

# Accuracy of Wood Resistance Sensors for Measurement of Humidity

**REFERENCE:** Carll, C. and TenWolde, A., "Accuracy of Wood Resistance Sensors for Measurement of Humidity," *Journal of Testing and Evaluation*, JTEVA, Vol. 24, No. 3, May 1996, pp. 154-160.

**ABSTRACT:** This work was undertaken to evaluate the accuracy of wood resistance sensors for measurement of relative humidity and to identify sources of error in this use. Relative humidity can be expressed as a function of the logarithm of the sensor's electrical resistance and of its temperature. We found that single-point calibration of each sensor compensates for most between-sensor variation, although care must be exercised during calibration. With careful calibration readings, error in relative humidity readings made with these sensors can be limited to  $\pm 10\%$  relative humidity under most conditions. The literature indicates that a lower degree of error than this is anticipated when electrical resistance is used to estimate moisture content measurements. Our data suggest that sorption hysteresis and sensor memory are significant contributors to this ( $\pm 10\%$ ) relative humidity error.

**KEYWORDS:** relative humidity, matchstick sensor, Duff sensor, sorption hysteresis, electrical resistivity

The wood electric resistance sensor developed at the USDA-Forest Service, Forest Products Laboratory [ 1 ], has been widely used for measuring moisture conditions within building components. It is not commercially available but is easy and inexpensive to fabricate. This sensor (Fig. 1), by virtue of its small size, has a negligible influence on the component being evaluated. Its response to changing conditions is fairly rapid; TenWolde and Courville [ 2 ] state that the fastest measured change in moisture conditions within building components was made with this sensor [ 3 ].

Originally, the sensor was meant to be read with a direct-current (DC) resistance moisture meter for wood with measurements reported in terms of percent moisture content (MC). However, when the sensor is used in or near materials other than wood, MC of the sensor may be different from that of the material of interest.

For building scientists, relative humidity (RH) is a more useful value than sensor MC. The RH expresses atmospheric humidity conditions in a building cavity or in the film of air adjacent to building materials. The RH is a measure of the degree of saturation of the air and of material in contact with that air, assuming that

the air and material are in moisture equilibrium. Sensor resistance is a function of its MC (which in turn is related to RH of the surrounding air) and, to a lesser extent, its temperature. Thus, RH at a location can be determined from sensor resistance and temperature at that location, assuming the relationship between these three variables is known. In addition to temperature and RH, sensor MC is influenced by sorption hysteresis [ 4 ], meaning that its equilibrium MC depends on the direction from which equilibrium is reached. When these sensors are used to estimate RH, further error results from the shape of the sorption (or desorption) isotherm for wood.<sup>3</sup> At low and moderate RH levels, the isotherms have low slopes [ 4-7 ], thus minor errors in estimate of sensor MC can translate into substantial errors in estimate of RH. In summary, when these sensors are used to estimate RH rather than MC of the sensor itself, the value obtained is more useful, but error associated with the value is anticipated to be of greater magnitude. The purpose of this work was to evaluate the accuracy of wood resistance sensors for measurement of RH and to identify sources of error.

## Background

### *Moisture Content, Relative Humidity, and Temperature*

An example of the relationship between RH and wood equilibrium MC over the range of 55 to 90% RH at 300 and 272 K is shown in Fig. 2. The data were taken from Table 3-4 of the *Wood Handbook* [ 8 ].<sup>3</sup> Although a complex polynomial equation containing terms for temperature and MC more accurately describes this relationship, it can be adequately approximated at a given temperature by the equation

$$\Phi = A + B \ln(M) \quad (1)$$

where

$\Phi = \text{RH} (\%)$ ,

$M = \text{wood MC} (\%)$ ,

$A = \text{a constant, or offset, and}$

$B = \text{a proportionality constant, or coefficient.}$

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<sup>3</sup>Sorption (or desorption) isotherms are plots of moisture content of a material as a function of RH at a given temperature. The isotherms for most building materials have the shape of a truncated "S" lying on its side.

<sup>4</sup>The data in Table 3-4 of the *Wood Handbook* give a single wood moisture content value for a given set of RH/temperature conditions, and thus ignore the influence of sorption hysteresis.

