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A Simple Distribution Method for Two-Dimensional Temperature/Humidity Bin Data

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ABSTRACT

A distribution model is developed for relative humidity, and additional relationships are presented that allow the distribution model to be used on an hourly basis with either monthly-average daily relative humidity or monthly-average daily dry-bulb temperature and clearness index as the only meteorological data input. A procedure is described that allows the estimation of two-dimensional dry-bulb temperature/humidity ratio bin data from the distribution models for dry-bulb temperature and relative humidity. Comparisons of measured and estimated dry-bulb temperature/humidity ratio bin data are presented. A design method for the cooling load on a residential air conditioner is described, and air conditioning loads are calculated using both measured and estimated dry-bulb temperature/humidity ratio bin data.

INTRODUCTION

Ambient humidity is measured and recorded at most airports and weather stations in the U.S. Historical humidity data are available in both printed and magnetic tape (Butson and Hatch 1979) form for several hundred locations. However, the large amount of data required to provide a representation of long-term average conditions makes use of such data inconvenient for most studies.

Ambient temperature bin data are tabulated (U.S. Air Force 1978) by month for a large number of locations with the mean wet-bulb temperature given for each dry-bulb temperature bin, but no information is provided on the distribution of the wet-bulb temperatures. The term "distribution" refers to the range of values observed for a variable over a duration of time and the probability of occurrence associated with each value. Dodd (1965) developed maps for the U.S. that show isolines of dew-point temperature and its standard deviation. Coincident dry-bulb/wet-bulb temperature data are available for many military stations in the United States and worldwide (NCC n.d.); these data, based on many years of hourly observations, are compiled in 2 F dry- and wet-bulb temperature bins and are reported in monthly tabulations broken out in three-hour increments. Research efforts are underway to provide coincident dry-bulb and wet-bulb temperature bin data for major population centers (Seaton and Wright 1983).

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Humidity ratio is the mass of water in a sample of air divided by the mass of the dry air. Initial modeling efforts for humidity data were directed at developing a distribution function for humidity ratio. Hourly values of humidity ratio were obtained from SOLMET data recorded at Madison, WI; Washington, DC; Albuquerque, NM; Miami, FL; Fort Worth; TX; Columbia, MO; New York, NY; Phoenix, AZ; and Seattle, WA, and probability density curves were developed for humidity ratio from these data for each hour of the day for each month of the year.

When the various distribution functions were compared, strong locational, seasonal, and even diurnal variations were observed in the distribution shapes. The unusual shapes of some of the measured distribution curves and the initial lack of success in trying to quantify the variations in the distribution curves led to a more detailed investigation of the humidity data in which the two-dimensional probability density function for dry-bulb temperature and humidity ratio was examined. The investigation revealed that the maximum probability density tends to follow lines of constant relative humidity, suggesting that relative humidity is a better variable for the development of a generalized distribution function than humidity ratio.

A DISTRIBUTION MODEL FOR RELATIVE HUMIDITY

Model Development

The probability density function for relative humidity is required to satisfy several constraints. The range for relative humidity is between 0 and 1 on a fractional basis, the total area under the probability density curve must be equal to 1, and the average value of relative humidity is fixed by the shape of the curve. These constraints do not uniquely determine the shape of the probability density function for relative humidity, but they do require the shape to be different for different monthly-average values of relative humidity.

The monthly-average hourly relative humidity, $\overline{RH}$, has a large diurnal variation for many locations. Diurnal variations as large as 0.4 in monthly-average hourly relative humidity were observed in the nine SOLMET locations. This causes the probability density function for relative humidity to be significantly different for different hours of the day. The measured hourly relative humidity data were separated by month of the year and hour of the day, and a probability density curve was developed for each data set, yielding 288 (12x24) probability density curves for each location. Probability density curves for different hours, months, and locations having the same nominal value of $\overline{RH}$ were compared to determine whether the distribution function for relative humidity could be generalized in terms of $\overline{RH}$. In other words, if the monthly-average hourly relative humidity is known, is the relative humidity distribution also known? Figure 1 shows probability density curves for values of $\overline{RH}$ from 0.2 through 0.9 in increments of 0.1 for all nine locations. This figure was developed by selecting months for which the monthly-average hourly relative humidity, $\overline{RH}$, were within plus and minus 0.01 of each incremental value. Hourly, seasonal, and locational variation of these curves were found to be too small to justify their inclusion in a model.

