A Methodology to Identify Monthly Energy Use Models

From Utility Bill Data for Seasonally Scheduled Buildings : Application to K-12 Schools

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ABSTRACT

The measured energy savings from retrofits in buildings is often determined as the difference between the energy consumption predicted by a baseline model and the measured energy consumption during the post retrofit period. Most baseline models are developed either by regressing the daily energy consumption versus the daily average temperature (daily model) or by regressing the monthly energy consumption versus the monthly average temperature (monthly model).

Savings measurement for buildings such as primary and secondary schools (k-12 school) is very difficult due to the special operating schedules of such buildings. Currently, savings are either determined by simple pre-post utility bill comparison or by a method where by the baseline model consists of two separate models: a 3-P model for non-summer months, and a mean model for the summer months. (Landman, 1996).

This paper proposes an improved methodology for identifying baseline models of energy use from utility billing data for buildings such as schools which have important daily and seasonal variations in occupancy. By explicitly considering the occupancy rate in the model, we are able to generalize it and retain the distinction between energy use levels during occupied and unoccupied days of the year. Thus the modified baseline model accounts, not only for the effect of weather, but also for the influence of school schedules. The proposed methodology has been evaluated against the previous 3-P-mean proposed by Landman for 10 schools in Texas for which several years

of monitored data are available. Incorporation of scheduling information reduced the average CV of the model from 23.6% using Landman's method to 10.9% using our proposed method.

INTRODUCTION

Energy use in commercial buildings accounts for 16% of total energy use in the United States (EIA, 1992). Since most buildings were constructed when energy was inexpensive, at least 30% of the energy use in the building sector is wasted due to inefficient equipment and operation (Bevington and Rosenfeld, 1990). This wasted energy can be saved in a highly cost-effective manner by operational improvements and retrofits. For example, the Texas LoanSTAR Program measured a 24% energy consumption reduction in 64 commercial buildings where retrofits with average pay back of 3 years were performed (Claridge, 1994).

The analysis of energy consumption data is a valuable tool for the management of buildings operation:

- it can help detect malfunctions (by identifying episodes of abnormally high consumption);
- it is essential for energy audits in order to improve the estimates of expected savings, and to verify the savings achieved by retrofit (Haberl and Komor, 1990)

Such an analysis requires an understanding of the factors that influence the energy consumption. Basically one needs a model of the building that can predict the consumption for any operating conditions of interest.

In most retrofit evaluation programs, energy savings are determined as the difference between the energy consumption predicted by using a baseline model and the measured energy consumption during the post retrofit period. The baseline can be developed using different approaches, such as simplified HVAC system models (Knebel, 1983) calibrated with the data taken before or after the retrofit (Katipamula and Claridge, 1992), and statistical regression models based on data taken before the retrofit (Fels 1986; Ruch et al., 1992; Claridge et al., 1992; Ruch et al., 1993; Kissock et al., 1992; Kissock et al., 1993; Reddy etal, 1997). The regression model approach is the simplest and most widely used. A number of regression models and simplified simulation models were developed in the LoanSTAR program (Reddy et al. 1994). The selection of the appropriate model is determined by how much and what types of monitored data are available.

In the LoanSTAR program the regression models are selected based on the values of the coefficient of determination (R^2) and the coefficient of variation of the root mean square error (CV-RMSE). These two statistical indices provide an indication of the goodness-of-fit of the model to the measured data during the pre-retrofit period. The difference in the annual value from the model and the measured value is defined as the annual prediction error (APE).

However, the baseline models only capture changes in energy consumption due to changes in weather. For seasonally scheduled buildings such as schools, a proper retrofit saving determination becomes more difficult due to having to explicitly account for their special schedules. Retrofit savings of schools in the LoanSTAR program are currently evaluated using simple pre- post utility bill comparison, or a procedure suggested by Landman (1996 a, b). The latter, however, only considers the influence of weather on the energy use without paying any attention to the schedule differences during the year. By explicitly considering occupancy rate in the model, we are able to generalize it and retain the distinction of how energy is consumed during occupied and unoccupied days of the year.

Thus we need the baseline models to account, not only for the effect of weather, but also for the variations in occupancy. We intend to use occupancy rate as a proxy for the operating mode of the building and its HVAC system.

BACKGROUND

The regression models can be divided into two categories: single variable (SV) models and multiple variable (MV) models. (Reddy etal, 1994).