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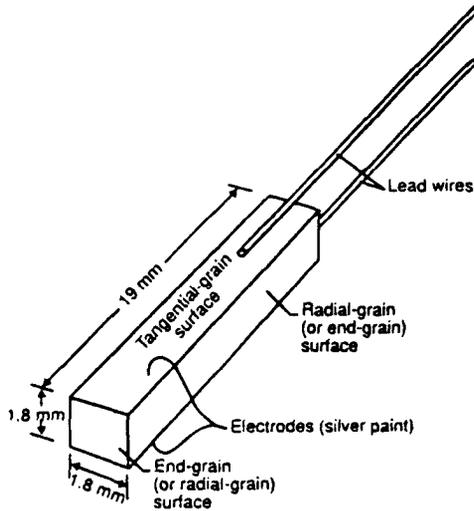


FIG. 1—Wood resistance sensor.

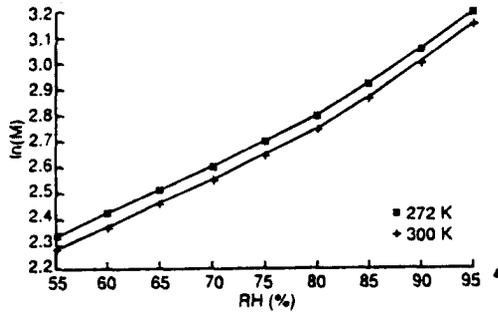


FIG. 2—Natural logarithm of MC with respect to RH. (Data from Wood Handbook, [8].)

*Electric Resistance and Moisture Content*

In the hygroscopic range and at a constant temperature, an approximately inverse linear relationship exists between the logarithm of the DC resistivity of wood and the logarithm of its MC [9]. This relationship is the basis for determining wood MC with DC resistance measurements. For a wood specimen of given size and grain orientation, the relationship may be expressed as

$$\ln(R) = k_M \ln(M) + C_1 \quad (2)$$

where

- $R$  = specimen resistance ( $\Omega$ ),
- $M$  = specimen MC (%),
- $k_M$  = a proportionality constant or coefficient, and
- $C_1$  = a constant.

The coefficient  $k_M$  is negative and virtually constant among wood species (Fig. 3).

*Electric Resistance and Temperature*

At a given MC in the hygroscopic range, an approximately exponential relationship exists between wood resistivity and temperature. For a wood specimen of given size and grain orientation, this relationship may be expressed as

$$\ln(R) = k_T T + C_2 \quad (3)$$

where

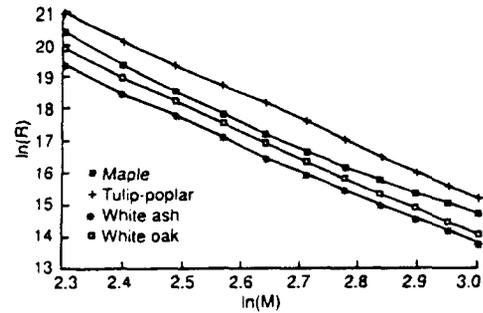


FIG. 3—Natural logarithm of direct-current resistance with respect to natural logarithm of MC for four hardwood species at 300 K. (Data from James [9].)

- $R$  = specimen resistance ( $\Omega$ ),
- $T$  = temperature (K),
- $k_T$  = proportionality constant or coefficient, and
- $C_2$  = a constant.

The coefficient  $k_T$  is negative. The data of Davidson [10], Lin [11], and James [12] indicate that the value of  $k_T$  varies with temperature and MC Davidson's data [10] further indicate that the value of  $k_T$  is essentially independent of wood species.

*Electric Resistance, Moisture Content, and Temperature*

The relationship between the resistance of a wood specimen of given dimensions and its MC and temperature can be derived from Eqs 2 and 3:

$$\ln(R) = k_M \ln(M) + k_T T + C_3 \quad (4)$$

which can be rearranged as

$$\ln(M) = \frac{1}{k_M} \ln(R) - \frac{k_T}{k_M} T - \frac{C_3}{k_M} \quad (5)$$

*Electric Resistance, Relative Humidity, and Temperature*

No data on this relationship are directly available from the literature. Therefore, we constructed a data set of corresponding RH, temperature, and DC resistance values over the range of 55% to 90% RH at 300 and 272 K from the following published data:

1. MC/RH data over the range of 55 to 90% RH at 300 and 272 K from the *Wood Handbook* [8] provided us with estimates of RH as a function of MC at two different temperatures.
2. The relationship between resistance and MC constructed from James' data [9] for hard maple specimens, along with the data from the *Wood Handbook* [8], provided us with estimates of RH as a function of sensor resistance at 300 K.
3. Estimates of the temperature coefficient  $k_T$  constructed from James' data [12], along with the previously mentioned data, enabled us to estimate RH as a function of sensor resistance at 272 K.

