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SYNTHESIZING HOURLY METEOROLOGICAL DATA TO IMPROVE THE ACCURACY OF CALIBRATED SIMULATION MODELS

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ABSTRACT

Dynamic building energy simulation models typically require a year of hourly meteorological data as input. For design purposes, the most common source of these data are the typical meteorological year TMY2 data sets. When calibrating simulation models to measured building energy consumption, the use of typical meteorological data introduces a source of error because the weather during the calibration period is different than the "typical" weather. Unfortunately, this is still common practice because of the difficulty of obtaining recent hourly meteorological data.

In this paper, the error from using typical meteorological data to calibrate simulation models is estimated by simulating annual energy consumption of a residence and large commercial building for 20 years in four U.S. cities. To reduce this error, we propose a method to synthesize hourly dry-bulb temperature, global solar radiation on a horizontal surface and specific humidity from readily available average daily temperatures. The method is based on regression results from TMY2 data sets. The synthetic data are shown to have very little bias and, in weather sensitive buildings, significantly reduce the error associated with calibrating models using typical meteorological data.

NOMENCLATURE

a	=	regression coefficient
amp	=	amplitude
b	=	regression coefficient
c	=	regression coefficient
dec	=	solar declination (degrees)
E	=	electricity consumption (kWh)
hl	=	hours of sunlight in a day (hours)
hr	=	hour of day (1-24)
I	=	solar radiation (W/m^2)
lat	=	latitude (degrees)
n	=	day of year (1-365)
NG	=	natural gas consumption (GJ)
R	=	correlation coefficient
T	=	temperature (C)
W	=	Specific humidity (kg water / kg air)

<u>Subscripts</u>

ac	=	refers to air conditioning
dp	=	refers to dew point
dy	=	refers to daily
fur	=	refers to furnace
hr	=	refers to hourly
i	=	refers to solar radiation
maxhr	=	refers to hour of day when max occurs
measured	=	refers to measured
mo	=	refers to monthly
range	=	refers to range of variation
sum	=	refers to summer
syn	=	refers to synthetic
tot	=	refers to total building
w	=	refers to specific humidity
win	=	refers to winter
yr	=	refers to yearly

INTRODUCTION

Dynamic building energy simulation models typically require a year of hourly temperature, solar and humidity data as input. A common source of these data are the revised typical meteorological year TMY2 (NREL, 1997) and the revised Weather Year for Energy Calculations WYEC2 (ASHRAE, 1998) data sets. Both data sets are based on long-term measurements from the SOLMET/ERSATZ data base and attempt to capture *typical* weather patterns (Hall et al., 1979). In building design, the use of typical-year data sets in hourly simulation models allows designers to predict and optimize the thermal performance of buildings.

Simulation models are also commonly employed for improving the performance of existing buildings. In these cases, a simulation model is typically calibrated, or adjusted, to match the measured energy consumption of the building. When calibrating simulation models to measured building energy consumption, the use of *typical* (i.e. TMY2 or WYEC2) weather data introduces a source of error because the weather during the calibration period is different from the typical weather. This error may lead to improperly calibrated models in which building characteristics are mistakenly adjusted to account for the deviation between the actual and typical weather. Using hourly meteorological data from the same period as the energy consumption data can eliminate this error. Unfortunately, recent hourly temperature, humidity and solar radiation data are often difficult to obtain; thus, the use of typical weather data sets is still common for calibration purposes.

In this paper, we seek to quantify the error caused by using *typical* (i.e. TMY2) weather data sets to simulate *actual* building energy consumption. To reduce this error, we propose a method to synthesize hourly dry-bulb temperature, specific humidity and global solar radiation on a horizontal surface from the calendar date and the average daily temperature. The method is based on relationships between hourly and daily data in the TMY2 data sets. Average daily temperature data were selected as the source for the synthetic hourly data since average daily temperature data are readily available in newspapers and over the internet. For example, the EPA/UD Average Daily Temperature Archive posts average daily temperatures extending back to 1985 and updated on a daily basis for 159 U.S. cities (Kissock, 1996). Hourly dry-bulb temperature, specific humidity and global solar radiation on a horizontal surface were selected as the synthetic variables since the weather input deck for most hourly simulation programs can be derived from these primary meteorological inputs.

