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Responding to Thermal Sensation Complaints in Buildings

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ABSTRACT

Computer simulation methods were used to compare two different strategies for responding to thermal sensation complaints in buildings. The baseline strategy involved changing the space temperature setpoint in the appropriate direction and leaving it there until another complaint occurred. The alternative strategy involved changing the setpoint in the appropriate direction for a finite time and then resetting it to a value expected to produce the fewest complaints on average. A complaint model recently proposed by Federspiel (2000) was used to simulate complaint behavior. A building heat transfer model that included a multi-layer wall, heat accumulation by furnishings, meteorological weather data, time-varying internal disturbances, temperature sensor dynamics, and a proportional plus integral (PI) temperature controller was used to model the building. A grid search was used to determine the optimal values of the setpoint change and duration for the resetting strategy. The optimization indicates that setpoint changes greater than 2°F and longer than two hours are most effective. A comparison of the resetting strategy and the baseline strategy shows that resetting the setpoint significantly lowers both the complaint rate and the complaint recovery period.

INTRODUCTION

Thermal sensation complaints are the most common kind of service request from occupants in commercial buildings. Federspiel (1998) found that thermal sensation complaints in buildings account for 75% of all environmental complaints from occupants. He estimated that the labor cost associated with HVAC maintenance could be reduced by 20% by reducing the frequency of thermal sensation complaints. Extrapolating this finding to all commercial buildings in the U.S., it is estimated that the cost avoidance potential from avoiding thermal sensation complaints is $2 billion annually.

The study of thermal sensation complaints and their effect on operation, maintenance, and energy use in buildings is a new area of research. Federspiel (1998) performed an empirical analysis of two large maintenance databases containing a variety of information, including thermal sensation complaints. In addition to finding that thermal sensation complaints are the most frequent, he concluded that thermal sensation complaints are usually the result of unsatisfactory performance of HVAC systems and controls rather than inter-individual differences in preferred temperature. In a follow-up paper, Federspiel (2000) proposed a mathematical model that predicts the average thermal sensation complaint rate as a function of the performance and settings of temperature controls in buildings. Since indoor temperature affects energy use, this model can quantitatively relate thermal discomfort, energy use, and maintenance cost.

There is a substantial body of work in the related areas of thermal comfort and thermal comfort control. Early work on modeling thermal comfort involved purely empirical relations between physical variables and thermal sensation ratings from occupants in laboratory studies (e.g., Yaglou and Drinker 1928). Fanger (1972) developed a model-based, semi-empirical thermal comfort model called the Predicted Mean Vote (PMV). Energy balance equations are used to compute a thermal load that is empirically associated with thermal sensation ratings. Gagge et al. (1986) proposed an extension of PMV that improves the accuracy under sweating conditions.

MacArthur (1986) proposed using PMV for controlling thermal conditions in buildings. Federspiel (1994) developed

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a control system based on a modified version of PMV that would respond to thermal sensation ratings from occupants by adjusting parameters of the comfort model so that it learned the occupant's preference.

Federspiel (1998) showed that the most common field actions taken in response to a complaint in rank order are (1) do nothing, (2) adjust the space temperature setpoint, and (3) start a work order to fix a failure. This paper is focused on how to most effectively respond to thermal sensation complaints that are currently handled by either taking no action or by changing the space temperature setpoint. In these cases, the cause of the complaint is not a system fault. Nothing is broken and in need of fixing.

There have been a number of studies focused on the optimization of setpoints, mainly for optimizing energy use or process productivity. Keeney and Braun (1997) developed a load shifting control strategy that involved changing space temperature setpoints to minimize peak electrical demand in commercial buildings. El-Nashar (1998) studied the problem of optimizing setpoints for a multi-stage flash desalination process. Lacroix and Kok (1999) determined optimal greenhouse heating setpoints.

Computer simulation methods are used to study the problem of responding to thermal sensation complaints. The models used in the simulation along with the methods for optimizing the response are described in the next section. The following section contains the results of the optimization and a comparison with a response strategy that represents the current practice of responding to thermal sensation complaints when no system fault has occurred.

