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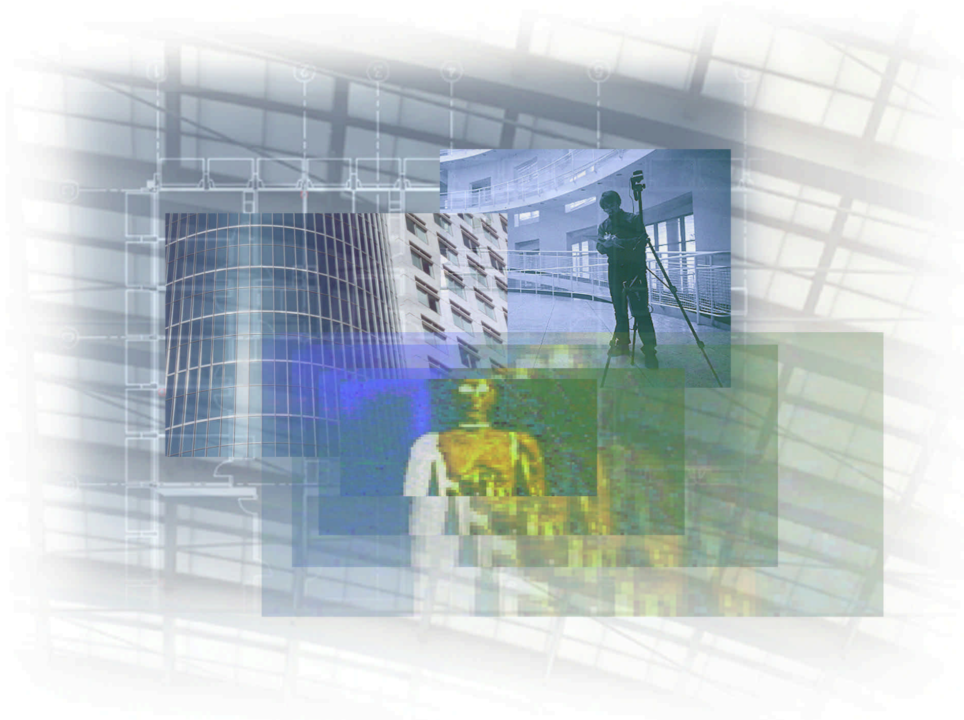

Thermal Comfort Models and Complaint Frequencies

Summary Report, April 2003

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EXECUTIVE SUMMARY

This report describes the results of a study designed to assess the accuracy of the complaint prediction model proposed by Federspiel (2000), and to re-calibrate it if necessary. The complaint prediction model predicts the average number of hot and/or cold complaints per square foot per year as a function of the statistical behavior of the indoor temperature. The significance of the model is that it allows us to quantitatively assign economic cost to thermal discomfort in buildings because the operations and maintenance labor cost associated with handling thermal complaints can be accurately quantified.

We collected temperature time series data from six buildings ranging in size from 60,000 square feet to 800,000 square feet. They were located in the Seattle, San Francisco, and Minneapolis areas. In two of the buildings we collected temperature time series twice, once during the winter and once during the summer. In the other four we collected the temperature time series just once. All six buildings used a computerized maintenance management system (CMMS). We determined the number of hot and cold complaints during each temperature monitoring interval from the CMMS data.

We found that the original complaint prediction model does not accurately predict complaint rates. It under-predicts the number of hot complaints, and the correlation between the number of observed and predicted complaints is low and not statistically significant. We re-calibrated the model and improved the match between predicted and observed complaint counts. For the re-calibrated model, the correlation coefficient between observed and predicted complaint counts is $r = 0.49$. This degree of correlation, though not high, is statistically significant ($p<0.05$).

There are three primary differences between the original model and the re-calibrated model. The re-calibrated model predicts that the temperature corresponding to the minimum number of complaints is lower than that of the original model. The re-calibrated model also predicts that the minimum number of complaints is greater than that of the original model. Finally, the re-calibrated model is not symmetrical. The re-calibrated model predicts that hot complaints will increase faster as the average temperature rises than will cold complaints as the average temperature decreases. This is a result of the variances associated with the cold complaint threshold being larger than the variances associated with the hot complain threshold. Larger variances for the cold complaint threshold may be due to the fact that behavioral adaptation to hot conditions by reducing clothing and metabolism are strictly limited, whereas the opposite adjustments in response to cold are not.

From the coefficients of the model, we can estimate the mean and variance of the temperatures at which occupants will complain it is too hot or too cold. In two of the buildings in the study these temperatures were sometimes available. We compared the predicted complaint temperature statistics to the hot complaint temperature statistics from one building and both the hot and cold complaint temperature statistics from the second building. This resulted in six tests of the model. We found that the differences between the predicted and computed complaint temperature statistics were not statistically significant in all six cases.

In one of the buildings the management independently decided to raise the building temperature by 3 °F during the summer of 2001 to save energy. They did this for one month, then reversed the policy because of complaints from occupants. We compared the complaint rate before and after the setup period with the complaint rate during the setup period. The hot complaint rate during the setup period was 2.36 times higher than the hot complaint rate before and after the setup period. This difference was statistically significant ($p \sim 0$). There were not enough cold complaints recorded during these periods to conduct a statistical test, but the cold complaint rate during the setup period was lower than before and after. The hot complaint rate after the setup period was nearly identical to the hot complaint rate before the setup period. The re-calibrated model predicted that the hot complaint rate during the setup period should have been 5.25 times higher than the hot complaint rate before and after the setup period. We asked the Chief Engineer at this building about the discrepancy between the two ratios. His response was “I think the number of complaints were under-reported 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.”

As benchmarks of model accuracy, we investigated the accuracy of energy prediction models and thermal comfort models. We found very little information on the accuracy of energy prediction models. A report published by the National Renewable Energy Laboratory (NREL) showed that when different energy models are used to predict energy consumption of the same building, the variation among the energy models is 10%. The accuracy was slightly worse for cases that involved the influence of indoor temperature on energy consumption. The scant information available comparing energy models to real energy consumption indicates that uncalibrated predictions may be off by as much as a factor of two (coefficient of variation, CoV of 100%) due to a combination of inaccurate input data and poorly characterized systems. Calibrated predictions have CoVs from a few percent to as much as 66%. For thermal comfort models, the correlation between predicted neutral temperature and outdoor effective temperature, described in ASHRAE RP-884, is $r = 0.65$ or $r = 0.55$, depending on how neutral temperature is calculated. This correlation is now the basis for an adaptive thermal comfort procedure in ASHRAE Standard 55. Given the fact that the complaint count data in this study were not recorded by researchers as were the thermal comfort surveys in RP-884, the correlation between predicted and observed complaint counts seems reasonably good.

We give examples of three ways that the complaint prediction model can be used for design, decisionmaking, and control of indoor temperatures in buildings. The model can be used to assess the cost-benefit analysis of engineering changes or retrofits designed to reduce complaints and discomfort by improving temperature control performance. Using the best control performance observed in this study as a benchmark for achievable performance, the complaint prediction model can be used to estimate the annual reduction in O&M cost achieved by reducing the variance of temperature controls. Variance could be reduced by replacing old controllers with newer technology or by tuning existing controllers.

We show how the complaint prediction model can be used to optimize indoor temperature settings. If the goal is to minimize the frequency of complaints, then the complaint prediction model can be used to determine the optimal average temperature that will achieve that goal. This temperature is called the minimum discomfort temperature (MDT). The model can also be used to determine the indoor temperature that will minimize the sum of energy cost and O&M cost of handling complaints. This temperature is called the minimum cost temperature (MCT).

Finally we show how MDT and MCT can be used as the basis of an economic criterion for thermal comfort standards. In the summer, operating a building at an average temperature greater than MCT or less than MDT is neither economical nor as comfortable as possible. Temperatures between MCT and MDT are a tradeoff between economics and comfort. We propose that MCT and MDT be used as the basis of upper and lower temperature limits for ASHRAE Standard 55. One advantage of this approach is that it eliminates the need to make arbitrary assessments of what constitutes “acceptable”. Current comfort standards are based on the assumption that a thermal sensation vote with a magnitude greater than 1 on a seven point scale from –3 to 3 is unacceptable. Another advantage of this method is that the upper and lower temperature bounds will be elastic functions of energy consumption and cost. Currently, thermal comfort standards specify a fixed level of comfort regardless of the energy required to deliver that comfort or the cost of energy. Since most energy codes and standards require an energy analysis, a standard based on MCT and MDT would not require significantly more engineering effort.