Single variable models:

Here the outside air dry-bulb temperature is taken to be the only regression variable. The models for weather dependent use include two-parameter (2-P), three-parameter (3-P) and four-parameter (4-P) models. The functional forms of these models are as follows:

2-P model: $E = a + bT_{db}$ (1)

3-P model: $E = a + b(T_{cp} - T_{db})^+$

for heating (2a)

and $E = a + b(T_{db} - T_{cp})^+$

for cooling (2b)

4-P model: $E = a + b_1(T_{db} - T_{cp})^+ + b_2(T_{cp} - T_{db})^+$ (3)

In these equations, a is the energy consumption at the change point temperature T_{cp}, b, b_1 and b_2 are the temperature slopes. Equation 2a is the 3-P heating regression model and Equation 2b is the 3-P cooling regression model. In this paper we consider only electricity use for cooling, and so only equation 2b is used.

Multiple variable regression models:

Multiple variable regression models include the effects of variables such as specific humidity, solar radiation and internal loads in addition to the impact of outdoor temperatures. Suitable multi-variable regression models can be developed by incorporating the engineering principles that govern the HVAC system operation (Forrester and Wepfer, 1984). An example of a simplified multi-variable regression model based on engineering principles can take the form (Katipamula et al., 1994):

$$E = a + b + cI + dIT_{db} + eIT_{db}^+ + fq_{sol} + gq_i$$

where a, b, c, d, e, f and g are the linear regression coefficients, T_{db} again is the temperature, q is the heat gain and I is an indicator variable that accounts for a change in slope due to the effect of outdoor temperatures at higher values. (Kissock, 1993)

MATHEMATICAL BASIS OF THE PROPOSED MODEL

The proposed model will consider the impact of the occupancy level as well as that of the outdoor air temperature. From equation 2b, the 3-P cooling regression model for school days can be re-written as:

$$E_{oc} = a_{oc} + b_{oc}(T_{db} - T_{cpoc})^{+} \quad (4)$$

the appropriate 3-P model for non-school days is:

$$E_{un} = a_{un} + b_{un}(T_{db} - T_{cpun})^{+} \quad (5)$$

Further,

$$E_{tot} = E_{oc}k + E_{un} (1 - k)$$

where k is defined to be the fraction of the days during each month which are school days. Then The above can be combined to give the following model:

$$E_{tot} = a_{oc}k + b_{oc}(T_{db} - T_{cpoc})^{+}k + a_{un}(1 - k) + b_{un}(T_{db} - T_{cpun})^{+}(1 - k) \quad (6)$$

Because there are 6 parameters to be identified from 12 monthly reference data points, the estimation will be unsound. Thus, in order to simplify the model our preliminary studies indicated that it is better to assume the two models to have the same slope and the same balance temperature. Then the model becomes a 4-P multiple linear regression model:

$$E_{tot} = a_{oc}k + a_{un}(1 - k) + b_{m}(T_{db} - T_{cpun})^{+}$$
$$= a_{un} + k (a_{oc} - a_{un}) + b_{m}(T_{db} - T_{cpun})^{+} \quad (7)$$

or:

$$E_{tot} = a_0 + a_1k + b_m(T_{db} - c)^{+} \quad (8)$$

where a_0 , a_1 , b_m and c are the four parameters of the model which need to be identified by regression of the 12 months utility bills. If we were to only assume that the unoccupied & occupied periods had the same balance point temperature ($T_{cpoc} = T_{cpun}$ in equation 6), then the model becomes a 5-P model as:

$$E_{tot} = a_0 + a_1k + b_{oc}(T_{db} - c)^{+} + b_{un}(T_{db} - c)^{+} \quad (9)$$

3-P-MEAN MODEL

The 3 parameter-mean model procedure suggested by Landman (Landman, 1996a, b) is to develop two models separately, a model using the non-summer monthly only of the standard 3-P form, normally is of the same form as described earlier,

$$E = a + b(T_{db} - c)^{+} \quad (10a)$$

Subsequently, a separate mean model is fit to the summer months such that:

$$E = E_{mean} \quad (10b)$$

Thus this methodology consists of fitting two separate models with the 12 utility bills of the school separated into summer (i.e. vocation) & non-summer (i.e. school-day) periods.

