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Recalibration of the Complaint Prediction Model

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This paper describes the evaluation and recalibration of the complaint prediction model developed by Federspiel (2000). We collected temperature time-series data and complaint data from six buildings ranging in size from 60,000 ft^2 to 800,000 ft^2 from three different geographical locations. Using these data, we found a low correlation between the observed number of complaint events and the Predicted Average Complaint Events (PACE) for the monitoring intervals and systematic underprediction of hot complaints. We recalibrated the model, increasing the correlation coefficient between observed number of complaint events and PACE to $r = 0.49$. *This degree of correlation, though still not high, is statistically significant (*$p = 0.044$*). The recalibrated model predicts that the temperature corresponding to the minimum number of complaints is lower than that of the original model. The recalibrated model also predicts that the minimum number of complaints is greater than that of the original model. Finally, the recalibrated model is not symmetrical. The recalibrated model predicts that hot complaints will increase faster as the average temperature rises than will cold complaints as the average temperature decreases. We used complaint temperatures and an observed setup in building-wide mean temperature to validate the recalibration. From observed complaint temperatures, we constructed six hypothesis tests on predicted values of the mean and standard deviation of complaint temperatures. The differences between the predicted and computed complaint temperature statistics were not statistically significant in all six cases. We compared the observed effect of raising the mean temperature 3°F with the predicted effect. The observed hot complaint rate during the high-temperature period was 2.4 times higher than during the low-temperature period. The predicted ratio was 5.3 times. The difference was explained by underreporting observed by the chief engineer. We expected a dependence of the mean complaint levels on mean outdoor temperature because correlations between mean outdoor temperature, clothing insulation, and indoor air velocity have been established. However, we did not find such an influence. The complaint model predicts that the mean temperature for minimizing complaint rate on arrival is lower than for minimizing complaint rate during the occupied period of the day. This can be explained by a higher metabolic rate on arrival.*

INTRODUCTION

This paper is focused on the relationship between the performance of HVAC systems and operating costs other than energy costs. In particular, we focus on predicting the value of thermal comfort in commercial buildings or, conversely, the cost of discomfort.

Much of the effort of relating HVAC system performance to non-energy operating cost has focused on the effect that HVAC systems have on human health and productivity. Research results relating HVAC system behavior to human health have been reported by Jaakkola et al.

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(1991), Hodgson et al. (1991), and Wyon (1992). Wyon (1993, 1996) and Sensharma and Woods (1997) review and discuss the effects of the indoor environment on productivity. Fisk (2000) estimated the economic benefits that would likely occur from improvements in indoor environments, including improvements in thermal comfort. The uncertainty of these estimates is large, but the magnitude is also large. Federspiel et al. (2002) studied the impact that ventilation and a number other factors, including temperature, have on the work performance of call center agents. They found that when the temperature was greater than 77.7°F, agents performed one of their tasks 16% slower. Since health and productivity costs are large compared to energy costs in buildings, significant findings from health and productivity research should lead to significant changes in the design and operation of HVAC systems. A limitation of health and productivity research to date is that it is case-based. This makes it difficult to extend the findings of a study to conditions not considered in the study.

There have been decades of research on predicting thermal comfort. The early efforts in this area were purely empirical. Houghten and Yaglou (1923) developed the first effective temperature index using empirical methods. Nevins et al. (1966) and McNall et al. (1967) describe examples of empirical predictions of thermal sensation ratings. Most recent work on thermal comfort has been at least partly based on heat and mass transfer models. Fanger (1972) describes a model-based, semi-empirical method of predicting thermal sensation ratings and for predicting the fraction of dissatisfied occupants. These indices are called *predicted mean vote* (PMV) and *predicted percent dissatisfied* (PPD), respectively. PMV predicts the average subjective thermal sensation rating of a large group based on six variables that affect the human heat balance, and PPD predicts the expected fraction of a large group with a subjective rating of hot or cold that exceeds an absolute value of 1.5 scale units on a scale that ranges from –3 to 3 units. Extensions of the model-based approach to predicting thermal sensation have been developed by others. Gagge et al. (1986) describe the 2-node model that is the basis of ET^*. A 64-node comfort model that captures details of human physiology, such as blood counterflow and differing temperatures in 16 body segments, was recently developed by Huizenga et al. (1999). All of these models predict what people will say or what their physiological state will be. This makes it difficult to compare the outputs of these models with other important variables, such as energy use, and limits their application to operations and decision-making.

Federspiel (2000) recently proposed a model that produces the Predicted Average Complaint Events (PACE) in an interval of time (days, weeks, months, or annually) based on three statistics of the space temperature in buildings. These statistics are mean space temperature, standard deviation of the space temperature, and standard deviation of the rate of change of the space temperature. The model treats complaints as a kind of alarm. The significance of this model is that it relates building temperature, which impacts energy performance, with operation and maintenance costs because complaints become corrective maintenance work orders in commercial buildings. Furthermore, the complaint prediction model is quantitative and predictive, rather than case-based, so it can be used for design and operational decision-making.

The parameters of Federspiel's original model were determined using data acquired from a set of buildings at a single geographical location. This paper describes an evaluation of the accuracy of the complaint model developed by Federspiel (2000) and the results of recalibrating it. The research involved collecting temperature time-series and complaint data from buildings, analyzing the data, assessing the accuracy of the original model, recalibrating the model, assessing the accuracy of the recalibrated model, and demonstrating the model's practical use.

The next section contains a summary of the complaint prediction model and the PACE metric. The following section describes the research methods used for this study. The next sections contain the results and a discussion of those results and their applicability to design, operations, and thermal comfort standards.

COMPLAINT PREDICTION MODEL

Federspiel (2000) proposed a complaint prediction model in which unsolicited thermal sensation complaints are modeled as stochastic temperature alarms. By stochastic, we mean that the complaint levels are random processes. Unsolicited thermal sensation complaints are discrete events. Unlike a control alarm, the temperature level at which a complaint occurs is not fixed. It is also not clearly related to any other variable. It is for these two reasons that complaint levels are modeled as random processes. This methodology could be used for modeling other kinds of complaints, such as air quality complaints, but doing so would have less utility because they are much less frequent (Federspiel 2001).

Figure 1 shows a graphical representation of the complaint model. The graph on the left side of the figure shows three time series. One is the high-temperature (hot complaint) level, one is the low-temperature (cold complaint) level, and the one that is mostly between these two levels is the building space temperature. All three of these are modeled as random processes. Complaints are modeled as the events corresponding to the building space temperature crossing above the hot level or below the cold level. Figure 1 shows two hot complaints and two cold complaints. The complaint levels in the model are not physical processes that can be monitored continuously as the building temperature can be monitored. Instead they are abstract processes designed to model the variable tolerance for temperature that we observe in practice. When complaints occur, the value of these levels can be measured because, at those instants, the building space temperature and the complaint level are equal by definition. We can estimate the statistical properties of the complaint levels by measuring the complaint temperatures along with the building space temperature time series.

