ESL-PA-96/07-03-2

Great Energy Predictor Shootout II: Modeling Energy Use in Large Commercial Buildings

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ABSTRACT

The 1994 Great Energy Predictor Shootout II (GEPS), sponsored by ASHRAE Technical Committees TC 4.7, Energy Calculations and TC 1.5, Computer Applications, involved modeling/predicting heating, cooling, and electric energy consumption in two large institutional buildings in central Texas (an engineering center and a business school building). This paper describes the methodology used by one of the winning GEPS entries.

Energy consumption ($\dot{E}$) in a large commercial building is a complex function of climatic conditions, building characteristics, building use, system characteristics, and type of heating, ventilating, and air-conditioning (HVAC) equipment used. Therefore, multiple linear regression (MLR) models and nonlinear modeling approaches, such as artificial neural network (ANN) models, tend to provide better modeling capabilities than simple linear regression modeling approaches (Katipamula et al. 1994; Kreider and Haberl 1994).

The heating and cooling energy consumption in both buildings is modeled using the MLR approach. The electric energy consumption at both sites is weather-independent and is a function of only the building's operating schedule; therefore, it is modeled using a daytyping algorithm.

At the engineering center, the coefficient of variation (CV) for electric energy end-uses varied from 1% to 6%, while the CV for cooling energy consumption ($\dot{E}_c$) and heating energy consumption ($\dot{E}_h$) varied from 10% to 33%. At the business school building, the CV for electric energy end-use varied from 5% to 14%, while the CV for $\dot{E}_c$ and $\dot{E}_h$ consumption varied from 27% to 36%.

INTRODUCTION

Heating and cooling energy consumption in large commercial buildings is a complex function of climatic conditions (outdoor dry-bulb and dew-point temperatures, solar insolation), building characteristics (e.g., loss coefficient, heat capacity, internal loads), building use (12 hours or 24 hours, amount of fresh air intake), system characteristics (such as total mass flow rate, hot- and cold-deck supply temperatures, economizer cycle), and type of HVAC equipment used (Katipamula et al. 1994; Reddy et al. 1995). Because some of these parameters are difficult to estimate in an actual building, they seldom appear explicitly as variables in the regression models. The building use and operational parameters (e.g., internal gains, supply temperatures, fresh air intake) change from hour to hour; consequently, hourly regression models tend to have a higher coefficient of variation (CV) and a lower coefficient of determination (R^2) than do the daily regression models (Katipamula et al. 1994).

One method to account for the hour-to-hour variation in the internal gains (which are influenced by the building's daily operating schedule) is to sort the hourly data into several subgroups. A logical grouping would be to first sort the data into weekday and weekend groups and then sort these two groups into 24 subgroups each (each subgroup representing one hour of the day).

On the other hand, the electricity consumption from lights and equipment (LE) and, in some cases, the whole-building electric (WBE) and motor control center (MCC) electricity consumption (air handlers with constant-speed drives) is primarily a function of the building's operating schedule.

This paper explains the methodology used to model/predict the heating energy consumption ($\dot{E}_h$), cooling energy consumption ($\dot{E}_c$), WBE, LE, and MCC in two large institutional buildings. In this paper, the two buildings are denoted as the EC (engineering center) and BUS (business school building). The data from the two buildings included independent variables (time stamp and weather variables) and the dependent variables (WBE, MCC, LE, $\dot{E}_h$ and $\dot{E}_c$). GEPS organizers removed a portion of the dependent variables (Thamilseran and Haberl 1995) to evaluate the relative superiority of the predictive capabilities of the entries. Models were then developed for WBE,

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MCC, LE, $\dot{E}_h$, and $\dot{E}_c$. Using these models, the consumption was predicted for the entire data set, including the removed portion of the dependent-variable data set.

HEATING AND COOLING ENERGY CONSUMPTION MODEL DEVELOPMENT

The independent variables in the data set include time stamp, outdoor dry-bulb temperature (T_o), outdoor relative humidity, global horizontal solar radiation (q_{sol}), and wind speed (q_i). Energy consumption in large commercial buildings is a complex function of weather conditions (dry-bulb and dew-point temperatures, etc.), building characteristics (loss coefficients, heat capacity, internal loads), building use (12 hours or 24 hours, amount of fresh air intake), system characteristics (total mass flow, hot- and cold-deck supply temperatures, economizer cycle), and HVAC equipment type. Therefore, an MLR model is used to model the $\dot{E}_h$:

$$\dot{E}_h = \alpha + \beta_0 T_o + \beta_1 qsol + \beta_2 qi \tag{1}$$

where α, β_0, β_1, and β_2 are regression coefficients.