MODELING AND SIMULATION

Figure 1 shows a block diagram of the system. The figure shows the continuous temperature feedback loop common to most controlled buildings. It also shows the discrete event feedback loop that involves a complaint event and the resulting corrective action. The continuous dynamics of the temperature control system are shown within the dotted line. The continuous dynamics include the building heat transfer dynamics, labeled "building plant," disturbances for internal loads and external weather-related loads, sensor dynamics, and a proportional plus integral (PI) controller. The discrete event dynamics of the system are the elements in the outer loop outside of the dotted line. They include the process of generating complaint events and the corrective action taken in response to an event. In this system, the corrective action involves changing the setpoint of the temperature controller in some way.

Room Model

A lumped-parameter room model was used to simulate the continuous dynamics of the system. Important components of the room model include a heating and cooling source for temperature control, ventilation air, internal loads from occupants and equipment, heat accumulation in furniture, and heat conduction through the walls.

Basic energy balance principles were used to derive the state equations for the room. This included modeling conductive and convective properties of the wall, as well as convective properties of furniture in the room. The external disturbance is the outside temperature T_{out} and is based on typical meteorological year (TMY) weather data from Sacramento, Calif. The internal heat generation disturbance within the room is due to building occupants and equipment (computers). This process is modeled as a pseudo-random binary process, in which each computer and person in the room output 140 W and 100 W of heat, respectively. Heat conduction through the wall was modeled with a lumped-parameter method similar to that described by Seem (1987). To improve the accuracy, five layers were used instead of one.

Sensor Model

The sensor was modeled as a first-order time lag with a time constant of 7.5 minutes. The transfer function for this component is as follows:

$$\frac{T_s(s)}{T_r(s)} = \frac{1}{\tau s + 1} \tag{1}$$

where τ is the time constant of the sensor, T_s is the sensor output, and T_r is the room temperature.

PI Controller

A standard PI controller was used to simulate the operation of a thermostat. The PI controller was tuned numerically to minimize the integrated squared error (ISE).

Complaint Model

Complaint events were modeled using the method proposed by Federspiel (2000). The model treats complaint events as a kind of alarm. The levels at which complaints occur are random processes to account for unpredictable factors, such as the health of occupants and attention to work tasks.

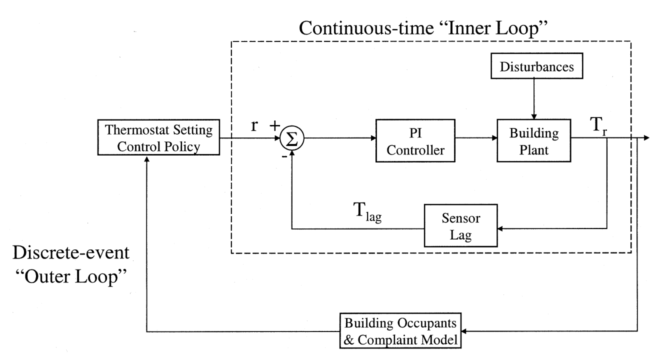

Figure 1 *Building occupants in feedback control loop.*

Consequently, complaints do not all occur at the same temperature.

The hot and cold complaint levels were modeled as second-order, linear, time-invariant systems with white, gaussian inputs. The transfer function for these processes is as follows:

$$\frac{T}{n} = \frac{\varpi^2}{s^2 + 2\zeta\varpi s + \omega^2} \tag{2}$$

where T is the temperature level at which building occupants complain, ϖ is the natural frequency of the complaint process, ζ is the damping ratio of the complaint process, and n is a white Gaussian input.

The coefficients of the Gaussian inputs were selected so that the mean, variance, and variance of the rate of change of the temperature levels matched the parameters determined by Federspiel (2000). The damping ratio was unity.