The constructed data are plotted in Fig. 4.

An approximate relationship between RH ( $\Phi$ ), resistance ( $R$ ), and temperature ( $T$ ) can be obtained by substituting Eq 5 for  $\ln(M)$  in Eq 1:

$$\Phi = a + b[\ln(R)] + c(T) \quad (6)$$

where

$a$  = a constant, or offset and  
 $b, c$  = proportionality constants, or coefficients.

When Eq 6 is fit to the constructed data in Fig. 4, the following values for the constants are obtained:  $a = -280.1$ ,  $b = -5.87$ ,  $c = -0.350$ . Although the coefficient of determination ( $R^2$ ) for this regression is 0.994, Eq 6 is an imperfect model, as the relationship between RH and the natural log of resistance is not perfectly linear (Fig. 4). Residuals of the fit of Eq 6 to the constructed data are shown in Fig. 5. The term residual refers to the difference between the value predicted by a regression and the measured value at a corresponding value(s) of the independent variable(s) for the regression. Thus, a residual is the amount by which the regression over- or underestimates the actual value at a given set of conditions. If the residual is positive, the regression equation overestimates the actual value; if the residual is negative, the regression underestimates the actual value. Figure 5 indicates that this model overestimates RH levels at high and low RH conditions and underestimates RH levels between 65 and 80% RH. Despite this shortcoming, errors do not exceed 2% RH over the range of conditions discussed.

#### Between-Sensor Variability

The data of James [9] and Davidson [10] indicate that the values of  $k_w$  and  $k_r$  are not species-dependent. Differences among species in density, morphology, and chemical composition (factors likely to influence electrical resistance) generally exceed differences in these properties within species. Therefore, we anticipate little between-sensor variation in the coefficients  $b$  and  $c$  in Eq 6. The offset value  $a$  in Eq 6 may, however, vary between sensors.

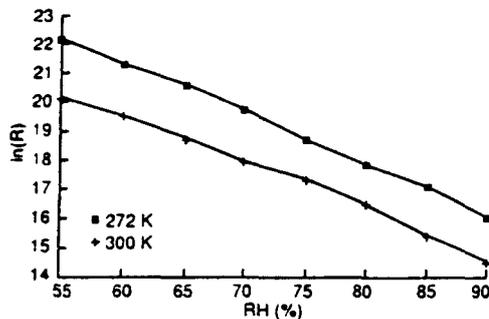


FIG. 4—Natural logarithm of wood specimen resistance with respect to RH at two temperatures. (Data from Wood Handbook [8], and James [9].)

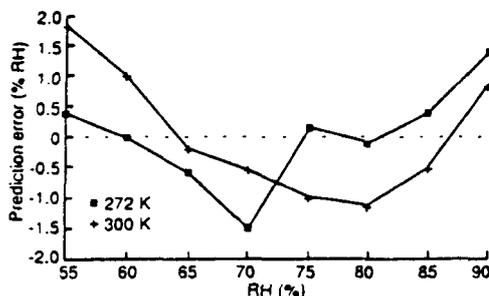


FIG. 5—Error in predicted RH level. (For data taken from Wood Handbook [8], and James [9].)

