On Using Degree-days to Account for the Effects of Weather on Annual Energy Use in Office Buildings

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ABSTRACT

To better quantify the effects of conservation measures, degree-day-based techniques are commonly used to isolate weather-induced changes in building energy use. In this paper, we use a building energy simulation model, which allows us to hold fixed all influences on energy use besides weather, to evaluate several degree-day-based techniques. The evaluation is applied to simulated electricity and natural gas consumption for two large office building prototypes located in five U.S. climates. We review the development of degree-day-based, weather-normalization techniques to identify issues for applying the techniques to office buildings and then evaluate the accuracy of the techniques with the simulated data. We conclude that, for the two office building prototypes and five U.S. locations examined, most techniques perform reasonably well; accuracy, in predicting annual consumption, is generally better than 10%. Our major finding is that accuracy among individual techniques is overwhelmed by circumstances outside the control of the analyst, namely, the choice of the initial year from which the normalization estimates are made.

INTRODUCTION

Quantifying conservation savings in buildings is difficult because one must answer a question that is inherently hypothetical: "But for this measure to save energy, how much energy would have been used?" Engineering estimates of the savings from conservation measures rarely agree with subsequent utility bills, since many of the assumptions embedded in the estimates are not realized in practice. One of the most important complicating factors is the influence of weather on the energy use of buildings. For example, a cold year can reduce apparent savings from a measure designed to save heating fuel as easily as a warm year can increase them. The relevant measure of the effectiveness of a measure must remove, or at least identify, the bias that weather exerts on a building's energy use.

Building energy researchers and energy service companies have developed empirical techniques to account for the effects of weather on energy use in retrofitted buildings*. The goal of these techniques is to extract a description of energy-use characteristics of the building from a given year of energy-use data that is wholly separable from the weather in that year. Given this separation, weather data representing a long-term average for the location can be introduced to produce a new "normalized" estimate of energy use, now taken to represent a long-term average. Performing this analysis on energy use data prior to and after the conservation improvement and subtracting one from the other provides a weather-normalized estimate of changes in consumption. Although no one technique is universally accepted, heating and cooling degree-days are commonly relied upon to represent the weather variable.

Despite the popularity of degree-day-based techniques, little is known, beyond theoretical considerations, about their accuracy in practice. Field tests to evaluate the accuracy of these techniques are very costly, in part because they require careful measurement of

**Energy Build.*, Vol. 9, Nos. 1 & 2 are devoted to discussions of the most well-known of these techniques, the Princeton Scorekeeping Method (PRISM).

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all influences on building energy use, not only weather. This paper outlines a practical alternative to field measurements in the form of an evaluation method based on building energy simulations. The basis of our evaluation is the simulated, historical electricity and natural gas demands of two hypothetical office buildings located in five U.S. climates.

Accounting for the effects of weather on energy use in office buildings is a rigorous challenge for degree-day-based techniques because the operation and complexity of office building heating, ventilating, and cooling (HVAC) systems tends to violate assumptions fundamental to formulation of these techniques. In this respect, an important aspect of our evaluation is a discussion of the appropriateness of degree-days in accounting for the influences of weather for this type of building.

This paper has six Sections following this introduction. In the next Section, we review the use of degree-days in accounting for the effects of weather on residential building energy use. Next, we use this review to identify factors that complicate application of these techniques to office building energy use. We then describe a simulation-based approach to evaluating normalization techniques. This Section includes descriptions of the simulation model, climates, and office building prototypes analyzed, the four normalization techniques evaluated, and the evaluation method. Following this, we describe our results for accuracy and reliability of the techniques. We then use these results to provide guidance to the practitioner on the applicability and limitations of the techniques. The final Section is a summary.

THE USE OF DEGREE-DAYS FOR WEATHER NORMALIZATION

Developers have considered ease of use and accuracy to be the most important features of weather normalization techniques. We will address only the issue of accuracy in the present work, but it is important to recognize the influence that ease of use, especially accessibility of data, has had on current formulations. For example, the most common normalization techniques rely on degree-days to represent weather because degree-days have been published by weather bureaus for many years and are familiar to most building owners and operators as an unbiased measure of climate severity. Both heating and cooling degree-days may be used depending on the end use affected.

Heating degree-days are defined as the sum of the positive differences between a base temperature and the average daily outdoor dry-bulb temperature for a given time period [1]. Formally,

$$\text{heating degree-days} = \sum_{i=1}^{N} (\text{base temp} - \text{average daily temp}) \qquad (1)$$

where:

$$(\text{base temp} - \text{average daily temp}) > 0 \qquad (2)$$

and

$$\text{average daily temp} = (\text{max daily temp} + \text{min daily temp})/2 \qquad (3)$$

Similarly, cooling degree-days are calculated by summing the negative temperature differences between the base and average daily outdoor temperature; i.e., when the average exceeds the base temperature. N may be, depending on the analysis, the number of days in the month, heating/cooling season, or year.

In the U.S., the base temperature has traditionally been defined as 18.3 °C (65 °F), but this is only a rule of thumb. The physical significance of the base temperature can be thought of as the outdoor temperature at which internal plus solar and other gains exactly offset heat losses. Outdoor temperatures below this threshold indicate the need for heating. Correspondingly, outdoor temperatures above the threshold indicate the need for heat removal or cooling (unless a dead-band increases the threshold value). For this reason, the term "balance point" temperature is often used interchangeably with base temperature. Nall and Arens have found that base temperatures lower than 18.3 °C (65 °F) are appropriate for residential structures in recent years because of better construction practices (e.g., higher insulation levels) [2].

We can solve an equation analytically for the appropriate balance point temperature by explicitly considering indoor temperature, internal and solar gains, the envelope heat loss from conduction, air leakage, and sky radiation, and equipment efficiency [3].

An illustrative, but highly simplified, derivation begins with the steady-state heat loss equation:

$$Q_{\text{loss}} = U*A*(T_{\text{in}} - T_{\text{out}}) \tag{4}$$

where:

Q_{loss} = heat loss (J)
U = U-value (J/m^2 °C)
A = area (m^2)
T_{out} = outside temperature (°C)
T_{in} = inside temperature (°C).