Thermostat Setting Control Policies

Figure 2 shows the two thermostat setting control policies that were studied. The most common corrective action taken in response to thermal sensation complaints is to adjust the thermostat setting appropriately, leaving it there indefinitely or until another complaint occurs (Smothers 1999; Haley 1999; Fisher 1999). That strategy is referred to as "current practice." The problem with current practice is that moving the setpoint in response to a complaint and leaving it at the new setting indefinitely increases the chance of triggering a complaint of the opposite kind later.

The alternative thermostat setting policy solves the problem with current practice by making the standard adjustment when a complaint is received but changing the setpoint back to the original setting after a period of time. This policy is parameterized by two variables—the magnitude of the setpoint change and duration of time at the new setting.

Data acquired from maintenance records for several facilities demonstrate that the magnitude of setpoint changes in response to thermal sensation complaints varies considerably. Therefore, the magnitude of the setpoint change for current-practice strategy was modeled as a random process. A Gaussian random number generator was used to choose the setpoint change, and then the sign of the change was selected to match the kind of complaint.

We investigated setpoint changes in the range of 0°F to 6°F. For larger setpoint changes, the current practice strategy can get "stuck" in a complaint condition because a large setpoint change may be followed by a small setpoint change that does not eliminate the complaint condition. If it were important to study larger setpoint changes, then it would be necessary to add a mechanism to the complaint model so that a second complaint is triggered if the complaint condition persists for longer than some time interval, such as 24 hours.

Simulation Methods

Numerical Integration. The differential equations were integrated by converting them to difference equations using a zero-order hold on the inputs. The variances of the inputs to the complaint levels were determined so that the statistics of the complaint levels matched the values reported by Federspiel (2000). A time step of five minutes was used. Reducing the time step further had a negligible impact on the results of the numerical integration.

Performance Metrics. Two performance metrics were used to assess the performance of the complaint response strategies. The first is the complaint rate. The second is the complaint recovery period, which is a metric derived from the complaint model. Figures 3 and 4 show how the complaint recovery period is defined. It is the time from the crossing event that defines the complaint to the reverse crossing event that undoes the complaint condition. Figure 3 shows the three processes of the complaint model: the hot complaint level, the space temperature, and the cold complaint level. The figure shows a hot complaint for the resetting response strategy. Figure 4 shows a close-up view of the hot complaint level and the space temperature just before and after a complaint event.

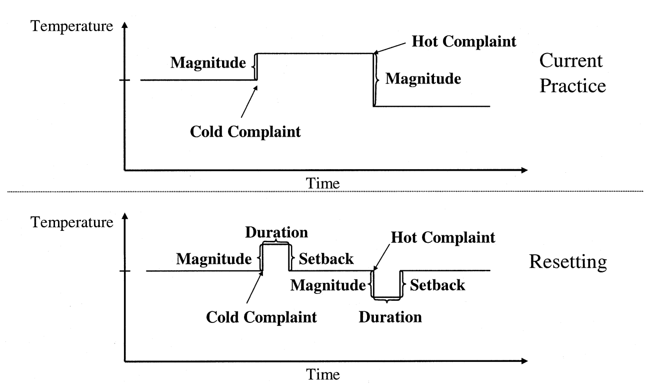

Figure 2 Comparison of thermostat setpoint control policies.

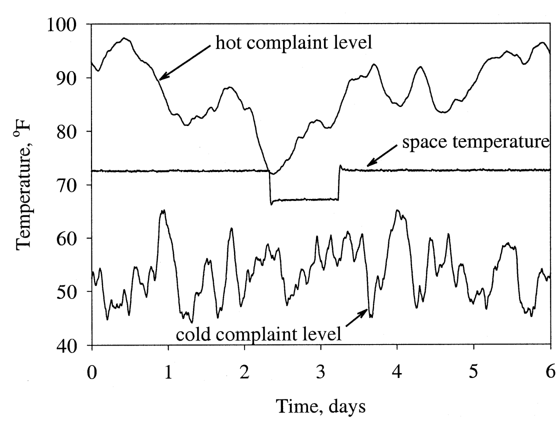

Figure 3 Example of a hot complaint.