CASES EXAMINED

We evaluated both our proposed model and the 3-P-Mean model with data from 10 schools in Texas. These ten schools are located in four different cities in Texas: Fort Worth, Victoria, Nacogdoches, and Galveston. Table 1 shows some key characteristics of these schools. Weather data for the four different sites are also available on a daily basis.

Table 1. ***List of Schools with Monitored Hourly Data***

School Name	School Code	Site	Conditioned Floor Area (ft^2)
Sims Elementary School	SES	Fort Worth	62,400
Dunbar Middle School	DMS	Fort Worth	92,884
Stroman High School	SHS	Victoria	210,414
Victoria High School	VHS	Victoria	257.014
Nacogdoches High School	NHS	Nacogdoches	202,515
Chamberlain Middle School	CMS	Nacogdoches	66,778
Oppe Elementary School	OES	Galveston	80,400
Weis Middle School	WMS	Galveston	80,769
Parker Elementary School	PES	Galveston	81,742
Morgan Elementary School	MES	Galveston	76,798

PROCEDURE

The baseline models has been developed using data for fiscal year 1994 (FY94) which is from 08/93 to 07/94 for all schools, the only exception being Sims Elementary school when FY93 was used. Based on the school schedule and the time series energy usage, the daily data has been divided into two or three different sub-groups defined below.

Two groups:

(1) school days during the academic year.
(2) non-schooldays during the academic year.

Three groups:

(1) school days during the academic year.
(2) holidays longer than 2 days during academic year.
(3) remaining days (weekends).

We sum up the daily data for each month, and divide by the number of days to get the monthly average value. We then use these values and the daily values to develop 3-P monthly and daily models. The results for daily models are shown in Table A1 in the appendix. results of which have the monthly models in Table A2.

<u>*Selection of Weather Data*</u>

We selected two years in the most recent five years which have the highest temperatures in summer and the lowest temperatures in winter. Figure 1 shows the time series behavior of the outside dry bulb temperature for one of the four sites (namely for Sims Elementary School). Figure 2 clearly illustrates the difference in the monthly average temperatures for this site between the extreme year and the year we selected to created the baseline models.