A heating load arises when there is a positive difference between heat losses and heat gains:

$$Q_{\text{load}} = Q_{\text{loss}} - Q_{\text{gain}} \tag{5}$$

Finally, purchased energy use to meet this load requires accounting for a conversion efficiency:

$$E = Q_{\text{load}}/\eta \tag{6}$$

where:

E = purchased energy (J)
η = efficiency of energy conversion system.

By substituting eqn. (4) into eqn. (5) and rearranging terms, the outside temperature at which no heating energy is required ($E = 0$) can be expressed by:

$$T_{\text{out}} = T_{\text{in}} - (Q_{\text{gain}}/U*A) \tag{7}$$

T_{out} is known as the "balance point" temperature since lower outside temperatures mean that heating energy will be required to maintain T_{in} at a constant level. In this simplified formulation, it is clear that the balance point temperature is uniquely determined by the desired indoor temperature, the physical properties of the building envelope, and the heat gains of the building operation of each structure. It is also clear that the balance point temperature will change over time as any of these quantities change, notably, T_{in}, heat gains, and η; our formulation suppresses the time dimension. In practice, consequently, the analytical solution for the balance point is extremely difficult to calculate, given the large amounts of data required.

Researchers at Princeton University's Center for Energy and Environmental Studies have developed perhaps the most sophisticated degree-day-based technique for explaining observed residential building energy performance. The Princeton technique, called PRISM, bypasses the need for analytical solution of the balance point temperature [4]. The technique uses linear regressions to decompose metered energy use (typically, monthly utility bills) into three parts: a non-weather-sensitive component or "intercept" (α); a weather-sensitive component, consisting of a heating "slope" (β); and the number of degree-days calculated to a given balance point or base temperature (τ).

$$\text{heating energy use} = \alpha + \beta*H(\tau) \tag{8}$$

where:

α = intercept (MJ)
β = heating slope (MJ/HDD)
$H(\tau)$ = heating degree-days to base temperature, τ(HDD).

In this technique, the base temperature corresponds to the best regression of energy use on degree-days, as measured by R^2 values. Many researchers have used this technique successfully in analyses of conservation measures designed to save heating energy in residential structures (see footnote to Introduction). Researchers have also studied cooling energy use in residences. In this case, total electricity use becomes the dependent variable and slope estimates increase to account for the non-weather-sensitive energy use of other electric appliances.

As with all normalization techniques, the assumption implicit in this analysis method is that the estimated α, β, and τ have identified the weather-sensitive and non-weather-sensitive components of energy use in a manner that is independent of the actual weather in a specific year. It follows, then, that energy use in any other year is simply the product of the appropriate degree-days in this other year and the weather-invariant parameters α, β, and τ. Consequently, it is crucial that these parameters be well defined by the regressions. A principal contribution of the Princeton research effort has been the development of procedures that measure this definition statistically [5].

Recently, variations of this technique have appeared in more sophisticated shared-savings contracts for commercial buildings [6]. These techniques should not be confused with PRISM, but they share many important features. For example, many of the techniques involve regressions of degree-days on energy use, although most use the familiar 18.3 °C (65 °F) base temperature for calculating degree-days. More sophisticated techniques attempt to find the appropriate balance point with regressions of energy use on degree-days to different base temperatures. As with PRISM, the best base temperature is typically determined by maximizing the R^2 value. Nevertheless, constraints are often imposed that compromise the rigor of the techniques *vis-à-vis* PRISM. Examples of such constraints include restrictions on the set of base temperatures evaluated, or restrictions on the range of possible values for α and β (e.g., >0) [7]. Finally, only PRISM provides statistical measures of the robustness of the individual parameters, α, β, and τ.

THE CHALLENGE FOR APPLICATION TO OFFICE BUILDING ENERGY USE

There are two major theoretical issues that challenge the applicability of degree-days for use in weather-normalizing office buildings energy use. First, techniques that are well-proven for residential structures may not be appropriate for office buildings which differ considerably from residential buildings, both in the types of systems used to provide space-conditioning, and in the manner in which the systems are operated [8]. Second, dry-bulb temperature, which is the basis for the degree-day, can be criticized as an inherently limited measure of the climatic forces affecting energy use in office buildings.

In general, energy use in buildings is a function of both climate and operation. Recalling eqn. (8), we observe that degree-day-based techniques represent the weather-sensitive interaction between these variables with what is essentially a steady-state heat loss equation integrated over time. However, the base temperature is not a literal temperature; it is an equivalent temperature below which heating is required. This equivalent temperature must include the effect of internal loads and other heat gains, as well as the effect of the desired interior set-point for the building. That is, these heat gains are re-expressed as a temperature that reduces the indoor temperature to the point below which heating is required (eqn. (7)).

This formulation is natural for residential buildings. Residences are generally thought of as single-zone, constant-temperature structures, so a steady-state equation is appropriate for capturing the influence of weather on energy use. Commercial buildings, however, are generally neither single-zone nor constant temperature, so a steady-state equation cannot accurately represent the relationship of weather and energy use.

From an operational standpoint, there is often a fundamental mismatch in the period of time during which energy is used in office structures and the 24-hour time period during which degree-days are measured. Many office buildings are operated during only a fraction of these hours. Similarly, monthly degree-days consider the contribution of weather from every day of the month, but many office buildings do not operate on weekends. In other words, there are two distinct time periods of (more or less steady-state) operation that must be represented by a single, equivalent balance point temperature, weather-sensitive slope, and non-weather-sensitive intercept. More importantly, the transient behavior of a building between the weekday and weeknight or weekend operating condition explicitly violates the steady-state operating assumption. Researchers applying the Princeton technique to residential buildings acknowledge this difficulty when evaluating residential buildings operated with night-setback, since night-setback for residential buildings is analogous to night and weekend shutdown of office buildings [4]. Researchers have also identified a related phenomenon when the assumed, constant non-weather-sensitive intercept is known to include non-random, seasonal variations [9].