To test the usefulness of the synthetic data, model calibration errors from using TMY2 and synthetic weather data sets are compared. To estimate these errors, the annual energy consumption of a typical residence and large commercial building is simulated using 20 years of measured hourly weather data from the SAMSON data sets (NOAA, 1993). These simulations are used to represent actual energy consumption in the buildings and provide a baseline against which the simulations using TMY2 and synthetic weather data can be compared.

TYPICAL VARIATIONS IN ANNUAL METEORLOGICAL DATA

The magnitude of the calibration error caused by using typical rather than actual weather data depends on how much annual weather conditions vary. The variations in annual, summer and winter dry-bulb temperature, dew-point temperature and global solar radiation on a horizontal surface for the years 1971 to 1990 for four U.S. cities are shown in Table 1. In every case, the variations of dry-bulb and dew-point temperatures are greater in winter than in summer. The standard deviation of solar radiation declines in the winter; however, this decline is attributable to the overall reduction in solar radiation during winter. The coefficient of variation of the standard deviation is an indication of the variation relative to the mean:

$$\text{StdDev} = \sqrt{\frac{n\sum x^2 - (\sum x)^2}{n(n-1)}} \qquad (1)$$

$$\text{CV-StdDev} = \text{StdDev} / \text{Mean} \qquad (2)$$

The larger CV-StdDev of solar radiation in winter indicates that the relative variation of solar radiation is greater in winter than summer. Thus, the larger variations of winter temperature, humidity and solar radiation suggest that heating energy use is more prone to calibration error than air conditioning energy use.

SYNTHESIZING HOURLY WEATHER DATA FROM AVERAGE DAILY TEMPERATURE

Synthesizing hourly weather data from readily available average daily temperature data has the potential to reduce the error associated with calibrating building energy simulation models using typical weather data. The method of synthesizing hourly meteorological data from average daily temperatures proposed here is to 1) identify the relationships between hourly and daily data in TMY2 data sets, 2) derive the values of the coefficients that describe these correlations, and 3) substitute the values into the proposed correlations to generate hourly data.

Synthesizing Hourly Dry-Bulb Temperature

If the mean daily temperature T_{dy} is known, then the hourly temperature T_{hr} can be approximated as a sinusoidal function that varies about the mean:

$$T_{hr} = T_{dy} + (T_{range} / 2)\ \text{Sin}\,[2\pi\ (hr - (T_{maxhr} - 6)) / 24] \qquad (3)$$

where T_{range} is the difference between the daily maximum and minimum temperatures and T_{maxhr} is the hour of day (1-24) when the maximum temperature occurs. TMY2 data sets for several U.S. locations were examined to determine whether T_{range} and T_{maxhr} remain constant throughout the year. For most locations, both T_{range} and T_{maxhr} increase in summer and decrease in the winter. However, as a first approximation, we simply used average annual values for T_{range} and T_{maxhr}. Once the values of T_{range} and T_{maxhr} are identified from the TMY2 data set, they can be used in Equation 3 to synthesize hourly temperature from the average daily temperature.

Synthesizing Hourly Humidity

Unlike dry-bulb temperature, hourly specific humidity does not demonstrate a strongly independent diurnal cycle. Instead, it is adequately correlated with ambient temperature (Figure 1).

Hence we estimate the hourly specific humidity W_{hr} as a function of hourly temperature from Equation 3:

$$W_{hr} = a_w + b_w\ T_{hr} + c_w\ T_{hr}^2 \qquad (4)$$

where a_w, b_w and c_w are regression coefficients derived from regressing hourly specific humidity against hourly temperature in the TMY2 data sets.

Table 1. The variation of annual, summer and winter dry-bulb temperature (T), dew-point temperature (Tdp) and global solar radiation on a horizontal surface (I) for the years 1971 to 1990 in four U.S. cities. Data are derived from the SAMSON data set (NOAA, 1993). Summer is June through September and winter is November through February.