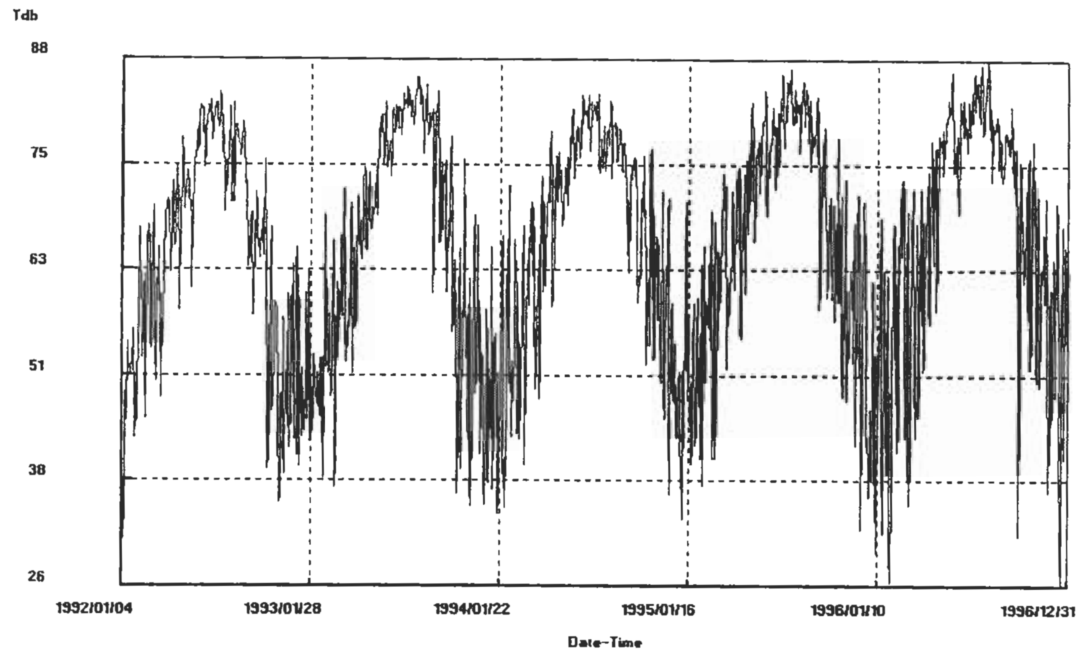

Figure 1. Daily Average Temperatures for Fort Worth from 1992 through 1996

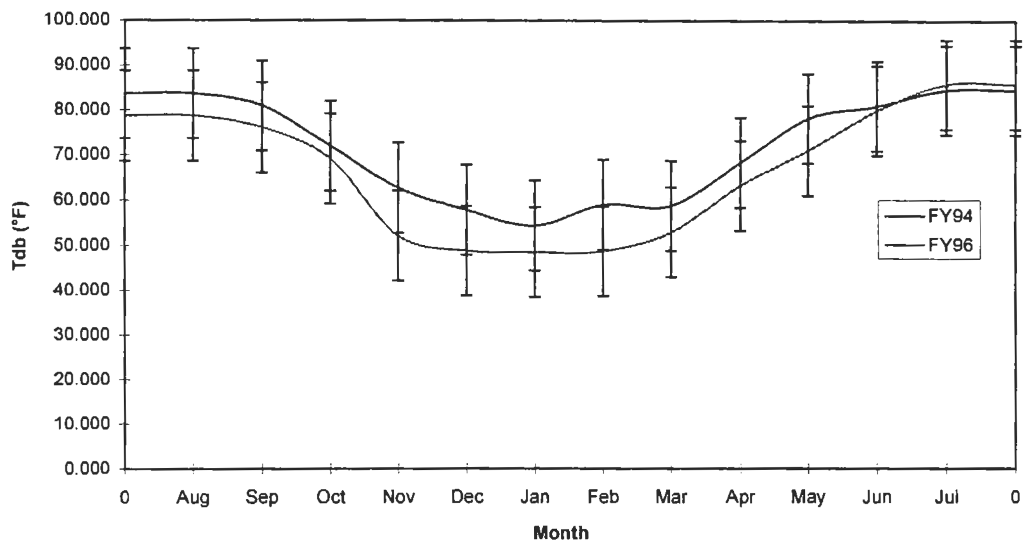

Figure 2. Monthly Average Temperature for Fort Worth for Two Different Years (FY93 & FY96)

The variation in schedule

The lighting load is closely related to the building HVAC and operating schedules. Figure 3. illustrates the seasonal variation of the measured daily lighting energy consumption for FY93 and FY96 for Sims. The difference between the lines implies that the schedules for FY93 and FY96 for the same school are quite different. Thus, as stated earlier, we can not use the actual data and assume the same schedule for different years at the same time. Hence in order that the evaluation of our proposed methodology for monthly baseline model identification not be confounded by changes in operating schedule from one year to the next, we decided to use an appropriate model (instead of monitored data) to create synthetic " Utility Bills " for the extreme years.

Figure 4. shows the difference between the predicted and measured daily electricity consumption for Sims Elementary school for FY 93, the year used to develop the model. We see clearly that the differences are large during summer months because of the special schedule of the school during summer vacation. This further illustrate the fact that schedule changes have a much larger impact on energy use than the outside temperature.

Figure 6. shows the difference between the predicted and measured daily electricity consumption for Sims Elementary school for FY 96, i.e. the extreme temperature year. It's not a surprise to us that the difference is so large, because the extreme temperature year schedule is quite different from the year used to create the model.