Precise intuitive definition of the balance point temperature for office buildings is also complicated by the existence of distinct thermal zones within office buildings. Large office buildings often require simultaneous heating and cooling because of the complexity of space-conditioning systems, which often serve multiple zones within the building. An equivalent balance point temperature must resolve all zones, over all hours of the year, into a single number.

The use of degree-days to account for the effect of weather on energy used can be complicated when energy is also used for end uses that are not affected by weather. In eqn. (8), this situation corresponds to regressions that yield large non-weather-sensitive intercepts relative to the weather-sensitive slope. Researchers have noted that R^2 values decline in these situations for either cooling or heating [10, 11]. This result may be exacerbated in office buildings since electricity used for cooling, for example, is only a part of the total demand for electricity. The cooling load on chillers, in turn, is primarily composed of the removal of heat from lights, people, and miscellaneous equipment, not the tempering of outside air.

Finally, dry-bulb air temperature, expressed as degree-days, is only one component of many climatic influences on building energy performance. Insolation, humidity, wind speed, and numerous other factors are all part of weather's effect on building energy use. In a regression of energy use on degree-days, degree-days become the surrogate for all influences, climatic or otherwise, on energy use. Researchers have documented great improvements from using more sophisticated degree-day-type measures, which include these other factors, to explain simulated residential heating and cooling loads [12]. For cooling loads, they found that regressions using a hybrid statistic combining dry-bulb temperature and humidity were superior to regressions based on cooling degree-days alone.

A SIMULATION-BASED EVALUATION METHOD

Field tests of the accuracy of weather-normalization techniques are costly and difficult to carry out. The primary reason is that a valid test of the accuracy of a weather-normalization technique must consider all influences on energy use, including variations in weather. In an ideal experiment, building operation and occupancy would be held constant to ensure that all changes in energy use were due solely to the effects of weather. In real buildings, these conditions cannot be met. For this reason, computerized building energy simulation models, in which all conditions can be fixed, are a practical alternative for studying the effects of weather on building energy use. In this Section, we outline the method with a description of the simulated energy use data we created for analysis, the four weather-normalization techniques evaluated, and the method developed to assess the accuracy of the techniques. We also briefly summarize our intermediate findings on the parameters developed for each normalization technique.

Simulation method, climates, and office building prototypes

The basis for our evaluation of degree-day-based weather-normalization techniques is a set of multi-year computer simulations for two different office building prototypes in five U.S. climates. For each annual simulation, the building specifications (structural components, operating schedules, and interior conditions) remain fixed. Although operating schedules were fixed, the historic chronology of days was preserved. Thus, as would be observed in monthly billing data, some months contain four weekend periods of operation, while others contain five. Over the course of years, the number of weekends in a given month changes. The monthly energy use for each office building and fuel (electricity and natural gas), and the corresponding heating and cooling degree-days are the data set for the analysis.

Monthly energy requirements were estimated using the DOE-2 building energy analysis program (version 2.1C). The DOE-2 program was developed by the Lawrence Berkeley and Los Alamos National Laboratories for the Department of Energy to provide architects and engineers with a state-of-the-art tool for estimating building energy performance [13]. The program simulates energy use on an hour-by-hour basis and has been extensively validated with measured data [14].

We ran the simulations with 13 years of weather data for five different U.S. locations, El Paso TX, Lake Charles LA, Madison WI, Seattle WA, and Washington DC. Taken together, these sites represent a broad range of U.S. climates. Twelve of the thirteen years of data are measured data from the SOLMET data set. The SOLMET data set was developed by the National Climatic Data Center to provide building energy researchers with quality-controlled, historical, hourly solar insolation and collateral meteorological data for 27 U.S. weather stations [15]. This data set was also the basis for the development of Weather Year for Energy Calculation (WYEC) weather tapes, which is the thirteenth year of data used in the analysis. The WYEC was synthesized from the entire set of SOLMET measurements (25 years) to reflect long-term averages for each site, so that energy use for this year can be thought of as "typical" [16]. Monthly heating and cooling degree-day statistics for base temperatures from 5 °C (41 °F) to 26.1 °C (79 °F) in 1.1 °C (2 °F) increments were calculated for each year.

The two office building prototypes we simulated are based on actual buildings of recent vintage, but modifications were made to ensure compliance with *ASHRAE Standard 90-1975* [17]. Operating schedules and temperatures were taken from the *Standard Building Operating Conditions* developed for the Building Energy Performance Standards [18]. The HVAC systems were designed so that only electricity would be used for cooling/chilled water and only natural gas would be used for heating (of course, electricity is also used for lighting, fans, pumps, etc.). Major features of the two office building prototypes are summarized in Table 1.

Tables 2 and 3 summarize the energy and climate data used in our evaluation. For each mean value, standard deviations are also reported. We normalized the energy data by area to account for differences in the sizes of the two buildings. Climate data have been expressed as degree-days to base 18.3 °C (65 °F).

The medium office building is more electricity-intensive than the large building because the assumed internal electrical loads are greater (see Table 1). These loads also increase electricity used for cooling. Higher internal loads in the medium office also explain why the large office consumes more natural gas. For a given climate, standard deviations for annual electricity are smaller than those for natural gas. This result follows from the fact that the non-weather-sensitive component of electricity usage is both large and held fixed from year to year.