Unlike $\dot{E}_h$, $\dot{E}_c$ is made up of sensible and latent effects; therefore, a different approach is required for modeling $\dot{E}_c$. In most large commercial buildings, a major portion of the latent cooling load is from ventilation (fresh air intake), which is a strong function of the outdoor dew-point temperature (T_{dp}). No latent cooling occurs when the mixed-air dew-point temperature (a function of return and outdoor air dew-point temperatures) is lower than the surface temperature of the cooling coil. To handle this situation while performing a regression analysis, it is better to use $(T_{dp} - T_s)^+$ as an independent variable instead of just the outdoor relative humidity. In this variable, T_s is the mean surface temperature of the cooling coil and "+" indicates that the term is set equal to zero when $T_{dp} < T_s$. Thus, the $\dot{E}_c$ model is

$$\dot{E}_c = \alpha + \beta_0 T_o + \beta_1 T_{dp}^+ + \beta_2 qsol + \beta_3 qi \tag{2}$$

where T_{dp}^+ represents $(T_{dp} - T_s)^+$ and α, β_0, β_1, β_2, and β_3 are regression coefficients.

The MLR analysis assumes that the regressor variables are independent of each other. Therefore, multicollinearity between the regressor variables results in large uncertainty bounds for the regression coefficients, which increases model uncertainty. A rule of thumb (Draper and Smith 1981) is that multicollinearity effects may be important if the simple correlation between two variables is larger than the correlation of one or either variable with a dependent variable. Earlier studies by Wu et al. (1992) and Katipamula et al. (1994) showed that at hourly time scales, the collinearity is not significant among T_o, T_{dp}^+, and q_i but may be significant between T_o and q_{sol}. Multicollinearity effects have not been considered for this study.

WBE, MCC, AND LE MODEL DEVELOPMENT

Inspection of WBE, MCC, and LE consumption for both buildings showed no dependence on the weather variables. Therefore, a daytyping methodology is used to develop models for these end-uses. The daytyping methodology is based on the premise that daily mean energy use (WBE, MCC, or LE) is different on each typical day, such as weekdays, weekends, holidays, and other special days (e.g., spring break, Christmas break). The method used for this analysis is a modified form of the daytyping method proposed by Katipamula and Haberl (1991).

The first step in the daytyping process is to sort the data into groups based on mean daily consumption. In general, three to four groups are sufficient to describe the entire data set (weekdays, weekends, holidays, and other days, such as spring break and Christmas break). The standard deviation of the mean consumption within a group is used as an indicator to see how well the data within each group are clustered. If the standard deviation is high (20% or 30% of the mean), then the group can be divided further. Using the daytyping methodology, the electric end-uses in both buildings are modeled.

HEATING AND COOLING ENERGY MODELING RESULTS

In this section, the methodology used to model $\dot{E}_h$ and $\dot{E}_c$ is described, and the modeling results are presented.

First, the outdoor relative humidity is converted to outdoor dew-point temperature with the use of a psychrometric routine (as described in the *1993 ASHRAE Handbook—Fundamentals* [ASHRAE 1993]). The hourly data are then sorted into weekday and weekend groups (holidays are treated as weekends), and these two groups are further sorted into 24 subgroups, each representing an individual hour of the day (hour 0 midnight, hour 100, ... hour 2200, and hour 2300). In most commercial buildings, the cold deck supply temperature is held constant at 55°F (12.7°C) throughout the year. If the surface temperature is an unknown, it can be estimated by selecting a value of T_s that minimizes the CV. However, for this analysis the T_s was assumed to be 55°F (12.7°C) at both sites.

EC Building Results

Using Equation 1, the $\dot{E}_h$ for the EC building is modeled. The R^2 and standard error at each hour of the day for both weekdays and weekends is shown in Table 1. The R^2 varies from 68% to 95% on weekdays and 71% to 99% on weekends. On weekdays, the unoccupied hours show slightly greater R^2 than the occupied hours, and on weekends, the R^2 is consistently higher than on weekdays. Because the building is typically less occupied on weekends than on weekdays, the variation in $\dot{E}_h$ on weekends is probably less than on weekdays. The overall root mean square error (RMSE) and CV are 0.43 mm Btu/h (1 mm Btu/h = 10^6 Btu/h) and 24% on weekdays and 0.69 mm Btu/h and 33% on weekends, respectively (Table 2). The mean $\dot{E}_h$ during weekdays (1.8 mm Btu/h) is slightly lower than that on weekends (2.1 mm Btu/h) because of higher heat gains from LE on weekdays. Figure 1 shows the actual and predicted $\dot{E}_h$ for the EC building. At low consumption (below 2.5 mmBtu/h), the predicted $\dot{E}_h$ compares well with the actual, but at high consumption, the model is underpredicting $\dot{E}_h$. The actual $\dot{E}_h$

and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 2. Again, positive residuals during the winter months (January and February) indicate that the model is underpredicting during that period. If the winter months are separated from the summer months, the modeling accuracy could be improved.