The important results of this study can be summarized as follows:

1. The re-calibrated model predicts lower MDT than the original model.
2. The re-calibrated model predicts higher minimum complaint rates than the original model.
3. The re-calibrated 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 can be used to perform cost-benefit analyses of retrofits and engineering efforts that would improve temperature control performance.
6. The model can be used to select optimal temperature at which to operate buildings.
7. The model can be used as the basis of an economic criterion for thermal comfort standards. Doing so eliminates the need to make arbitrary assessments of what constitutes “acceptable”, and allows the thermal comfort standard to be elastic with respect to the amount and cost of energy required to provide comfort.

1 INTRODUCTION

When building occupants become sufficiently hot or cold and have exhausted all ways of coping with their discomfort, they often complain to the facility manager. These complaint events are called unsolicited complaints because they are not solicited by the facility management as are complaints obtained through surveys.

This project was motivated by the fact that there is a substantial need for research relating the performance of HVAC systems to operating costs other than energy cost. In particular, we are interested in being able to quantify the value of 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 Jaakola et al. (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 of 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 the 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.

This study focused on quantitatively predicting the direct impact of HVAC system performance on maintenance cost. Unsolicited complaints contribute to the operation and maintenance (O&M) cost of buildings because they lead to a kind of unscheduled maintenance service request. In the most common scenario a technician is dispatched to the site to investigate the cause of the complaint and resolve the problem. In this scenario the cost of the complaint is at least equal to the cost of the technician’s labor. This study also focused indirectly on the impact of HVAC system performance and energy cost because factors that affect complaint cost also affect energy cost. Complaint behavior is affected by controlled environmental variables such as temperature. Indoor temperature also affects energy cost. If the relationship between indoor temperature and complaint rate could be predicted with reasonable accuracy, then decisions about building operations could be optimized so that the sum of maintenance and energy costs are minimized.

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 assessment of hot or cold above an absolute PMV level of 1.5 scale 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).

Complaint behavior in buildings has been studied much less than other processes that affect the operating cost of buildings such as energy usage, equipment reliability, and scheduled or predictive maintenance. This is in spite of the fact that hot and cold complaints have been shown to be the most common kind of maintenance service call (Federspiel, 1998), and a significant fraction (5.3 cents per square foot) of the cost of maintenance. Complaint behavior has also been studied much less than thermal comfort. Complaints are related to but not the same as thermal comfort. Therefore, a complaint model should be similar to but not the same as a comfort model. One difference lies in the fact that complaints are discrete events while discomfort is a state of being. This means that a complaint model should predict the frequency of occurrence, while a discomfort model should predict the degree of discomfort.

Unlike the relationships between HVAC system performance and health and productivity costs, the relationship between HVAC system performance and complaint cost can be predicted. Federspiel (2000) recently proposed a model that predicts thermal complaint rate 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 theory of stochastic processes that deals with a random processes crossing a level (Cramer and Leadbetter, 1967) was used to formulate the model. In the model, there are two levels, one representing tolerance for high temperatures and the other representing tolerance for low temperatures. When the space temperature crosses the high-temperature tolerance level, the occupants complain that it is too hot, and when the space temperature crosses below the low-temperature tolerance level, the occupants complain that it is too cold. A key difference between the levels of the complaint model and the levels of a standard control alarm is that the levels of the complaint model are random processes, while the levels of a control alarm are fixed and known. Modeling the levels as random processes accounts for the fact that occupants do not always complain at the same temperature every time. Since the levels are random processes and cannot be measured directly except at the instant that someone complains, the time in the future when someone will complain cannot be predicted. However, it is possible to predict the mean complaint rate, which is what affects the operating cost of a building.

The parameters of Federspiel's original model were determined using data acquired from a set of buildings at a single geographical location. The accuracy of the model has not yet been tested because the data required to assess the accuracy has not been acquired. The objective of this project was to evaluate the accuracy of the complaint model proposed by Federspiel (2000), and to improve it if necessary and possible so that it can be used for analysis purposes, economic decisions about the operation of buildings, or incorporated into standards such as ASHRAE Standard 55. The project involved collecting temperature time series and complaint data from buildings, analyzing the data, assessing the accuracy of the original model, re-calibrating the model, assessing the accuracy of the re-calibrated model, and demonstrating the model's practical use.

The next section contains a summary of the complaint prediction model (Federspiel, 2000). Section 3 describes the research methods used for this study. Section 4 contains the results, and Section 5 contains a discussion of those results and their applicability to design, operations, and thermal comfort standards.

2 COMPLAINT PREDICTION MODEL

Federspiel (2000) proposed a complaint prediction model in which unsolicited thermal sensation complaint 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.

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 one of the levels. For example, a hot complaint occurs when the building space temperature crosses above the high-temperature 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. It is by measuring the complaint temperatures along with the building space temperatures that we can estimate the statistical properties of the complaint levels.

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 the rounding to the nearest marking on the thermometer from which the temperatures were read.

To make analytical predictions, we assume that the three temperature distributions in Figure 1 are stationary (time-invariant statistics) and Gaussian. 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 non-stationary processes. The mean frequency that a stationary Gaussian processes crosses a fixed level L is determined from the following simple formula:

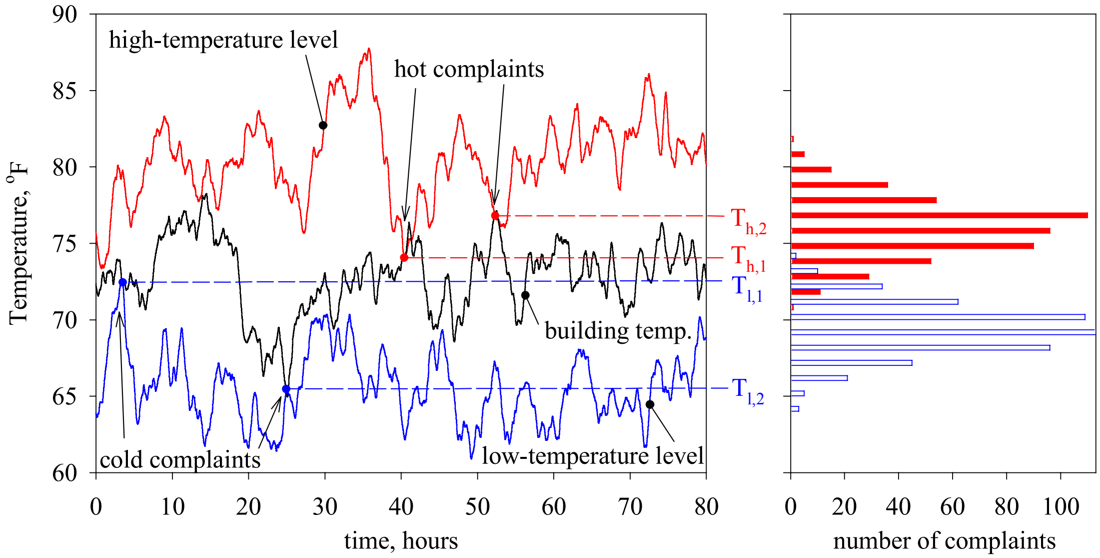

Figure 1: Thermal sensation complaint process model.