#### Accuracy in Use

Duff [1] claimed that the sensor registers accurately to within 1% MC. However, experience suggests that this level of accuracy is not commonly attained. Sherwood [13] claimed an error of  $\pm 2\%$  MC, but presented no empirical evidence for this estimate of error. The error stated by Duff [1] was not based on empirical evidence but on a screening procedure in which all sensors that do not read to within 0.5% MC (with a resistance moisture meter for wood) of the value expected at 90% RH are discarded. The claim of accuracy to within 1% MC thus appears conservative if based on such a strenuous screening procedure. This procedure, however, reportedly results in discarding more than half the sensors tested. Variation in the values  $C_1$  or  $C_2$  (in Eqs 2 and 3), variation in grain direction, and less-than-perfect uniformity during sensor fabrication could result in variation in sensor resistance. In contrast to the wasteful screening procedure proposed by Duff, sensors may be individually calibrated. Zarr et al. [14] performed individual calibrations of sensors for MC level. They found that with individual sensor calibration, error in estimate of sensor MC could be small, although they do not state a specific level. One author has informed us that the level is roughly  $\pm 1\%$  MC (personal communication). Without individual sensor calibration, Zarr et al. [14] indicate that error resulting from sensor variability will be roughly  $\pm 3\%$  MC. This is in general agreement with Rose [15], who estimated a between-sensor variability of approximately 4% MC.

When these sensors are used to estimate local RH rather than MC of the sensor, additional error in the estimated value is anticipated. Sources of this additional error are sorption hysteresis and the fact that the slopes of sorption or desorption isotherms are shallow at RH levels between 50 and 80%; thus, small errors in estimate of sensor MC translate into substantial errors in RH value. Table 1 indicates expected error in RH estimates from these sensors resulting from sorption hysteresis and from small errors in estimating sensor MC. The values in Table 1 are based on the relationships (adsorption and desorption) between RH and wood MC for hard maple published by Hedlin [16], over the range of 50 to 95% RH. This range was selected because it is the approximate useable range of these sensors and roughly corresponds to the RH ranges we cited previously to calculate values of  $a$ ,  $b$ , and  $c$  for Eq 6. Within this range, RH can be accurately predicted from MC using third-degree polynomial equations. Table 1 indicates that sorption hysteresis will contribute significantly to error in estimated RH. Error attributable to sorption hysteresis when these sensors are used in building structures is probably less than Table 1 would suggest. This is because the data in Table 1 are based on adsorption measurements made at increasing RH from the oven-dry condition and desorption measurements made at decreasing RH from fiber saturation. Within building structures the sensors usually will not be exposed to such extremes. Sensor MC at a given set of conditions depends not only on the hysteresis (sorption vs. desorption) but also on past conditions to which the sensor has been subjected [17, 18]. Nevertheless, Table 1 suggests that sorption hysteresis has the potential to contribute significantly to error when these sensors are used to estimate RH. In addition, Table 1 indicates that a 1% error in estimating sensor MC (the level claimed by Duff [1] and verbally related to us by Zarr et al. [14]) translates into substantial error in RH estimate, particularly at RH levels between 50 and 70%.

Unless sensors are individually calibrated, errors well in excess of 10% RH would be expected solely as a result of error in estimate

TABLE 1—Predicted RH values at specified wood MC levels.<sup>a</sup>

Wood MC (%)	RH during adsorption			RH during desorption		
	RH (%)	% RH error given		RH (%)	% RH error given	
		+1% MC	-1% MC		+1% MC	-1% MC
10.0	55.6	5.5	-6.1	40.5	6.0	-6.6
12.5	68.3	4.1	-4.6	54.6	4.7	-5.2
15.0	77.9	3.0	-3.5	65.5	3.7	-3.1
17.5	84.8	2.2	-2.5	74.1	2.8	-3.1
20.0	89.6	1.5	-1.7	80.7	2.2	-2.5
22.5	92.9	1.0	-1.2	85.9	1.9	-2.0

<sup>a</sup>Adsorption vs. desorption and error in predicted values attributable to ±1% error in MC measurement. Data for adsorption and desorption of hard maple at 294 K from Hedlin [16]. Data over the range of 50 to 95% RH were fit separately for desorption and adsorption to third-degree polynomial equations with MC as the independent variable.

of sensor MC from resistance. Since the research literature suggests that between-sensor variation is primarily due to difference in the offset value *a* in Eq 6 and not in sensitivity (i.e., coefficients *b* or *c*), it may be possible to adequately compensate for between-sensor variation with a single-reading calibration for each sensor.