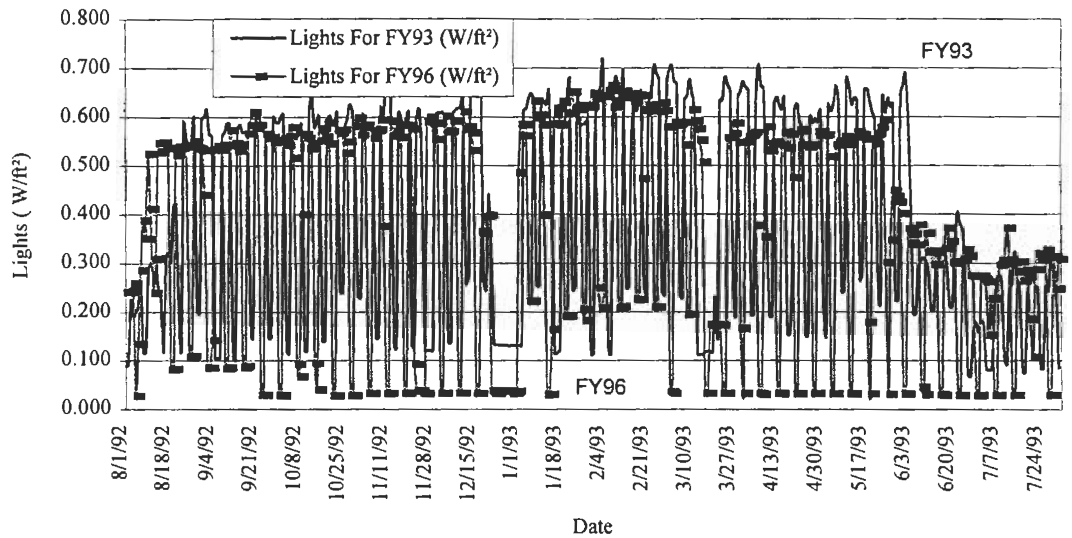

Figure 3. Daily Lighting Load for Sims (FY93 & FY96)

CREATION OF SYNTHETIC UTILITY BILL DATA

The intent to which our proposed methodology for identifying a monthly baseline model from utility bill data for seasonally scheduled buildings such as schools, is superior to the Landman methodology has been evaluated as follows. First, we reiterate the need to base on evaluation "Synthetic daily data" predicted by a daily model to the baseline year (FY93) hereby we can remove random and unknown changes in building operating schedules as well as changes in installed plug-loads from year to year. Instead of picking all arbitrary year for model prediction purpose, we looked at climatic data over the last five years and selected FY96 which was extreme in that it was hotter in summer and colder in winter than other baseline year of FY93. Thus differences in predictive ability of our proposed methodology verses Landman's method are likely to be accentuated.

The basis of predictive accuracy of both approaches is the daily model which has been identified from daily data from FY93 subdivided into 2 or 3 day-types (as appropriate) and a separate 3-P regression model identified for each day-type. This set of base models are then used with FY96 Tdb data (assuming identical day-to -day schedule operation over both FY93 & FY96) to predict daily energy use values for FY96. These daily values are summed into monthly values to mimic utility bill data. Whichever of the two baseline methodologies is able to better predict the Synthetic utility bill data can be easy determined, and the predictive errors qualified in terms of APE values.

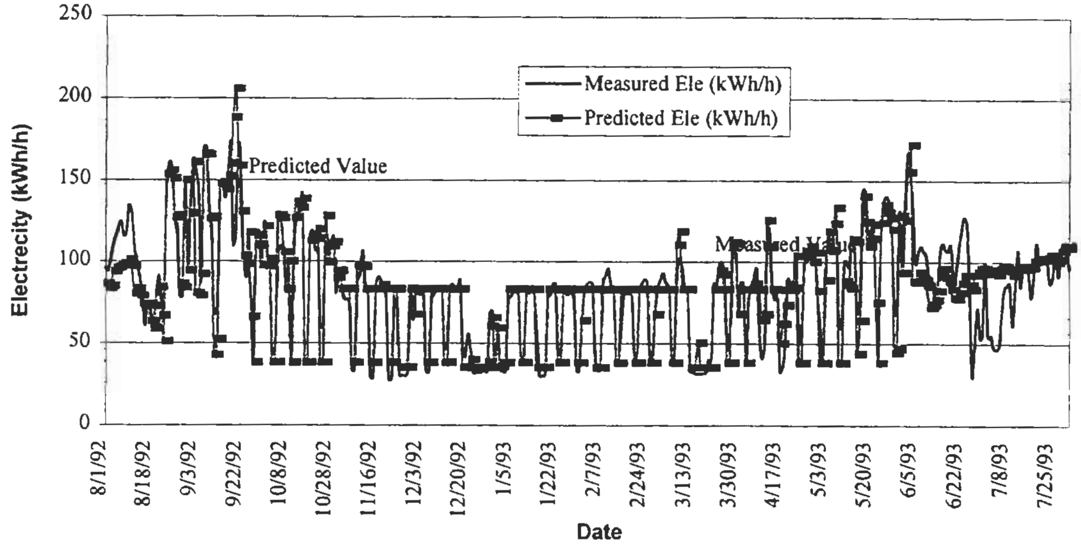

Figure 4. Daily Electricity Use for Sims (08/92 - 07/93)