Year	Tyr (C)	Tsum (C)	Twin (C)	Tdp,yr (C)	Tdp,sum (C)	Tdp,win (C)	Iyr (W/m2)	Isum (W/m2)	Iwin (W/m2)
Dayton, OH									
Mean	10.99	21.52	0.32	5.55	15.30	-3.21	162.8	228.0	82.0
StdDev	0.63	0.81	1.57	1.10	1.14	2.51	5.0	8.6	4.3
CV-StdDev	-	-	-	-	-	-	0.031	0.037	0.052
Max Abs Dev	1.08	1.45	3.65	2.26	2.19	6.36	11.2	17.0	10.2
Miami, FL									
Mean	24.48	27.71	21.29	19.15	22.86	16.28	200.6	226.6	152.0
Std Dev	0.59	0.46	1.47	0.77	0.50	2.04	8.5	11.6	6.2
CV-StdDev	-	-	-	-	-	-	0.042	0.051	0.041
Max Abs Dev	0.72	0.81	1.81	1.23	1.33	3.58	23.8	34.0	12.3
Los Angles, CA									
Mean	16.90	19.97	14.42	11.14	15.32	7.39	206.5	268.4	127.4
StdDev	0.54	0.75	1.09	0.80	0.69	1.54	5.2	9.5	5.9
CV-StdDev	-	-	-	-	-	-	0.025	0.035	0.046
Max Abs Dev	1.01	1.60	1.51	1.92	1.83	3.47	9.4	19.1	11.2
Boston, MA									
Mean	10.83	20.79	1.78	5.11	15.48	-3.69	161.5	226.9	81.6
StdDev	0.70	0.75	1.78	1.61	2.67	2.81	3.9	7.8	3.6
CV-StdDev	-	-	-	-	-	-	0.024	0.034	0.044
Max Abs Dev	0.80	1.92	2.08	3.44	8.16	7.01	8.3	16.2	7.5

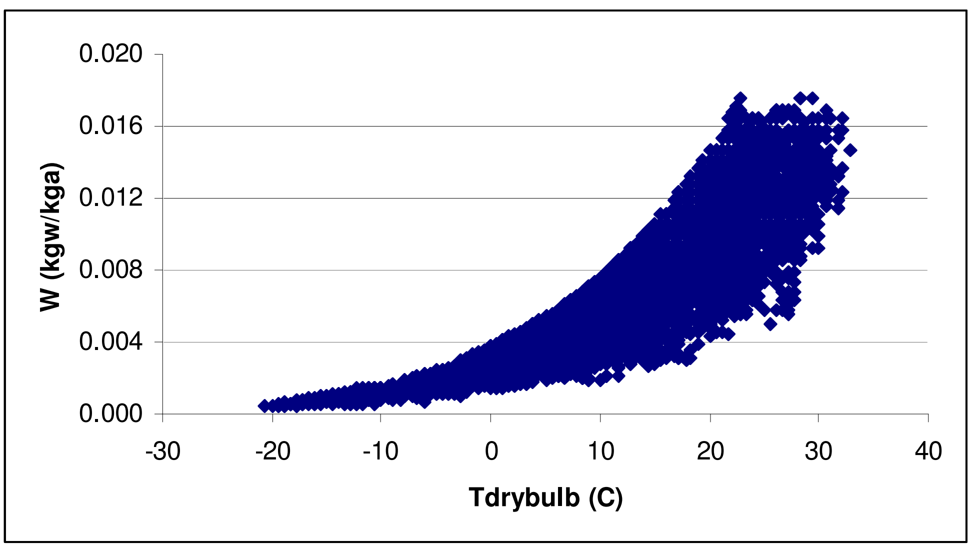

Figure 1. Hourly specific humidity versus dry-bulb temperature for Dayton, Ohio from TMY2 data set (NREL, 1995).

Synthesizing Hourly Solar Radiation

In the original ASHRAE modified bin method, solar radiation was estimated as a linear function of ambient temperature. Vadon et al. (1991) proposed an improvement on this method based on a correlation between the solar radiation and the standard deviation of ambient temperature. However, this approach was for bin data and is not directly applicable for our purposes. Knight (1998) developed a method for synthesizing hourly meteorological data based on average monthly temperature and solar radiation values.

We investigated several relationships between temperature and global solar radiation on a horizontal surface. As the time scale of the data increases (for example from daily to monthly data), the statistical correlation between temperature and solar radiation grows stronger. For example, the correlation between monthly solar radiation and average dry-bulb temperature for Dayton, OH is shown in Figure 2. The elliptical shape indicates a time lag; and indeed the correlation between monthly solar radiation I_{mo} and temperature T_{mo} improves from $R^2 = 0.84$ for:

$$I_{mo} = a_i + b_i \; T_{mo} \qquad (5)$$

to $R^2 = 0.98$ when the time lag is included as:

$$I_{mo} = a_i + b_i \, Tmo + c_i \sin [2\pi \; (mo-1) / 12] \qquad (6)$$

where a_i, b_i and c_i are regression coefficients and mo is the month number (1-12).