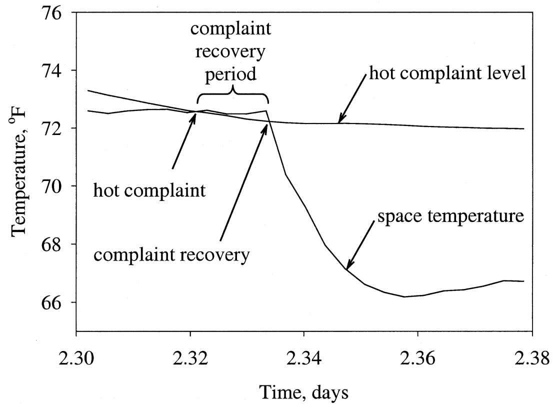

Figure 4 *Definition of complaint recovery period.*

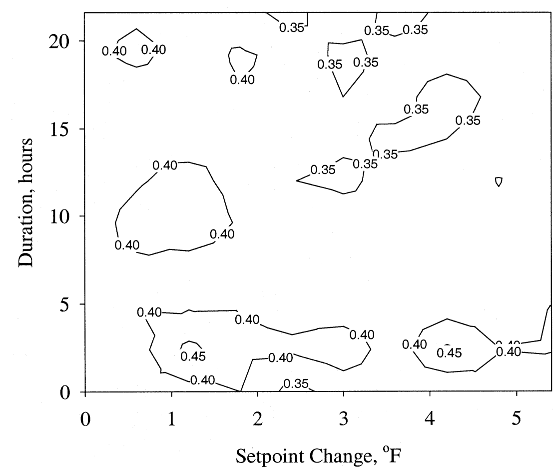

Figure 5 *Impact of setpoint change and duration on complaint rate.*

The complaint recovery period for this complaint event is marked on the figure.

Reduction of Statistical Uncertainty. The number of complaints observed per simulation is a random variable. It is important to be able to characterize the uncertainty in order to ensure that observed differences are significant. One method of characterizing the stochastic uncertainty in the number of complaints per simulation would be to run many simulations under the same conditions and numerically compute the variability. The problem with this method is that it is time-consuming.

To solve this problem, we relied on the fact that under certain conditions, the distribution of crossing events approaches a Poisson distribution as the levels diverge (Cramer and Leadbetter 1967). We used this fact to design a termination strategy for the simulations that produced a consistent amount of stochastic uncertainty for each simulation. The coefficient of variation is defined as the ratio of the standard deviation of the complaint rate to the mean of the complaint rate and is equal to the inverse of the mean of the complaint rate for a Poisson process. Additionally, the number of complaints divided by the simulation time is a maximum likelihood estimate of the mean complaint rate. We ran each simulation until the number of complaints was large enough that the coefficient of variation was below a tolerance, typically 5%. The stochastic uncertainty in the complaint recovery period was computed numerically because each simulation had numerous complaint events (400 to achieve the 5% tolerance on the complaint rate uncertainty).

Event Management. In order to simulate the discrete-event system described above, it is necessary to keep track of hot complaints, cold complaints, the corresponding crossing events that mark the end of the complaint intervals, and the timing events for resetting the setpoint. Finite state machines (FSMs) were designed to manage these events and keep track of the performance metrics. One FSM was designed to keep track of the complaint events, another FSM was designed to keep track of complaint recovery events, and a third FSM was designed to time the setpoint resetting.

Optimization Methods

The resetting response strategy has two design parameters—the magnitude and duration of the setpoint change. We used a grid search method to find the optimal magnitude and duration pair. We studied magnitude changes from 0°F to 5.4°F in increments of 0.6°F and durations of 0 to 21.6 hours in increments of 1.4 hours. In order to account for stochastic uncertainty in the grid height, we determined the minima by finding the centroid of the set of points that were not significantly different from the lowest point on the grid.