A number of probability density functions were curve fit to the data and it was found that a Weibull function (Hines and Montgomery 1980) could represent any of the curves by varying the Weibull function parameters. A nonlinear regression routine was used to fit the set of relationships for the distribution model to all 2592 (9x288) probability density curves. The results for the probability density function, P(RH), and the cumulative distribution function, Q(RH), are:

$$P(RH) = (\theta_2/\theta_1)(RH/\theta_1)^{(\theta_2-1)}\exp(-(RH/\theta_1)^{\theta_2})(1-\exp(-1/\theta_1)^{\theta_2})) \tag{1}$$

and

$$Q(RH) = (1-\exp(-(RH/\theta_1)^{\theta_2}))/(1-\exp(-(1/\theta_1)^{\theta_2})) \tag{2}$$

where

$$\theta_1 = -0.02691 + 1.2276\overline{RH} - 0.14880\overline{RH}^2 \tag{3}$$

$$\theta_2 = 0.08165\exp(5.3801\overline{RH}) + 2.2747\exp(-0.59958\overline{RH}) \tag{4}$$

Figure 2 compares the cumulative distribution functions for the model (dashed lines) with those for the measured data for nominal values of $\overline{RH}$ between 0.2 and 0.9 (i.e., the same data used to construct Figure 1). The model is smoother than the measured data, with the best agreement at the higher values of $\overline{RH}$. The difference between the model and the measured data is within one standard deviation of the individual monthly-average hourly distribution curves that make up each nominal average curve.

Relationships for Monthly-Average Relative Humidity

The input required to use the relative humidity distribution model (Equations 1-4) are the monthly-average hourly relative humidities. However, these data are not generally available. It is shown in this section that the monthly-average hourly relative humidity can be estimated from the monthly-average daily relative humidity. The daily value can be obtained from published information or correlated to other readily available weather data.

Long-term average relative humidity values are tabulated in annual local climatological data (LCD) summaries for several hundred locations in the U.S. (Butson and Hatch 1979); the observations are for four hours of the day equally spaced six hours apart, but the four hours used vary among locations. Figure 3 shows good agreement between the monthly-average daily relative humidities, $\overline{RH}_d$, for the nine locations used in the present study (obtained by averaging the long-term hourly SOLMET data for each month) and the averages of the four hourly monthly-average values (normals) given in the annual LCD summaries.

A relationship was also developed that allows the monthly-average daily relative humidity to be estimated from the monthly-average daily dry-bulb temperature, $\overline{T}_a$, and the monthly-average clearness index, $\overline{K}_T$, the ratio of the horizontal surface solar radiation to the extraterrestrial radiation on a horizontal surface. The relationship between atmospheric clearness and relative humidity is primarily the result of cloud cover and haze, both of which are strongly dependent on the presence of atmospheric moisture.

$$\overline{RH}_d = 0.53 + 0.799\overline{K}_T - 2.2039\overline{K}_T{}^3 + 0.00315\overline{T}_a \tag{5}$$

where $\overline{T}_a$ is in degrees Celsius. The comparison between measured and estimated values of $\overline{RH}_d$, shown in Figure 4, is not as good as the agreement in Figure 3, but the RMS error for values of $\overline{RH}_d$ estimated using Equation 5 is less 0.05.

The diurnal variation of the monthly-average hourly relative humidity was fit to the following Fourier series.

$$\begin{aligned}(\overline{RH} - \overline{RH}_d)/A &= 0.4672\cos(t^*-0.666)\\ &+ 0.0958\cos(2t^*-3.484) + 0.0195\cos(3t^*-4.147)\\ &+ 0.0147\cos(4t^*-0.452)\end{aligned} \tag{6}$$

where dimensionless time, t^*, is

$$t^* = 2\pi(t-1)/24 \tag{7}$$

and t is in hours with 1 corresponding to 1 a.m. and 24 to midnight. Figure 5 shows Equation 6, the average data for the nine locations and plus and minus one standard deviation of the 108 monthly curves (12 months x 9 locations). The amplitude of the diurnal swing, A, is given by

$$\begin{aligned}A = &-0.516 + 1.933\overline{K}_T - 1.663\overline{K}_T{}^3\\ &+ 0.00669\overline{T}_a - 1.993\times10^{-4}\overline{T}_a{}^2\end{aligned} \tag{8}$$

where $\overline{T}_a$ and A are in degrees Celsius.

Equation 8 is compared to the measured diurnal amplitude of $\overline{RH}$ in Figure 6. Although there is some scatter evident in Figure 6, the estimation of the monthly-average hourly relative humidity with Equations (6) and (8) represents a considerable improvement over using the monthly-average daily value for all hours of the day.

THE ESTIMATION OF DRY-BULB TEMPERATURE/HUMIDITY RATIO BIN DATA.

The Use of Single-Variable Distribution Models

The energy required to maintain comfort within a building is often a function of both the dry-bulb temperature and the humidity ratio of the ambient air. Accurate estimation procedures for the building load may require information about the coincidence of temperature and humidity. Two-dimensional dry-bulb temperature/humidity ratio bin data provide a representation of the coincidence and the distributions for dry-bulb temperature and humidity ratio. The dependent variable for a two-dimensional dry-bulb temperature/humidity ratio bin is the number of hours (or the fraction of the time) that the temperature and humidity ratio were both within the intervals of dry-bulb temperature and humidity ratio that define the bin.