Unfortunately, the correlation between solar radiation and temperature deteriorates at the daily time scale of interest here. Therefore, we propose that daily global solar radiation on a horizontal surface I_{dy} be estimated simply as a function of the day number during the year n (1 to 365):

$$I_{dy} = a_i + b_i \, \text{Sin} [2\pi \; (n - 80.75) / 365] \qquad (7)$$

where a_i and b_i are regression coefficients determined from regressing daily solar radiation against day number in the TMY2 data set. This relation is analogous to, but simpler than, estimating daily solar radiation as a function of hours of sunlight per day. Adding average daily temperature as an additional independent variable does not substantially improve the correlation.

After the daily solar radiation has been estimated using Equation 7, the hourly radiation can be estimated by assuming that 1) the solar radiation varies sinusoidally around a peak at noon and is bounded by the hour of sunrise and sunset , 2) the area under the sinusoid is equal to the daily solar radiation estimated by Equation 7. The solar declination dec and number of hours of sunlight hl can be calculated as (Duffie and Beckman, 1991):

$$dec = 23.45 \, \text{Sin} [2\pi \; (284 + n) / 365] \qquad (8)$$

$$hl = (2/15) \, \text{Cos}^{-1} [(-\text{Tan (lat)}) \, \text{Tan (dec)}] \qquad (9)$$

where lat is the site latitude. The amplitude of the sinusoid amp and estimated hourly radiation I_{hr} can then be computed as:

$$amp = \frac{-I_{dy}}{2\left[(hl/2)\,\text{Cos}\,(hl\,\pi/24) + (12/\pi \;\; \text{Sin}\,(hl\,2\pi)\right]} \qquad (10)$$

$$I_{hr} = -amp \, \text{Cos} \, (hl \, \pi/24) + amp \, \text{Cos} \, [(hr-12) \, \pi/24] \qquad (11)$$

where hr is the hour of day (1-24) and I_{dy} is daily solar radiation.

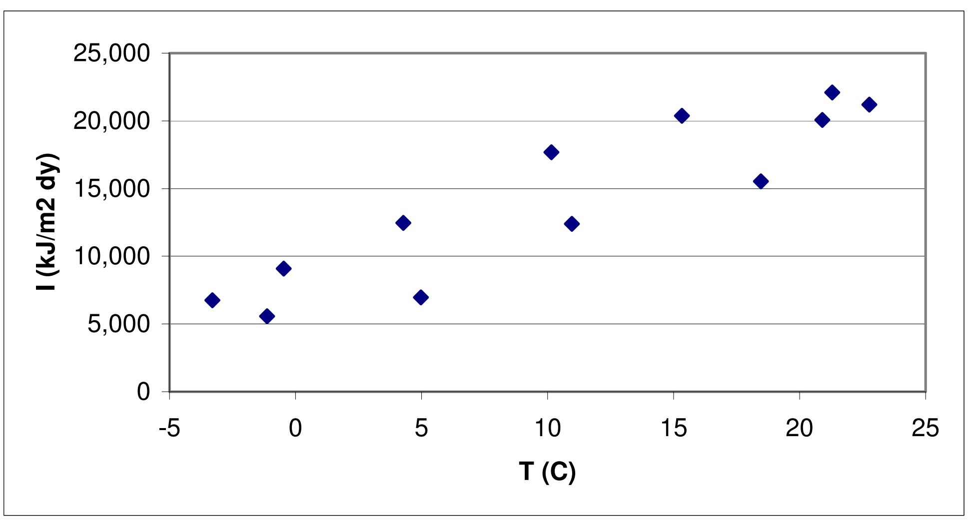

Figure 2. Average solar radiation on a horizontal surface integrated over a month plotted against the average monthly temperature for Dayton, OH from TMY2 data (NREL, 1993).

