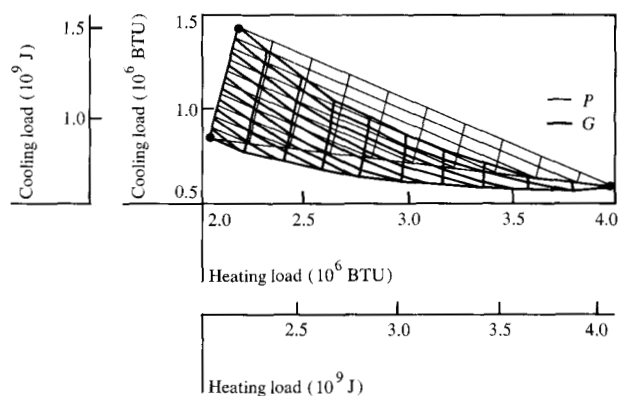


Figure 4 The two-dimensional sets P and G [see Eq. (9)]. The difference between the two sets is due to the nonlinearity of the thermal loads function E (in this example, NBSLD) with respect to weather factors.

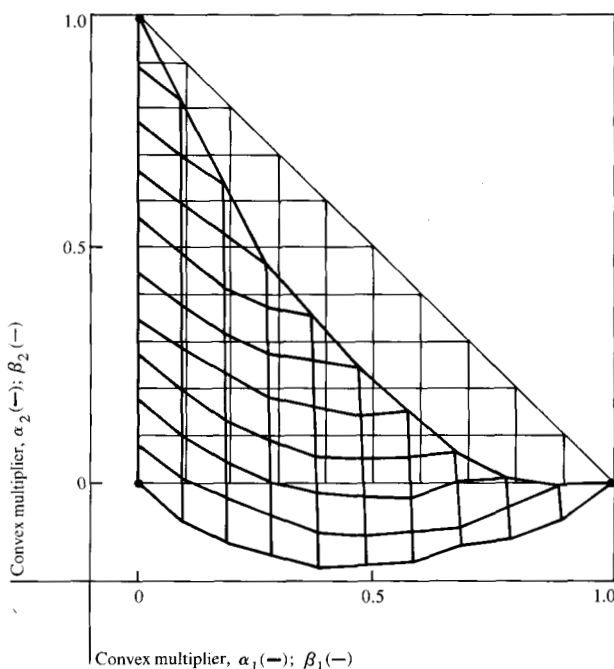


Figure 5 The surrogate "energy" function ϵ corresponding to the P and G of Fig. 4. If $w = \sum_{j=1}^n \beta_j w_j$, then $(h, c) = \sum_{j=1}^n \alpha_j (h_j, c_j)$. Points on the darker grid represent the (α_1, α_2) corresponding to the associated points (β_1, β_2) on the lighter grid.

$$\sum_{j=1}^n \alpha_j^* E(B, U, w_j) = E\left(B, U, \sum_{j=1}^n \beta_j^* w_j\right). \quad (8)$$

Note that if E were linear with respect to weather (which it most certainly is not), then $\beta^* = \alpha^*$ would be a solution. Next, define the two sets (examples are shown in Fig. 4):