If the process on the left-hand side of Figure 1 is observed for a long time, and if the temperatures at which the crossings occur are recorded, the complaint temperatures will form two distributions as shown in the graph on the right-hand side of Figure 1. Figure 2 shows actual complaint temperatures. The figure shows two distinct distributions. Spikes are attributed to rounding the temperature to the nearest marking on the thermometer from which the temperatures were read.

Note that complaints can only occur when and where spaces are occupied. This means that low, high, or highly variable temperatures during unoccupied periods such as nights and weekends do not affect complaint rates.

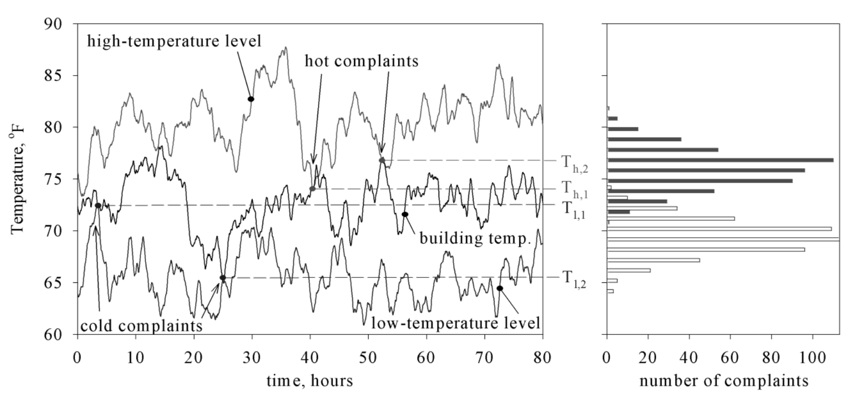

Figure 1. Thermal sensation complaint process model.

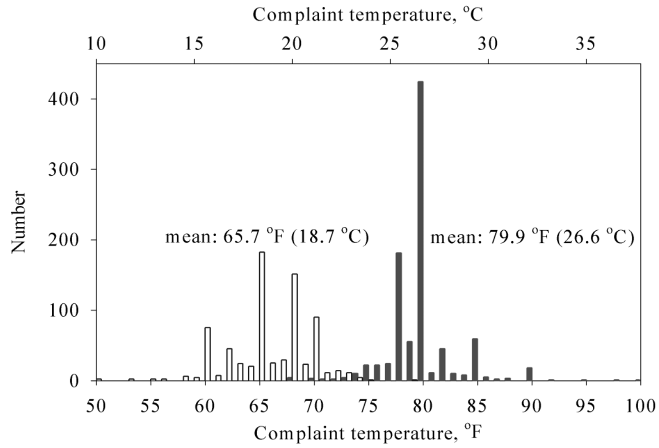

Figure 2. Temperatures at which occupants complained (Federspiel 1998).

To make analytical predictions, we assume that the three temperature distributions in Figure 1 are stationary (time-invariant statistics) and Gaussian. Federspiel (2000) showed that building temperatures are approximately Gaussian, and Fanger (1972) showed that probit (Gaussian) regression lines adequately predict dissatisfied thermal sensation votes. The standard level-crossing process is one in which a stationary Gaussian process crosses a fixed level. The mathematical theory for predicting the mean frequency of the standard level-crossing process was first developed by Rice (1945). Cramer and Leadbetter (1967) developed additional mathematical properties of the level-crossing problem, as well as extensions of the theory to nonstationary processes. The mean frequency that a stationary Gaussian process crosses a fixed level L is determined from the following simple formula:

$$v_x = \frac{\sigma_{\dot{x}}}{2\pi\sigma_x}\exp\left(-\frac{1}{2}\frac{(L-\mu_x)^2}{\sigma_x^2}\right) \tag{1}$$

where x refers to the random process, v_x is the mean crossing frequency, $\sigma_{\dot{x}}$ is the standard deviation of the rate of change of x, σ_x is the standard deviation of x, and μ_x is the mean value of x. The standard deviation of the rate of change is important because if x can change rapidly, then it can cross L more frequently. The value of $\sigma_x/\sigma_{\dot{x}}$ is the nominal time constant of the process, and $\sigma_{\dot{x}}/\sigma_x$ is the bandwidth. If the process is oscillatory, then $\sigma_{\dot{x}}/\sigma_x$ will be the natural frequency. For a given value of σ_x, as $\sigma_{\dot{x}}$ increases, the natural frequency increases, and, therefore, the average rate at which x crosses L increases.

There are two differences between the standard level-crossing process and the complaint process. The first is that the levels of the complaint process are not fixed, and the second is that buildings are not always continuously occupied. The fact that buildings are not continuously occupied implies that there will be arrival complaints that occur in the morning when occupants arrive and the temperature is either higher than the hot complaint level or lower than the cold complaint level. For arrival complaints, the "crossing" occurs prior to arrival and the complaint condition still exists when occupants arrive. The first difference is handled by a change of variables, and the second difference is handled by computing the probability of an arrival complaint.

The complaint prediction model has more notation than the standard level-crossing process because it involves the interaction of three processes. The notation is described here. The high-temperature level at which a hot complaint occurs will be referred to as T_H, the building temperature will be referred to as T_B, and the low-temperature level at which a cold complaint occurs will be referred to as T_L. The parameters μ_{T_H}, σ_{T_H}, and $\sigma_{\dot{T}_H}$ are the mean, standard deviation, and standard deviation of the rate of change of T_H. The parameters μ_{T_B}, σ_{T_B}, and $\sigma_{\dot{T}_B}$ are the mean, standard deviation, and standard deviation of the rate of change of T_B. The parameters μ_{T_L}, σ_{T_L}, and $\sigma_{\dot{T}_L}$ are the mean, standard deviation, and standard deviation of the rate of change of T_L. The parameters $\rho_{T_H T_B}$, $\rho_{T_L T_B}$, $\rho_{\dot{T}_H \dot{T}_B}$, $\rho_{\dot{T}_L \dot{T}_B}$ are the correlation coefficients between T_H and T_B, T_L and T_B, $\dot{T}_H$ and $\dot{T}_B$, $\dot{T}_L$ and $\dot{T}_B$, respectively.