RESULTS

Optimization Results

Figure 5 shows a contour plot of the complaint rate as a function of the magnitude and duration parameters. The lowest point is at a magnitude of 3.6°F and a duration of 21.6 hours. The centroid of the points not significantly different from that point is at a magnitude of 4.2°F and a duration of 16.8 hours. However, the grid is fairly flat. The lowest point is 71% of the highest point, and the coefficient of variation of each point is 5%.

Figure 6 shows a contour plot of the complaint recovery period as a function of the magnitude and duration parameters. The grid is steep when the magnitude and duration are less that 2°F and two hours, respectively. At larger magnitudes and larger durations, the grid has a low plateau with no clear minimum. This result combined with the complaint rate contour indicates that the magnitude and duration should be greater than 2°F and two hours.

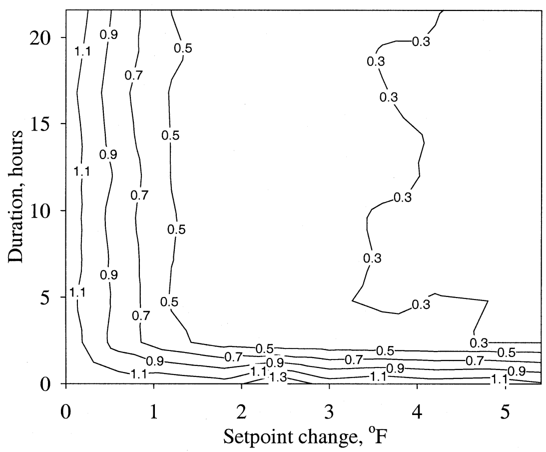

Figure 6 *Impact of setpoint change and duration on complaint recovery period.*

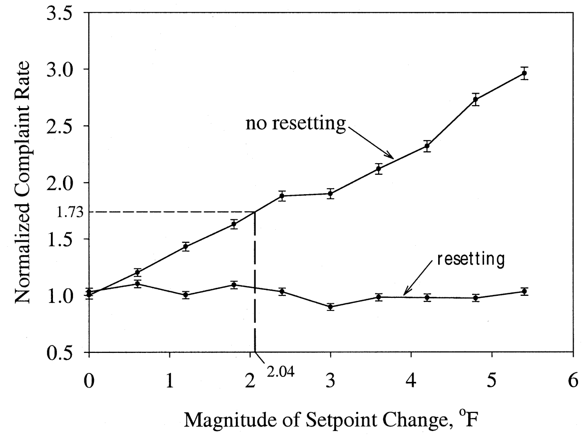

Figure 7 *Comparison of complaint rate with and without resetting.*

Comparison

The current practice strategy can now be compared to the resetting strategy developed from optimization, using the performance metrics as the basis for the comparison. Figure 7 shows how each strategy affects the complaint rate. For the current practice strategy, the horizontal axis is the standard deviation of the setpoint change. For the resetting strategy, the horizontal axis is the magnitude of the setpoint change for a duration of 16.8 hours. The error bars are based on the Poisson approximation.

Data from a large facility in Minnesota were analyzed to get an estimate of the magnitude of the setpoint change that is typical of current practice. A total of 981 complaints covering a period of 24 months indicates that the setpoint was changed on average by 2.04°F. This point is shown in Figure 7. The results indicate that the complaint rate from the resetting strategy would be less than 60% of the complaint rate of the current practice strategy with a magnitude of 2.04°F. Based on the findings of Federspiel (1998), it is estimated that a 40% reduction in "no-fault" complaints would eliminate approximately 100 complaints. If the cost of programming DDC controls to reset the setpoints automatically were $2000 and the cost per complaint were $70, then the payback period would be 3.5 months. The cost reduction is great enough that it would usually be cost-effective to make a second trip to the complaint location if the controls could not be reset remotely or automatically. This is because the second trip would require less time than the first.