The estimation of two-dimensional bin data requires a bivariate distribution function describing the probability of occurrence for any particular combination of the two independent variables. If the two independent variables are not cross-correlated, it is possible to use two single variable distribution functions in place of the bivariate distribution function. In this case, the joint probability of occurrence for the two variables is given by the product of the probabilities for each of the variables considered separately.

The correlation of two variables can be measured by the cross-correlation coefficient, ρ_{xy}, which is defined as

$$\rho_{xy} = \frac{\sum_{i=1}^{n} (X_i - \overline{X})(Y_i - \overline{Y})}{\sum_{i=1}^{n} (X_1 - \overline{X})^2 \quad \sum_{i=1}^{n} (Y_i - \overline{Y})^2} \tag{9}$$

where X and Y are the variables of interest.

Monthly values of the cross-correlation coefficients for dry-bulb temperature and relative humidity (ρ_{Ta-RH}) were calculated from the long-term hourly data for each location and are given in Table 1. During the summer months ρ_{Ta-RH} is negative at all nine locations, with magnitudes ranging from 0.2 to 0.85. The negative cross-correlation coefficients indicate that when the dry-bulb temperature is above normal, the relative humidity is below normal, and vice versa. During the fall, winter, and spring months, the correlations between deviations of dry-bulb temperature and relative humidity are of both signs, with magnitudes generally less than 0.4.

Although there is significant cross-correlation between dry-bulb temperature and relative humidity for some months and locations, the additional complexity required to model the correlation would result in methods that are too difficult to use. It was assumed that the distribution functions for these two variables could be treated as uncorrelated, with the errors introduced by this assumption becoming part of the overall errors of the estimation procedure.

Estimation Procedure

The estimation of dry-bulb temperature/humidity ratio bin data with the distribution models of dry-bulb temperature developed in an earlier study (Erbs et al. 1983; Erbs 1984) and relative humidity is described below. The large diurnal variation of the monthly-average hourly relative humidity results in significant differences in the relative humidity distribution function for different hours of the day. The procedure described is intended for the estimation of bin data for an individual hour of the day. The bin data are then summed for all hours in the day to obtain daily bin data.

The estimation of dry-bulb temperature/humidity ratio bin data from the distribution functions for dry-bulb temperature and relative humidity begins with the distribution of the total number of hours in the month for an hour of the day into the dry-bulb temperature bins. This procedure is described in Erbs et al. (1983). The next step is to distribute the hours for each temperature bin among the humidity ratio bins. The humidity ratio bins and the dry-bulb temperature bins can be represented on a psychometric chart as sets of parallel lines, with the spacings between the lines equal to the bin sizes. The lines for dry-bulb temperature are orthogonal to those for humidity ratio, and their intersection results in a grid of rectangles. The intersection of a bin for dry-bulb temperature and a bin for humidity ratio is illustrated in Figure 7.

Each dry-bulb temperature bin has a set of humidity ratio bins corresponding to it, and the values of humidity ratio defining the humidity ratio bins are the same for each dry-bulb temperature bin. Since a distribution function model was not developed for humidity ratio, the dry-bulb temperature/humidity ratio bins must be approximated by dry-bulb temperature/relative humidity bins. This approximation is shown in Figure 7, where the area $\overline{abcd}$ is replaced by the area $\overline{wxyz}$. The accuracy of this approximation improves as the dry-bulb temperature bin size is made smaller. Because relative humidity is a function of humidity ratio and dry-bulb temperature, the set of relative humidity values that corresponds to the set of humidity ratio bins is different for each dry-bulb temperature bin.

The relative humidity for each value of humidity ratio is calculated from

$$RH = \omega(0.62198 + \omega_s)/\ \omega_s(0.62198 + \omega) \tag{10}$$

The saturation humidity ratio, ω_s, is a function of dry-bulb temperature. Relationships for the estimation of ω_s are provided by ASHRAE (1981). The midpoint dry-bulb temperature for each temperature bin is used to find ω_s, and the set of values of relative humidity corresponding to the humidity ratio bins for each temperature bin are determined using Equation 10. If the relative humidity is greater than 1 for any of the bins, it is set equal to 1. The relative humidity distribution function is then used to estimate the fraction of the total hours in a temperature bin in each of the relative humidity bins.

Comparisons of Measured and Estimated Bin Data

Dry-bulb temperature/humidity ratio bin data were generated from the long-term hourly SOLMET data sets on both a monthly and an annual basis. A bin size of 4 F was chosen for dry-bulb temperature. The humidity ratio bin size was varied so that approximately 20 bins covered the range of occurrence for humidity ratio. Monthly and annual bin data were also estimated for each of the nine locations using the estimation procedure outlined above. Measured values of monthly-average hourly dry-bulb temperature and relative humidity were used as input to the estimation procedure. The annual measured bin data are compared in Figure 8 with the estimated bin data for four of the locations. (The bin size shown in the figure is for double the interval of dry-bulb temperature and humidity ratio as used in generating the measured and estimated data.) The RMS errors are based on the differences in the number of hours between the measured data and the estimated data for each bin where either the measured or estimated value for a bin contained one or more hours.