Sensor Calibration / Screening

After sensors are fabricated, it is advisable to screen and calibrate them to identify outlier sensors to be discarded and to identify the offset value *a* in Eq 6 for the rest of the sensors. Alternatively, multipoint calibration over a range of temperature and RH conditions (as done by TenWolde and Mei [ 19 ] on a sample of sensors) could be performed for each sensor to derive sensor-specific values for coefficients *b* and *c* and the offset value *a* in Eq 6. In this study, we performed such multipoint calibrations to determine if this procedure improves the measurement accuracy.

Objectives and Methodology

A data set consisting of resistance values for 70 wood resistance sensors with 20 or more readings per sensor taken over a range of temperature and RH conditions identified the following:

1. Goodness of fit of individual sensor calibration data to Eq 6,
  - a. Error in predicted RH values.
  - b. Distribution of error: Randomly distributed error would indicate non-repeatability of measurements, whereas systematic distribution of error would indicate a deficiency in Eq 6 as a model.
2. The nature and magnitude of between-sensor variation.

Methodology

Sensors were fabricated from hard maple (*Acer succharum*) as shown in Fig. 1, with the 1.8- by 1.8-mm surface being end-grain. This specimen configuration was expected to result in slower sensor response to changing RH than the other configuration shown in Fig. 1 (in which the unpainted 1.8- by 19-mm surfaces are end-grain surfaces). Although the alternative configuration would allow quicker sensor response, we have not identified any published work in which this alternative configuration was used. Copper lead wires were bonded to the electrode surfaces with silver-filled epoxy adhesive.

Calibration data were obtained in two runs: Data for 31 sensors were obtained on the first run and data for the other 39 sensors were obtained on the second run. A room with controlled variable temperature and humidity was used and room conditions were monitored with a dewpoint hygrometer and mercury thermometer, in some cases with wet-bulb/dry-bulb thermometers. The series of temperature/RH conditions during the two runs were not identical. At any given setpoint, room conditions varied on the order of ± 2% RH and ± 2.7 K over time.

Room conditions were changed rapidly in approximate step changes. The time period between programming a change in room conditions and taking resistance readings ranged from 1 h to approximately 46 h. In general, the change in RH setting divided by the time between change in RH setting and sensor reading was less than 10% RH change per hour. This ratio was slightly higher for two readings, which were taken after increases in RH setting. The data from these readings suggested that despite the fast increase in RH conditions, the sensors were approximately at equilibrium at the time of measurement.

Sensor resistances were measured indirectly via voltage readings from signal conditioner circuits that were calibrated for electrical resistance (Fig. 6). Resistance readings were taken within 4 min of voltage application to the sensors.

Data Analysis

Distribution of Error

Figure 7 shows a representative plot of residuals around Eq 6 as a function of RH. The data in this figure are from a randomly selected sensor from the first calibration run. The distribution of residuals with respect to RH level is largely random, suggesting that the form of Eq 6 is appropriate. The systematic deficiency in

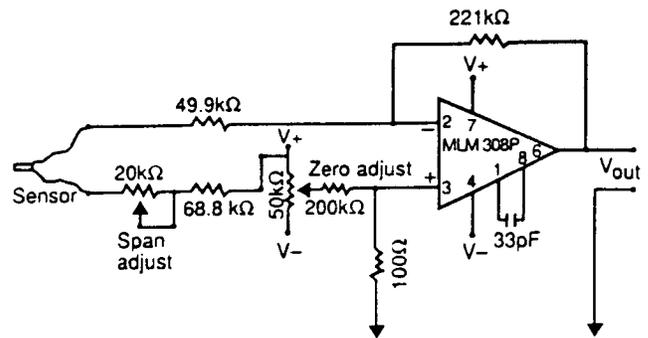


FIG. 6—Signal conditioner circuit used for indirect measurement of sensor resistance.