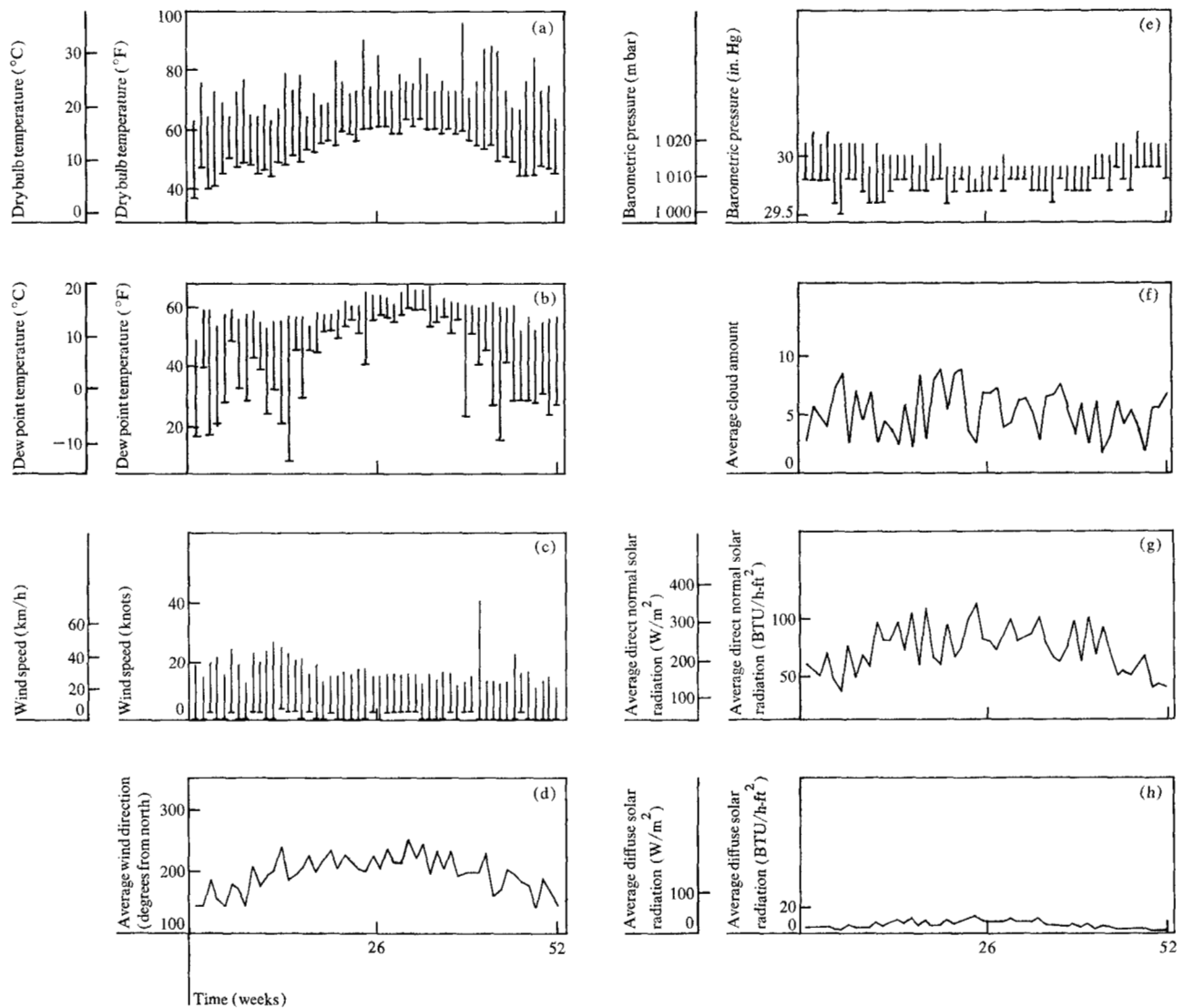


Figure 6 Weekly summaries of selected weather variables in Los Angeles for 1973.

$$G = \left\{ (h, c) \mid (h, c) = E \left(B, U, \sum_{j=1}^n \beta_j w_j \right), \beta \in A_n \right\}$$

and

$$P = \left\{ (h, c) \mid (h, c) = \sum_{j=1}^n \alpha_j (h, c)_j, \alpha \in A_n \right\}, \quad (9)$$

where G is the set of all heating-cooling-load pairs that can be obtained by convex combinations of $\{w_1, \dots, w_n\}$, while P is the set of all convex combinations of $\{(h, c)_1, \dots, (h, c)_n\}$. In general, these two sets intersect but are not equal; i.e., $P \cap G \neq \emptyset$ but $P \neq G$. If α^* is a member of both P and G , it is said that the group $\{w_1, \dots, w_n\}$ is valid. If not, a solution β^* does not exist and new weather "weeks" must be inserted into the group or current ones deleted until validity is obtained. Note that a singleton group is always valid. Suppose that a valid group exists.