TABLE 1

Summary of office building prototypes

	Large office	Medium office
Size	55 530 m^2	4517 m^2
Shape	38 floors, 2 basement levels, flattened hexagon in cross section, approximately 1670 m^2/floor	3 floors, rectangular in cross section, approximately 1500 m^2/floor.
Construction	Steel frame, limestone cladding	Steel frame superstructure, exterior walls of 10-cm precast concrete panels
Glazing	25% of wall area	36% of wall area
Operation	08:00 - 18:00 weekdays, with some evening work; 30% occupancy on Saturday, closed Sundays and holidays	Identical to large office
Thermostat settings	25.6 °C cooling 22.2 °C heating (night and weekend setback 17.2 °C)	Identical to large office
Internal loads	25.8 W/m^2 lighting 5.4 W/m^2 equipment	26.9 W/m^2 lighting 10.8 W/m^2 equipment
HVAC air-side	2 VAV systems zoned separately for perimeter (w/terminal reheat) and core (no reheat); dry bulb economizer set at 16.7 °C	Four-pipe fan coil for perimeter, single zone terminal reheat for core
Outside air	3.3 l/s per person	Identical to large office
Heating plant	2 gas-fired hot water generators (eff. = 75%)	1 gas-fired hot water generator (eff. = 75%)
Cooling plant	2 hermetic centrifugal chillers w/cooling tower (COP = 4.3)	1 air-cooled hermetic reciprocating chiller (COP = 2.6)

TABLE 2

Natural gas consumption: 12-year average (kWh/m^2 yr)

Locations*	Large office		Medium office		Heating degree-days (18.3 °C)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Lake Charles	28.1	5.0	10.0	2.6	880.2	144.1
El Paso	35.6	2.9	14.9	1.5	1414.9	130.9
Washington	69.0	4.8	22.0	2.2	2526.2	192.2
Seattle	74.5	6.7	22.8	3.0	2967.3	244.0
Madison	74.8	3.8	32.0	2.1	4129.4	207.2

*Locations ordered by increasing energy use.

TABLE 3

Electricity consumption: 12-year average (kWh/m^2 yr)

Location*	Large office		Medium office		Cooling degree-days (18.3 °C)	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Seattle	145.9	1.5	149.9	1.5	59.1	48.3
Madison	152.9	1.6	160.8	1.8	355.9	79.4
El Paso	158.4	0.9	176.0	1.6	1302.0	79.6
Washington	158.9	1.4	167.0	1.6	739.4	130.7
Lake Charles	165.0	1.5	180.3	2.1	1526.4	90.7

*Locations ordered by increasing energy use.

It is tempting, but incorrect, to conclude that the prototypes do not exhibit much weather-sensitivity, given the relatively constant levels of annual consumption. The monthly data contradict this observation, as shown in Figs. 1 and 2, where a seasonal pattern of energy use can be clearly identified.

Four weather-normalization techniques

We evaluated four generic weather-normalization techniques based on techniques that are in common use by energy service companies. Equation (7) is a model for describing each technique.

The most elementary technique, no correction, ignores weather variations altogether. This technique simply takes one year's consumption and assumes that consumption in other years will be identical. In our model, this is represented by simply setting the slope term, β, equal to zero.

The next technique, zero intercept, assumes that all energy use is correlated with degree-day variations in weather. In our model, the intercept term, α, is set equal to zero. In keeping with the most popular formulation of the technique, the base temperature for the degree-days is set at 18.3 °C (65 °F).

The third technique, fixed base temperature, relies on both an intercept, α, and a slope, β. The parameters, α and β, are developed by regressing monthly degree-days on monthly energy use. The base temperature for the degree-days is fixed at 18.3 °C (65 °F). Degree-days and energy use were first normalized for varying numbers of days per month.

The fourth technique, variable base temperature, requires a two-stage analysis of statistical correlations between degree-days and energy use. Both degree-days and energy use are first normalized to daily values and then regressed as in the fixed-base temperature technique. The intercept, α, slope, β, and number of degree-days $H(\tau)$ are selected from the best correlation of degree-days, at a given base temperature, with energy use. The best correlation is defined as the correlation having the highest R^2 value for the range of base temperatures examined (5 °C to 26.1 °C).

Evaluation method

Our evaluation methods attempt to replicate current application of degree-day-based weather-normalization techniques. Following these applications, energy use from one year of simulated data is taken to be the base year

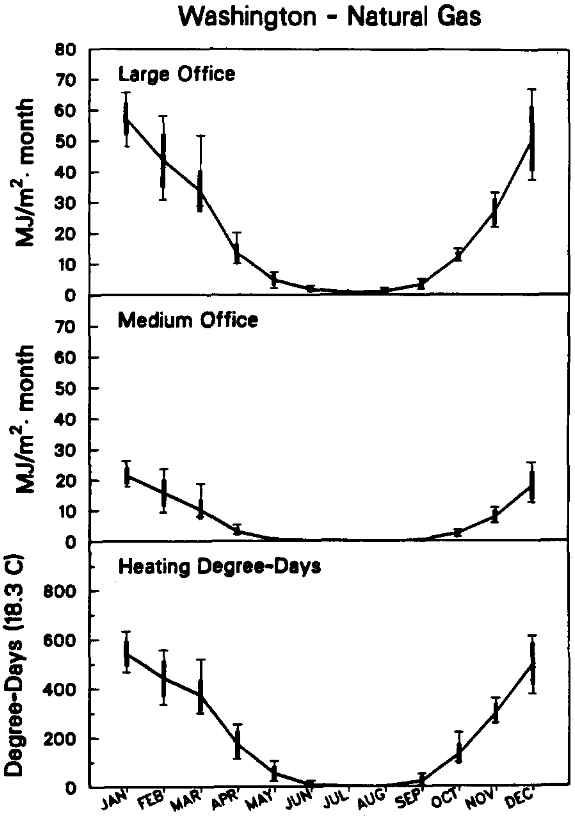

Fig. 1. Comparison of monthly natural gas energy use intensity and heating degree-days (base 65 °F) for Washington, DC. Monthly data from 12 years of simulated energy performance suggest a recurring annual pattern of energy use intensities that is correlated with degree-days. Mean monthly values are connected. Mean monthly values ±1.0 std. dev. are indicated by a darker vertical line about the connected monthly mean values. Upper and lower horizontal bars indicate minimum and maximum values for each month.