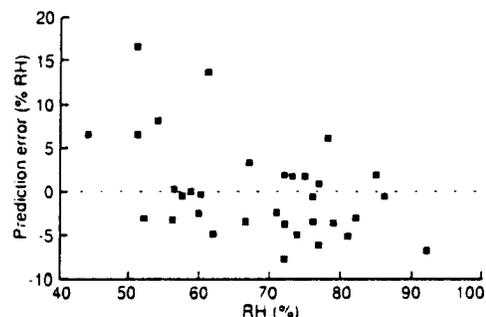


FIG. 7—Error in predicted RH with respect to RH level for a randomly selected sensor.

the model (Eq 6), as shown in Fig. 5 and discussed previously, is insignificant relative to random error and is, therefore, not apparent in Fig. 7. The two largest residuals in Fig. 7 suggest that the distribution of error was not completely random, but the readings associated with these points were taken after large or reasonably fast reductions in RH level and were most likely influenced by sorption hysteresis or failure of the sensors to attain moisture equilibrium before being read. If these two points are ignored, the distribution of error with respect to RH level is random and approximately the same over the entire RH range. This indicates that Eq 6 is a useful model. Table 1 suggests that error in RH estimate arising from small errors in measuring sensor MC will result in greater errors in RH estimate at low RH levels than at RH levels around 90%. This expectation is not reflected in our data, which show error to be largely independent of RH.

Figure 8 indicates that distribution of error was significantly influenced by sorption hysteresis. Equation 6 tended to overestimate RH when sensors had recently been exposed to conditions of decreasing RH (desorption) and to underestimate RH when sensors had recently been exposed to conditions of increasing RH (adsorption).

Figure 9 indicates that distribution of error was also influenced by the rate of reduction in RH (desorption). The largest residual shown in Figs. 8 and 9 was associated with a reading taken after a reduction in RH level of only 10%, but at the fastest nominal rate change (the change in RH since the previous resistance reading divided by hours since the last reading) of 3.6% per hour. This suggests that these sensors respond slowly to reductions in atmospheric humidity. They will overestimate RH even at rates of RH reduction slower than 10% per hour, the rate cited by TenWolde and Courville [ 12 ]. In contrast, Fig. 9 suggests that the sensors were able to respond adequately to rates of increase in RH in excess of 10% RH per hour.

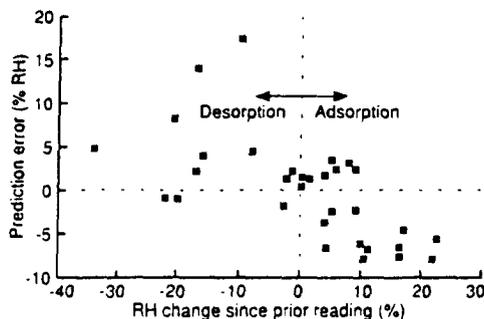


FIG. 8—Error in predicted RH with respect to change in atmospheric conditions prior to sensor reading for a randomly selected sensor from the first calibration run.

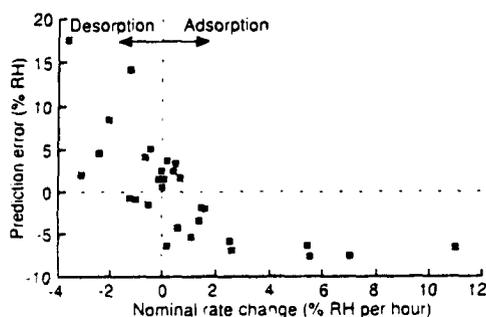


FIG. 9—Error in predicted RH with respect to rate of change in atmospheric conditions prior to sensor reading for a randomly selected sensor from the first calibration run.

We then deleted readings taken after desorption and fit the resulting data sets to Eq 6. This, we believed, would result in biased estimates of the offset value  $a$ , but in accurate estimates of the coefficient values and substantially tighter error distributions. As expected, error distributions were substantially tightened. Distributions of residuals with respect to RH remained random. No deficiency in the form of Eq 6 was apparent, even when the masking effect of sorption direction was removed.

#### Confidence in Calculated Regression Coefficient Values

Because sorption hysteresis influenced sensor resistance, we used truncated data sets (data sets from which readings taken after resorption had been deleted) to evaluate the issue of confidence in calculated coefficient values. As indicated previously, fitting Eq 6 to such data sets should give biased estimates of the offset  $a$ , but should yield accurate estimates of the coefficients  $b$  and  $c$ .