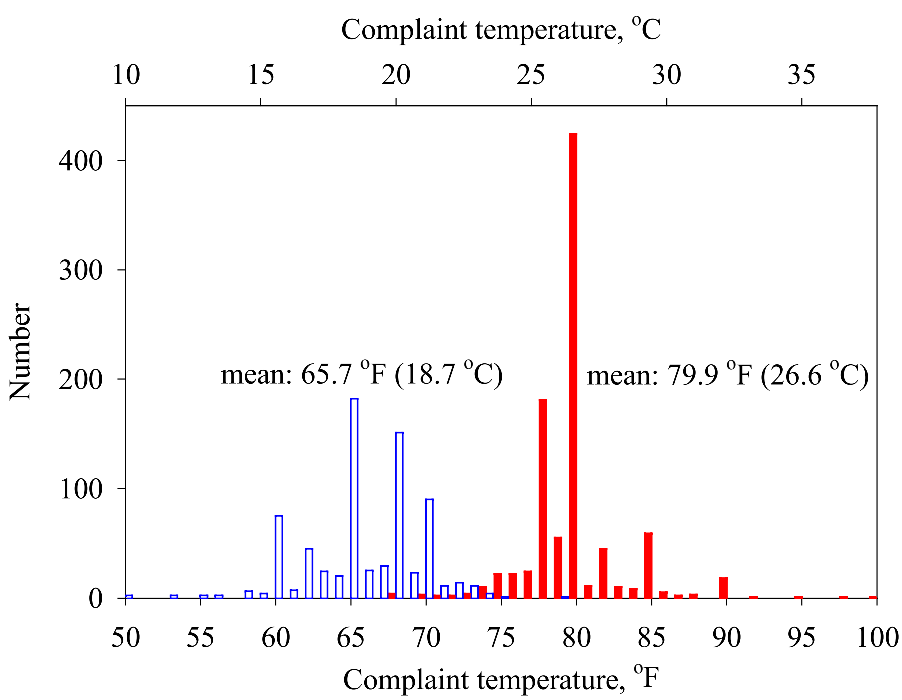

Figure 2: Temperatures at which occupants complained (Federspiel, 1998).

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

where x refers to the random process, ν_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 $\frac{\sigma_x}{\sigma_{\dot{x}}}$ is the nominal time constant of the process, and $\frac{\sigma_{\dot{x}}}{\sigma_x}$ is the bandwidth. If the process is oscillatory, then $\frac{\sigma_{\dot{x}}}{\sigma_x}$ 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 building 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.

Mathematically, the expected number of complaints per zone per day is as follows

$$E[n_h] = P_h + \nu_h t \tag{2}$$

$$E[n_l] = P_l + \nu_l t \tag{3}$$

where

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

$$P_l = \int_{-\infty}^{Z_l} \frac{e^{-\frac{z^2}{2}}}{\sqrt{2\pi}} dz \tag{5}$$

$$Z_h = \frac{\mu_{T_B} - \mu_{T_H}}{\left(\sigma_{T_H}^2 + \sigma_{T_B}^2 - 2\sigma_{T_H}\sigma_{T_B}\rho_{T_H T_B}\right)^{1/2}} \tag{6}$$

$$Z_l = \frac{\mu_{T_L} - \mu_{T_B}}{\left(\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B}\right)^{1/2}} \tag{7}$$

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

$$\nu_l = \frac{1}{2\pi}\left(\frac{\sigma_{\dot{T}_L}^2 + \sigma_{\dot{T}_B}^2 - 2\sigma_{\dot{T}_L}\sigma_{\dot{T}_B}\rho_{\dot{T}_L \dot{T}_B}}{\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B}}\right)^{1/2} \exp\left(-\frac{1}{2}\frac{\left(\mu_{T_B} - \mu_{T_L}\right)^2}{\left(\sigma_{T_L}^2 + \sigma_{T_B}^2 - 2\sigma_{T_L}\sigma_{T_B}\rho_{T_L T_B}\right)}\right) \tag{9}$$

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 is the seventh 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 disturbances, 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 correlation coefficients in Equations 6-9 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.

The predicted complaint rate 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 estimating 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 (temperature recorded shortly after the problem was resolved) for humidity and air motion complaints and the difference between the complaint time and the resolution time. 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 10AM) 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.

3 METHODS

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

3.1 Human Subjects Protocol

This project involved the collection of human subjects data because complaint logs contain "identifiable, private information" about building occupants such as their name, work location, and work phone number. Appendix A includes the human subjects protocol that was approved by the Committee for the Protection of Human Subjects at UC Berkeley. Among other things, this protocol requires that we not identify the buildings or organizations involved in this study by name. Consequently we refer to them as Buildings A – F.

3.2 Identification of Buildings

We contacted three organizations that manage a large number of non-residential, non-industrial 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 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

3.3 Data Collection

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

3.3.1 Temperatures

We collected temperature time series data with a between-sample interval of 5 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.

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

3.3.2 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 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 were an average of 12.5 complaints recorded during this same interval in previous years. We used the average of 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.

3.4 Analysis

3.4.1 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 re-calibrated. Instead they were not used.

3.4.2 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

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

$$\sigma_{\dot{T}} = \frac{\pi \sigma_T}{T} N \tag{10}$$

where T is the interval over which temperature measurements were recorded, and N is the number of crossings of the mean level. We used the sample standard deviation in Equation 10. This method assumes that the temperature time series are normally distributed but correlated.

3.4.3 Time Constant

Thermostats are known to have a long time constant relative to the external temperature probes used in Buildings B and E. We tested the impact of thermostat time constant by attaching 17 micro-dataloggers to 17 thermostats in Building D as shown in Figure 3.

Figure 3: Example of logger and thermostat pairs used to evaluate time constant.

We computed the standard deviation and standard deviation of the rate of change for the readings from the thermostats and the reading from the dataloggers using the method described in Section 3.4.2. The results of this analysis are described in Section 4.1.

Based on the results of Section 4.1, we adjusted the standard deviation of the rate of change measured by thermostats using the following procedure. We computed the time constant using the following equation:

$$\tau = \frac{\sigma_T}{\sigma_{\dot{T}}} \tag{11}$$

We subtracted 0.4 hours (24 minutes) from this value to eliminate the effect of the thermostat. Differences less than 24 minutes were set equal to 24 minutes. Then we re-computed the standard deviation of the rate of change. Mathematically, we did this:

$$\sigma_{\dot{T},adj} = \frac{\sigma_T}{\max(\tau - 0.4, 0.4)} \tag{12}$$

3.4.4 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 the predicted observations, and deviations of the coefficients from those of the original model. The penalty function we used is as follows:

$$V = (V_c + V_d)(1 - \alpha) + \alpha\beta\, V_p \tag{13}$$

where

$$V_c = \sum \left| N_o - N_p \right| \tag{14}$$

$$V_d = \sum \left| \left(N_{h,o} - N_{c,o}\right) - \left(N_{h,p} - N_{c,p}\right) \right| \tag{15}$$

$$V_p = \sum_i \frac{\left| P_{o,i} - P_{n,i} \right|}{S_i} \tag{16}$$

and where N_o is the observed number of hot or cold complaints, N_p is the predicted number of hot or cold complaints, $N_{h,o} - N_{c,o}$ is the observed difference between the number of hot and cold complaints, $N_{h,p} - N_{c,p}$ is the predicted difference between the number of hot and cold complaints, P_o are the values of the original parameters of the model, P_n are the values of the new 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 coefficient of the model equal the values of the original model, then $\beta = \left(V_c + V_d\right)$. We used the largest value of α that resulted in a statistically significant model. Table 4 shows the values used for parameter estimation.

Table 4: Values of coefficients used for parameter estimation.

i	1	2	3	4	5	6	7
Label	A	μ_{T_L}	σ_{T_L}	$\sigma_{\dot{T}_L}$	μ_{T_H}	σ_{T_H}	$\sigma_{\dot{T}_H}$
P_o	2209	54.5	4.39	3.69	91.0	4.24	0.84
S	2209	4.39	4.39	3.69	4.24	4.24	3.69

4 RESULTS

4.1 Time Constant

Using the analysis method described in Section 3.4.1, we found that the standard deviations of the thermostat temperatures were indistinguishable from the standard deviations of the logger temperatures. Figure 4 shows the standard deviations of the 17 thermostat time series plotted against the standard deviations of the 17 micro-datalogger time series.