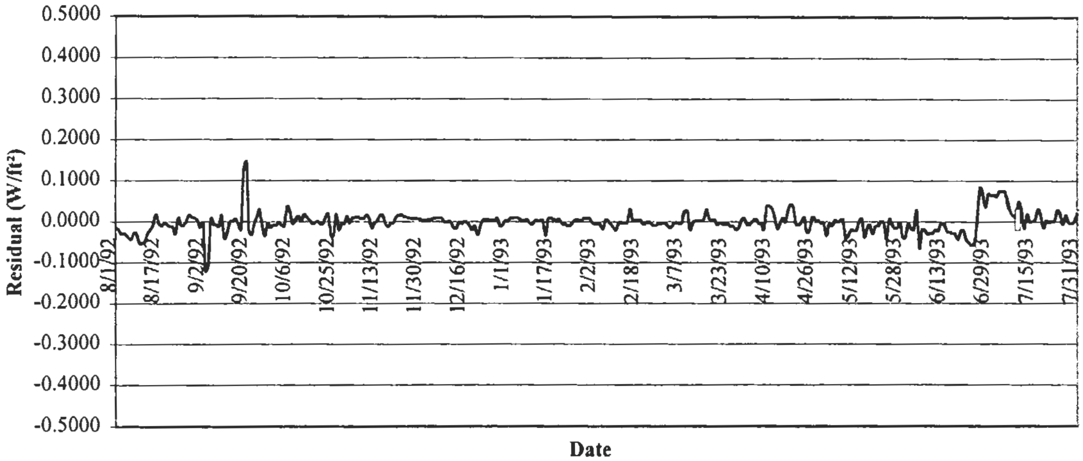

Figure 5. Daily Electricity Residual Plot for Sims (08/92 - 07/93)

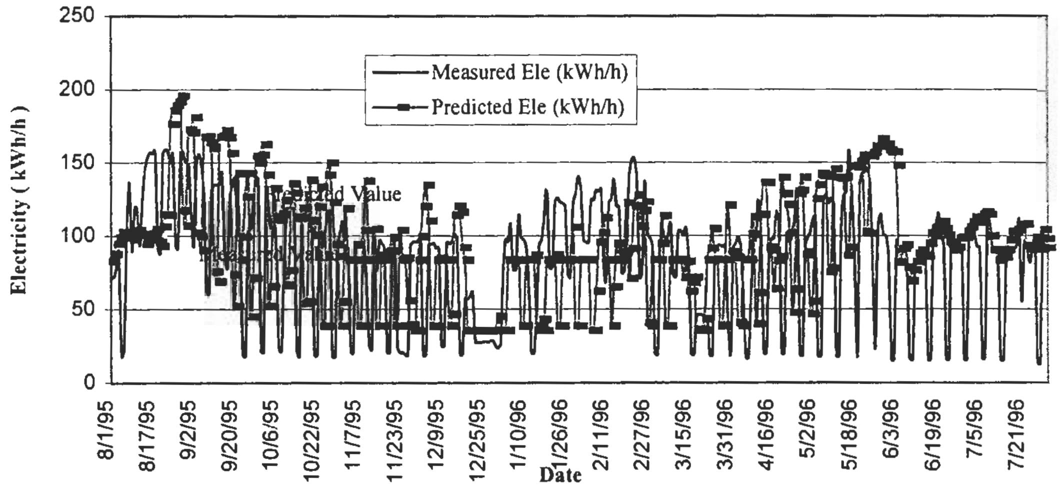

Figure 6. Daily Electricity Use for Sims (08/95 - 07/96)