*Confidence in Calculated Temperature Coefficient* – In fitting adsorption-only data sets to Eq 6, we obtained values for the temperature coefficient  $c$  substantially different from the value  $-0.35$  calculated from data in the research literature. Furthermore, the two calibration runs yielded different temperature coefficient values, significant at  $\alpha < 0.001$ . The two calibration runs consisted of exposure to a similar range of conditions, but in a different order. Thus it appeared that the order of conditions somehow influenced the calculated temperature coefficient. As will be discussed later, we feel that this was due to sensor “memory.” Regardless of the explanation, the discrepancies between values from different calibration runs and between those from our calibration runs and the value calculated from the research literature suggest that it is difficult to obtain accurate temperature coefficient values for Eq 6 by multipoint calibration. This is in agreement with TenWolde and Mei [ 19 ], who could not identify a consistent temperature influence on sensor resistance during multipoint calibrations.

Figure 10 shows the relationship between natural logarithm of resistance and RH for one sensor for three consecutive adsorption cycles at three progressively higher temperatures (288.7, 294.2, and 299.8 K). It shows that resistance tends to decrease as temperature increases, in agreement with James [ 12 ]. However, using the data shown in Fig. 10, the calculated temperature coefficient  $c$  in Eq 6 is  $-0.893$ —substantially in excess of the value previously calculated from data in the research literature. Part of the reason for this excessively large calculated temperature coefficient value is that resistance values during the first part of the first adsorption cycle (288.7 K) were substantially higher at equivalent RH levels

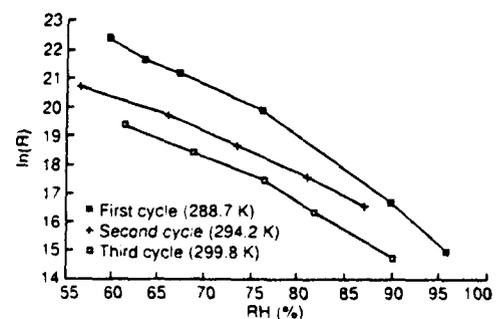


FIG. 10—Relationship between natural logarithm of resistance and RH for a randomly selected sensor on three consecutive sorption cycles at progressively higher temperatures.

than were those on the subsequent cycles (294.2 and 299.8 K). The first sorption cycle occurred after the sensors had been stored under dry conditions for years. Thus, Fig. 10 suggests that sensor resistance is influenced not only by hysteresis (sorption vs. desorption) and rate, but also by history of exposure prior to the most recent change in environmental conditions. According to Skaar [17] and Suchsland [18], equilibrium MC of wood and wood products is influenced by past history as well as by hysteresis. We supposed that sensor memory influenced MC to such a degree that it obscured the influence of temperature on resistance, making determination of an accurate temperature coefficient for Eq 6 impossible.

**Confidence in Calculated Resistance Coefficient Value** — Figure 10 also indicates that sensor memory and the range of conditions over which the sensors are conditioned during calibration can affect the calculated values of the coefficient  $b$  in Eq 6. The slope of the trace of the first adsorption cycle in Fig. 10 is influenced by the high resistance values recorded at the start of that cycle. When the data from the three cycles are individually fit to Eq 6 (with no temperature correction factor, as each cycle was isothermal), the values of coefficient  $b$  obtained for the first, second, and third cycles are  $-4.74$ ,  $-7.31$ , and  $-6.09$ , respectively. The disparity between these values shows that obtaining a value for the coefficient  $b$  from any single cycle is risky. However, the average of the three coefficient values ( $-6.05$ ) is close to that obtained from the data set we constructed from the research literature ( $-5.87$ ).

#### Between-Sensor Variation

We based our estimate of between-sensor variation on data obtained during the third sorption cycle in the second calibration run. These data were composed of five resistance readings for each sensor taken at approximately 300 K at successively higher RH levels. For each sensor, a linear regression of RH as a function of the natural logarithm of resistance was fit to the five data points. The two distributions of intercept and slope values for the different sensors are both approximately normal. Figure 11 shows data for sensors at the extremes of the distributions (with the exception of one outlier), plus data for a sensor approximately in the middle of the distributions. Although there is some between-sensor variation in resistance change with RH change, ( $b$  in Eq 6), between-sensor variation is primarily due to difference in offset value ( $a$  in Eq 6). The offset value can be easily determined with a single-point calibration procedure. Figures 7, 8, and 10, however, indicate that the single-point reading should not be taken after large changes in RH, fast changes in RH, or after conditioning from an unusual