Mathematically, the Predicted Average Complaint Events (PACE) per zone per day is as follows:

$$PACE = (P_h + P_l) + (v_h + v_l)t \tag{2}$$

where

$$P_h = \int_{-\infty}^{Z_h} \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz \tag{3}$$

$$P_l = \int_{-\infty}^{Z_l} \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz \tag{4}$$

$$Z_h = \frac{\mu_{T_B} - \mu_{T_H}}{(\sigma_{T_H}^2 + \sigma_{T_B}^2 - 2\sigma_{T_H}\sigma_{T_B}\rho_{T_H T_B})^{1/2}} \tag{5}$$

$$Z_l = \frac{\mu_{T_L} - \mu_{T_B}}{(\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B})^{1/2}} \tag{6}$$

$$v_h = \frac{1}{2\pi}\left(\frac{\sigma_{\dot{T}_H}^2 + \sigma_{\dot{T}_B}^2 - 2\sigma_{\dot{T}_H}\sigma_{\dot{T}_B}\rho_{\dot{T}_H \dot{T}_B}}{\sigma_{T_H}^2 + \sigma_{T_B}^2 - 2\sigma_{T_H}\sigma_{T_B}\rho_{T_H T_B}}\right)^{1/2} \exp\left(-\frac{1}{2}\frac{(\mu_{T_B} - \mu_{T_H})^2}{(\sigma_{T_H}^2 + \sigma_{T_B}^2 - 2\sigma_{T_H}\sigma_{T_B}\rho_{T_H T_B})}\right) \tag{7}$$

$$v_l = \frac{1}{2\pi}\left(\frac{\sigma_{\dot{T}_L}^2 + \sigma_{\dot{T}_B}^2 - 2\sigma_{\dot{T}_L}\sigma_{\dot{T}_B}\rho_{\dot{T}_L \dot{T}_B}}{\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B}}\right)^{1/2} \exp\left(-\frac{1}{2}\frac{(\mu_{T_B} - \mu_{T_L})^2}{(\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B})}\right) \tag{8}$$

and where t is the length of time each day that the building is occupied. The quantities P_h and P_l are the probabilities of hot and cold arrival complaint conditions, respectively. To estimate the complaint rate for a whole building, it is necessary to determine the number of zones. The number of zones is the plan area of the building divided by the nominal area of a zone. The nominal area of a zone, denoted as A, is an additional parameter of the complaint prediction model. It is not necessarily the same as the size of individual HVAC zones. The temperature in individual HVAC zones may be correlated for a number of reasons, such as being side-by-side, being exposed to the same exterior convective and solar radiation, and being served by the same primary equipment. The correlation will make the nominal area of a complaint zone greater than the size of individual HVAC zones.

The temperatures at which hot complaints occur is denoted as T_h, and the temperature at which cold complaints occur will be denoted as T_l. While T_H, T_B, and T_L are continuous random processes, T_h and T_l are discrete random sequences. When a hot complaint occurs, $T_H = T_B = T_h$. When a cold complaint occurs, $T_B = T_L = T_l$. The relation between the variances of T_H, T_h, and T_B is as follows:

$$\sigma_{T_H}^2 = \frac{\sigma_{T_h}^2(2\sigma_{T_H}\sigma_{T_B}\rho_{T_HT_B} - \sigma_{T_B}^2) - \sigma_{T_H}^2\sigma_{T_B}^2\rho_{T_HT_B}^2}{\sigma_{T_h}^2 - \sigma_{T_B}^2} \tag{9}$$

The relation between the variances of T_L, T_l, and T_B is as follows:

$$\sigma_{T_L}^2 = \frac{\sigma_{T_l}^2(2\sigma_{T_L}\sigma_{T_B}\rho_{T_LT_B} - \sigma_{T_B}^2) - \sigma_{T_L}^2\sigma_{T_B}^2\rho_{T_LT_B}^2}{\sigma_{T_l}^2 - \sigma_{T_B}^2} \tag{10}$$

The relation between the means and variances of T_H, T_h, and T_B is as follows:

$$\mu_{T_H} = \frac{\mu_{T_h}(\sigma_{T_H}^2 + \sigma_{T_B}^2 - 2\sigma_{T_H}\sigma_{T_B}\rho_{T_HT_B}) + \mu_{T_B}(\sigma_{T_H}\sigma_{T_B}\rho_{T_HT_B} - \sigma_{T_H}^2)}{\sigma_{T_B}^2 - \sigma_{T_H}\sigma_{T_B}\rho_{T_HT_B}} \tag{11}$$

The relation between the means and variances of T_L, T_l, and T_B is as follows:

$$\mu_{T_L} = \frac{\mu_{T_l}(\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_LT_B}) + \mu_{T_B}(\sigma_{T_L}\sigma_{T_B}\rho_{T_LT_B} - \sigma_{T_L}^2)}{\sigma_{T_B}^2 - \sigma_{T_L}\sigma_{T_B}\rho_{T_LT_B}} \tag{12}$$

The correlation coefficients in Equations 5 through 8 are included for mathematical completeness. In all subsequent sections, we assume that the correlation coefficients are zero, meaning that the tolerance for indoor temperature is independent of the indoor temperature itself.

PACE depends on the rate of change of the complaint levels in addition to the rate of change of the temperature itself. The importance of the rate of change of the complaint levels is similar to the importance of the rate of change of the building space temperature, though the physical causes of variations in the complaint levels are not generally the same as the causes of variations in building space temperature. Variations in the complaint levels may be caused by changes in activity, posture, clothing, attention to work, health, etc.

The original complaint prediction model was calibrated using data from a complaint database. Building space temperature time series were not available for determining the values of μ_{T_B}, σ_{T_B}, and $\sigma_{\dot{T}_B}$. Instead, the value of μ_{T_B} was computed from the complaint temperatures in the complaint database that were associated with humidity and air motion complaints. We assumed that the mean value of the complaint temperatures for humidity and air motion complaints was the same as the mean building temperature. The value of $\sigma_{\dot{T}_B}$ was computed from the complaint and resultant temperatures for humidity and air motion complaints and the difference between the complaint time and the resolution time. The resultant temperature is the temperature recorded by the maintenance technician after the problem causing the complaint had been fixed. The resolution time is the time at which the resultant temperature was recorded. Only the complaints for which either no action was taken or no action could be taken by the time that the complaint was resolved were used so that the temperature changes represented "normal" variations in building space temperature. The value of σ_{T_B} was estimated by numerically determining the value that makes the estimated ratio of the complaints logged in the morning (prior to 10 a.m.) to the total number per day equal to the measured ratio. The nominal area per zone was computed by searching the database for the number of unique complaint locations and dividing the total plan area of the facility by this count. This method assumes that complaints have been observed from every thermal zone at least once, and that different locations recorded in the database are in fact in different thermal zones. More details about the original calibration can be found in Federspiel (2000).

METHODS

In this section, we describe methods used to identify buildings, collect data, analyze data, and protect the confidentiality of human subject data.

Identification of Buildings

We contacted three organizations that manage a large number of nonresidential, nonindustrial buildings and that use modern computerized maintenance management systems (CMMS) containing records of hot and cold complaints. One of these organizations had a set of 143 buildings from which to choose. A second organization had a set of 107 buildings from which to choose. The third organization had a set of six buildings from which to choose. Ultimately, the second organization with the 107 buildings was unable to participate in the study. From the two remaining organizations, we selected eight buildings for the study that included two with pneumatic controls, a large range of sizes, and (based on a pre-analysis of the CMMS data) a wide range of complaint rates. We found that the control system infrastructure was inadequate in two of these buildings, so they were dropped from the study. We later found that hot/cold complaint data were no longer recorded in another one of the original eight buildings, so we dropped that building from the study. These two organizations use the same kind of CMMS system.