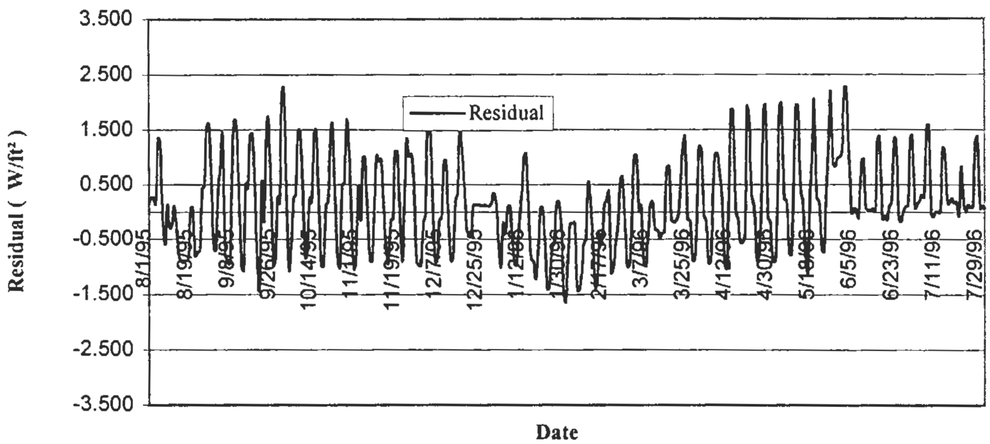

Figure 7. Daily Electricity Residual Plot for Sims (08/95 - 07/96)

Energy use for these ten schools has been monitored hourly for several years. One way of evaluating our methodology is to use one year's data, sum them into monthly values (to mimic utility bill data), develop the baseline regression model & then use this model over the next year in order to compare model predictions against measured data. A major problem which we encountered was that the data was noisy in that building operation was found to be variable not only from year to year but also from month to month. Hens we decided to evaluate our utility bill baseline model methodology, not against monitored data, but against data predicted from a daily model to the monitored data which is deemed more accurate & removes "noise" due to random operation.

Development of MLR Models

We start by selecting the change point value c of the model for the 9 non-summer months. This is then used to determine (Tdb - C), for each of the 12 months during the current year. We then identify a monthly multiple linear regression model for this year which we called the "Proposed Model", described earlier:

$$E_{tot} = a_0 + a_1 k + b_m(T_{db} - c)^+ \qquad (8)$$

where a_0, a_1, b_m and c are the multiple linear regression coefficients. $a_0 = a_{un}$; $a_1 = a_{oc} - a_{un}$.

Then calculate CV-RMSE and APE (Annual Prediction Error).

CV-RMSE

$= 100(1/Y_{mean})[MSE/(12 - 4)]^{0.5}$

and

APE = 100 ($E_{measured}$ - $E_{predict}$) / $E_{measured}$

We then tune the model by determining how CV varies when the c value is varied incrementally. The plot of k vs [E - b_m(T_{db} - c)] is shown in . Figure 8. If we find a linear relationship, it means that the fernetional form of the model is correct because from equation (8):

$$E_{tot} - b_m(T_{db} - c)^+ = a_0 + a_1 k$$

We note from Figure 8., that a linear relationship indeed exits which further lends credence to our model formulation.

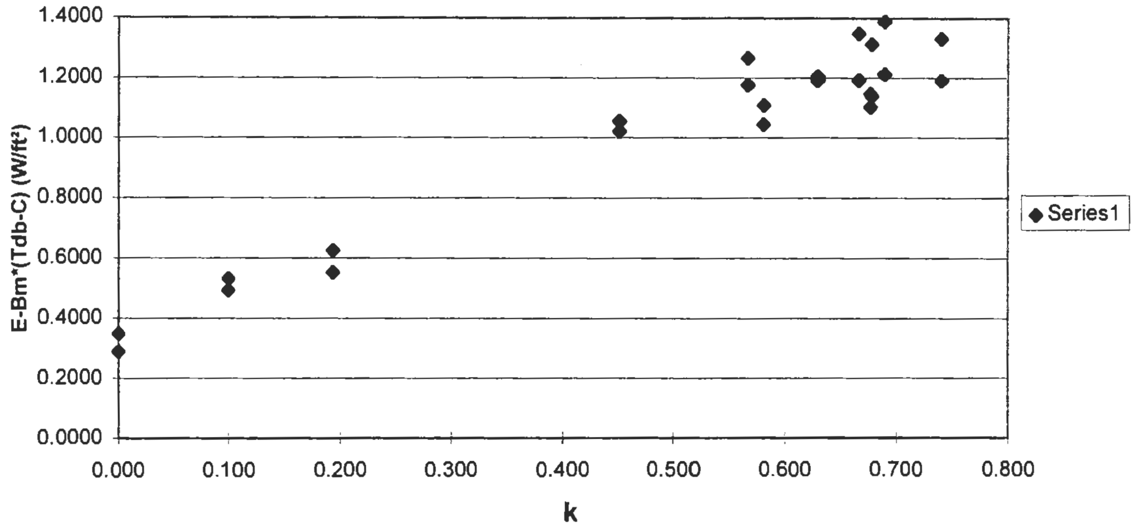

Figure 8. k vs [E - b_m (T_{db} - c)] for Sims FY95 & FY96

Calculate CV-RMSE and APE for the extreme years

We predict the monthly consumption of the two extreme years using the M.L.R. model and the corresponding temperature data. The predictions M.L.R model are compared with the "measured utility bills " by computing the CV-RMSE and APE for the extreme years.