It will prove useful in the sequel to extend the range of α from A_n to $\Delta_n = \{(\delta_1, \dots, \delta_n) \mid \sum_{j=1}^n \delta_j = 1\}$, i.e., relaxing the restriction that (h, c) lie in the convex hull of $\{(h, c)_1, \dots, (h, c)_n\}$. It is also assumed, without loss of generality, that for a given $(h, c) \in \mathbb{R}^2$ a canonical (unique) $\alpha \in \Delta_n$ can be defined such that $(h, c) = \sum_{j=1}^n \alpha_j (h, c)_j$. We are now in a position to define a surrogate "energy" function, $\varepsilon: A_n \rightarrow \Delta_n$ with respect to B, U , and the group $\{w_1, w_2, \dots, w_n\}$. For $\beta \in A_n$, we define

$$\varepsilon(\beta) = \alpha, \quad (10)$$

where α is the unique element of Δ_n such that

$$\sum_{j=1}^n \alpha_j E(B, U, w_j) = E \left(B, U, \sum_{j=1}^n \beta_j w_j \right). \quad (11)$$

If the group is valid, then β^* is a solution to the equation

$$\varepsilon(\beta) - \alpha^* = 0. \quad (12)$$

This formulation is considerably more tractable because the dimensions of the domain and range spaces are the same; indeed,

$$A_n \subseteq \Delta_n \subseteq \mathbb{R}^n. \quad (13)$$

A number of solution approaches exist for the problem of finding β^* . The first is the construction of a contraction map $T: A_n \rightarrow A_n$, whose fixed point is β^* . An example of such a contraction map is

$$T(\beta) = \beta - \delta[\varepsilon(\beta) - \alpha^*], \quad (14)$$

where $\delta \geq 0$ is sufficiently small. Experimental results indicate that this approach is successful but slow in converging.

The second approach, the one we adopted, is to form a sequence of simple functions $\{e_k\}$ that approximates ε , and to continually refine e_k in such a way that $e_k^{-1}(\alpha^*) \rightarrow \beta^*$. A detailed description of the approximating function $e_k: A_n \rightarrow \Delta_n$ will appear in a later publication [12]. The form of ε is of interest in that it reveals the very simple underlying structure of E . Figure 5 illustrates $\varepsilon: A_3 \rightarrow \Delta_3$ for a particular $\{w_1, w_2, w_3\}$. Note that neither α_3 nor β_3 need be considered explicitly since they are completely determined by $\{\alpha_1, \alpha_2\}$ and $\{\beta_1, \beta_2\}$, respectively.

Numerical example

In order to illustrate the concepts of the weather data filter a simple example is presented and solved. For the purpose of this illustration the filter was based on heating and cooling loads, although actual energy consumption could have been used.

To compute these loads, the energy function E was chosen to be the National Bureau of Standards program for thermal loads, NBSLD [7]. Los Angeles was chosen as the site for the simulation because a significant number of weather "weeks" produced both heating and cooling loads, thus offering a more interesting test than a location where weeks of heating and weeks of cooling are mutually exclusive. Preliminary tests with New York weather were also performed, producing essentially the same results with respect to the accuracy and robustness of the grouping. There are different sufficient subsets of weather factors for NBSLD. For this example we use hourly values of the following, over a period of one year: dry-bulb temperature ($^{\circ}\text{C}$), dew-point temperature ($^{\circ}\text{C}$), wind speed (m/s), wind direction ($^{\circ}$), air pressure (bars), cloud amount (0-10), direct solar radiation (W/m^2), diffuse solar radiation (W/m^2), declination of sun ($^{\circ}$), and hour angle ($^{\circ}$). Thus, the volume of weather data measurements is 87 600 (10 variables $\times$ 24 hours $\times$ 365 days). Weekly summaries of the first eight of these variables are displayed in Fig. 6.