A fourth organization approached us with an interest in participating. We included one building from that organization because they sometimes recorded complaint temperatures when responding to temperature complaints. Most maintenance organizations do not record the building space temperature in the maintenance database.

Table 1 shows characteristics of the six buildings in the study.

Table 1. Building Characteristics

Building Label	A	B	C	D	E	F
Organization Number	1	2	1	2	3	1
Area, 100K ft^2	0.6	1.08	2.84	5.42	6.33	7.98
Location	Seattle	SF Bay Area	Seattle	SF Bay Area	Minneapolis	Seattle
Type	Lab/Office	Office	Office	Office	Bank/Office	Office

Data Collection

We collected temperature time-series data and CMMS data. The CMMS data contained records of hot and cold complaints.

Temperatures. We collected temperature time-series data with a between-sample interval of five minutes for all buildings. For each building, we collected temperature data for intervals of at least three weeks. For Buildings E and F, we collected temperature time series twice—once during the winter and once during the summer. All temperature time series were recorded during 2001. In Buildings A, C, D, and F, we used the existing direct digital control (DDC) system to record temperatures. In Buildings B and E, we used micro-dataloggers to record temperatures. Table 2 shows the temperature data collection parameters.

Complaint Data. Organization 1 operates a centralized CMMS call center that occupants of Buildings A, C, and F used to report service requests, which include hot and cold complaints. The call center agents create a work order in the CMMS system, enter data in the DESCRIPTION field in the database, and contact the appropriate maintenance personnel about the service request. The maintenance personnel complete the ACTION field in the database before closing the work order. One field in the CMMS data from Organization 1 contained a label called HOT/COLD. Starting in January 2001, they separated HOT from COLD to make our work easier.

Occupants of Buildings B, D, and E called the local maintenance department to report hot and cold complaints. The maintenance personnel created a new work order, inserted the DESCRIPTION data, performed the required work, inserted the ACTION data in the database, and then closed the work order.

Complaint data were supplied to us as spreadsheet tables exported from CMMS databases or converted to another database format that was easier for us to use. We performed a semi-automated search of the CMMS data from each building for hot and cold complaint records, running queries on the DESCRIPTION and ACTION fields for “hot,” “warm,” “boiling,” “cold,” “cool,” and “freezing.” For buildings from Organization 1, we did not rely exclusively on the HOT and COLD labels.

For some of the buildings, the number of hot and/or cold complaints during the temperature monitoring intervals shown in Table 2 was low. In these cases, we extrapolated beyond the temperature monitoring interval in both directions equally until we either observed at least five complaints of each type or until the extended interval was equal to twice the temperature monitoring interval. Table 3 shows the intervals used for counting complaints. The complaint counting intervals for Buildings A, B, D, E, and Interval 2 of Building F were extended in this way.

Table 2. Characteristics of Temperature Time Series

Building Label	A	B	C	D	E	F
Source	DDC	Logger	DDC	DDC	Logger	DDC
Init. points	52	50	39	172	169/110	272/272
Final points	51	49	39	136	152/88	187/187
Interval 1	Jan 10 – Apr 19	Jan 8 – Feb 4	Feb 23 – May 16	Feb 2 – Mar 21	Jan 21 – Feb 16	Mar 26 – May 12
Interval 2	-	-	-	-	Aug 23 – Sep 25	Aug 1 – Aug 24

Table 3. Complaint Counting Intervals for Each Building

Building	A	B	C	D	E	F
Interval 1	Dec 18 – May 2	Dec 25 – Feb 18	Feb 23 – May 16	Jan 9 – Apr 14	Jan 17 – Feb 20	Mar 26 – May 12
Interval 2	-	-	-	-	Aug 12 – Oct 7	Jul 27 – Aug 29

During January 2001, rolling blackouts were occurring in California. These conditions probably caused the number of complaints in the two California buildings to be lower than normal because well-documented energy conservation efforts were in place, and occupants were likely to comply with them because of the severity of the energy crisis. The energy conservation measures involved increasing the thermostat deadbands, among other things. In Building A, there was just one complaint recorded during the extended interval, whereas there was an average of 12.5 complaints recorded during this same interval in previous years. We used the data from the two previous years for the Building A count. We did not rely on previous years for Building D because it is a relatively new building, so significant changes in operations could have occurred since the previous year.

Analysis

Calibration. When DDC systems were used to collect temperature data, we performed a single-point calibration of the thermostat. When micro-dataloggers were used to record temperatures, we used a two-point calibration procedure: once in an ice bath and once at room temperature. Dataloggers that were found to be out of calibration were not recalibrated. Instead they were not used.

Descriptive Statistics. For each time series, we computed the minimum, mean, median, maximum, standard deviation, and standard deviation of the rate of change for every time series in the study. For time series from DDC trend logs, we also computed the calibration error. We used the calibration error to correct the mean values.

We computed the standard deviation of the rate of change using the following equation:

$$\sigma_{\dot{T}} = \frac{\pi \sigma_T}{T} N \tag{13}$$

where T is the interval over which temperature measurements were recorded, and N is the number of crossings of the mean level. It is equivalent to Equation 1, except that the rate in Equation 1 is replaced by the number divided by the interval, and the equation is rearranged so that the standard deviation of the rate of change is alone on the left-hand side.We used the sample standard deviation in Equation 13. This method assumes that the temperature time series are normally distributed.

Time Constant. Thermostats are known to have a long time constant relative to the external temperature probes used in Buildings B and E. To account for the difference between the time response of the thermostats and the data loggers, we adjusted the values of the standard deviation of the rate of change of the time series acquired from the thermostats using the method described in Federspiel et al. (2003). This procedure eliminates the time lag associated with the thermostat.

Parameter Estimation. We adjusted the coefficients of the original model using a cost function that penalized differences between the observed data in this study and PACE and using deviations of the coefficients from those of the original model. We used a sequential quadratic programming algorithm to make the adjustments. The penalty function we used is as follows:

$$V = (V_c + V_d)(1 - \alpha) + \alpha\beta V_p \tag{14}$$

where

$$V_c = \sum_i |N_{o,h} - PACE_h|_i + \sum_i |N_{o,l} - PACE_l|_i \tag{15}$$

$$V_d = \sum_i |(N_{h,o} - N_{l,o}) - (PACE_h - PACE_l)|_i \tag{16}$$

$$V_p = \sum_i \frac{|P_{o,i} - P_{n,i}|}{S_i} \tag{17}$$

and where N_o is the observed number of hot or cold complaints, $PACE_h$ is the predicted number of hot complaints, $PACE_l$ is the predicted number of cold complaints, $N_{h,o} - N_{l,o}$ is the observed difference between the number of hot and cold complaints, $PACE_h - PACE_l$ is the predicted difference between the number of hot and cold complaints, P_o are the original values of the parameters of the model, P_n are the new values of the parameters, and S is the parameter used to scale the differences between original and new parameters. The value of β was chosen so that when the coefficients of the model equal the original values of the model, then $\beta = (V_c + V_d)$. We used the largest value of α that resulted in a statistically significant model. Table 4 shows the values used for parameter estimation.