The estimated data reproduce the general shapes of the two-dimensional distributions for the measured data reasonably well, although it should be noted that a significant error in the number of hours estimated for any individual dry-bulb temperature/humidity ratio bin may occur. The estimation procedure tends to overestimate the number of hours at high values of humidity ratio. The estimated bin data are more spread out than the measured bin data, and the gradients in the number of hours between adjacent bins are generally not as large in the estimated bin data.

The cross-correlation between dry-bulb temperature and relative humidity, which is not included in the estimation method, is one possible source of error. Other possible sources of error are differences between the distribution models and the measured data for dry-bulb temperature and relative humidity.

EXAMPLE APPLICATION: A DESIGN PROCEDURE FOR RESIDENTIAL AIR CONDITIONER PERFORMANCE

Method of Calculation

An application for two-dimensional humidity ratio/dry-bulb temperature bin data is the estimation of the performance of a residential air conditioner. The capacity and COP of an air conditioner are functions of the indoor and outdoor dry-bulb temperatures and the indoor humidity ratio. Although interior humidity is generally not controlled directly in a residence, moisture is removed from the air when its temperature is brought below the dew point. Thus, there can be both a sensible and a latent load on the air conditioner coil.

When an air conditioner is operated to control the temperature inside a building, the fraction of each hour the air conditioner must run is equal to the ratio of the sensible building cooling load to the sensible cooling capacity of the machine. The sensible load on the air conditioner is assumed to always be equal to the instantaneous load for the house, unless the house load exceeds the steady-state capacity of the air conditioner.

The latent load on an air conditioner is dependent on a number of factors. If the dew point of the air inside a building is below the evaporator coil temperature, there is no condensation of moisture and no latent load. When there is condensation, the latent load is determined by the instantaneous water removal rate and the fraction of the time the air conditioner is operating to meet the sensible load. The problem is complicated by the fact that the sensible capacity of the machine, and thus the fraction of the time it is running, is dependent on the latent load.

Performance data were obtained for a single-package heat pump with a nominal total (sensible plus latent) capacity of 3 tons (10.64 kW). The tabular data provided give the steady-state sensible capacity, latent capacity and power consumption as a function of outdoor dry-bulb temperature and indoor wet-bulb temperature for an indoor dry-bulb temperature of 80.6 F (27 C). The sensible load for the house was calculated using the UA-degree hour approach with a cooling base temperature of 68 F (20 C), a cooling thermostat set point of 80.6 F (27 C) and a UA of 580 Btu/hr-F (306 W/C). The difference between the set point and base temperatures accounts for internal heat generation and gains due to solar radiation. Infiltration rates of 0.5 and 5.0 air changes per hour were considered with an internal volume of 12,070 ft^3 (340 m^3). Internal generation of moisture and the effect of cycling the heat pump on its performance were not considered. Ventilation with ambient air was assumed to satisfy the cooling load when the outdoor dry-bulb temperature was less than 75.2 F (24 C).

An iterative procedure is required to determine the performance of the air conditioner when it is operating. The inside dry-bulb temperature, the outside dry-bulb temperature and the outside humidity ratio are known and fixed for a given bin. What remains is to solve for the inside humidity ratio for each bin (when the air conditioner is operating). A moisture balance for the interior air can be written as:

$$\dot{m}_{a,infil}(\omega_a - \omega_{r,f}) = \dot{m}_{a,coil}(\omega_{r,f} - \omega_{coil})(PLF) \tag{11}$$

where PLF, the part-load factor, is the ratio of the sensible building load to the sensible air-conditioner capacity (with an upper bound of one), $\dot{m}_{a,coil}$ is the mass flow rate of infiltration air, $\omega_{r,f}$ is the inside humidity ratio, ω_a is the outside air humidity ratio, $\dot{m}_{a,coil}$ is the mass flow rate of air past the evaporator and ω_{coil} is the exit humidity ratio of the air flowing over the evaporator. Since the sensible capacity of the machine and the humidity ratio at the coil exit are a function of the room humidity ratio, it is necessary to solve Equation 11 numerically for room humidity ratio. The sensible load, latent load and power consumption of the air conditioner are found by summing the product of the PLF, the number of hours in the bin and the steady-state rate for each of these variables over those bins having an ambient temperature greater than 75.2 F (24 C).

Performance Comparisons for Measured and Estimated Bin Data

Monthly and annual loads were calculated for the air conditioner-house system described above using both the measured and estimated humidity ratio/dry-bulb temperature bin data. The estimated bin data were determined from the distribution models for relative humidity and dry-bulb temperature as described in the previous section. Two sets of estimated bin data were generated for each location. The first set used measured values of the monthly-average daily dry-bulb temperature and relative humidity as input, with the diurnal variation of the monthly-average hourly values of dry-bulb temperature and relative humidity estimated. The second set used measured values of the monthly-average daily dry-bulb temperature and clearness index as input data, with the monthly-average daily relative humidity and the diurnal variations of the monthly-average hourly dry-bulb temperature and relative humidity estimated.