Using Equation 2 the $\dot{E}_c$ for the EC building is modeled. The R^2 and standard error at each hour of the day for both weekdays and weekends is shown in Table 3. The R^2 varies from 71% to 94% on weekdays and 34% to 93% on weekends. On weekdays, the unoccupied hours show slightly greater R^2 than the occupied hours. On weekends, with the exception of hours 6 and 7, the R^2 is consistently higher than on weekdays. At hours 6 and 7, the number of data points available for modeling are less than at other hours; therefore, those hours have a poor correlation. The overall RMSE and CV are 0.60 mmBtu/h and 10% on weekdays and 0.66 mmBtu/h and 12% on weekends, respectively (Table 2). The mean $\dot{E}_c$ during weekdays (5.8 mmBtu/h) is slightly higher than that on weekends (5.4 mmBtu/h) because of increased heat gains from LE on weekdays.

Figure 3 shows the actual and predicted values of $\dot{E}_c$ for the EC building. In general, the predicted $\dot{E}_c$ compares well with the actual. The actual $\dot{E}_c$ and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 4. Again, as in the case of $\dot{E}_h$, the magnitude of the residuals is higher during the winter months (January and February) than during the rest of the year. Again, if the winter months are separated from the summer months, the modeling accuracy can be improved.

TABLE 1 R^2 and Standard Error for the Hour-of-the-Day $\dot{E}_h$ Models

HOD	Weekdays		Weekends	
	R^2	Std. Err	R^2	Std. Err
0	0.7995	0.3044	0.9019	0.3540
1	0.7446	0.3609	0.8792	0.3077
2	0.8611	0.2393	0.7717	0.4402
3	0.9020	0.3049	0.7567	0.3708
4	0.7854	0.3309	0.7078	0.4457
5	0.7919	0.3975	0.9183	0.2804
6	0.8877	0.2669	0.9269	0.2262
7	0.9157	0.2277	0.9892	0.1062
8	0.9507	0.1806	0.9424	0.2636
9	0.8767	0.2662	0.8954	0.3443
10	0.9050	0.2150	0.9891	0.0978
11	0.8310	0.2540	0.8902	0.2922
12	0.6824	0.3800	0.9423	0.2227
13	0.8199	0.2363	0.8905	0.3163
14	0.8416	0.2261	0.8678	0.3313
15	0.8117	0.2541	0.9208	0.2636
16	0.7860	0.2540	0.9106	0.2924
17	0.7436	0.2746	0.8741	0.2964
18	0.6783	0.3228	0.8780	0.2946
19	0.8001	0.3096	0.8869	0.3425
20	0.8222	0.2980	0.8935	0.3548
21	0.8293	0.3055	0.8721	0.3508
22	0.8728	0.2666	0.8660	0.3813
23	0.8577	0.2842	0.8911	0.3677

BUS Building Results

Because the summertime $\dot{E}_h$ at the BUS building is near zero, $\dot{E}_h$ is modeled separately for summertime and nonsummertime periods. The summertime model is a simple mean model (i.e., flat consumption of 0.063 mm Btu/h). The nonsummer models were based on Equation 1. The R^2 and standard error at each hour of the day for both weekdays and weekends are

TABLE 2 Overall RMSE and CV for the Entire Data Set (EC)

Variable	Weekdays		Weekends		Weekday	Weekend
	RMSE (kW or mmBtu/h)	CV (%)	RMSE (kW or mmBtu/h)	CV (%)	Mean (kW or mmBtu/h)	Mean (kW or mmBtu/h)
HW	0.43	24	0.69	33	1.8	2.1
CW	0.60	10	0.66	12	5.7	5.4
WBE	38	3	18	2	1151	1012
LE	41	6	27	5	670	528
MCC	7	2	5	1	371	372