Accuracy of Method for Synthesizing Hourly Data

The proposed method for synthesizing hourly weather data requires that eight coefficients be determined from TMY2 data or a similar indicator of typical weather. The values of coefficients required to synthesize hourly temperature, specific humidity and global solar radiation on a horizontal surface are shown in Table 2. Also shown are the squared correlation coefficients of the regression fits for specific humidity R^2_w and daily solar radiation R^2_i. The correlation between specific humidity and dry-bulb temperature is much stronger in climates with large annual temperature swings, such as Dayton and Boston. The weak correlation between solar radiation and day number in Miami indicates the influence of significant seasonal cloudiness pattern

To test the prediction accuracy of the proposed method, 20 years of measured hourly data from the SAMSON data set are compared with 20 years of synthesized hourly data. The synthetic data are the generated from the average daily temperatures in the SAMSON data set and the coefficients in Table 2. Two measures of accuracy are considered: the mean deviation and the mean absolute deviation.

$$\text{Mean Deviation} = \frac{\sum_{i=1}^{n}(y_{i,syn} - y_{i,measured})}{n} \qquad (12)$$

$$\text{Mean Abs Deviation} = \frac{\sum_{i=1}^{n}\left|y_{i,syn} - y_{i,measured}\right|}{n} \qquad (13)$$

The mean deviation is measure of bias. Synthetic hourly temperatures will be unbiased because they vary symmetrically around the mean daily temperature. Synthetic specific humidity and solar radiation may be biased because the regression relation in the TMY2 data does not exactly represent the relationship in any specific year.

The mean deviation (bias error) and mean absolute deviation between hourly synthetic and measured data for the period 1971 to 1990 are shown in Table 3. The mean deviations for each variable and location are relatively small, indicating that in general the proposed method of synthesizing hourly weather data does not introduce a significant bias into the data. The relatively large bias error for solar radiation in Miami (4.21 W/m^2) was primarily caused by four exceedingly cloudy years from 1982 to 1985 when solar radiation was significantly below average. The average absolute deviations of dry-bulb temperature and specific humidity appear to be sufficiently. small so as to minimally impact building energy simulations. The relatively larger mean absolute deviations of solar radiation are caused by the use of local rather than

Table 2. Values of coefficients required to synthesize hourly temperature, specific humidity and global solar radiation on a horizontal surface as determined from TMY2 data (NREL, 1995), and correlation coefficient squared of specific humidity regressions R^2_w and daily solar radiation regressions R^2_i.

	Dayton	Miami	Los Angeles	Boston
T_{range} (C)	10.21	6.68	7.43	7.97
T_{maxhr} (1-24)	14.64	14.23	13.17	14.34
a_w (kg_w/kg_a)	0.002894	-0.00251	0.004049	0.001709
b_w (kg_w/kg_a C)	0.000241	0.001079	0.002465	0.000207
c_w (kgw/kga C^2)	0.00000508	-0.000003	-0.000017	0.00000143
a_i (W/m^2)	3,945	4,910	4,979	3,920
b_i (W/m^2)	2,329	1,397	2,174	2,250
Lat (degrees)	39.90	25.42	33.93	42.37
R^2_w	0.80	0.57	0.29	0.78
R^2_i	0.65	0.44	0.66	0.59

Table 3. Mean deviation and mean absolute deviation between hourly synthetic and measured data from 1971 to 1990 based on SAMSON data.

	Temperature (C)		Glob Solar on Horz (W/m^2)		Specific Humidity (kg_w/kg_a)	
	Mean Dev	Mean Abs Dev / Mean	Mean Dev	Mean Abs Dev / Mean	Mean Dev	Mean Abs Dev / Mean
Dayton	0.00	2.21 / 10.99	1.66	74.63 / 162.8	0.0000	0.0016 / 0.0056
Miami	0.00	1.42 / 24.48	4.21	73.92 / 200.6	-0.0003	0.0021 / 0.0138
Los Angeles	0.00	1.40 / 16.90	1.31	60.95 / 206.5	-0.0002	0.0018 / 0.0082
Boston	0.00	1.88 / 10.83	1.29	56.30 / 161.5	-0.0001	0.0016 / 0.0054

solar noon in the calculation procedure and the relatively large random and systematic variation in hourly solar radiation. Future work might be directed at improving the method of estimating hourly solar radiation

VARIATION IN ANNUAL BUILDING ENERGY CONSUMPTION DUE TO VARYING WEATHER

It is well known the heating energy use increases during cold winters and air conditioning energy use increases during hot summers. In this section, we attempt to quantify the magnitude of this annual variation by simulating building energy consumption using 20 years of measured hourly data from the SAMSON data base. This variation is the source of the error associated with attempting to calibrate simulation models using *typical* rather than actual meteorological data.