The monthly and annual bias and RMS errors are given in Table 2 for the combined results of all nine locations. The average loads are also provided in the table. When measured values of monthly-average daily dry-bulb temperature and relative humidity are used as input, the performance for the estimated bin data is typically within 10% on a monthly basis and 5% on an annual basis of the performance for the measured bin data. The estimated bin data were found to be equally accurate for locations with large latent loads, such as Miami and Fort

Worth, and locations with small latent loads, such as Phoenix or Albuquerque. The estimation of the monthly-average daily relative humidity from other weather variables results in an increase in the RMS and bias errors.

For some applications it may be possible to simplify the estimation procedure for dry-bulb temperature/humidity ratio bin data without a large increase in the error of the calculated load or equipment performance (compared to that obtained with the detailed procedure). Bin data were also estimated for each location by assuming the relative humidity was a constant equal to the monthly-average daily value. The dry-bulb temperature distribution function was still used, but the diurnal variation of dry-bulb temperature was neglected. This allows the bin data to be estimated for the entire day in a single step, rather than hour by hour as in the procedure given in the previous section. The use of a constant relative humidity still results in a distribution of humidity ratio values due to the fact that there is a distribution of dry-bulb temperature.

The RMS and bias errors for the combined results of the nine locations are also given in Table 2 for this simplified bin data estimation procedure. The errors are somewhat larger when compared to the errors for the more detailed bin data estimation procedure, but on an annual basis they are still within 10% of the average load. This simplified approach may be useful for calculations requiring a distribution of humidity ratio values, which are not highly sensitive to the nature of the distribution.

SUMMARY

The distribution model for relative humidity and the supporting relationships presented allow the estimation of relative humidity bin data with readily available monthly-average inputs: the monthly-average daily values of relative humidity, dry-bulb temperature and clearness index. The procedure described for the estimation of dry-bulb temperature/humidity ratio bin data provides a simple means of obtaining two-dimensional bin data useful in the calculation of building cooling loads and equipment performance. These bin data are generally not available for most locations, but the monthly-average daily inputs required for the estimation procedure are available for hundreds of locations in the U.S.

The estimated dry-bulb temperature/humidity ratio bin data for nine U.S. locations were found to agree reasonably well with data compiled from long-term hourly measurements, although significant errors were observed for some of the individual bins. Performance estimates for a residential air conditioner were obtained with both measured and estimated bin data, and the performance for the estimated bin data is within 5% of the performance for the measured bin data on an annual basis. A simplified procedure for the estimation of two-dimensional bin data was also demonstrated with performance calculations for the air-conditioner system. The agreement between the performance for the simplified and measured bin data is within 10% on an annual basis.

NOMENCLATURE

A	=	amplitude of the diurnal variation of monthly-average hourly relative humidity [°C]
$\overline{K}_T$	=	clearness index defined as the ratio of monthly or total solar radiation incident on a horizontal surface to the monthly total extraterrestrial radiation
$\dot{m}_{a,coil}$	=	mass flow rate of air passing by the evaporator coil [kg/s]
$\dot{m}_{a,infil}$	=	mass flow rate of infiltration air [kg/s]
$P(RH)$	=	probability density function for relative humidity
PLF	=	part-load factor defined as the sensible building load to the sensible air-conditioner capacity
$Q(RH)$	=	cumulative distribution function for relative humidity

RH = instantaneous (or hourly) relative humidity

$\overline{RH}$ = monthly-average hourly relative humidity

$\overline{RH}_d$ = monthly-average daily relative humidity

T_a = instantaneous (or hourly) ambient temperature

$\overline{T}_a$ = monthly-average daily dry-bulb temperature [°C]

$\overline{T}_{a,h}$ = monthly-average hourly dry-bulb temperature [°C]

t = time in hours with 1 corresponding to 1 a.m. and 24 to midnight [hours]

t^* = dimensionless time defined by Equation 7

UA = building overall energy loss coefficient [W/°C]

θ_1 = defined by Equation 3

θ_2 = defined by Equation 4

ρ_{T_a-RH} = cross-correlation coefficient between dry-bulb temperature and relative humidity

ω = instantaneous (or hourly) humidity ratio

ω_a = outside air humidity ratio

ω_{coil} = humidity ratio of air exiting from the evaporator coil

$\omega_{r,f}$ = indoor air humidity ratio

ω_s = saturation humidity ratio

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TABLE 1

Cross-Correlation Coefficients between Variations of Hourly Dry-Bulb Temperature and Relative Humidity from their Respective Monthly-Average Values