Figure 8 shows how each strategy affects the complaint recovery period. The horizontal axis and the duration in this figure are the same as in Figure 7. The error bars are twice the numerically computed standard deviation. The figure demonstrates that the resetting strategy improves the speed of response in addition to reducing the complaint rate. At a magnitude of 2.04°F, the resetting strategy recovers twice as fast as the current practice strategy.

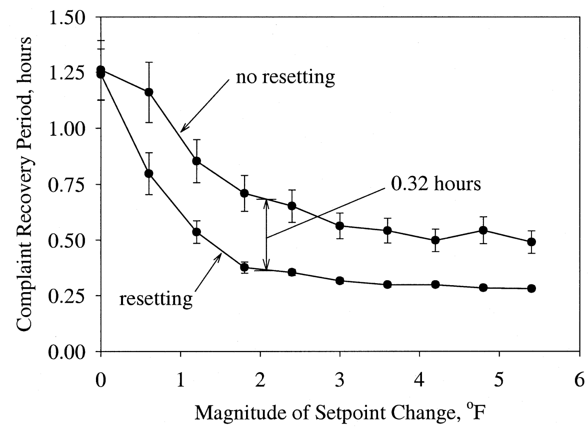

Figure 8 *Comparison of CRP with and without resetting.*

CONCLUSIONS

1. Resetting the setpoint when responding to thermal sensation complaints reduces the predicted complaint rate and the predicted complaint recovery period. For setpoint changes typical of current practice, resetting would reduce the complaint rate by 40% and cut the complaint recovery period in half.
2. Setpoints should be changed by more than 2°F and should be reset after two hours or more has passed.
3. The predicted reduction in the complaint rate caused by resetting is large enough to pay back the cost of programming DDC controls in as little as 3.5 months and is great enough to warrant a second trip to the complaint location for manual resetting if resetting cannot be automated or performed remotely.

REFERENCES

Cramer, H., and M.R. Leadbetter. 1967. *Stationary and related stochastic processes: Sample function properties and their application.* New York: John Wiley and Sons.

El-Nashar, A.M. 1998. Optimization of operating parameters of MSF plants through automatic setpoint control. *Desalination* 116(1): 89-107.

Fanger, P.O. 1972. *Thermal comfort.* New York: McGraw-Hill.

Federspiel, C.C., and H. Asada. 1994. User-adaptable comfort control for HVAC systems. *Journal of Dynamic Systems, Measurement and Control* 116(3): 474-486.

Federspiel, C.C. 1998. Statistical analysis of unsolicited thermal sensation complaints in commercial buildings. *ASHRAE Transactions* 104(1): 912-923.

Federspiel, C.C. 2000. Predicting the frequency of hot and cold complaints in buildings. *International Journal of HVAC&R Research* 6(4): 217-234.

Fisher, D.C. 1999. Stationary engineer physical plant—Campus services. University of California at Berkeley, personal interview.

Gagge, A.P., A.P. Fobelets, and L.G. Berglund. 1986. A standard predictive index of the human response to the thermal environment. *ASHRAE Transactions* 92(B): 709-731.

Haley, R. 1999. Supervisor physical plant—Campus services zone 4. University of California at Berkeley, personal interview.

Keeney, K.R., and J.E. Braun. 1997. Application of building precooling to reduce peak cooling requirements. *ASHRAE Transactions* 103(1): 463-69.

Lacroix, R., and R. Kok. 1999. Simulation-based control of enclosed ecosystems—A case study: Determination of greenhouse heating setpoints. *Canadian Agricultural Engineering* 41(3): 175-183.

MacArthur, J.W. 1986. Humidity and predicted-mean-vote-based (PMV-based) comfort control. *ASHRAE Transactions* 92(1B): 5-17.

Seem, J.E. 1987. Modeling of heat transfer in buildings. Ph.D. thesis, University of Wisconsin-Madison.

Smothers, F.J. 1999. Technical coordinator—Investor services. Jones Lang Wooton California, Inc., personal interview.

Yaglou, C.P., and P. Drinker. 1928. The summer comfort zone: Climate and clothing. *J. Ind. Hygiene and Toxicology* 10: 350-363.