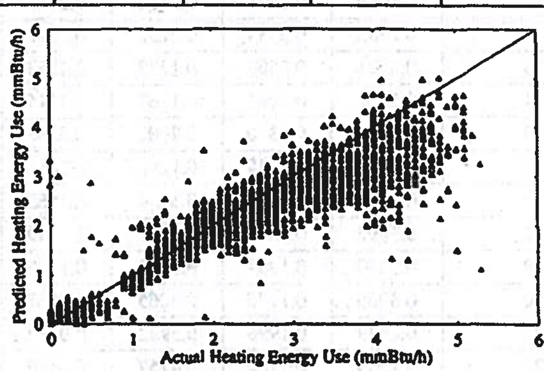

Figure 1 Actual and predicted $\dot{E}_h$ (EC).

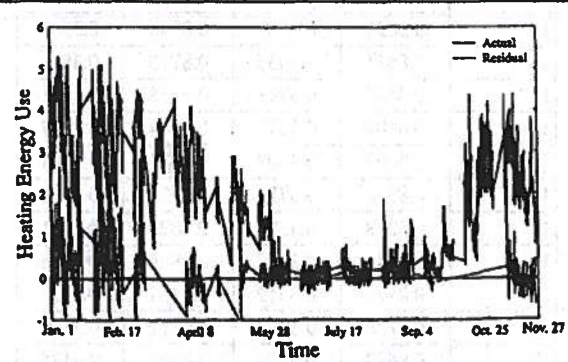

Figure 2 Actual $\dot{E}_h$ and residual (actual – predicted) (EC).

shown in Table 4. The R^2 varies from 18% to 60% on weekdays and from 12% to 88% on weekends. Because there are fewer data points in each hour of the day bin, the model statistics are not as good as those of the EC model. The overall RMSE and CV are 0.15 mmBtu/h and 30% on weekdays and 0.14 mmBtu/h and 27% on weekends, respectively (Table 5). The mean $\dot{E}_h$ during both weekdays and weekends is 0.5 mmBtu/h.

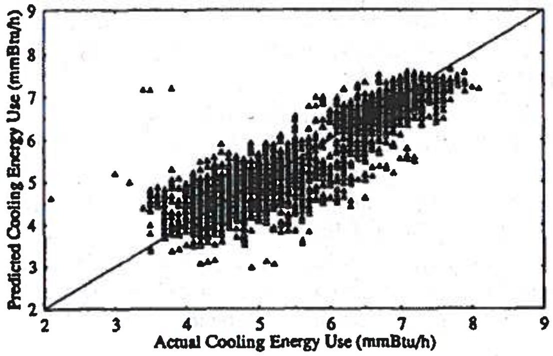

Figure 3 Actual and predicted $\dot{E}_c$ (EC).

Figure 5 shows the actual and predicted $\dot{E}_h$ for the BUS building. It appears that the overall slope of the model is slightly lower than the slope of the actual. This suggests that the model is underpredicting at high outdoor temperatures and overpredicting at low outdoor temperatures. The actual $\dot{E}_h$ and the residuals (actual $\dot{E}_h$ minus predicted $\dot{E}_h$) are plotted as time-series graphs in Figure 6.

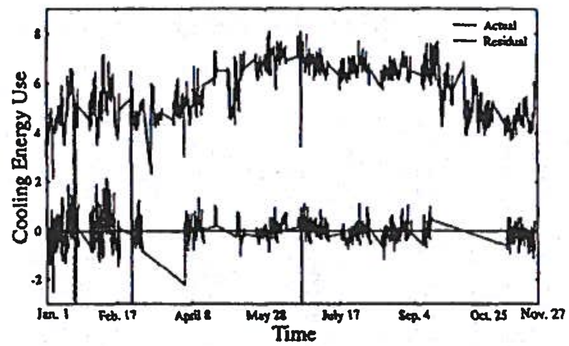

Figure 4 Actual $\dot{E}_c$ and residual (actual – predicted) (EC).