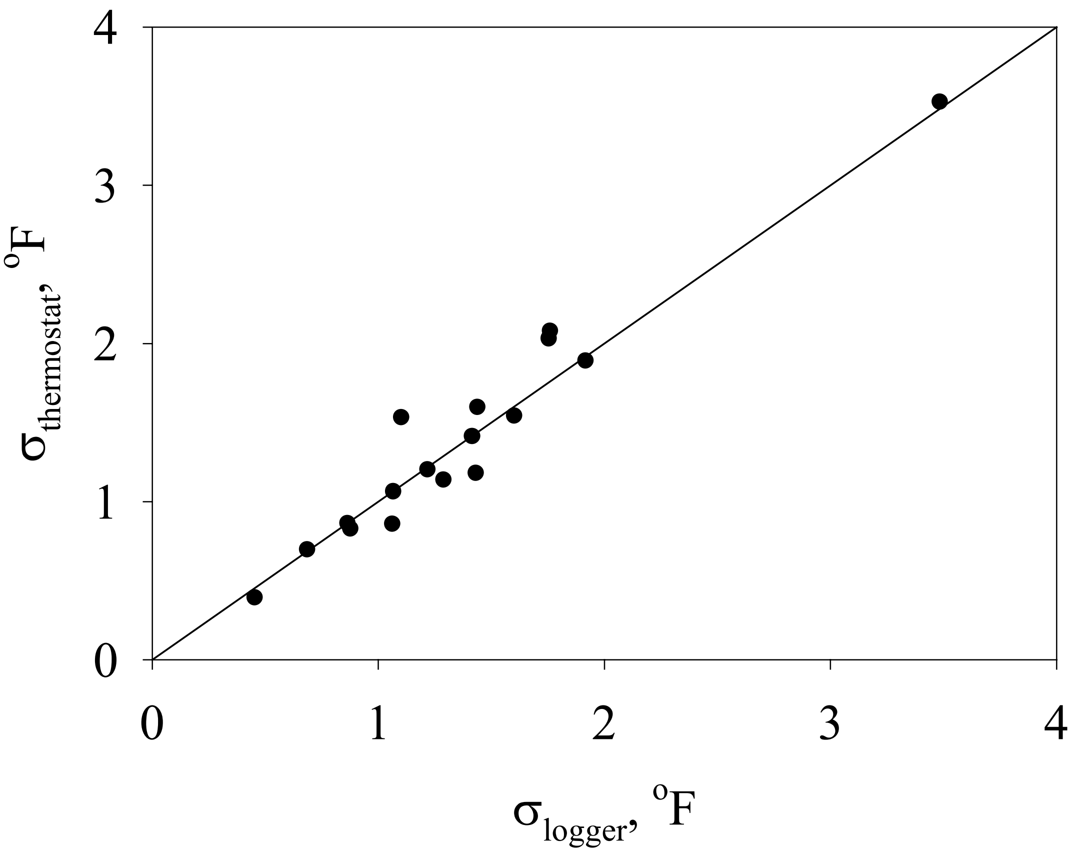

Figure 4: Standard deviation of temperature: thermostat vs logger

We found that the standard deviation of the rate of change of the thermostat readings was lower than the standard deviation of the rate of change of the micro-datalogger readings. The standard deviation divided by the standard deviation of the rate of change is the "time-constant" of the system. We found that the average difference between the time constant of the thermostat and the time constant of the micro-datalogger was 20.5 minutes. This compares favorably with the time constant specified by the manufacturer of this thermostat (JCI, 2000) and the datalogger (Onset, 2002). The thermostat is a "first-generation" device, meaning that it is the first version of this thermostat sold by this manufacturer. The second-generation device has a time constant of 8 minutes, which is 70% of the time constant of the first generation device, so the time constant of the first-generation thermostat is 26.7 minutes. According to Drees (2002), this is typical of most thermostats on the market. The time constant of the logger with an external probe is rated by the manufacturer as less than 3 minutes in air.

We used this finding to adjust the standard deviation of the rate of change of temperature so that all readings are associated with the response of a datalogger with an external probe. We assumed that the actual difference between the thermostat and the logger was 24 minutes. This was accomplished using the method described in Section 3.4.1.

The table of results from this time response experiment are shown in Appendix B.

4.2 Accuracy of Original Model

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, and subtracted it from the minimum, mean, median, and maximum. These statistics and the corrected standard deviation of the rate of change are shown in Appendix C. The values of the minimum, mean, median, and maximum in Appendix C are uncorrected (i.e., not adjusted by the calibration error).

After computing these 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 5 shows the number of hot and cold complaints from each building plotted versus the number predicted by the original model. The size and color corresponds to the kind of complaint (hot is large/red, cold is small/blue).

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

The two small/blue 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 posted notices about their actions that were designed to elicit cooperation (i.e., reduce complaints) from occupants. 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 red point in the upper left corner of Figure 5 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.

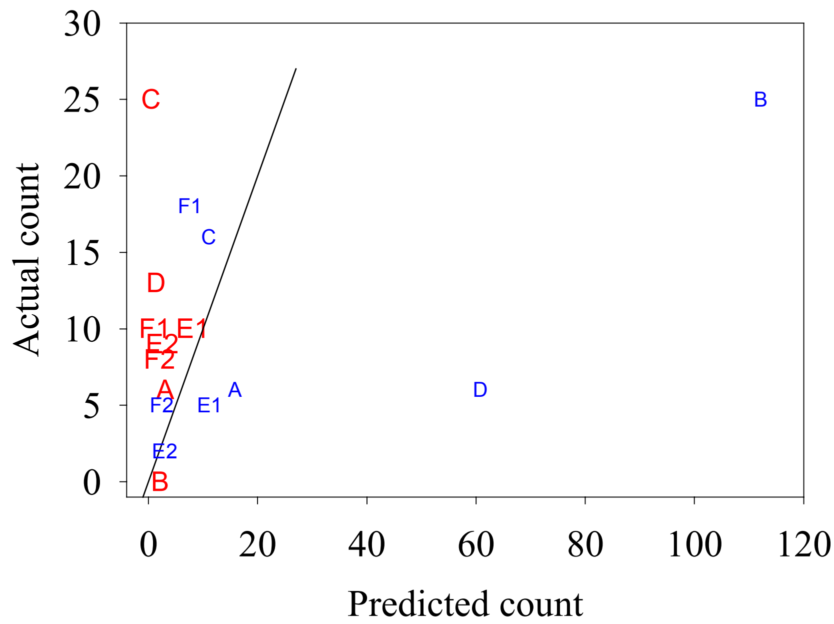

Figure 5: Predicted versus actual complaint counts of original model.

Figure 6 shows the actual versus predicted complaint counts with the three outliers removed. The figure shows that the correlation between the predicted and actual counts is low ($r = 0.19$) and not statistically significant ($p = 0.27$), and that the model is under-predicting the number of hot complaints.

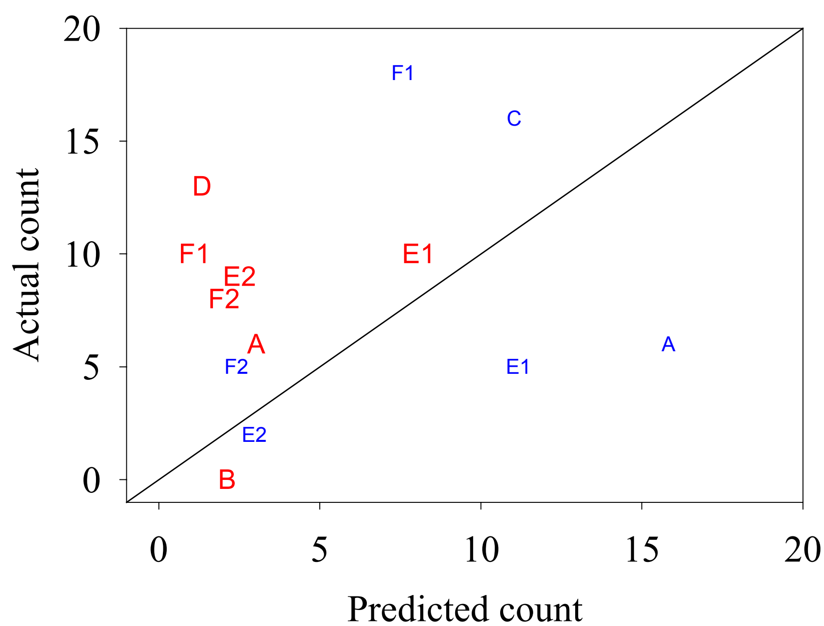

Figure 6: Predicted versus actual counts of original model with outliers removed.