We included the absolute difference between the original coefficients and the estimated coefficients for two reasons. First, we found that without the term with the original coefficients, there could be a wide range of estimates that would produce nearly identical error performance. Adding the difference between the estimated and original coefficients is sometimes called regularization. It is used to induce a unique solution on problems that could otherwise have a non-unique solution. Morozov (1993) describes regularization methods for a wide variety of problems. Brown (1993) describes the use of regularization for regression problems. The second reason for using the original parameters in the penalty function is that the original calibration provides some information about the best coefficients of the model; we should not just throw that information away. There are formal methods, such as those that use the Bayes theorem, for using prior information. However, they require more prior information than was available. Both Morozov (1993) and Brown (1993) discuss the relationship between regularization and Bayes estimators.

Table 4. Values of Coefficients Used for Parameter Estimation

i	1	2	3	4	5	6	7
Label	A, ft^2/zone	Mean μ_{T_L}, °F	St. Dev. σ_{T_L}, °F	St. Dev. $\sigma_{\dot{T}_L}$, °F/h	Mean μ_{T_H}, °F	St. Dev. σ_{T_H}, °F	St. Dev. $\sigma_{\dot{T}_H}$, °F/h
P_o (original parameters)	2209	54.5	4.39	3.69	91.0	4.24	0.84
S (scaling parameters)	2209	4.39	4.39	3.69	4.24	4.24	3.69

RESULTS

Descriptive Statistics

Figure 3 shows descriptive statistics of the temperature in each of the six buildings during the one or two monitoring intervals for each building. The lower end of the whiskers corresponds to the 5% quantile of the temperatures from all locations and all times in that building and monitoring interval. The upper end of the whiskers corresponds to the 95% quantile. The dash along the whisker corresponds to the median.

The figure illustrates that from building to building there was a moderate variation in the median temperature and a larger variation in the spread of the temperatures over space and time (11°F). The difference between the highest median and the lowest median was 3.9°F, while the difference between the largest interquantile difference and the smallest was 11°F.

Accuracy of Original Model

After computing the descriptive statistics, we computed the estimated number of complaints of each kind for each building and compared them with the observed number of hot and cold complaints from each building. Table 5 shows the number of observed hot and cold complaints for each building during each interval. E1 and F1 correspond to Interval 1 in Table 3. E2 and F2 correspond to Interval 2 in Table 3. Figure 4 shows the number of hot and cold complaints from each building plotted versus the number predicted by the original model. The size of the letters corresponds to the kind of complaint (hot is large, cold is small). The letter corresponds to the building.

The two small points on the right-hand side are from Buildings B and D. These data points may have been affected by the blackouts that were occurring in California in late 2000 and early 2001. Operations personnel made changes intended to reduce energy consumption, and they

Table 5. Observed Hot and Cold Complaint Counts

Building	A	B	C	D	E1	E2	F1	F2
Cold	6	25	16	6	5	2	18	5
Hot	6	0	25	13	10	9	10	8

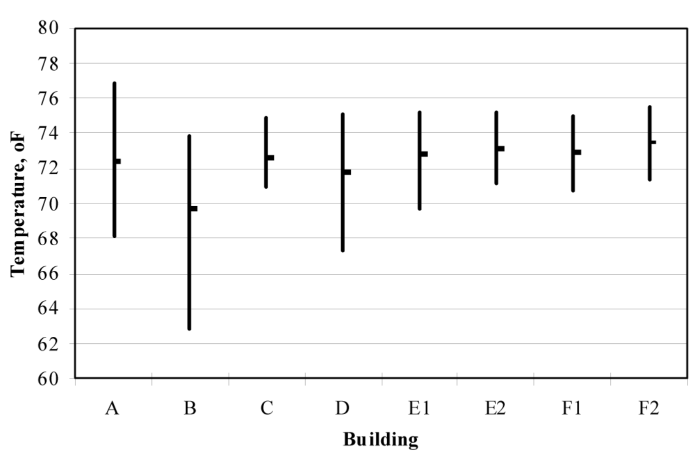

Figure 3. Descriptive statistics of temperatures in each building during each interval.

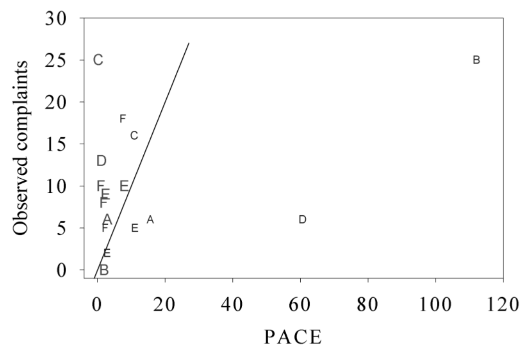

Figure 4. Observed number of complaints versus PACE of original model.

posted notices about their actions that were designed to elicit cooperation (i.e., reduce complaints) from occupants. For Building B, we used complaint counts from the two previous years to avoid the impact that the notices may have had on the human response in that building. However, the operations personnel did not use the energy conservation measures during the two previous years, so exposures during those periods were probably less extreme than during the monitoring interval. These data points may also be affected by the fact that Organization 2 uses a "catch-all" labor category in their CMMS system for short jobs that are not considered important enough to warrant a work order of their own. Hot or cold complaints handled this way would be lost from the count. The chief engineers in Buildings B and D told their employees not to use the catch-all category for hot or cold complaints, but they said that it still may have happened some of the time. It seems even more likely considering that another building from Organization 2 had to be dropped from the study because all of the hot and cold complaints in that building during 2001 were fielded using the catch-all labor category. We flagged these two points as outliers and removed them from further analyses.

The large point in the upper-left corner of Figure 4 is from Building C. Building C is a converted industrial building with a combination of pneumatic and digital controls. The point density in this building is low, which makes it more likely that hot spots were missed by incomplete sampling of the temperature distribution in this building. Consequently, we flagged this point as an outlier and removed it from further analyses.

We did not remove the hot complaint data from Buildings B and D or the cold complaint data from Building C because they do not appear to be outliers, and we did not want to eliminate any more data than necessary.

Figure 5 shows the observed complaints versus PACE using the original model with the three outliers removed. The figure shows that the correlation between the observed complaints and PACE is low ($r = 0.19$) and not statistically significant ($p = 0.27$), and that the model is underpredicting the number of hot complaints.