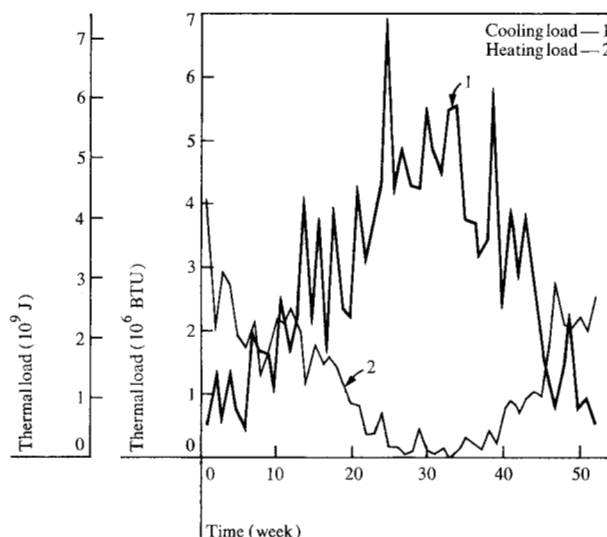


Figure 7 Heating and cooling loads for the modified Fort Myer test building (shown in Fig. 3), and the given usage schedule and weather.

The test building B is a slightly modified version of the building used by Kusuda [7] in testing NBSLD. The building and its usage schedule are pictured in Fig. 3.

With W , B , and U specified, the hourly heating and cooling loads can be computed for the entire year. The result of this computation and subsequent aggregation by week is shown in Fig. 7, while Fig. 2 shows the actual cross plot of these weekly loads. In addition, the grouping shown in Fig. 2 was actually performed. At this stage, there are 15 "weeks" of hourly weather data that yield (when the 15 heating-cooling load pairs are properly weighted by the number of weeks in each group) precisely the same annual heating and cooling load as the 52 actual weeks of the year, at less than one-third the computational cost. This result assumes, of course, that the building B and the usage schedule U are fixed.

The next step is to construct a hierarchy of groups, i.e., to further group the 15 "weeks." The dashed lines in Fig. 2 define nine of the 15 groups, which were consolidated into three larger groups. At the conclusion of the second grouping, we have nine "weeks" of weather precisely representing the original 52 for the same B and U .

Finally, as shown by the dotted lines in Fig. 2, the remaining nine groups are consolidated into three. These three "weeks" of hourly weather data accurately represent the ten weather variables mentioned previously (see Fig. 8). For fixed B and U , the annual heating and cooling load can be computed with no error and at a computational cost of less than six percent of that required for the entire 52 weeks. Thus, there is zero error if the building B