Figure 7 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 under-predicting the number of hot complaints relative to the number of cold complaints. The largest differences are Buildings C and D, which were flagged as outliers in Figure 5. The other outlier building is B. The low cold complaint count doesn't significantly affect the ratio plotted in Figure 7 because zero hot complaints were observed. The relative loss of data would be small.

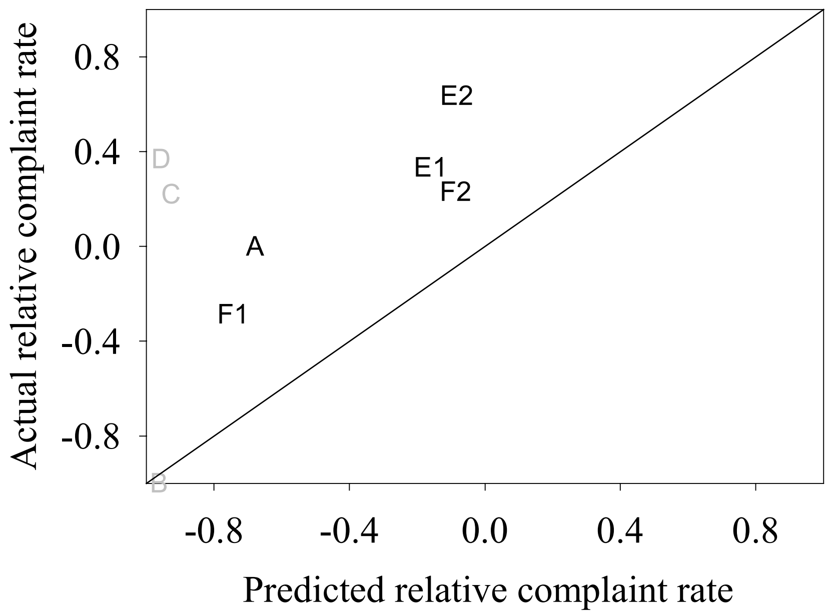

Figure 7: Predicted versus actual relative complaint rate for original model.

4.3 Parameter Estimation

Using the method described in Section 3.4.2, we re-calibrated the original model to improve the fit to the observed data. Figure 8 shows the predicted versus actual complaint counts, with the two outliers removed (analogous to Figure 6). The correlation is not high ($r = 0.49$), but it is statistically significant ($p<0.05$). The coefficient of variation (CoV; standard deviation of prediction error divided by the mean of the actual counts) is 57%.

Figure 9 shows the predicted versus actual relative complaint rate for the re-calibrated model. The agreement is significantly better than the original model. The correlation coefficient between the five points not flagged as outliers and Building B is $r = 0.94$.

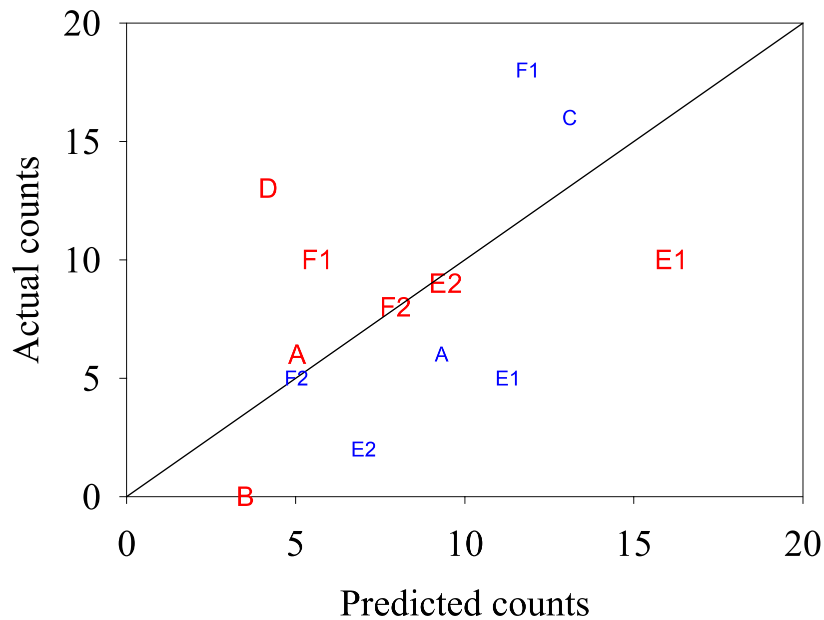

Figure 8: Predicted versus actual counts for re-calibrated model.

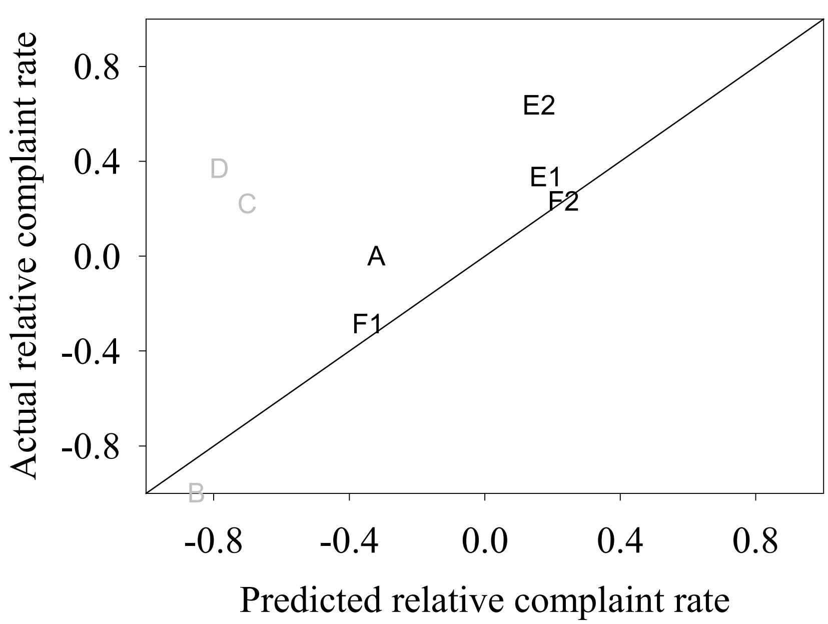

Figure 9: Predicted versus actual relative complaint rate for re-calibrated model.

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 clothing insulation can be reduced to deal with hot stress, but no hard limit to how much it can be increased to deal with cold stress, and likewise for metabolism.

Table 6: Parameters of original and re-calibrated model.

Parameter	A, ft^2/zone	μ_{T_L}, °F	σ_{T_L}, °F	$\sigma_{\dot{T}_L}$, °F/hr	μ_{T_H}, °F	σ_{T_H}, °F	$\sigma_{\dot{T}_H}$, °F/hr
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

Figure 10 shows how the complaint rate predicted by the original model and the re-calibrated model when the standard deviation of the temperature is 0.98 °F and the standard deviation of the rate of change is 0.90 °F/hour. These were the average values for the time series from the first temperature monitoring interval in Building F. The figure shows that the recalibrated model predicts that the mean temperature that 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.

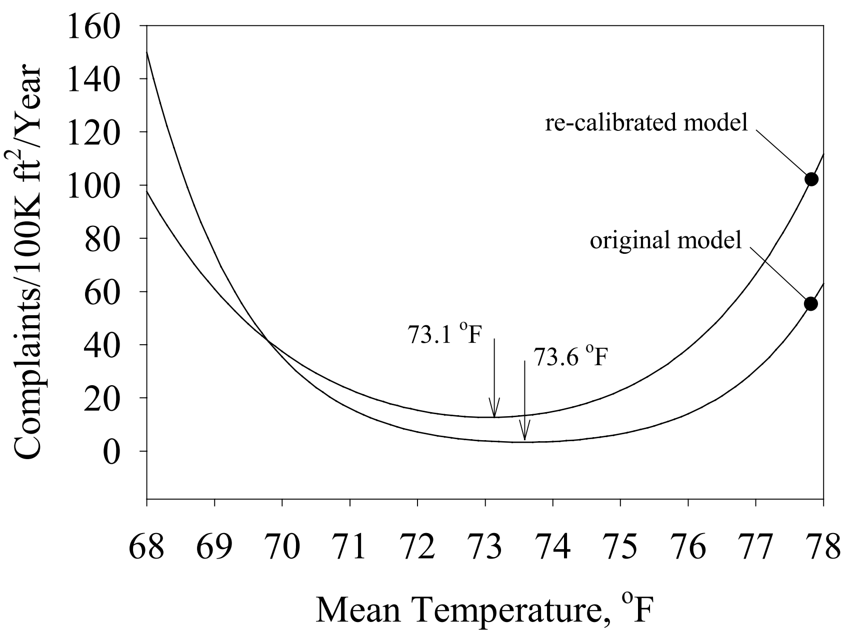

Figure 10: Comparison of original and re-calibrated model.