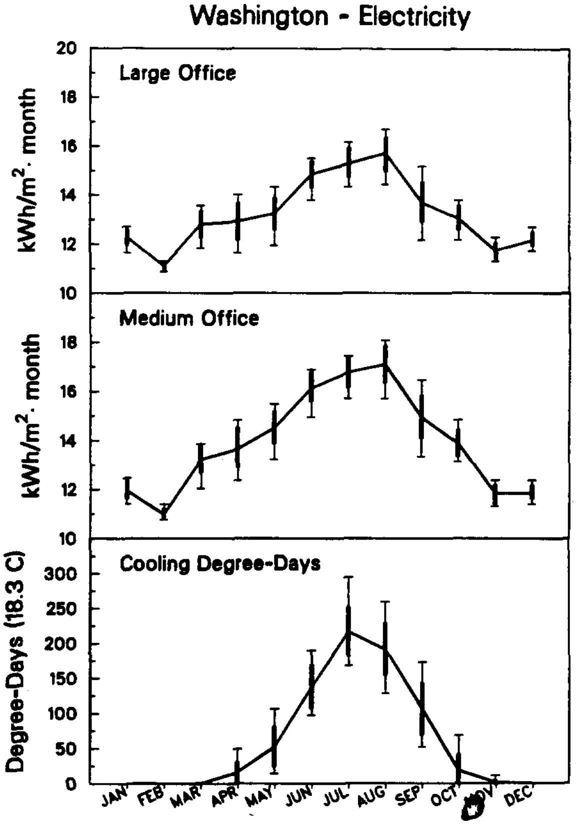

Fig. 2. Comparison of monthly electricity energy use intensity and cooling degree-days (base 65 °F) for Washington, DC. Monthly data from 12 years of simulated energy performance suggest a recurring annual pattern of energy use intensities that is correlated with degree-days. Mean monthly values are connected. Mean monthly values ±1.0 std. dev. are indicated by a darker vertical line about the connected monthly mean values. Upper and lower horizontal bars indicate minimum and maximum values for each month.

of consumption. For each choice of base year, we calculated a unique set of parameters (α, β, and τ) for each technique. Throughout the discussion, we will refer to each set of parameters as the parameter estimates or estimators.

The primary analysis of accuracy uses the parameter estimates along with degree-days from other years to calculate a second estimate of total energy use in each of these other years (the first estimate is generated by DOE-2). For clarity, we will refer to this second set of energy use estimates as the predicted values, since, in one sense, they are predictions generated from the parameter estimates. Our basic test is to compare these predictions to the DOE-2 estimates of energy use using the same year of weather data.

This test is motivated by the basic assumption underlying all normalization techniques, which is that the parameter estimates are a complete characterization of the energy-using behavior of a building. This characterization, furthermore, is independent of the specific year of data (weather and energy) from which it was developed. If it were not independent, it would not be useful in normalizing energy use from other years. Therefore, if the characterization is perfect, the new estimate will be identical to the original computer-simulated results.

We use this test to develop two evaluation procedures. The first compares predictions for a normalized year of energy use by following the approach for estimating conservation savings outlined in the Introduction. Parameter estimates extracted from a base year of energy use are combined with degree-days from a typical year to produce a normalized estimate of energy use in this typical year. In this case, the typical year is defined by the degree-days from the WYEC weather tape.

A second procedure compares annual predictions of energy use for every year of historic data to the original DOE-2 estimates for these years. In this procedure, degree-days from each historic year are combined with the parameter estimates (generated from an individual base year) to produce a second estimate of consumption in the historic year.

Parameter estimates

We selected four different base years for each combination of office building and fuel type. Three base years were drawn from the years exhibiting the lowest (*low*), highest (*high*), and closest to mean level of annual energy use (*mid*), for each fuel (electricity or natural gas). The *high*, *low*, and *mid* base years were allowed to be different for each fuel for a given building. The fourth year used the data simulated with WYEC weather tape.

For the no correction and the zero intercept techniques, the parameter estimates were generated directly from the data set. For the fixed- and variable-base temperature techniques, regressions were performed on the data using a statistical software package [19]. Prior to estimation, all consumption data were normalized by area. In all, sixteen different sets of parameters (four techniques applied to each of four base years) were developed for each of the four office building and fuel combinations.

The R^2 values for the regressions of natural gas on heating degree-days were quite high, generally in excess of 0.95 for either the fixed- or variable-base temperature techniques. The best base temperature for the variable-base temperature technique was usually lower than the traditional 18.3 °C (65 °F) used by the fixed-base temperature technique.

As expected, the intercepts, α, from the regressions of electricity on cooling degree-days were large relative to the slope, β, since electricity has many end uses in addition to cooling. The R^2 values for these regressions were lower than those for natural gas on heating degree-days, typically in excess of 0.70 for either the fixed- or variable-base temperature technique. Once again, the best base temperature for the variable-base temperature technique was generally lower than the traditional 18.3 °C (65 °F) used by the fixed-base temperature technique.

For some regressions of electricity on cooling degree-days, the lowest base temperature evaluated (5 °C or 41 °F), had the highest R^2. This indicates we did not find the best base temperature; i.e., a lower base temperature might yield a higher R^2. If this is the case, the estimated parameters have been underdetermined and will affect the accuracy of the subsequent predictions.

RESULTS

Comparison of estimates of normalized consumption

Tables 4 and 5 summarize the results from using the techniques to generate a second estimate of energy use in a typical year for the larger office building prototype. (The results for the smaller office building prototype are qualitatively similar.) Our presentation takes the form of percent differences between predicted annual energy use and the original DOE-2 estimate for the WYEC year of weather data. The Tables also include the degree-days, to base 18.3 °C (65 °F), for each of the four base years.

As might be expected, the lowest percentage differences result when the base year for a given technique is the year in which the prediction is made (base year = WYEC). Indeed, for the zero intercept and no correction techniques, the percentage differences ought to be, and are, zero, except for small rounding errors. Also, not surprisingly, the percentage differences for the zero intercept technique applied to electricity are large for other base years, since electricity has many end uses, the majority of which are schedule-, not climate-driven. The remainder of our discussions will omit reference to this technique applied to electricity.