Figure 6 shows the actual relative complaint rate (number of hot complaints minus the number of cold complaints divided by the total) versus the predicted relative complaint rate. The relative complaint rate is a measure of hot versus cold. Negative values correspond to persistently cold conditions, while positive values correspond to persistently hot conditions. One of each of the two points corresponding to Buildings B, C, and D were flagged as outliers earlier. The graph shows that the observations covered a wide range on this scale, from –1 for Building B to 0.63 for Building E. The graph shows that the original model is underpredicting the number of

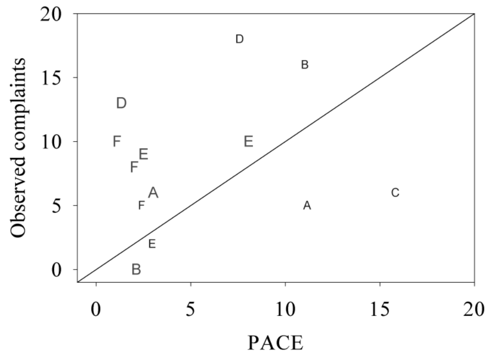

Figure 5. Observed complaints versus PACE of original model with outliers removed.

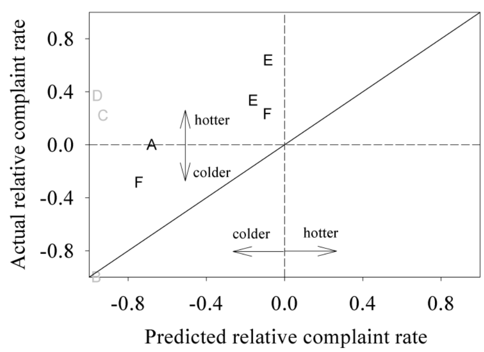

Figure 6. Predicted versus actual relative complaint rate for original model.

hot complaints relative to the number of cold complaints. The largest differences are Buildings C and D, which were flagged as outliers in Figure 4. The other outlier building is B. The low cold complaint count doesn't significantly affect the ratio plotted in Figure 6 because zero hot complaints were observed. The relative loss of data would be small.

Parameter Estimation

Using the method described above under "Parameter Estimation," we recalibrated the original model to improve the fit to the observed data. Figure 7 shows the predicted versus actual complaint counts, with the two outliers removed (analogous to Figure 5). The correlation is not high (r = 0.49), but it is higher than that of the original model, and it is statistically significant (p = 0.044). The coefficient of variation (CoV, standard deviation of prediction error divided by the mean of the actual counts) is 57%.

Figure 8 shows the predicted versus actual relative complaint rate for the recalibrated model. The agreement is significantly better than the original model. The correlation coefficient for the five points not flagged as outliers and Building B is r = 0.94.

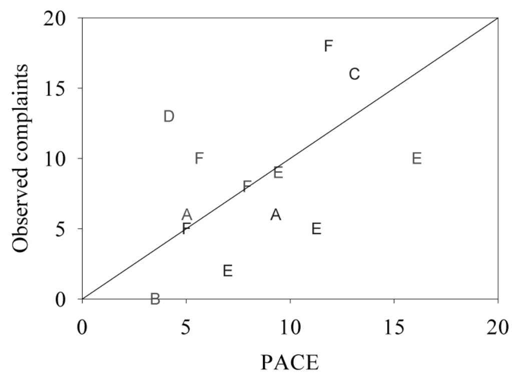

Figure 7. Observed number of complaints versus PACE for the recalibrated model.

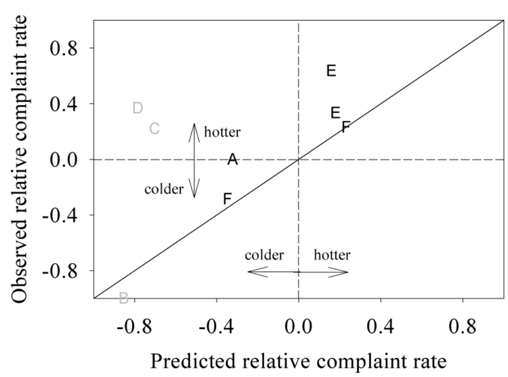

Figure 8. Predicted versus actual relative complaint rate for recalibrated model.

Table 6. Parameters of Original and Recalibrated Model

Parameter	A, ft^2/zone	Mean, μ_{T_L}, °F	St. Dev. σ_{T_L}, °F	St. Dev. $\sigma_{\dot{T}_L}$, °F/h	Mean, μ_{T_H}, °F	St. Dev. σ_{T_H}, °F	St. Dev. $\sigma_{\dot{T}_H}$, °F/h
Original	2209	54.5	4.39	3.69	91.0	4.24	0.84
Re-cal	4657	50.43	6.14	4.08	91.0	5.06	1.14

Table 6 shows the parameters of the original model and the parameters of the recalibrated model. All four standard deviations increased. The standard deviations associated with the cold complaint level are both greater than the standard deviations associated with the hot complaint level. This may be related to the fact that there is a hard limit to how much occupants can reduce clothing insulation to deal with hot stress, but there is no hard limit to how much they can increase it to deal with cold stress, and likewise for metabolism.

Figure 9 shows the complaint rate predicted by the original model and the recalibrated model as a function of mean temperature when the standard deviation of the temperature is 0.98°F and the standard deviation of the rate of change is 0.90°F/h. These were the average values for the time series from the first temperature-monitoring interval in Building F. The recalibrated model

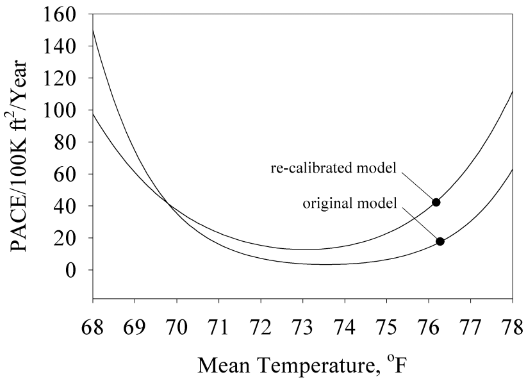

Figure 9. Comparison of original and recalibrated model.

predicts that the mean temperature, which will minimize complaints, is lower than that of the original model (73.1°F versus 73.6°F), and that the minimum number of complaints is greater than the original model.

Model Validation

Complaint Temperatures. In Building E, the maintenance personnel would sometimes record complaint temperatures either by reading the digital thermostat, by reading a temperature from a handheld meter once on site, or both. In Building F, the maintenance personnel agreed to record complaint temperatures during the first temperature-monitoring interval. We used these data to validate the model. Note that these data were not used to calibrate the model.

We compared the mean and variance of the complaint temperatures predicted by the recalibrated model with the sample mean and variance from each building. Note that these are not the same as the mean and variance of the complaint levels. All complaint temperatures and relevant statistics can be found in Table 7. The upper and lower limits are based on 95% confidence intervals. In Building E, only two hot complaint temperatures and zero cold complaint temperatures were recorded during the monitoring interval. In Building F, eleven cold complaint temperatures and six hot complaint temperatures were recorded during the monitoring interval. Means were compared using a single-sample t-test. Variances were compared using a chi-squared test. All six predicted statistics fall within the confidence intervals.