TABLE 3 R^2 Standard Error for the Hour-of-the-Day $\dot{E}_c$ Models (EC)

HOD	Weekdays		Weekends	
	R^2	Std. Err	R^2	Std. Err
0	0.9044	0.3028	0.8693	0.4116
1	0.9026	0.2961	0.8967	0.3755
2	0.9084	0.3036	0.9056	0.3879
3	0.9161	0.3069	0.8903	0.4798
4	0.9440	0.2597	0.9005	0.4767
5	0.9319	0.2638	0.8583	0.4828
6	0.8894	0.3227	0.6050	0.5536
7	0.8023	0.3910	0.3369	0.3642
8	0.7124	0.4179	0.7614	0.2256
9	0.7316	0.3790	0.8936	0.1343
10	0.7114	0.4217	0.7987	0.6954
11	0.8897	0.3754	0.8915	0.4795
12	0.8691	0.3687	0.8940	0.3962
13	0.8471	0.3938	0.8713	0.3874
14	0.8458	0.3714	0.8778	0.3681
15	0.8602	0.3517	0.8874	0.3527
16	0.8603	0.3509	0.9039	0.3295
17	0.8378	0.3715	0.8851	0.3702
18	0.8238	0.4322	0.9020	0.3421
19	0.9140	0.3000	0.8849	0.3626
20	0.8827	0.3319	0.9252	0.2825
21	0.8723	0.3398	0.9112	0.3109
22	0.8633	0.3569	0.8347	0.4175
23	0.9314	0.2570	0.8557	0.3956

TABLE 4 R^2 Standard Error for the Hour-of-the-Day $\dot{E}_h$ Models (EC)

HOD	Weekdays		Weekends	
	R^2	Std. Err	R^2	Std. Err
0	0.1793	0.3202	0.3362	0.1770
1	0.2251	0.1994	0.7861	0.0485
2	0.2097	0.1802	0.7449	0.0779
3	0.2620	0.2012	0.4709	0.1130
4	0.2384	0.1895	0.7456	0.0786
5	0.4225	0.1956	0.8762	0.0467
6	0.4284	0.2680	0.1843	0.2161
7	0.5898	0.2076	0.3730	0.3528
8	0.5601	0.1981	0.3411	0.3281
9	0.5990	0.1886	0.3871	0.2857
10	0.4990	0.1791	0.3177	0.2609
11	0.5060	0.1821	0.2156	0.2411
12	0.2985	0.2334	0.2232	0.2391
13	0.3171	0.2507	0.1278	0.2853
14	0.3891	0.2283	0.1567	0.2445
15	0.3366	0.2330	0.2001	0.2582
16	0.3868	0.1745	0.1246	0.2411
17	0.5402	0.1461	0.3554	0.2565
18	0.3992	0.1654	0.2041	0.1949
19	0.3260	0.1969	0.3913	0.1105
20	0.3965	0.1770	0.7065	0.0567
21	0.2439	0.1995	0.5932	0.0789
22	0.2734	0.1784	0.4757	0.0939
23	0.3219	0.2619	0.6088	0.0594

Using Equation 2, the $\dot{E}_c$ for the BUS building is modeled. The R^2 and standard error at each hour of the day for both weekdays and weekends are shown in Table 6. The R^2 varies from 5% to 23% on weekdays and from 7% to 59% on weekends. The overall RMSE and CV are 0.69 mmBtu/h and 37% on weekdays and 0.42 mmBtu/h and 31% on weekends, respectively (Table 5). The mean $\dot{E}_c$ during weekdays (1.9 mmBtu/h) is slightly higher than it is on weekends (1.3 mmBtu/h) because of higher heat gains from LE on weekdays.

Figure 7 shows the actual and predicted $\dot{E}_c$ for the BUS building. In general, the predicted $\dot{E}_c$ compares well with actual $\dot{E}_c$ except for a few hours (especially when consumption is low) where the difference between predicted and actual consumption is significant. It appears that on some days the air-handling units during unoccupied hours (at night) are shut down and on other days they are not. Therefore, the major portion of this difference between predicted and actual consumption can be attributed to this phenomenon. This can be clearly seen in Figure 8, where the actual $\dot{E}_c$ and the residuals (actual $\dot{E}_c$ − predicted $\dot{E}_c$) are plotted as time-series graphs.

WBE, MCC, AND LE MODELING RESULTS

In this section, the methodology used to model WBE, MCC, and LE is explained and the modeling results are presented. The hourly data are summed to daily and and then sorted into 12 groups, with each group representing one calendar month.

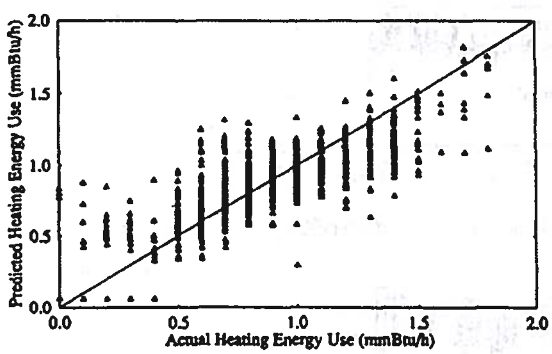

Figure 5 Actual and predicted $\dot{E}_h$ (BUS).