For the other techniques the percent differences are small, generally, less than 10% for natural gas and less than 3% for electricity. No technique appears significantly better (or worse) than the others. For natural gas, the no correction technique appears to produce

TABLE 4

Normalized annual energy use: large office — natural gas

Location	Base year degree-days*	Percentage differences from DOE-2			
		Variable base	Fixed base	Zero intercept	No correction
El Paso					
High	1497	14.1	14.9	15.3	15.4
Low	1196	4.6	4.6	6.9	−14.5
Mid	1357	8.1	8.1	9.0	−1.1
WYEC	1494	−0.3	−0.3	0.1	0.0
Lake Charles					
High	1072	1.4	4.0	2.4	28.6
Low	671	−3.8	−7.6	−6.3	−26.4
Mid	889	−5.3	−5.3	−5.1	−1.2
WYEC	853	−0.1	−0.1	0.1	0.0
Madison					
High	4384	0.3	4.3	4.8	7.2
Low	3736	7.3	6.3	4.9	−8.5
Mid	4102	2.6	3.5	2.8	−1.6
WYEC	4283	−0.1	−0.1	0.1	0.0
Seattle					
High	3493	−7.3	−2.6	3.7	24.7
Low	2428	7.5	7.6	7.4	−10.2
Mid	2994	3.1	1.8	2.5	5.8
WYEC	2902	0.0	0.0	0.0	0.0
Washington					
High	2864	−1.0	−1.9	−0.8	20.7
Low	2304	1.4	−0.4	−0.3	−2.5
Mid	2377	5.9	5.2	5.3	6.3
WYEC	2353	−0.1	−0.1	0.1	0.0

*Calculated to a base temperature of 18.3 °C (65 °F).

the largest percentage differences, although not consistently for each choice of base year. For electricity, it is very difficult to select a most or least accurate technique among the remaining three. In general, the *low* base years tend to underpredict, while the *high* base years tend to overpredict. Nevertheless, the trend is not well-defined; exceptions to both trends can be identified.

Comparison of estimates for historical consumption

We develop two statistics to evaluate the ability of the techniques to estimate historical energy use. The first is the mean of the differences between the original DOE-2-generated energy use estimates and those predicted by the techniques for all twelve years of data expressed as a percentage of mean energy use. As so formulated, the metric allows discrepancies between predictions and DOE-2 estimates to offset each other over the years. The metric, then, is a measure of the bias of the estimators, not their efficiency. To measure the efficiency of the techniques, we also present the associated standard deviations of the individual differences about this mean value. To facilitate comparison, the standard deviation is also normalized by the mean consumption and hence is dimensionless. The standard deviation is a measure of the reliability of the techniques. Tables 6 and 7 summarize these results for natural gas and electricity consumption in the larger office building prototype, respectively.

In general, we continue to observe that no one technique performs significantly better than the others. Most of the techniques yield differences of less than 10%. The notable exception is again the zero intercept technique applied to electricity consumption, which is inferior. Still, there are some choices of base year in which the zero intercept technique produces results that are comparable to the others.

TABLE 5

Normalized annual energy use: large office — electricity

Location	Base year degree-days*	Percentage differences from DOE-2			
		Variable base	Fixed base	Zero intercept	No correction
El Paso					
High	1299	0.8	1.0	−7.5	1.6
Low	1207	−0.7	−0.1	−2.0	0.0
Mid	1353	0.3	0.0	−11.7	0.9
WYEC	1183	0.0	0.0	0.0	0.0
Lake Charles					
High	1589	1.5	1.5	−3.7	2.1
Low	1366	−0.2	−0.2	8.7	−1.0
Mid	1645	−0.3	−0.8	−8.7	0.1
WYEC	1498	0.0	0.0	0.1	0.0
Madison					
High	516	0.5	−0.1	−50.5	2.9
Low	383	−2.2	−2.7	−35.3	−0.3
Mid	271	0.3	0.3	−7.3	1.0
WYEC	248	0.0	0.0	0.0	0.0
Seattle					
High	165	−0.1	−0.1	−66.2	2.5
Low	3	3.9	10.3	1513.6	−1.2
Mid	44	0.7	0.4	24.3	0.2
WYEC	54	0.0	0.0	1.0	0.0
Washington					
High	1009	0.7	−0.2	−20.0	1.8
Low	633	−0.3	−0.2	22.9	−1.8
Mid	743	−0.1	0.0	6.2	−0.5
WYEC	792	0.0	0.0	0.1	0.0

*Calculated to a base temperature of 18.3 °C (65 °F).

Our major finding is that the differences between the techniques are overwhelmed by the choice of base year for a given technique. It appears that this choice is the dominant factor in determining the accuracy of each technique. For natural gas consumption, in particular, the percent differences are relatively uniform for each technique for a given base year, but very different for other choices of base year. This observation is reinforced by the standard deviations for each technique and either fuel. Standard deviations are small compared to the average percent differences. In other words, the predictions are very tightly grouped around the mean level of the differences. Once the choice for the base year has been made, the error introduced will influence all subsequent predictions in a consistent fashion.

Assuming some correlation with degree-days appears to be somewhat more resilient to the choice of base year than assuming no correlation (no correction). For all techniques, the largest errors result from base years whose consumption is farthest from the mean (the *high* and *low* base years). For such choices, the techniques that assume some correlation produce lower percent differences. Nevertheless, the percent differences for these choices remain large relative to those for choices of a base year with consumption close to the mean (the *mid* and WYEC base years).

Among the techniques that assume some correlation between degree-days and consumption, no one technique is clearly superior. Again, the exception is assuming all electricity use is correlated with cooling degree-days (zero intercept), which is clearly inferior to the others. In particular, the oft-touted variable-base temperature technique does not appear to be demonstrably superior to the fixed-base temperature or even the zero intercept technique (when the latter is applied to natural gas).