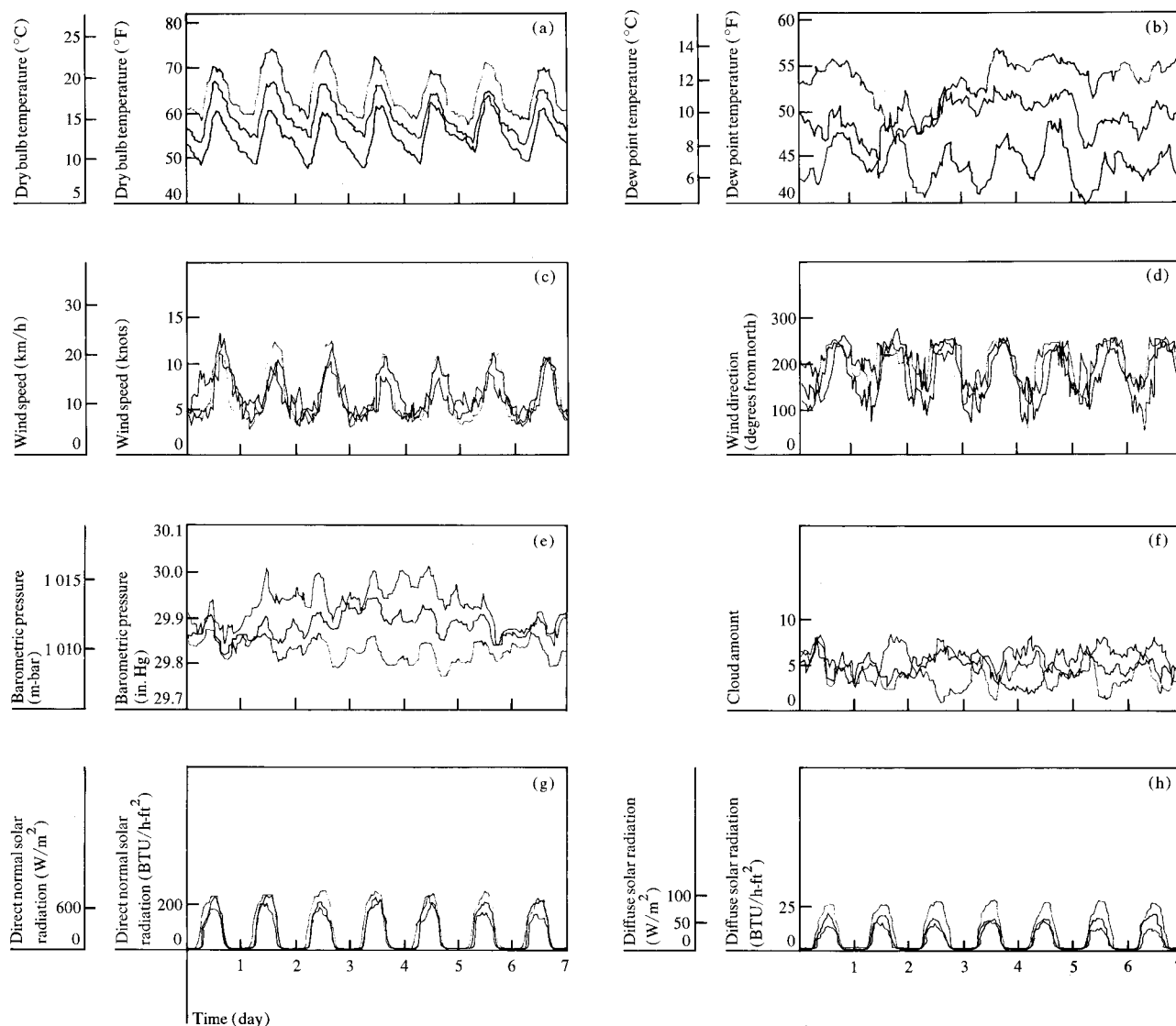


Figure 8 Hourly weather profiles (w^*) representing each of the final three groups. The weighting factors for the upper left (week 1, red curves), the middle (week 2, black curves), and the lower right (week 3, blue curves) groups shown in Fig. 2 are 24, 14, and 14, respectively.

does not change. The next section demonstrates, however, that the error incurred by using filtered weather data is small, even when B changes.

Validation experiments

In order to demonstrate the validity of the directed data filter when changes are made in the building, two experiments are presented. Although building parameters were varied in these validation experiments, one could also have chosen to vary the building usage parameters, including heating, ventilating, and air conditioning (HVAC) equipment set points, control strategies for the use of outside air, and schedules for internal loads such as those caused by people, equipment, and lights.

The first experiment involved rotating the building in fifteen-degree increments through a full 180° . (Since the building is symmetrical about the axis of rotation, it need not be rotated more than 180° .) At each rotation angle, the annual heating and cooling loads were computed by using the full 52 weeks (8760 consecutive hours) of weather data, and by using the three "weeks" of filtered data. (Note: The entire experiment with filtered data can be completed in less time than that required for a single rotation angle with the unfiltered data.)