Effect of Temperature Setup. In Building E, the facility management has a standard setpoint policy of 74°F. The management decided to raise this standard setpoint during the summer of 2001 to 77°F for energy conservation reasons. The controls have a deadband of 0.5°F above the setpoint and 1.5°F below the setpoint, meaning that cooling was not enabled until the temperature was above 74.5°F (before setup) or 77.5°F (after setup), and heating was not enabled until the temperature was below 72.5°F (before setup) or 75.5°F (after setup). During the set-up period, heating was turned off. The energy-saving policy was in effect for one month. After that, the policy was reversed because of complaints from some occupants. According to the chief engineer, trend logs indicated an average building temperature of 76.4°F during the setup period. We found that the average calibration error for Building E during the summer of 2001 was –0.49°F, indicating that the average temperature was probably 75.9°F.

Table 7. Complaint Temperatures and Statistics

Building	Building E	Building F	
Interval	Aug 12 – Oct 7	Mar 26 – May 12	
Complaint Temperature	T_h, °F	T_l, °F	T_h, °F
1	75.1	71	72
2	78.9	73.15	72
3	–	71	73
4	–	67	71
5	–	73.17	74
6	–	71.5	74
7	–	71.23	–
8	–	70	–
9	–	72	–
10	–	71	–
11	–	68	–
Mean	77	70.82	72.67
Pred. mean	73.54	72.03	73.23
Lower. limit	52.8	69.54	71.40
Upper limit	101.1	72.10	73.94
Std	2.69	1.90	1.21
Pred. Std.	1.24	1.41	1.36
Lower limit	1.20	1.33	0.76
Upper limit	85.7	3.34	2.97

Table 8. Complaints Before, During, and After Setpoint Change

duration	hot	cold	total
4/19/01 through 5/16/01 (setpoint = 74)	12	2	14
5/17/01 through 6/14/01 (setpoint = 77)	26	3	29
6/15/01 through 7/12/01 (setpoint = 74)	10	5	15

Table 8 shows the number of complaints recorded in the maintenance database for the month prior to increasing the setpoint, the month that the setpoint was raised, and the month following the reversal of the set-up policy. The table reveals that there were more hot complaints during the period when the setpoint was 77 than the months before or after. We used a statistical test described in Fleiss (1981) to determine if the difference was statistically significant. The test statistic for the hot complaints was 12.3. The critical value for a 95% confidence interval was 1.645, which implies that the increase in the number of hot complaints during the month when the setpoint was raised was highly statistically significant ($p \sim 0$).

The results provide strong evidence that increasing the temperature increased the hot complaint rate. The number of hot complaints increased by a factor of 2.4. If we assume that the variance of the temperature and the variance of the rate of change during the interval from April 19 through July 12 were the same as during the interval from August 23 through September 25, then the model predicts that the number of hot complaints should have increased by a factor of 5.3, which is about twice the observed increase. We asked the chief engineer about the discrepancy between the two ratios. His response was: "I think the number of complaints were underreported, as there were so many of them that the guys would 'lump them together' under one work order (at best) and possibly just didn't record them. It does not surprise me if your model would predict the complaint quantity should be higher."

DISCUSSION

Practical Evaluation of Accuracy

The degree of correlation between observed and predicted complaint counts for the original model was not high (r = 0.49), so we compared the accuracy of the complaint prediction model with the reported accuracy of energy models and comfort models to establish benchmarks.

Accuracy of Energy Models. We anticipate that the complaint prediction model will be used in conjunction with energy models. If one of the two is much more accurate than the other, then the accuracy of any decisions arising from using both would be dependent on the accuracy of the worst of the two. Therefore, the accuracy of energy models becomes a practical benchmark for the accuracy of the complaint prediction model.

Neymark and Judkoff (2002) describe the results of the International Energy Agency's efforts on benchmarking the performance of energy models. Their results show that the coefficient of variation (CoV) of the differences between seven models is approximately 10%.

Errors in predicting actual energy use can be large. Norford et al. (1994) found that *uncalibrated* energy predictions and actual energy consumption could differ by a factor of two. This would correspond to a coefficient of variation (standard deviation of prediction error divided by mean of actual value) of 100%. These errors are due to a combination of inaccurate input data and poorly characterized systems.

The accuracy of calibrated models has been assessed in two "energy predictor shootouts." These shootouts were contests in which contestants competed for who could design an energy predictor that would give the best match to an unknown "validation" data set from a building given a training set. All contestants received the same training set, and all were evaluated on how well they predicted the validation set. In the first shootout, summarized by Kreider and Haberl (1994), contestants were required to predict hourly consumption of electricity, hot water, and chilled water during a test period. No descriptions of the building or other specific details about the data were provided. Twenty-one contestants submitted predictions. The CoV of the predictions (mean squared prediction error divided by the mean of the variable being predicted) submitted by the contestants ranged from 3% to 66% depending on the variable, data set, and contestant. The average CoV ranged from 10% for the best contestant to 30% for the worst. In this shootout, the best predictors were neural networks, not models based on first principles. Neural networks are nonlinear models constructed from an interconnected network of simple functions. They were originally developed to mimic the behavior of neurological networks such as the brain. They have been widely used for engineering applications. See Kosko (1992) for background information on neural networks.

In the second shootout, summarized by Haberl and Thamilseran (1998), contestants were given pre-retrofit and post-retrofit energy data and asked to predict some pre-retrofit data that were withheld. Four contestants submitted predictions for five variables from two buildings. The CoV ranged from 3% to 56% depending on the building, variable, and contestant. The average CoV ranged from 17% for the best contestant to 30% for the worst. In this shootout, the best models were neural networks and statistical models.

The CoV of the recalibrated complaint model, which is 57%, is within the range of CoVs reported for energy models, though it is greater than the average CoVs of calibrated energy models.

Accuracy of Comfort Models. Another benchmark for the accuracy of the complaint prediction model is the accuracy of comfort models; de Dear et al. (1997) used linear regressions to relate neutral indoor operative temperature to mean outdoor effective temperature. For naturally ventilated buildings, they found that the correlation coefficient relating the two was $r = 0.65$. They also compared predicted neutrality based on PMV calculations to mean outdoor effective temperature. For naturally ventilated buildings, they found that the correlation coefficient relating predicted neutrality to mean outdoor effective temperature was $r = 0.55$. The former relationship is being proposed as the basis of an alternative for naturally ventilated buildings in ASHRAE Standard 55.

The correlation coefficient of the recalibrated complaint model is only slightly lower than the correlation coefficient for neutral temperature predicted using PMV. Given the fact that complaint counts were recorded as part of the normal process of operating buildings, and not by researchers, the accuracy seems comparable to the accuracy of adaptive comfort models.

Impacts of Clothing, Metabolism, and Other Factors

The complaint prediction model is based entirely on the statistical behavior of indoor air temperature. It does not explicitly use other factors, such as clothing and metabolism, even though they influence thermal comfort. This is intentional. Building designers do not know *a priori* what building occupants will wear or how much metabolic power it will take them to perform their work except in very general average terms. Building operators cannot continually survey occupants to see what they are wearing or how much they are exerting. They can continually monitor temperature, but sensors to measure radiant temperature, air velocity, and even humidity are rare in commercial buildings.