Between the two fuel types, the results suggest that every technique is more accurate

TABLE 6

Historical results for large office: natural gas

Location	Base year degree-days*	Accuracy of techniques over 12 years							
		Variable temp.		Fixed temp.		Zero intercept		No correction	
		(%)	Std. dev.	(%)	Std. dev.	(%)	Std. dev.	(%)	Std. dev.
El Paso									
High	1497	7.8	(19.0)	8.6	(19.2)	8.7	(24.6)	14.8	(51.4)
Low	1196	−1.0	(14.9)	−1.0	(14.9)	0.8	(18.1)	−14.9	(36.2)
Mid	1357	2.2	(15.6)	2.2	(15.6)	2.7	(19.4)	−1.6	(49.8)
WYEC	1494	−5.7	(15.6)	−5.7	(15.6)	−5.7	(15.1)	−0.5	(33.7)
Lake Charles									
High	1072	4.7	(19.2)	7.8	(19.4)	6.5	(25.9)	29.6	(84.2)
Low	671	−0.4	(20.1)	−4.1	(17.2)	−2.6	(18.8)	−25.9	(62.8)
Mid	889	−1.7	(17.2)	−1.7	(17.2)	−1.3	(19.5)	−0.5	(55.6)
WYEC	853	3.5	(18.4)	3.6	(17.7)	4.1	(23.7)	0.7	(45.4)
Madison									
High	4384	−1.9	(14.6)	0.4	(18.8)	1.5	(20.9)	7.7	(24.9)
Low	3736	4.7	(15.5)	2.5	(18.5)	1.6	(20.8)	−8.1	(23.0)
Mid	4102	−0.1	(13.6)	−0.3	(18.5)	−0.4	(21.7)	−1.1	(27.7)
WYEC	4283	−2.5	(13.8)	−3.8	(18.5)	−3.1	(23.0)	0.5	(20.1)
Seattle									
High	3493	−9.3	(32.2)	−4.8	(24.4)	0.5	(25.8)	18.2	(29.0)
Low	2428	4.6	(19.0)	4.4	(24.5)	4.1	(24.9)	−14.9	(22.5)
Mid	2994	0.4	(17.9)	−0.9	(23.5)	−0.6	(26.0)	0.2	(19.0)
WYEC	2902	−2.6	(18.0)	−2.7	(23.6)	−3.0	(26.7)	−5.2	(18.8)
Washington									
High	2864	−1.0	(10.8)	−1.2	(13.7)	−0.5	(13.5)	12.8	(34.9)
Low	2304	1.4	(10.9)	0.0	(13.4)	0.0	(13.5)	−8.8	(26.5)
Mid	2377	5.7	(11.7)	5.3	(13.4)	5.6	(14.0)	−0.7	(27.6)
WYEC	2353	0.0	(10.6)	0.1	(13.7)	0.4	(13.4)	−6.5	(23.5)

*Calculated to a base temperature of 18.3 °C (65 °F).

for electricity consumption than gas. This result can be easily misinterpreted. A substantial portion of electricity consumption results from fixed, schedule-driven, non-weather-sensitive end uses (This is not true of natural gas.) Thus, the portion of energy use that can be affected by cooling degree-days is small.

DISCUSSION

We have analyzed the accuracy of several degree-day-based weather-normalization techniques. The results indicate that no technique is perfect and that some amount of error must be tolerated. The question is how much and at what cost. In this Section, we re-cast some of our results in the form of considerations that must be evaluated by users of these techniques.

Let us begin by emphasizing that the real value of normalization, and, hence the accuracy required of a technique, must be determined exogenously. For example, when measuring conservation savings, we would consider unacceptable an error of ten percent for a measure designed to save only five percent. For a measure designed to cut energy use in half, an error of ten percent may be acceptable. Thus, the first question the practitioner must answer is whether the application warrants the use of a weather-normalization technique, and, if so, whether the inherent imprecision of the techniques is tolerable.

We found that no technique was clearly superior to the rest. This results suggests that field applications of these techniques need not be bound to a single method. Considerations of data availability and the constituents of energy use for a given fuel, consequently, should be considered explicitly prior to blind application of any given technique. For example, we found that the variable-base tem-

TABLE 7

Historical results for large office: electricity

Location	Base year degree-days*	Accuracy of techniques over 12 years							
		Variable temp.		Fixed temp.		Zero intercept		No correction	
		(%)	Std. dev.	(%)	Std. dev.	(%)	Std. dev.	(%)	Std. dev.
El Paso									
High	1299	0.5	(4.4)	0.7	(4.9)	1.0	(105.8)	0.7	(5.7)
Low	1207	−1.0	(4.5)	−0.4	(5.1)	7.0	(112.6)	−0.9	(5.4)
Mid	1353	0.0	(4.4)	−0.2	(4.9)	−3.6	(100.6)	0.1	(5.5)
WYEC	1183	−0.2	(4.5)	−0.1	(5.0)	9.2	(115.1)	−0.9	(4.7)
Lake Charles									
High	1589	1.4	(4.4)	1.4	(4.6)	−2.1	(81.0)	1.8	(5.7)
Low	1366	−0.4	(4.5)	−0.3	(4.6)	10.5	(92.6)	−1.2	(5.1)
Mid	1645	−0.5	(4.4)	−0.8	(4.6)	−7.2	(76.3)	−0.1	(5.2)
WYEC	1498	−0.1	(4.4)	0.0	(4.6)	1.8	(84.6)	−0.2	(4.7)
Madison									
High	516	0.5	(4.5)	0.0	(5.8)	−29.7	(101.8)	1.8	(5.3)
Low	383	−1.6	(4.5)	−1.8	(5.1)	−8.1	(136.0)	−1.3	(6.2)
Mid	271	2.3	(8.0)	2.3	(8.0)	31.7	(199.0)	−0.1	(6.8)
WYEC	248	0.7	(5.1)	1.8	(7.3)	42.1	(215.5)	−1.0	(5.1)
Seattle									
High	165	−0.2	(4.6)	−0.2	(4.6)	−63.0	(86.0)	2.3	(5.6)
Low	3	3.6	(9.1)	11.2	(29.2)	1665.6	(4295.2)	−1.5	(5.4)
Mid	44	0.3	(4.1)	0.3	(4.6)	36.0	(326.8)	−0.1	(4.9)
WYEC	54	−0.3	(4.3)	0.1	(6.6)	10.6	(264.9)	−0.2	(4.9)
Washington									
High	1009	0.6	(4.2)	−0.3	(4.5)	−25.0	(88.3)	2.2	(5.2)
Low	633	−0.5	(4.1)	−0.4	(4.6)	15.2	(140.7)	−1.5	(5.8)
Mid	743	−0.3	(4.5)	−0.2	(4.7)	−0.5	(120.3)	−0.2	(6.5)
WYEC	792	−0.2	(4.4)	−0.2	(4.6)	−6.1	(112.9)	0.4	(4.9)

*Calculated to a base temperature of 18.3 °C (65 °F).

perature technique did not perform significantly better than the fixed-base temperature technique, or the zero intercept technique for natural gas, or the no correction technique for electricity. In the U.S., data are published regularly for degree-days to base 18.3 °C (65 °F) and, for an acknowledged level of inaccuracy, may be wholly sufficient for weather normalization.