4.4 Model Validation

4.4.1 Complaint Temperatures

In Building E, the maintenance personnel would sometimes record complaint temperatures by either by reading the digital thermostat or 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 compared the mean and variance of the complaint temperatures predicted by the re-calibrated model with the sample mean and variance from each building. All complaint temperatures and relevant statistics can be found in Appendix D. 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.

4.4.2 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 or 77.5 F, and heating was not enabled until the temperature was below 72.5 F or 75.5 F. During the setup 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 set-up 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 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 setup 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 $\alpha = 0.05$ was 1.645, which implies that the increase in the number of hot complaints during the month when the setpoint was raised was statistically significant.

Table 7: 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

The results provide strong evidence that increasing the temperature increased the hot complaint rate. The number of hot complaints increased by a factor of 2.36. 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 Aug 23 – Sep 25, then the model predicts that the number of hot complaints should have increased by a factor of 5.25, which is almost 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 under-reported 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."

5 DISCUSSION

5.1 Practical Evaluation of Accuracy

5.1.1 Accuracy of Energy Models

We reviewed the existing literature on the accuracy of energy models because energy models are likely to be used on conjunction with the complaint 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 are 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 energy models have been assessed in two "Energy Predictor Shootouts". The first shootout, summarized by Kreider and Haberl (1994), involved empirical predictions of hourly energy consumption. Contestants were given a training set and were required to predict hourly consumption of electricity, hot water, and chilled water during a test period. No description of the building or other specific details about the data were provided. 21 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 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 a 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.

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.

5.1.2 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 used as the basis of an alternative for naturally ventilated buildings in ASHRAE Standard 55.

5.2 Utilization

The complaint prediction model has a number of practical uses. One is cost-benefit analysis of improving temperature control performance. Another is the determination of optimal temperature settings. A third involves its use in thermal comfort standards. These three applications are described in more detail below.

5.2.1 Cost-Benefit Analysis

Temperature control performance and complaint rates are not the same in all locations within a building. For example, Federspiel (2001) shows that complaint rates in a small fraction of zones can be more than 10 times higher than in most zones. The complaint prediction model can be used to determine the cost-benefit tradeoff from investing in improved control performance in order to reduce the operation and maintenance cost of responding to hot and cold complaints. Figures 11 and 12 show the minimum complaint rate as a function of σ_{T_B} and $\sigma_{\dot{T}_B}$. These figures convey the same information. The only difference is that the statistic on the horizontal axis has been switched.

The average values of these two statistics in Building F during the first temperature monitoring interval was 0.98 °F and 0.90 °F/hour. This corresponds to a predicted minimum complaint rate of 12.7 complaints per year per 100K ft^2.

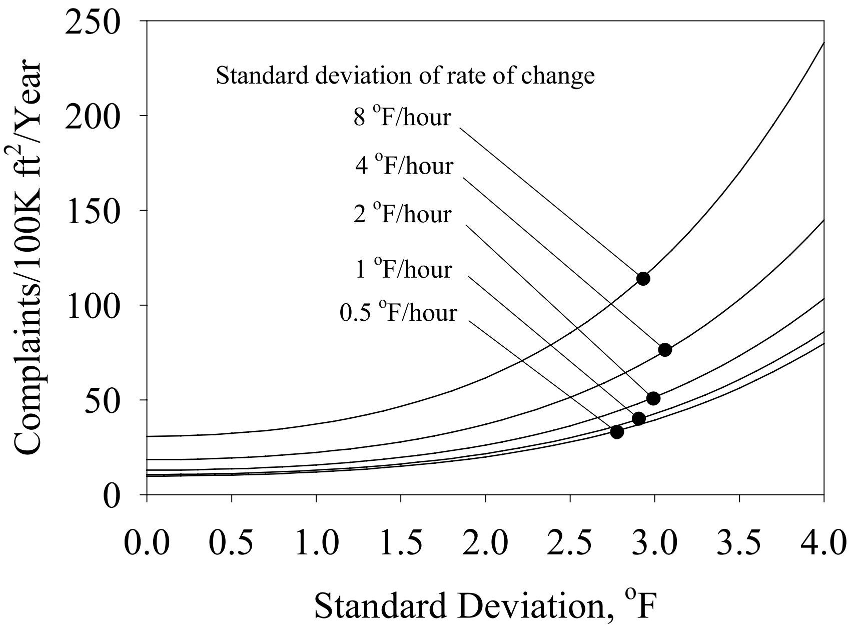

Figure 11: Minimum complaint rate versus standard deviations.

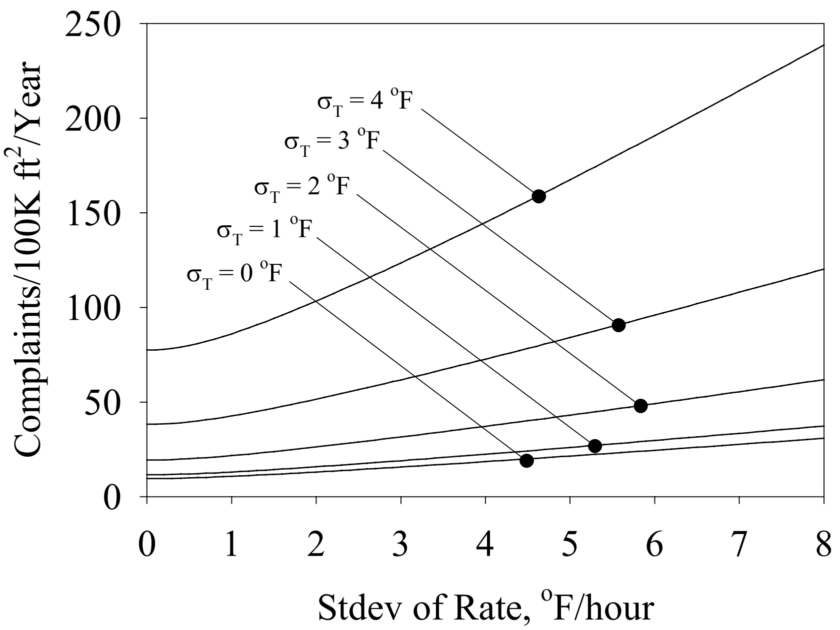

Figure 12: Minimum complaint rate versus standard deviations.

To use these figures to determine the cost-benefit analysis, record the temperature in the space where a retrofit or engineering change is being considered. Compute σ_{T_B} and $\sigma_{\dot{T}_B}$. Find the point on Figure 11 or 12 that corresponds to these two statistics, and read the predicted complaint rate from the left-hand axis. Compute the predicted annual costs savings as follows:

$$S = A(R - 12.7)H\,L \tag{17}$$

where S is the cost savings in dollars per year, A is the area of the zone divided by 100K, R is the predicted complaint rate from Figure 11 or 12, H is the average number of hours to handle a complaint, and L is the fully burdened hourly labor rate for technicians who handle complaints. Federspiel (2001) found that H = 1.85 hours. The U.S. Bureau of Labor Statistics estimates that the hourly wage for an HVAC mechanic in Sacramento, California, in 2001 was \$20.85, and the ratio of total compensation to wage was 1.48. This gives L = \$30.78/hour. The average labor rate that HVAC service companies in Sacramento charge their customers is \$110/hour.

If R = 127 (10 times the minimum complaint rate corresponding to the median values of σ_{T_B} and $\sigma_{\dot{T}_B}$ during Interval 1 of Building F), then the annual potential cost reduction for a 1000 ft^2 zone using the \$30.78 labor rate is \$65. Changes to the temperature controls that would likely reduce the variability, and therefore the complaint rate, include replacing pneumatic controllers with digital controllers, tuning the PID gains of digital controllers, and reducing the deadband of the controller.