The magnitude of the annual variation in space conditioning energy use depends not only on the weather, but is also determined by the relative fraction of weather-dependent and independent heating and cooling loads. The space-conditioning loads of residences are typically dominated by heat and air exchange through the building envelope, and are therefore highly weather dependent. In contrast, the space-conditioning loads of large commercial buildings are frequently dominated by internally generated heat from people, lights and electrical equipment. Thus, the weather sensitivity of energy use in commercial buildings is generally less than for residential buildings. In an attempt to bracket this effect, the energy consumption of a typical residence and a large commercial building are simulated. The variation of the annual energy consumption of small commercial buildings or buildings with large outside air requirements will lie somewhere in between.

The residence modeled is a 163 m^2, two-story, wood-frame house with 21 m^2 of R = 0.33 m^2C/W windows, R = 1.97 m^2C/W walls and a R = 2.81 m^2C/W ceiling. The seasonal COP of the air conditioner is 2.93 and the seasonal efficiencies of the gas-fired furnace and water heater are 80%. Internal electricity consumption averages 420 kWh per month and the average hot-water usage is 9.46 liters per hour. The interior set-point temperature is 23.3 C in the summer and 22.2 C in the winter.

The commercial building modeled is an 18,400 m^2, six-story, brick-sided building with R = 0.77 m^2C/W walls, 302 m^2 of R = 0.33 m^2C/W windows and a flat R = 1.76 m^2C/W roof. The combined lighting and plug load is 28.0 W/m^2 and 400 people occupy the building during weekdays between 8 am and 10 pm. A constant-air-volume HVAC system, with a minimum of 10% outside air conditions the building. The system employs an enthalpy-based economizer cycle to use outside air for cooling whenever possible and reduces the hot-deck supply air temperature in warm weather. The nominal efficiency of the gas-fired boiler is 80% and the nominal COP of the chiller is 5.02. The interior set-point temperature is 23.3 C year-round.

Energy consumption is simulated using ESim building energy simulation software (Kissock, 1994). ESim is an hour-by-hour building energy simulation tool developed at the University of Dayton that combines powerful computational capabilities and data-graphics in an easy-to-understand user interface. Building load calculations consider heat exchange through the building envelope, solar loads, internal sources of heat, latent loads and air exchange. Transient effects are considered using transfer-function based conduction algorithms. The hourly solar radiation on each of the building's surfaces is computed from global solar radiation on a horizontal surface using the HDKR ansiotropic sky model (Duffie and Beckman, 1991). The effect of part-loading and variable outdoor air temperatures on the efficiency of primary heating and cooling equipment is considered. The performance of important HVAC control systems such as night-setback thermostats, economizer cycles, hot-deck reset schedules and VAV controls can be simulated.

Annual energy consumption of the residence is simulated for 20 years using SAMSON data in four U.S. locations. The variations of annual air-conditioning electricity usage, whole-building electricity use, furnace natural-gas use and whole-building natural-gas usage are shown in Table 4. The standard deviations of annual air-conditioning electric usage at most sites were about 9%, but occasionally varied by up to 23.4%. [The standard deviation can be interpreted to mean that, given a normal distribution, deviations from the mean will be equal to or less than the standard deviation about 68% of the time.] The variation in annual whole building electricity consumption due to weather fluctuations was somewhat less, with standard deviations in the 3% range and peak deviations in the 7% range. Annual heating energy consumption varied by about 4% to 7% on average and occasionally up to 28.9%.

Simulated values of annual air-conditioning electricity use E_{ac}, whole-building electricity use E_{tot} and boiler gas use NG_{tot} for the commercial building are shown in Table 5. The results indicate that, as expected, annual deviations due to changing weather are significantly smaller in commercial buildings. For the internal-load dominated building considered here, the maximum deviations of annual air-conditioning electric usage were about 6% and the maximum deviations of annual boiler gas use was about 4% for locations with significant heating loads. The unexpectedly high heating load for Los Angeles requires further investigation.

These results roughly bracket the range of variation of annual building energy consumption due to the changing weather. This variation is the source of the error associated with attempting to calibrate simulation models using *typical* rather than *actual* meteorological data. Air conditioning and heating energy consumption in envelope-dominated buildings were seen to vary up to $\pm$30% from the mean during abnormally hot or cold years. In the commercial building, annual variation of cooling and heating energy consumption due to changing weather was very small, indicating that the potential error from calibrating a simulation model using typical data may be insignificant. The variation of the annual energy consumption of small commercial buildings or commercial buildings with large outside air requirements will lie somewhere in between.