TABLE 5 Overall RMSE and CV for Entire Data Set (BUS)

Variable	Weekdays		Weekends		Weekday	Weekend
	RMSE (kW or mmBtu/h)	CV (%)	RMSE (kW or mmBtu/h)	CV (%)	Mean(kW or mmBtu/h)	Mean(kW or mmBtu/h)
HW	0.15	30	0.14	27	0.5	0.5
CW	0.69	36	0.42	31	1.9	1.3
WBE	16	5	20	8	332	245
LE	4	7	5	14	62	36
MCC	8	8	5	6	98	82

EC Results

After the daily mean WBE and LE in each monthly data set are analyzed, three distinct groups are identified for each month: weekday, weekend, and other (e.g., holidays, spring break, Christmas break). Although three distinct groups are required for WBE and LE, only one distinct group emerged for MCC (which

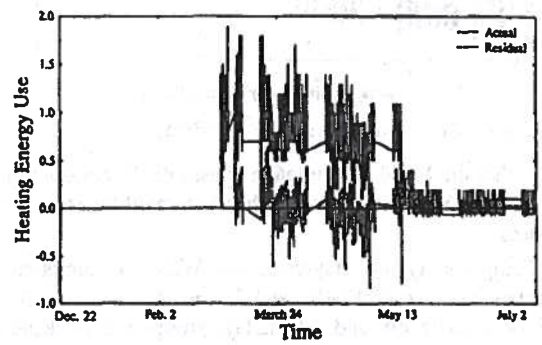

Figure 6 Actual $\dot{E}_h$ and residual (actual - predicted) (BUS).

TABLE 6 R^2 and Standard Error for the Hour-of-the-Day $\dot{E}_c$ Models (BUS)

HOD	Weekdays		Weekends	
	R^2	Std. Err	R^2	Std. Err
0	0.0904	0.7319	0.0729	0.4389
1	0.0479	0.6399	0.2159	0.4062
2	0.0570	0.6146	0.2859	0.4129
3	0.0598	0.6120	0.1914	0.3980
4	0.0729	0.6010	0.0956	0.4710
5	0.1401	0.5510	0.0659	0.4632
6	0.1467	0.7820	0.1135	0.5364
7	0.2213	0.7302	0.5840	0.5653
8	0.1368	0.7574	0.5922	0.5287
9	0.2304	0.7358	0.5422	0.5251
10	0.0814	0.8162	0.5623	0.4765
11	0.1836	0.7490	0.5273	0.4778
12	0.1923	0.7392	0.5510	0.4421
13	0.1613	0.7413	0.4175	0.5116
14	0.0918	0.7864	0.4669	0.4596
15	0.0916	0.7850	0.4839	0.4577
16	0.1682	0.6895	0.4272	0.5347
17	0.1429	0.6949	0.4266	0.4882
18	0.1836	0.6675	0.3343	0.4824
19	0.0905	0.7876	0.1738	0.3922
20	0.2157	0.7220	0.1856	0.3986
21	0.1750	0.7425	0.2687	0.3958
22	0.2006	0.7033	0.1529	0.3847
23	0.2259	0.7537	0.1717	0.4175

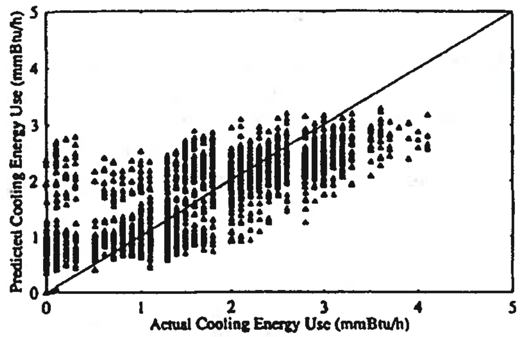

Figure 7 Actual and predicted $\dot{E}_c$ (BUS).

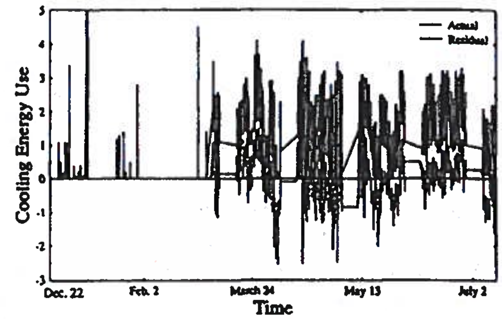

Figure 8 Actual $\dot{E}_c$ and residual (actual - predicted) (BUS).

means that the MCC consumption is essentially constant on a daily basis). Typical daytypes are then generated for each of the end-uses.