Month	Cross-Correlation Coefficients								
	Madison	Washington	Albuquerque	Miami	Fort Worth	Columbia	New York	Phoenix	Seattle
Jan	0.55	0.18	−0.22	0.27	0.05	0.15	0.48	−0.14	0.21
Feb	0.43	0.14	−0.38	0.29	−0.09	0.02	0.46	−0.22	−0.10
Mar	0.08	−0.04	−0.48	0.26	−0.11	−0.25	0.17	−0.50	−0.31
Apr	−0.21	−0.16	−0.54	0.05	−0.03	−0.21	−0.13	−0.52	−0.50
May	−0.24	−0.18	−0.44	−0.36	−0.34	−0.20	−0.23	−0.46	−0.60
June	−0.32	−0.35	−0.46	−0.74	−0.66	−0.39	−0.35	−0.29	−0.67
July	−0.37	−0.42	−0.80	−0.85	−0.78	−0.42	−0.37	−0.66	−0.75
Aug	−0.34	−0.36	−0.70	−0.82	−0.73	−0.43	−0.17	−0.65	−0.74
Sep	−0.22	−0.15	−0.49	−0.77	−0.42	−0.30	0.13	−0.34	−0.60
Oct	−0.07	0.02	−0.40	−0.12	−0.06	−0.13	0.36	−0.34	−0.44
Nov	0.13	0.07	−0.36	0.12	0.07	−0.06	0.44	−0.40	0.02
Dec	0.42	0.20	−0.33	0.25	0.03	−0.04	0.46	−0.32	0.00

TABLE 2

Monthly and Annual Bias and RMS Errors for Air Conditioning Loads Estimated with Humidity Ratio/Dry Bulb Temperature Bin Data

Description of Bin Data Estimation Procedure	Monthly Loads		Annual Loads	
	RMS Error, GJ	Bias Error, GJ	RMS Error, GJ	Bias Error, GJ
T_a and RH distributions, $\overline{T}_{a,h}$ and $\overline{RH}$ estimated from $\overline{T}_a$ and $\overline{RH}$	0.254	0.016	1.43	0.19
T_a and RH distributions, $\overline{T}_{a,h}$ and $\overline{RH}$ estimated from $\overline{K}_T$ and $\overline{T}_a$	0.353	0.035	2.02	0.42
T_a distribution, RH = $\overline{RH}$, no diurnal variation of T_a or RH, measured $\overline{T}_a$ and $\overline{RH}$	0.411	-0.076	1.95	-0.92
Average Load for Measured Bin Data	2.18 GJ		26.11 GJ	

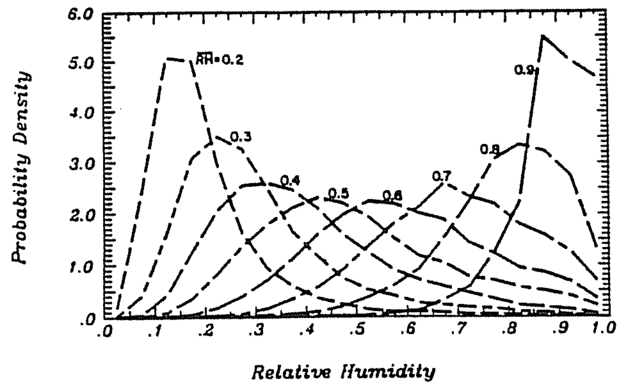

Figure 1. *Relative humidity probability density curves for nominal values of monthly-average hourly relative humidity*

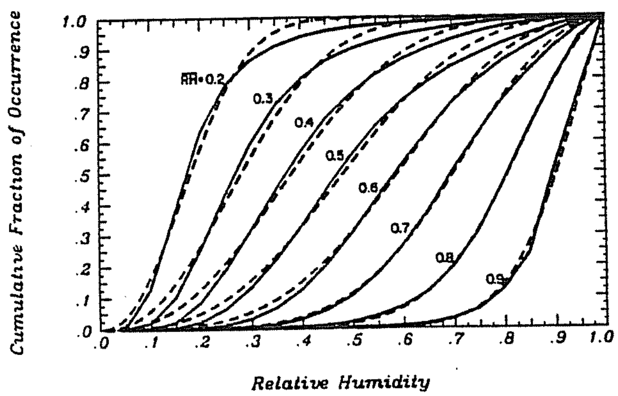

Figure 2. *Cumulative distribution function model (---) Measured data (——) curves for relative humidity*

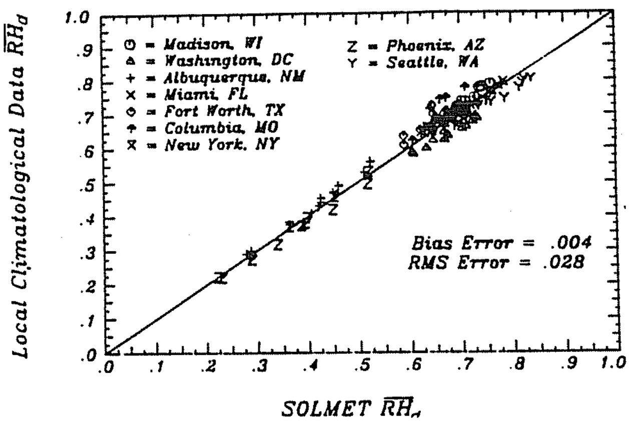

Figure 3. *Comparison of SOLMET and local climatological data monthly-average daily relative humidity values*