The experimental results are presented in Fig. 9. There are three points to be made about the results. First, the error is zero at 0° and 180° rotation (since both these values represent the original building). Second, the maxi-

imum error incurred in either heating or cooling load is on the order of one percent. Finally, the same 75° optimal orientation for the building was found by using either filtered or unfiltered data. Within the precision of the experiment (15° increments), the computation with filtered data gave sufficient accuracy (0.0 to 0.6 percent error) in 1/17 the time required for the computation with unfiltered data.

In the second experiment, window size was varied from 12.8 to 55.2 percent of the total wall area. Note that this causes the cooling load to vary by approximately 25 percent of the nominal value and indicates the importance of window size as a determinant of cooling load in a climate like that of Los Angeles. The original (nominal) building's windows covered 33.6 percent of the wall area; thus, the error vanishes at this point. Figure 10 gives both the experimental results for the whole year's weather data and the results obtained by using each of the three different groupings developed earlier in the paper, i.e., the groups of fifteen, nine, and three "weeks." Again, there is no error in the nominal building (33.6 percent). The maximum error in either heating or cooling loads was less than one percent. Figure 11 summarizes the variation of the total heating and cooling load with window size. The maximum absolute error varies from less than 0.4 percent (for the group of "three" weeks) to less than 0.2 percent (for the group of 15 "weeks"). To eliminate the 0.4 percent error, one would have to expend more than 17 times as much computer resource.

Summary

A method of reducing the cost of computing heating and cooling loads in buildings has been presented. The method is most useful in cases where many such computations are required (as in optimization), and where reasonably small changes are made to the building. The method produces zero error for the original building, and experimental results indicate that errors on the order of only one percent are incurred even when some building parameters are changed over a wide range. In one experiment it was shown that 99.6 percent accuracy could be maintained at about six percent of the cost of 100 percent accuracy. (Here, 100 percent accuracy refers to the results obtained by the energy function E when the full 8760 values of each of ten weather variables are used.)

Jurovics [11], as a result of his formulation of first partial derivatives of thermal load with respect to various building design parameters, has shown the feasibility of using constrained optimization techniques to arrive at values of these parameters that minimize thermal load, subject to given constraints. The use of filtered weather data lowers the cost of such optimization runs by a factor of $n/52$, where n is the number of weather groups. One possible sequence of events based on the hierarchical

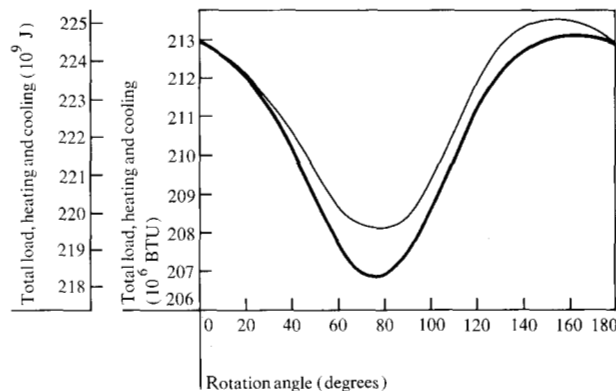
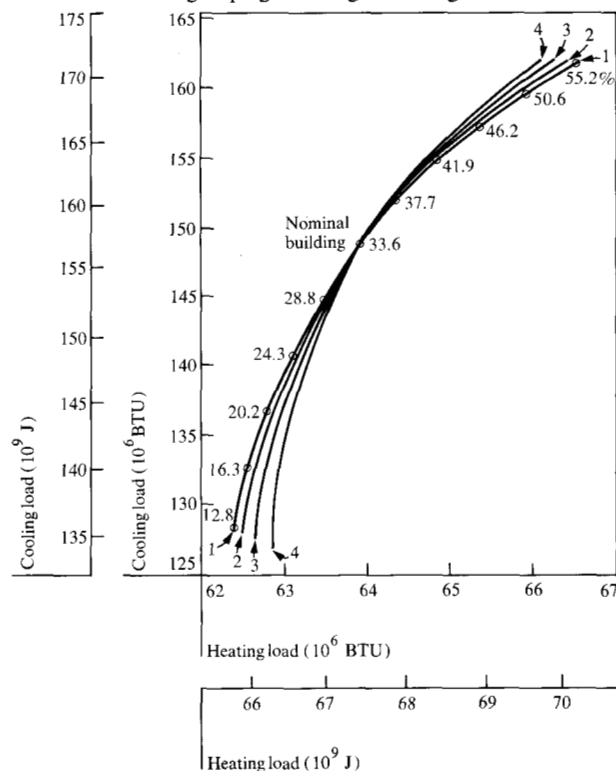