CALIBRATION ERROR FROM USING TMY2 VERSUS SYNTHETIC WEATHER DATA

The error associated with using typical meteorological data to calibrate a simulation model can be reduced by using meteorological data synthesized from readily available average daily temperatures during the calibration period. In this section, the calibration errors caused by using typical, i.e. TMY2, and synthetic data are compared. Annual building energy consumption is simulated for 20 years from 1971 to 1990 using SAMSON, TMY2 and synthetic data. The calibration error from using TMY2 weather data is defined as the deviation between the hourly energy consumption predicted using TMY2 weather data and the "actual" energy consumption of the building using the SAMSON data. Similarly, the calibration error from using synthetic weather data is defined as the deviation between the energy consumption predicted based on synthetic data and the "actual" energy consumption of the building using the SAMSON data. In each case, the calibration error is normalized by dividing by the TMY2 energy consumption.

Mean absolute normalized calibration error =

$$\frac{\sum_{i=1}^{8,760} \left| \mathrm{Energy}_{i,\mathrm{TMY2\ or\ syn}} - \mathrm{Energy}_{i,\mathrm{acutal}} \right|}{\sum_{i=1}^{8,760} \mathrm{Energy}_{i,\mathrm{TMY2}}} \tag{14}$$

Table 4. The variation of annual air conditioning E_{ac}, whole-building electricity E_{tot}, furnace NG_{fur} and furnace plus hot water heater NG_{tot} energy consumption of a typical residence simulated using SAMSON weather data for the years 1971 to 1990. MaxAbsDev is the maximum absolute deviation from the mean. CV-MaxAbsDev is the maximum absolute deviation from the mean divided by the mean.

Year	E_{ac} (kWh/yr)	E_{tot} (kWh/yr)	NG_{fur} (GJ/yr)	NG_{tot} (GJ/yr)
Dayton, OH				
Mean	2,734	7,777	65.3	90.0
StdDev	246	246	7.6	7.8
CV-StdDev	0.090	0.032	0.116	0.087
MaxAbsDev	386	386	18.9	19.5
CV-MaxAbsDev	0.141	0.050	0.289	0.217
Boston, MA				
Mean	2,366	7,408	63.7	88.5
StdDev	229	228	4.1	4.4
CV-StDev	0.097	0.031	0.065	0.049
AbsMaxDev	553	554	8.6	9.2
CV-AbsMaxDev	0.234	0.075	0.135	0.104
Miami, FL				
Mean	6,283	11,323	0.8	18.5
StdDev	203	203	0.4	0.5
CV-StDev	0.032	0.018	0.483	0.027
AbsMaxDev	524	521	0.7	1.0
CV-AbsMaxDev	0.083	0.046	0.928	0.053
Los Angeles, CA				
Mean	2,583	7,626	5	27
StdDev	251	251	1.4	1.6
CV-StDev	0.097	0.033	0.253	0.058
AbsMaxDev	537	536	2.9	3.2
CV-AbsMaxDev	0.208	0.070	0.527	0.120

Table 5. The variation of annual air conditioning E_{ac}, whole-building electricity E_{tot}, and boiler NG_{tot} energy consumption of a large commercial building simulated using SAMSON weather data for the years 1971 to 1990. MaxAbsDev is the maximum absolute deviation from the mean. CV-MaxAbsDev is the maximum absolute deviation from the mean divided by the mean.

Year	E_{ac} (MWh/yr)	E_{tot} (MWh/yr)	NG_{tot} (GJ/yr)
Dayton, OH			
Mean	1,424	6,374	37,656
StdDev	32	30	652
CV-StdDev	0.022	0.005	0.017
MaxAbsDev	68	49	1,287
CV-MaxAbsDev	0.048	0.008	0.034
Boston, MA			
Mean	1,376	6,325	38,838
StdDev	23	23	639
CV-StDev	0.017	0.004	0.016
AbsMaxDev	40	40	1,472
CV-AbsMaxDev	0.029	0.006	0.038
Miami, FL			
Mean	2,075	7,024	18,495
StdDev	24	24	981
CV-StDev	0.012	0.003	0.053
AbsMaxDev	44	44	1,755
CV-AbsMaxDev	0.021	0.006	0.095
Los Angeles, CA			
Mean	1,709	6,658	35,446
StdDev	52	53	802.9
CV-StDev	0.031	0.008	0.023
AbsMaxDev	99	100	1,497.0
CV-AbsMaxDev	0.058	0.015	0.042