It is well known that clothing levels are correlated with outdoor temperature and that indoor velocities are also correlated with outdoor temperature. De Dear et al. (1997) provide empirical functional relationships between clothing estimates and mean outdoor temperature and indoor velocity measurements and mean outdoor temperature. We tried models in which the mean complaint levels were linearly dependent on mean outdoor temperature. The thinking is that the mean values of both complaint levels should be higher when it is warmer outdoors because occupants are wearing less clothing and indoor air velocities are higher.

The mean outdoor temperatures for the buildings and data collection intervals are shown in Table 9. There was a wide range of outdoor temperatures because of seasonal and geographical differences.

We did not find that mean outdoor temperature improved the predictive capability of the model. The parameter estimator generally selected coefficients for the relationship between mean complaint level and mean outdoor temperature that were close to zero. It is possible that the minimum or maximum clothing that people can wear to avoid discomfort is less dependent on outdoor temperature than the clothing that they routinely wear under normal conditions. Although indoor velocity is correlated with outdoor temperature, the influence in buildings with HVAC is small. These factors, combined with the fact that the complaint data in this study are very noisy, may explain why there seems to be no influence of mean outdoor temperature on mean complaint levels.

Table 9. Average Temperatures (°F) for the Monitoring Intervals

	A	B	C	D	E	F
Interval 1	44.0	48.0	47.7	54.0	15.9	49.7
Interval 2	-	-	-	-	54.0	64.8

De Dear et al. (1997) found almost no correlation between mean outdoor temperature and estimated metabolic rates. However, metabolic rates can vary substantially as task requirements change. Walking from one part of a building to another can increase metabolic power considerably over the power required to sit still and read a document.

The complaint prediction model distinguishes between complaints that occur on arrival and those that occur during the normally occupied period of the day. An arrival complaint occurs when the temperature is either higher than the hot complaint level or lower than the cold complaint level when the occupants arrive in the morning. This is different from an operating complaint, which occurs during the occupied period of the day when the temperature crosses above the hot complaint level or below the cold complaint level.

On arrival, occupants will generally have a higher metabolic power than during the occupied period because they were just walking. We compared arrival complaints with operating complaints in two ways. Figure 10 shows how arrival complaint rates and operating complaint rates are influenced by the mean value of the indoor temperature. The values of σ_T and $\sigma_{\dot{T}}$ used in Figure 10 are the same as those used in Figure 9.

There are three important features. The first is that the arrival complaint rate is much lower than the operating complaint rate. This is consistent with data reported by Federspiel (2001), which show that the complaint rate is highest in the first half of the morning but that the extra early-morning complaints are a minor fraction of the total number of complaints.

The second feature is that arrival complaints are less sensitive to the mean indoor temperature than operating complaints, and the third feature is that the mean indoor temperature that minimizes the frequency of arrival complaints is lower than the mean indoor temperature that minimizes operating complaints. Both of these features are consistent with an influence of metabolic rate on complaint behavior. Since metabolic rates are higher at arrival time, the optimal temperature at that time should be lower. Furthermore, the sensitivity of thermal comfort metrics such as PMV to temperature is less at elevated metabolic rates. That fact is consistent with the reduced sensitivity of arrival complaints to mean indoor temperature.

Figure 11 shows the mean indoor temperature that minimizes arrival complaints and operating complaints. With perfect control (standard deviation zero), the temperature that minimizes the frequency of arrival complaints is 0.7°F degree lower than the temperature that minimizes operating complaints. The difference grows to 1.2°F as the standard deviation of the temperature grows to 4°F.

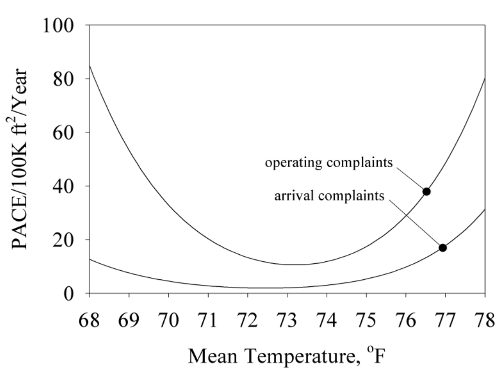

Figure 10. Comparison of arrival complaint rate with operating complaint rate.

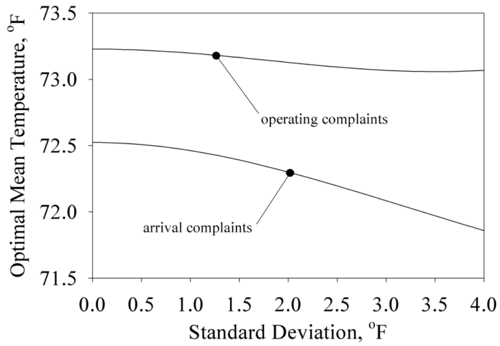

Figure 11. Mean temperatures that minimize arrival and operating complaints.

The fact that the optimal mean temperature for arrival complaints differs from that of operating complaints has important implications for building control and operation. It implies that buildings should be slightly cooler at the start of the work day than later in the day. Optimal night setback strategies are typically designed to return the building temperature to its fixed operating level at the time that occupants arrive. The complaint prediction model predicts that doing so is suboptimal. When heating, temperatures should be set to a lower level at night and over the weekend. The controls should return the temperature to a level that is approximately 1°F lower than the operating temperature at the arrival time. Doing this will reduce discomfort and reduce energy consumption. When cooling, the building should be precooled so that the arrival temperature is approximately 1°F lower than the operating temperature, and the temperature should be allowed to float up to the operating temperature. Doing so will reduce discomfort and shift cooling loads to an earlier part of the day. Rabl and Norford (1991) and Morris et al. (1994) describe strategies for precooling buildings. Future work should include the use of the complaint prediction model in optimal alarm, optimal control, and optimal design of buildings.

The original model was calibrated with data from a hot and humid climate. The coefficients from the original model were used as the starting point for the recalibration, so the model now is based on a wide range of climatic conditions. We feel that it is broadly applicable to mechanically conditioned buildings.

CONCLUSIONS

The complaint prediction model originally proposed by Federspiel (2000) was analyzed and recalibrated with data from six buildings in three new geographical areas comprising a total of 2.4 million ft^2 of floor space. The significant findings from this study are as follows:

1. The recalibrated model predicts lower optimal mean temperature than the original model.
2. The recalibrated model predicts higher minimum complaint rates than the original model.
3. The recalibrated model is more asymmetrical than the original model. The hot complaint rate increases faster with increasing temperature than the cold complaint rate increases with decreasing temperature.
4. The accuracy of the model is comparable to the accuracy of uncalibrated energy models and field measurements of neutral temperature.
5. The model predicts that optimal mean temperature when occupants arrive in the morning is about 1°F lower than the optimal operating temperature later in the day.

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