5.2.2 Optimal temperature settings

We can compute the mean temperature that minimizes the total complaint rate as a function of the standard deviation and standard deviation of the rate of change of the building temperature. We refer to this temperature as the minimum discomfort temperature (MDT). Figure 13 shows curves of MDT for a range of these two statistics. The figure shows that MDT decreases slightly as the standard deviation of the building temperature increases. It also decreases slightly as the standard deviation of the rate of change of the building temperature increases.

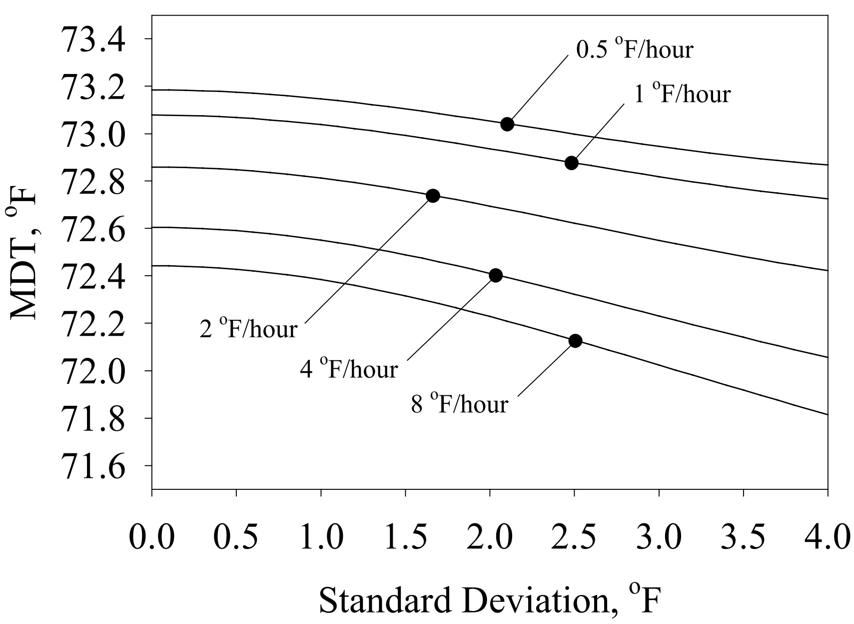

Figure 13: Minimum discomfort temperature versus standard deviations.

Since indoor temperature affects energy consumption, we can combine the O&M cost of complaints with the energy cost, and determine the mean temperature that minimizes the sum of O&M cost and energy cost. We refer to this temperature as the minimum-cost temperature (MCT). Figure 14 shows MCT as a function of the standard deviation and standard deviation of the rate of change of the building temperature for a fictitious 100K ft^2 building in Sacramento California operating on the E-19 electrical energy tariff and the G-NR2 gas tariff, both offered by PG&E. We used a commercially available energy analysis program to estimate the impact of indoor temperature on energy costs. The simulated fictitious building has variable-air-volume (VAV) HVAC systems and two centrifugal chillers. We used the labor statistics cited above to convert complaint rates to O&M costs.

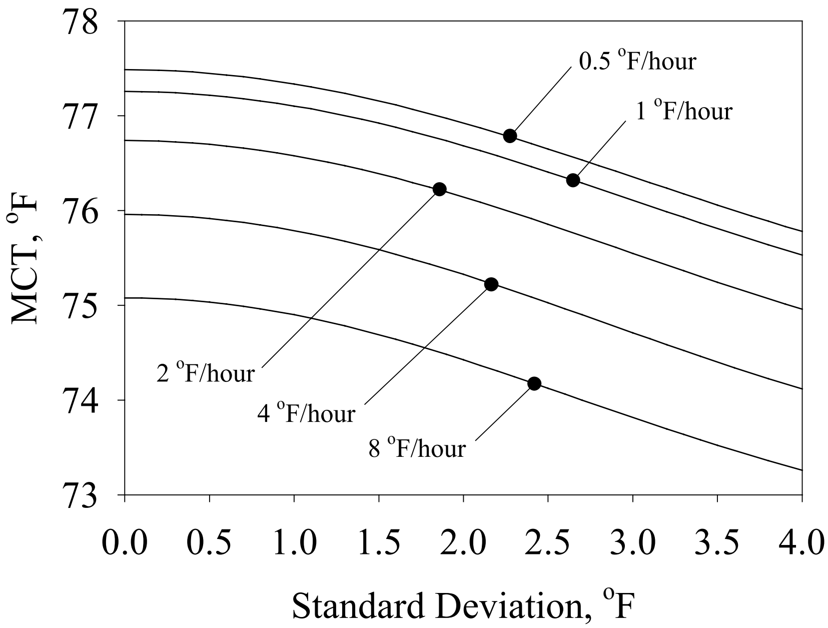

Figure 14: Minimum-cost temperature versus standard deviations.

The figure shows the benefit of good control performance. When the variability is low, the temperature can be raised higher to achieve greater energy savings because the cost of additional hot complaints is less when the variability is less.

5.2.3 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 occupant 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 8 There was a wide range of outdoor temperatures because of seasonal and geographical differences.

Table 8: 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

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 and maximum clothing that people can wear to avoid discomfort are 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.

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 15 shows compares how arrival complaint rates and operating complaint rates are influenced by the mean and standard deviation of the indoor temperature. The values of σ_T and $\sigma_{\dot{T}}$ used in Figure 15 are the same as those used in Figure 10.

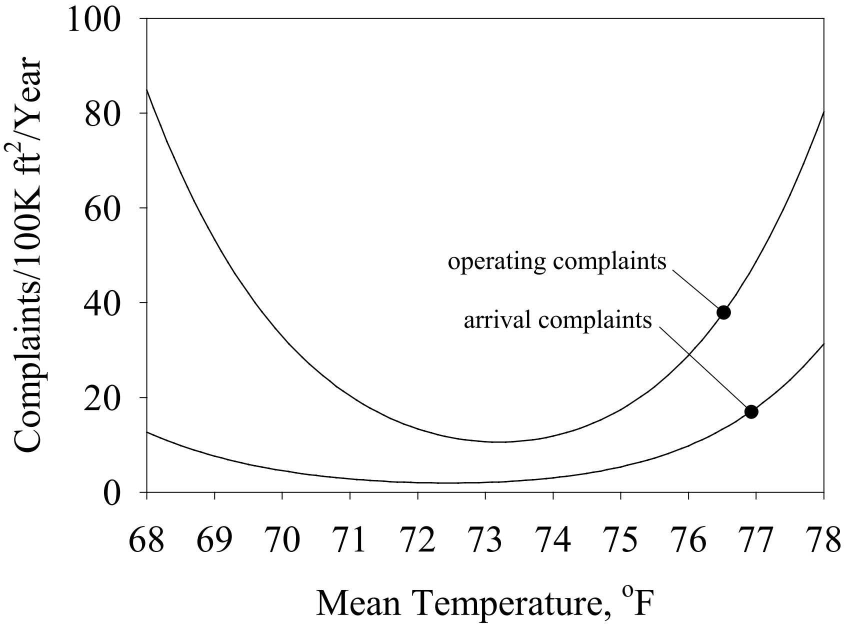

Figure 15: Comparison of arrival complaint rate with operating complaint rate.

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 shows that the complaint rate is highest in the first half of the morning, but 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 16 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 degrees 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.

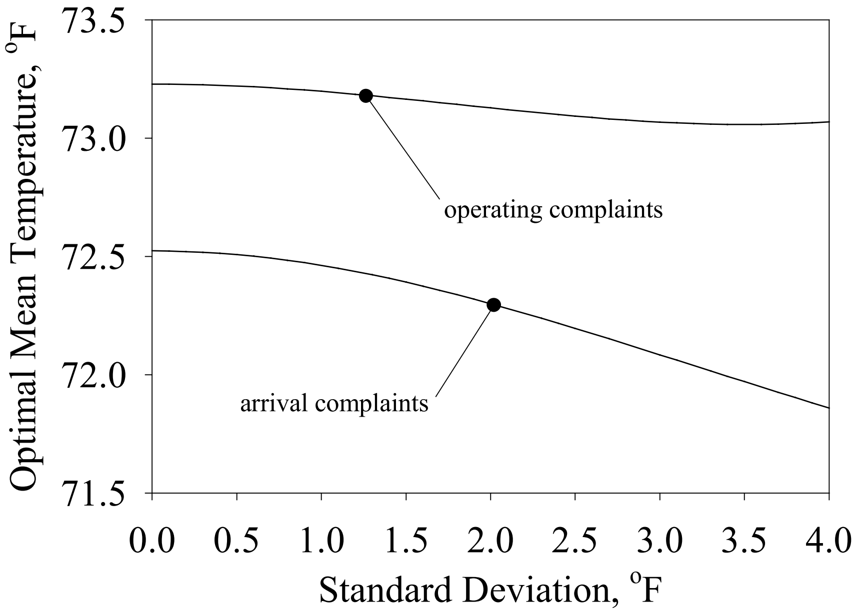

Figure 16: Mean temperatures that minimize arrival and operating complaints.