Max absolute normalized calibration error =

$$\frac{Max\left|\text{Energy}_{i,\text{TMY2 or syn}} - \text{Energy}_{i,\text{acutal}}\right|}{\left[\sum_{i=1}^{8,760}\text{Energy}_{i,\text{TMY2}} \Big/ 8,760\right]} \quad (15)$$

Average and maximum absolute normalized calibration errors from simulating 20 years of energy consumption in the residence are shown in Table 6. In every case, use of the synthetic data dramatically reduces calibration error. For example, in Dayton the average calibration error when simulating air conditioning energy use would be 12.1% when using TMY2 data and only 2.1% using the synthetic data. If the building energy consumption used to calibrate the model happened to be from an extreme weather year, the calibration error from using TMY2 data could be even greater. For example, in Dayton the maximum calibration error when simulating heating energy use was 32.0% using TMY2 data and only 3.9% using the synthetic data. Average and maximum absolute normalized calibration errors from simulating 20 years of energy consumption in a commercial building are shown in Table 7. The potential calibration errors are substantially less than for the residential case, indicating the error involved in using of TMY2 data when calibrating simulation models of large commercial buildings may be acceptably low. If better precision is desired, however, use of the synthetic data generally reduces the calibration error. The exception seems to be air conditioning in Miami and Boston where the calibration error is almost negligible to begin with and use of synthetic data actually increased the error. As predicted, the use of synthetic data in place of TMY2 data is more important when calibrating heating rather than cooling energy consumption.

Table 6. Average and maximum absolute normalized calibration errors from simulating energy consumption in the residence using 20 years of weather data.

			Dayton	Miami	Los Angeles	Boston
Air Cond	Avg	TMY2	0.121	0.031	0.104	0.093
		Synthetic	0.021	0.015	0.063	0.063
	Max	TMY2	0.245	0.073	0.299	0.297
		Synthetic	0.063	0.049	0.100	0.105
Heating	Avg	TMY2	0.086	0.621	0.237	0.052
		Synthetic	0.015	0.589	0.410	0.028
	Max	TMY2	0.320	1.80	0.681	0.141
		Synthetic	0.039	1.00	0.170	0.055

Table 7. Average and maximum absolute normalized calibration errors from simulating energy consumption in a commercial building using 20 years of weather data.

			Dayton	Miami	Los Angeles	Boston
Air Cond	Avg	TMY2	0.022	0.009	0.024	0.015
		Synthetic	0.015	0.012	0.023	0.018
	Max	TMY2	0.051	0.022	0.054	0.037
		Synthetic	0.026	0.026	0.051	0.031
Heating	Avg	TMY2	0.023	0.041	0.021	0.015
		Synthetic	0.005	0.011	0.006	0.002
	Max	TMY2	0.053	0.108	0.051	0.048
		Synthetic	0.010	0.026	0.016	0.004

SUMMARY AND CONCLUSIONS

Simulation results indicate that annual heating and cooling energy consumption in small, envelope-load dominated buildings typically varies by about ± 5% to ± 10% in response to changing weather conditions. In extreme weather years, it can vary by ± 30% from the mean. In large commercial buildings with substantial internal loads and moderate outside-air requirements, space conditioning energy consumption typically varies by only about ± 3% or less due to changing weather. Thus, the possible calibration error from using typical meteorological data to calibrate simulation models is highly dependent on the weather sensitivity of a building's energy use.

A method was proposed to synthesize hourly meteorological data from readily available average daily temperatures in order to reduce this type of calibration error. The proposed method generated no appreciable bias error in any of the meteorological variables. The mean absolute deviation between synthetic and measured temperature was approximately 2 C. Specific humidity was synthesized from its relatively strong correlation with hourly temperature. The relatively small average errors of temperature and specific humidity indicate that the method can adequately capture the diurnal variation of these variables for calibration purposes. However, no adequate correlation between solar radiation and ambient temperature could be found for time intervals of a day or less; thus the method was less accurate at predicting hourly solar radiation.

For buildings and climates with relatively large changes in annual energy consumption due to changing weather, the use of synthetic in place of typical meteorological data significantly reduced calibration errors; for example, in extreme weather years heating energy calibration errors were reduced by a factor of ten. Based on these results, we recommend using synthetic rather than typical hourly meteorological data for calibrating models of buildings with weather-sensitive energy consumption.

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