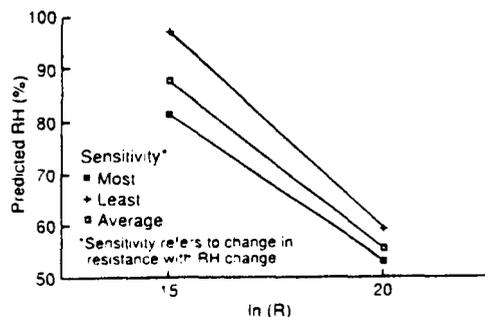


FIG. 11—Regression fit plots for three sensors of RH versus natural log of resistance on one adsorption cycle at 300 K. Sensors chosen to show range of variability.

set of conditions. Between-sensor variation for this batch of sensors is as much as 15% RH, and roughly equivalent to the 4% MC “interchangeability error” stated by Rose [15]. This error can be reduced with single-point calibration to determine the offset value  $a$  for individual sensors.

Although between-sensor variation is primarily an issue of difference in offset value  $a$  in Eq 6, we found that a few sensors showed unusual values for the coefficient  $b$  in Eq 6. Therefore, we believe a two-point screening procedure is warranted to identify such outlier sensors.

#### Error in Readings From Individual Sensors

As indicated previously, sensor resistance at any set of temperature and RH conditions is influenced by sorption hysteresis and sensor memory. This has importance both for sensors in use and (as also suggested previously) for determination of the offset value  $a$  during calibration. The reading made for determination of the offset value will always be biased by hysteresis to some extent, because that reading will be made after either adsorption or desorption. To limit the extent of bias, the single-point calibration reading should not be made after large or rapid changes in RH or after reconditioning from extremes in RH. Figure 9 suggests that if these precautions are taken, errors in RH estimate can be limited to  $\pm 10\%$  RH (except for after drops in RH exceeding 3% RH per hour). This is roughly the same magnitude of error that we observed for between-sensor variation.

#### Conclusions

1. The error associated with these sensors when used to estimate relative humidity (RH) does not exceed  $\pm 10\%$  RH, except when RH decreases at rates in excess of 3% RH per hour. Our data suggest that this error is associated with sorption hysteresis and sensor memory.
2. Equation 6 is a sufficiently accurate model. Errors that are random with regard to RH level obscure any deficiency in the model caused by the fact that the relationship between RH and wood moisture content is not perfectly exponential.
3. Variation between sensors is of similar magnitude to the error for individual sensors. Between-sensor variation can be reduced with a single-point calibration procedure.
4. Between-sensor variation is primarily an issue of difference in resistance level (the offset value  $a$  in Eq 6), rather than differences in resistance change in response to change in RH or temperature ( $b$  or  $c$  coefficients in Eq 6).
5. Accurately identifying values of resistance and temperature coefficients ( $b$  and  $c$  coefficients in Eq 6) for individual sensors by multipoint calibration is difficult. This is particularly true for the temperature coefficient.

#### Recommendations

1. We do not recommend performing full multipoint individual sensor calibrations to obtain coefficient values for Eq 6. Sorption hysteresis and sensor memory obscure the influence of temperature on sensor resistance, making accurate determination of the temperature coefficient essentially impossible. The value of coefficient  $b$  as determined by the calibration procedure will depend on how the sensors are cycled before and during the calibration procedure. We recommend using  $-5.87$  and  $-0.35$  as values for coefficients

$b$  and  $c$ , respectively, in Eq 6. These values are derived from previously published data.

2. We recommend a two-point screening procedure consisting of resistance readings taken at different relative humidity (RH) levels at one temperature to identify sensors with unusual resistance/RH sensitivities (for discard) and to identify offset value  $a$  for Eq 6 (for sensors that will be used). The offset value  $a$  will be determined from one of the two data points (using the values -5.87 and -0.35 for coefficients  $b$  and  $c$ , respectively). To avoid serious bias, this data point should not be taken after large increases or decreases in RH. Cycling the sensor between 65 and 80% RH twice during the course of a week and then making the resistance reading after sorption from 65% RH to equilibrium at 70% RH should avoid serious bias in determination of the offset value  $a$ .

#### Acknowledgments

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