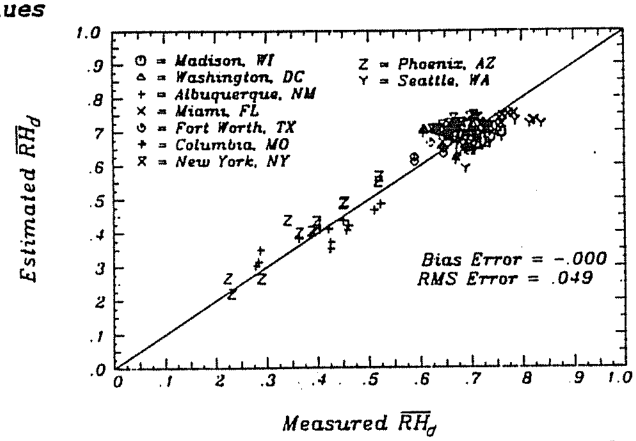

Figure 4. *Comparison of measured and estimated monthly-average daily relative humidity*

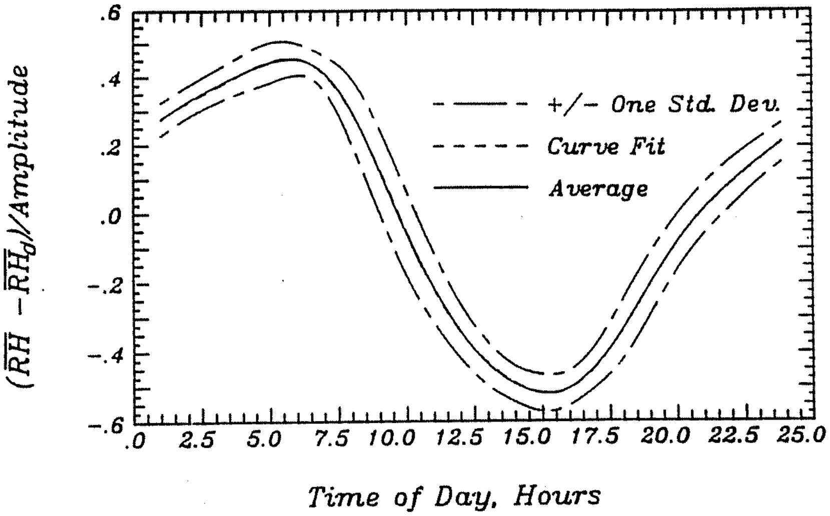

Figure 5. Standardized diurnal variation of monthly-average hourly relative humidity for nine U.S. locations

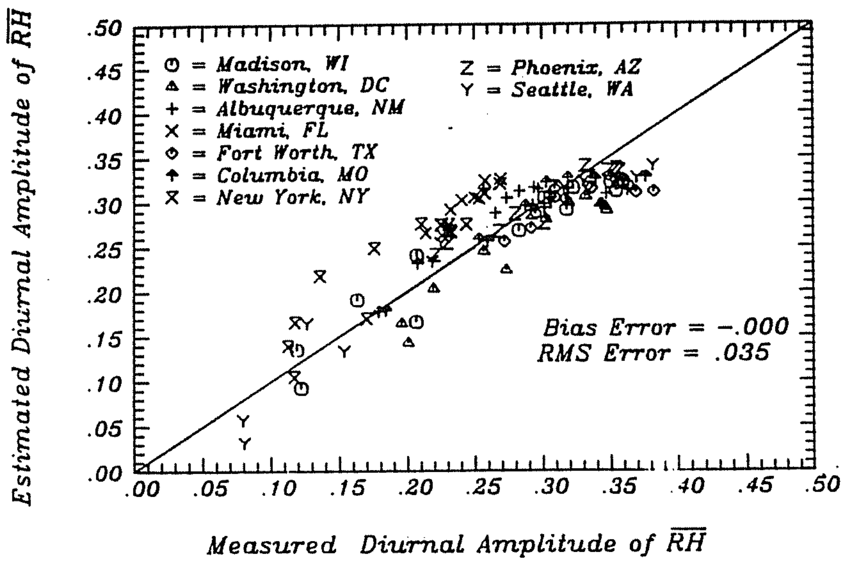

Figure 6. Estimated and measured values of the amplitude for the diurnal variation of monthly-average hourly relative humidity