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 it's 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 pre-cooled 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 pre-cooling buildings.

5.2.4 An Economic Criterion for ASHRAE Standard 55

The current ASHRAE thermal comfort standard, ASHRAE Standard 55, specifies a level of comfort regardless of the amount or cost of energy required to achieve that level of comfort. The standard has been formulated this way in part because there has not been methodology for quantitatively estimating the economic value of comfort, or conversely, the economic cost of discomfort. The complaint prediction model now allows us to do that.

Consider the case of August in Sacramento, California. Figure 17 shows two curves, the MDT and the MCT for the case where $\sigma_{\dot{T}_B}$ = 1.0 °F/hour, which is the average value of this statistic for Building F, and the most frequent (mode) for all the time series recorded in this study. The figure shows three regions, labeled A, B, and C, that fall above both curves, between the curves, and below both curves, respectively. Raising the average temperature into Region A increases the total cost (energy plus O&M cost of handling complaints) AND increases discomfort. Likewise, decreasing the average temperature into

Region C increases the total cost AND discomfort. However, in Region B there is a tradeoff between total cost and discomfort. In Region B, raising the temperature reduces total cost, but at a penalty of more discomfort.

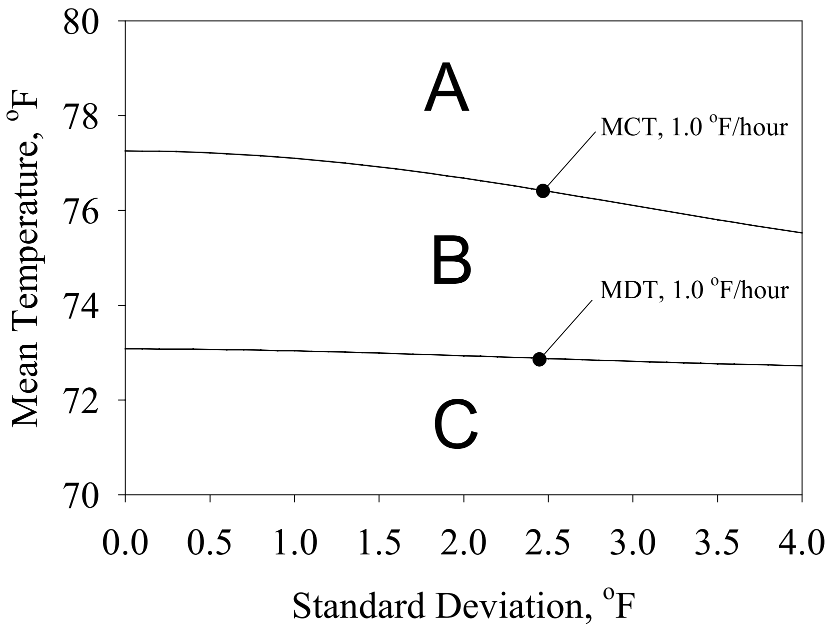

Figure 17: Unacceptable (A & C) and acceptable (B) temperature regions.

We propose that the MDT and the MCT form the basis for an economic criterion for ASHRAE Standard 55. Temperatures greater than MCT or less than MDT are unacceptable because they are undesirable from the point of view of both economics and comfort. There is no rational reason to design or operate buildings for temperatures in regions A or C of Figure 17.

To determine the acceptable upper and lower temperature limits, an energy analysis would be performed so that the influence of energy cost could be computed as a function of indoor temperature. It is becoming increasingly common that energy codes and standards require an energy analysis, so this will not constitute much additional engineering effort. The values of MCT and MDT with σ_{T_B} = 0.6 °F and $\sigma_{\dot{T}_B}$ = 1.0 °F/hour should be used as the design standard conditions. These values are the most frequent (mode) in the data set from this study, and lower values do not significantly increase the temperature range.

Figure 18 shows the MCT – MDT interval for summer in Sacramento superimposed on the ASHRAE comfort chart. The interval overlaps both the Winter (clo = 1.0) and Summer (clo = 0.5) comfort zones. It is narrower that both the high-clo and low-clo comfort zones.

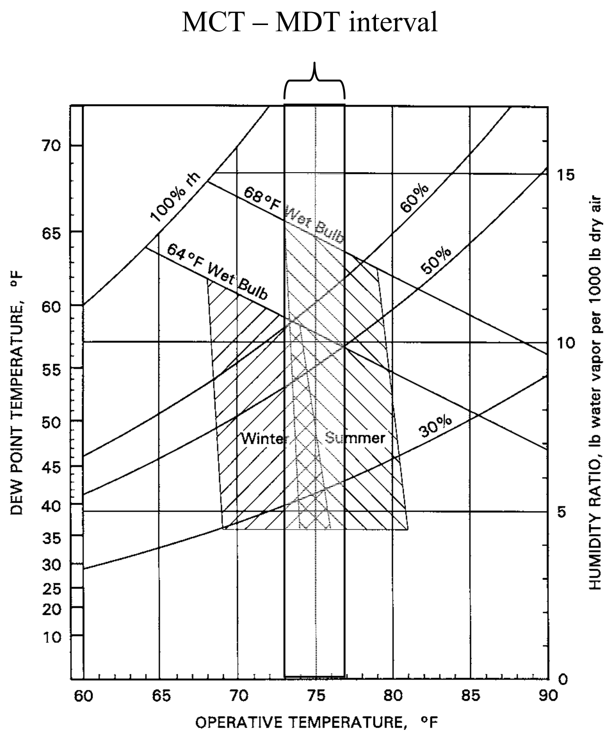

Figure 18: MCT - MDT interval for Sacramento superimposed on the ASHRAE comfort chart.

To use the MCT – MDT interval, designers would have to go through the following steps. First they would have to ensure that their design meets the requirements of energy codes and standards. Then they would have to determine the dependence of energy consumption on indoor temperature for the design outdoor condition using computer simulations. Most energy simulation codes have deadbands for thermostats that must be set to zero in order to determine this relationship. We found that running the simulation in increments of 2 °F and interpolating between the points is sufficient. Next the designer must compute MCT at the design conditions of σ_{T_B} = 0.6 °F and $\sigma_{\dot{T}_B}$ = 1.0 °F/hour. This involves searching for the value of the mean temperature that minimizes the sum of energy cost and complaint cost. The designer must look up the prevailing wage for the area where the building will be located as described in Section 5.2.1 to be able to compute complaint cost.

6 CONCLUSIONS

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

1. The re-calibrated model predicts lower MDT than the original model.
2. The re-calibrated model predicts higher minimum complaint rates than the original model.
3. The re-calibrated 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 can be used to perform cost-benefit analyses of retrofits and engineering efforts that would improve temperature control performance.
6. The model can be used to select optimal temperature at which to operate buildings.

7. The model can be used as the basis of an economic criterion for thermal comfort standards. Doing so eliminates the need to make arbitrary assessments of what constitutes "acceptable", and allows the thermal comfort standard to be elastic with respect to the amount and cost of energy required to provide comfort.

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The following appendices have been omitted for brevity. They are available in the full ASHRAE report.

8 APPENDIX A: HUMAN SUBJECTS PROTOCOL

9 APPENDIX B: IMPACT OF THERMOSTAT ON TRANSIENT RESPONSE

10 APPENDIX C: DESCRIPTIVE STATISTICS OF TEMPERATURE TIME SERIES

11 APPENDIX D: ANALYSIS OF COMPLAINT TEMPERATURES