Figure 9 Building rotation experiment with the building shown in Fig. 3. The total (heating and cooling) load is plotted for each of eleven rotation angles, ranging from 0 to 180° in 15° increments. Results produced with filtered weather data (thick line, 3 groups) are within one percent of the unfiltered-data results (thin line, 52 weeks), at approximately six percent of the cost.

Figure 10 Window area experiment. The heating and cooling load variation is given as a function of the total percentage of wall area covered by glass. The nominal building has 33.6 percent window area. The points on curve 1 represent individual values of percent glass. One year's worth of weather data was used for each point on curve 1 (52 weeks), while curves 2, 3, and 4 are for grouped data (15, 9, and 3 grouped "weeks," respectively). The figure demonstrates the sensitivities of the three levels of hierarchical grouping to changes in the glass area.



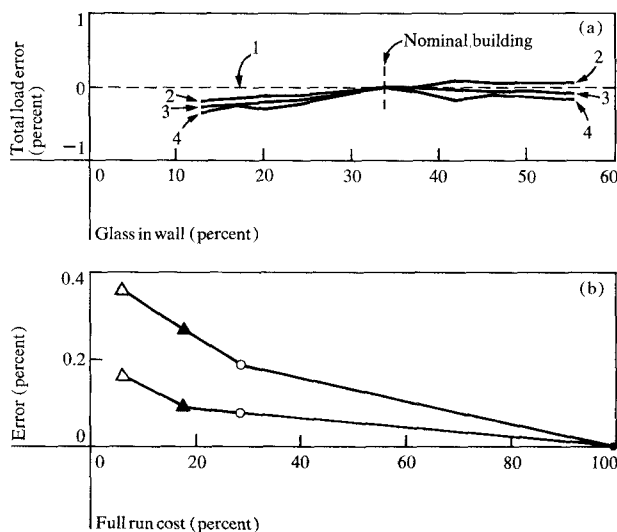


Figure 11 (a) Error and (b) cost analyses of the glass area experiment. An accuracy of 99.6 percent in the total load can be obtained by the three-“week” grouping (curve 4 and Δ) at six percent of the cost of using the full year’s weather data (curve 1 and $\bullet$). Curve 3 (and Δ) and curve 4 (and $\circ$) represent errors and costs for the nine- and 15-“week” groupings, respectively.

grouping described in this paper might be: 1) optimize a “weeks” of weather; 2) take these results as starting values for an optimization run, using the group of nine “weeks”; 3) use these results in turn as starting values for a run using 15 “weeks”; and 4) use the 15-“week” results as starting values for the run using the entire year’s weather data. Early experience indicates that the optimal results from one level of the hierarchical grouping are very nearly optimal for the next finer (containing more groups) level. Thus, it is expected that the total cost of energy-function evaluations should be greatly reduced. This subject is currently under investigation.

The directed weather data filter could also be exploited to aid designers in complying with legislated energy budgets [13, 14]. For example, in the interest of calculating stringent but economically feasible energy budgets [13, 15], the state of California has standardized on the following: an energy function, nine classes of non-residential buildings, 15 weather regions (each with its corresponding weather data), and a single usage schedule.