Using the typical daytypes, the WBE consumption is predicted. The overall RMSE and CV are 38 kW and 3% on weekdays and 18 kW and 2% on days grouped as weekend or other, respectively (Table 2). The CV for the weekend group is smaller than that for the weekday group because weekends are relatively less occupied; consequently, there is probably a smaller variation in WBE from day to day. The mean WBE consumption during weekdays is 1,151 kW and on weekends it is 1,012 kW.

The actual WBE and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 9. Except for a few hours, the residuals are low and unbiased. Using the typical daytypes, LE consumption is predicted. The overall RMSE and CV are 41 kW and 6% on weekdays and 27 kW and 5% on weekends and other days combined (Table 5). Again, the weekend group has a lower CV than the weekday group. The mean LE consumption during weekdays is 670 kW; on weekends, it is 528 kW. The actual LE and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 10. Again, with the exception of a few hours, the residuals are low and unbiased.

Using the typical daytype, the MCC consumption is predicted. The overall RMSE and CV are 7 kW and2% on weekdays and 5 kW and 1% on weekends and other days (Table 2). The mean MCC consumption during weekdays and weekends is 372 kW. The actual MCC and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 11.

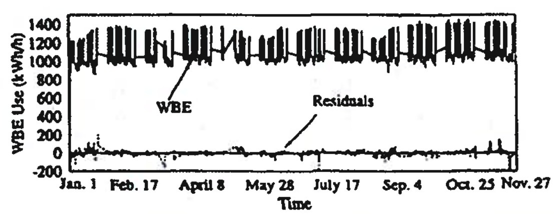

Figure 9 Actual WBE and residual (actual - predicted) (EC).

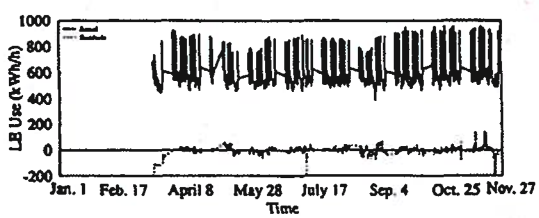

Figure 10 Actual LE and residual (actual - predicted) (EC).

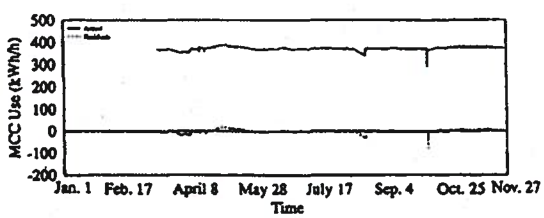

Figure 11 Actual MCC and residual (actual -predicted) (EC).

BUS Results

After the daily mean WBE, LE, and MCC in each monthly data set are analyzed, three distinct groups are identified for each month: weekday, weekend, and other (holidays, spring break, Christmas break). Typical daytypes are then generated for each of the end-uses.

Using the typical daytypes, the WBE consumption is predicted. The overall RMSE and CV are 16 kW and 5% on weekdays and 20 kW and 8% on weekends and other days, respectively (Table 5). Unlike the EC building, the BUS building CV for the weekend group is higher than that of the weekday group. The mean WBE consumption during weekdays is 332 kW; on weekends, it is 245 kW.

The actual WBE and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 12. Except for a few hours, the residuals are low and unbiased. Using the typical daytypes, the LE consumption is predicted. The overall RMSE and CV are 4 kW and 7% on weekdays and 5 kW and 14% on weekends and other days, respectively (Table 5). Again, the weekend group has a higher CV than does the weekday group. The mean LE consumption during weekdays is 62 kW; on weekends, it is 36 kW. The actual LE and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 13. Again, with the exception of a few hours, the residuals are low and unbiased.

Using the typical daytype, the MCC consumption is predicted. The overall RMSE and CV are 8 kW and 8% on weekdays and 5 kW and 6% on weekends and other days, respectively (Table 2). The mean MCC consumption during weekdays is 98 kW; on weekends, it is 82 kW. The actual MCC and the residuals (actual minus predicted) are plotted as time-series graphs in Figure 14.