The generally small net errors associated with the no correction technique (see Tables 4 and 5 and the annual results presented in Tables 2 and 3) highlight the fact that, for the climates examined, the buildings do not, on an annual basis, exhibit tremendous variation in energy use. They are relatively weather insensitive on an annual basis. What sensitivity there is, furthermore, tends to even-out in the long run. On the other hand, for a conservation measure designed to pay back in a short time, the long-run accuracy of a technique may prove to be of little comfort. Our findings further indicate that such recourse may be futile due to the influence of the base year.

In general, the constituents of demand for a fuel will help determine the need for weather normalization. We found that the techniques were more accurate (with one exception) when applied to electricity consumption. The irony in this result is that the R^2 values from the regression-based techniques were significantly lower than those found in applying the techniques to natural gas consumption. Thus, simply acknowledging a non-weather-sensitive or baseload component for electricity (i.e., fixed base temperature, variable base temperature, or no correction) appears to be the source of this accuracy. Relative to this large baseload the impact of degree-days on total consumption, and hence on possible errors, is small. In this case, incorporating a relationship with weather may introduce additional error (the extreme example being the zero intercept technique). Indeed, the no correction technique was not a particularly bad choice for normalization. This last result, that the no correction techniques perform reasonably well relative to the other techniques, also reinforces the notion that the normalization techniques, themselves, introduce error, rather than reduce it.

Perhaps the most disturbing finding for field applications of the techniques was the influence of the choice of base year. If this influence is, as our findings suggest, the most important determinant of accuracy, field applications are for the most part hostage to some level of inaccuracy. If weather in the pre- or post-retrofit year deviates greatly from long-term averages, the influence on accuracy may be unavoidable. Once again, the practitioner must determine whether this level of error is tolerable relative to what is being measured.

An encouraging finding was that the direction of bias may be predictable on the basis of degree-days. Referring to Tables 6 and 7, the *low* and *high* base years tend to correlate with low and high numbers of degree-days. The correlations appear weakest when there are few degree-days, such as in Seattle for cooling degree-days and in El Paso for heating degree-days. Thus, when faced with a base year with degree-days far from the average for a location, the practitioner may introduce less error by choosing another base year, using several years of data for estimating parameters, or not using a weather-normalization technique at all.

Finally, in reviewing the estimated parameters from the regression-based techniques, it is extremely important to distinguish physical significance from statistical significance. For example, the parameter estimates for the best base temperature in the variable-base temperature technique were in general lower that 18.3 ℃ (65 ℉). A naive interpretation would view such results as confirmation that the appropriate balance point for office buildings is less than conventional 18.3 ℃ (65 ℉). Similarly, the best base temperatures for the variable-base temperature technique are lower for the regressions of cooling degree-days on electricity than those for heating degree-days on natural gas. A literal interpretation of this result might be that simultaneous heating and cooling is taking place.

We must strongly emphasize that such conclusions are not supportable with our data. Specifically, the statistical package we used did not estimate standard errors for the individual parameters. (Indeed, a primary contribution of the work at Princeton, described above, has been the development of techniques for direct evaluation of the statistical properties of estimated parameters [5]. Without such analysis, one can not conclude that, statistically speaking, our findings for the base temperature are significant. Without statistical evidence on our side, physical interpretation is, at best, tenuous. For example, we also found that R^2 values for fits at lower base temperatures were not noticeably higher than those found using the 18.3 ℃ (65 ℉) base temperature. For the regressions of natural gas consumption on heating degree-days, in particular, the R^2 values for either technique were typically greater than 0.95.

SUMMARY

Comparisons of predicted energy consumption with DOE-2 estimates are one means of evaluating weather normalization techniques. By holding most features of the simulations fixed except weather, we assume that variations in estimated energy use are caused by variations in the weather. To represent field operating conditions, we violated this assumption by introducing weekly and diurnal cycles of operation.

The evaluation was carried out for four normalization techniques with the aid of computer simulations of office building energy use. We used many years of real weather data for five U.S. sites. The evaluation consisted of applying the normalization techniques to individual years of simulated data and using the parameters estimated from this year to predict consumption in other years, given the degree-days from those other years. The accuracy of the techniques was measured by comparing the predictions with the original DOE-2 estimates. Several different base years were evaluated for each technique.

The results indicate that all of the techniques performed reasonably well for the building types and climatis examined, with the exception of the zero intercept technique when applied to electricity consumption. That is, with this exception, the accuracy of the techniques was generally better than 10% over the twelve years; most were within a few percent. The techniques also do not seem to have inherent biases.

All of the techniques exhibited substantial sensitivity to the choice of base year. This sensitivity overwhelmed differences among the techniques and is a very tempering influence, because, in the field, one has little control over the selection of the base year. We noted that assuming some correlation with the weather led to better accuracy.

An important result was that the sophisticated techniques (statistical correlations with degree days to a fixed or variable base temperature) did not perform noticeably better than the simpler techniques. We also noted the dangers associated with naive physical interpretations of the underlying parameters from the regressions, notably the physical significance of the balance point temperature.

A final Section summarized considerations for practitioners. At the heart of these considerations is the need to consider the required accuracy of the results.

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