In order to help building designers reduce the cost of necessary energy computations, and to make optimization economically feasible, the following steps could be taken:

1. Perform a set of hierarchical weather data groupings for each combination of building class (as represented by an existing building) and weather region and distribute the resulting reduced weather sets along with the (currently distributed) full year’s data.

2. Perform a set of experiments (roughly similar to those reported in this paper) for each such combination and publish the results.
3. Allow building designers, in the early stages of design, to use the appropriate set of filtered weather data on their own design(s). As a design progresses, finer and finer groupings can be used until the last computation (i.e., that required for the building permit), is made with the full year’s data. Also, the building’s actual usage schedule and HVAC system should reasonably be considered during the finer stages.

It appears that the directed weather data filter can substantially reduce computational time without introducing significant error. The filter has potential application in the design process both in stagewise design optimization and in helping governments and designers to define and comply with energy budgets.

It should be recognized that considerably more validation work must be done. Planned work and work in progress include the simulation of actual buildings with grouped weather data from widely differing climatic regions. Also, no particular *physical* significance is claimed for the reduced weather data; rather, they have *computational* significance.

The potential value of this work is not simply that energy functions will consume less time, but that the magnitude of this reduction makes possible a qualitative change in the way energy analysis can be done; i.e., constrained optimization techniques become feasible. Thus, it is possible that buildings that use less energy can now be more easily and economically designed.

Appendix: Partial list of energy analysis programs

In this list we enumerate a few of the more widely known computer programs in the area of energy analysis in buildings. A more complete list, along with short descriptions, can be found in [8].

- (1) *NBSLD: National Bureau of Standard Load Determination Program*, developed by T. Kusuda, National Bureau of Standards, Washington, DC, 1972.
- (2) *ACCESS: Alternate Choice Comparison for Energy Systems Selection*, developed by Seeyle, Stevenson, Value, and Dreht under contract to the Edison Electric Institute, New York, NY.
- (3) *ECUBE: Energy Conservation Utilizing Better Engineering*, developed by the American Gas Association, Arlington, VA.
- (4) *M-27: Giffels Building Heating Energy Estimate*, developed by M. N. Wahim, Giffels Associates, Inc., Detroit, MI.
- (5) *BUILDSIM: Honeywell Total Building Simulation*, developed by G. Shavit, Honeywell, Inc., Arlington Heights, IL.

- (6) *MACE: McDonnell Douglas Automation Company's Annual Consumption Energy Program*, developed by McDonnell Douglas Automation Company, St. Louis, MO.
- (7) *Meriwether Energy Systems Analysis Series*, developed by Ross F. Meriwether and Associates, Inc., San Antonio, TX.
- (8) *NECAP: NASA's Energy Cost Analysis Program*, developed by Gard, Inc. under contract to the National Aeronautics and Space Administration, University of Georgia, Athens, GA.
- (9) *Program for Analysis of Energy Utilization in Postal Facilities*, developed by General American Transportation Corporation, Research Division, Niles, IL.
- (10) *SCOUT: Gard Program for Facility/HVAC Design and Energy Analysis*, developed by GARD, Inc., Niles, IL.
- (11) *TRACE: Trane Air Conditioning Economics*, developed by the Trane Company, LaCrosse, WI.
- (12) *HACE: WTA Heating and Air Conditioning System Energy Analysis*, developed by William Tao and Associates, Inc., St. Louis, MO.
- (13) *CAL/ERDA Computer Program*, developed by California State Energy Commission, Sacramento, CA, and National Laboratories at Berkeley, CA, Argonne, IL, and Los Alamos, NM.

Acknowledgments

This work has been supported by the Energy Programs Department, Real Estate and Construction Division, IBM Corporation. The author wishes to thank C. Garcia for many helpful suggestions. Also, the extensive experimental work would not have been possible without the programming and analytical skill of P. Neiswander.

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Received June 31, 1977; revised March 17, 1978

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