DISCUSSION OF RESULTS

Heating and Cooling Energy Models for the EC Building

For the EC building, the model-predicted $\dot{E}_h$ for summer months is higher than actual (Figure 1); therefore, the CV is higher (24%). It appears that by separating the winter months from the summer months, the modeling accuracy can be improved. The $\dot{E}_c$ model for the EC building appears to be unbiased, i.e., the actual $\dot{E}_c$ is evenly distributed about the model-predicted $\dot{E}_c$ (Figure 3). The CV for the $\dot{E}_c$ model is only 10% compared to 24% for the $\dot{E}_h$ model.

Heating and Cooling Energy Models for the BUS Building

The CV for both the $\dot{E}_h$ and the $\dot{E}_c$ models is high (30% and 36%, respectively). The actual reason for this behavior is not evident from the available information. The high CV may be due to the random shutdown of the air-handling units during some unoccupied periods.

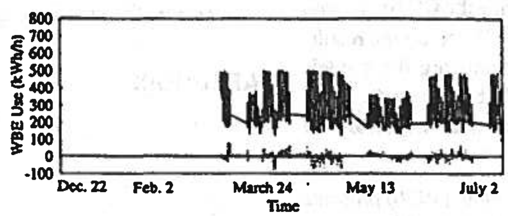

Figure 12 Actual WBE and residual (actual - predicted) (BUS).

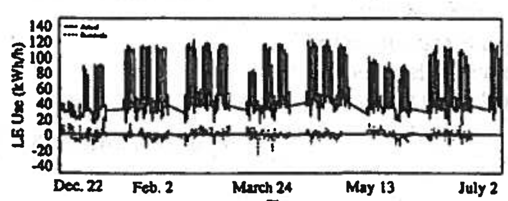

Figure 13 Actual LE and residual (actual - predicted) (BUS).

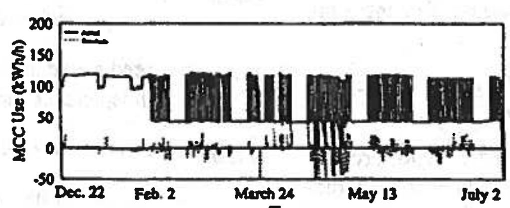

Figure 14 Actual MCC and residual (actual -predicted) (BUS).

WBE, LE, and MCC Energy Models for the EC

All models appear to be relatively unbiased because the CV is low (Table 2).

WBE, LE, and MCC Energy Models for the BUS

All models with the exception of the MCC weekend model appear to be relatively unbiased (Table 5). Again, the random shutdown of the air-handling units during unoccupied periods may be the cause.

SUMMARY

The heating, and cooling energy and electric energy consumption was modeled/predicted in two large institutional buildings in central Texas (an engineering center and a business building).

The heating and the cooling energy consumption in both buildings was modeled using an MLR approach. The electric energy consumption at both sites is weather independent and is only a function of the buildings' operational schedule; therefore, it was modeled using a daytyping algorithm.

At the engineering center, the CV for electric energy end-uses varied from 1% to 6%, while the CV for cooling energy consumption ($\dot{E}_c$) and heating energy consumption ($\dot{E}_h$) varied from 10% to 33%. At the business building, the CV for electric energy end-use varied from 5% to 14%, while the CV for $\dot{E}_c$ and $\dot{E}_h$ consumption varied from 27% to 36%. Based on the results from the training set, it appears that customizing the models (separating summer/winter data) may yield better results in the case of the EC building. For the BUS building, it is not clear how the models can be improved.

An overview paper written by Haberl et al. (1996) presents the comparison of how well this entry performed with respect to the other entries and a comparison of savings predicted by this entry using the test set. This is the only entry based on a non-neural-network approach and it still managed to come in second in the overall rankings. No discussion is provided here on how well the models performed with the testing data set because the overview paper provides this discussion.

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APPENDIX

$$\text{Coefficient of Variation (CV) \%} = \frac{\sqrt{\dfrac{\sum_i^n (y_{p,i} - y_{data,i})}{n-m}}}{\bar{y}_{data}} \times 100 \qquad \text{(A1)}$$

$$\text{Mean Bias Error (MBE) \%} = \frac{\dfrac{\sum_i^n (y_{p,i} - y_{data,i})}{n-m}}{\bar{y}_{data}} \times 100 \qquad \text{(A2)}$$

where

$y_{data,i}$ = data value of the dependent variable corresponding to a particular set of the independent variables,

$y_{p,i}$ = predicted dependent variable for the same independent variables above,

$\bar{y}_{data}$ = mean value of the dependent variable of the data set,

n = number of data points in the data set, and

m = total number of regression parameters in the model.