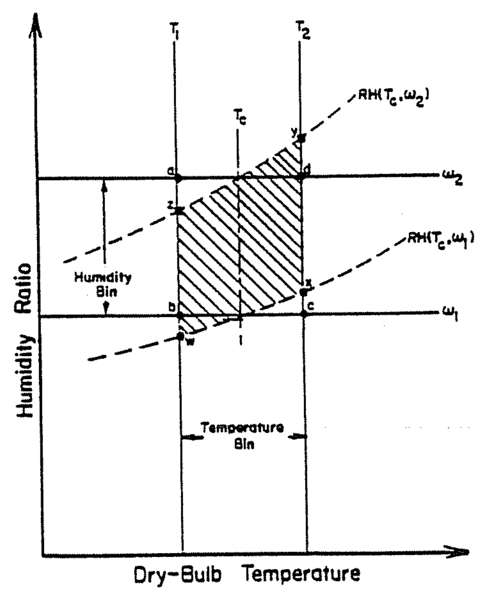

Figure 7. A two-dimensional humidity ratio/dry-bulb temperature bin

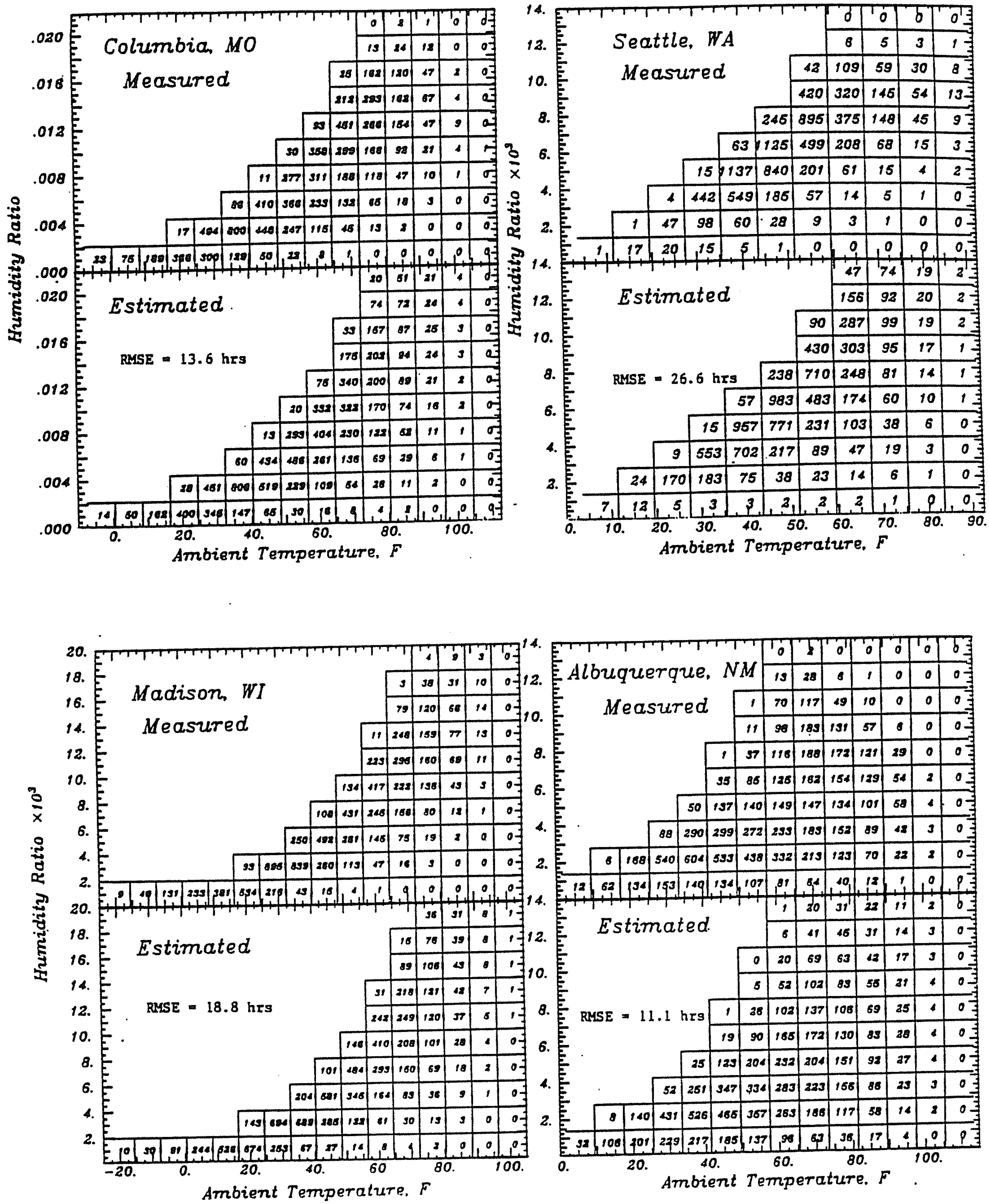

Figure 8. Comparison of measured and estimated dry-bulb temperature/humidity ratio bin data