For the two-year data, CV-RMSE are computed, through we now use 24 instead of 12.

The M.L.R. model results for different years for the ten schools are summarized in Table A3 in the Appendix.

Develop 5-P M.L.R. model

For the 4-P MLR models, we assume that both B and C values for occupied and unoccupied periods are unchanged. For the 5-P model, the occupied and unoccupied period do not have the same slope (b value), but the same change point (c value). The 5-P monthly multiple linear regression model for this year is of the form:

$$E_{tot} = a_0 + a_1 k + b_{oc}(T_{db} - c)^+ + b_{un}(T_{db} - c)^+$$

From the final results of the 4-P M.L.R. models for the ten schools in Texas, we can see that the CV values for some schools for the model-year (such as for NHS and CMS) are higher than 10%. So we tried 5-P models for these schools and have found that the 5-P models for these schools are not sufficiently robust. Thus we can not use it as the baseline. Similar conclusions were reached when the entire evaluation was repeated using 5-P M.L.R. models.

CONCLUSIONS

The CV and APE values for the proposed methodology are much smaller than those of the 3-P-Mean method, implying that the proposed methodology is suitable for developing a baseline model for buildings that experience large seasonal changes in occupancy patterns such as schools. Although this method is a little more complicated it allows a more intuitive and unified model to be identified than the standard 3-P model.

Using daily data from Sims, we illustrated that the effect of schedule on energy use is much larger than that of outside temperatures for heavily scheduled buildings. And so selection of data periods for baseline model identification should be done with great care.

We recommend the 4-P multiple-linear regression model. It was found to be more accurate compared with the 5-P model multiple-linear regression model or the Landman model approach.

FUTURE STUDY

From the final results we can see that for some schools (for example WMS, PES and MES); the CV and APE values are low for the baseline year, but high for the predicted years. For the other schools, such as SES, DMS and NHS, when CV and APE values are higher for the model year, they are lower for the predicted years. We do not know the relationship between the CV and APE for the different years, so we can not foresee whether the predicted data are good or not just based on the model's fit. This is one short coming of this methodology.

APPENDIX 1

Table A1. ***Model Coefficient & Goodness-of-fit Indices of the Different Day Types for Daily Models (3-P)***

	For School-day					For Holidays longer than 2 days					For the remaining weekend days					For Non-school days (combination of group 2 & 3)				
School Name	a	b	Tcp	R^2	CV (%)	a	b	Tcp	R^2	CV (%)	a	b	Tcp	R^2	CV (%)	a	b	Tcp	R^2	CV (%)
SES	1.3364	0.0620	61.934	0.91	7.2	0.5698	0.0348	56.142	0.60	28.4	0.6173	0.0556	66.611	0.81	16.2	0.5928	0.0407	60.751	0.66	27.1
DMS	1.5077	0.1425	67.060	0.88	16.7	0.6392	0.1367	67.988	0.78	26.8	0.6107	0.1607	72.035	0.59	63.3	0.6072	0.1508	69.620	0.78	34.3
SHS	0.8321	0.0235	57.367	0.66	14.1	0.2834	0.0189	57.964	0.37	42.9	0.3009	0.0058	53.185	0.14	40.8	0.3365	0.0334	71.648	0.39	45.0
VHS	0.9602	0.0384	62.325	0.75	13.8	0.3896	0.0502	74.191	0.46	41.1	0.3410	0.0077	73.280	0.07	32.4	0.3613	0.0423	74.191	0.39	44.1
NHS	1.3374	0.0768	61.513	0.86	12.7	0.5599	0.0286	60.730	0.24	49.0	0.4757	0.0100	48.116	0.17	43.5	0.5286	0.0279	60.730	0.27	49.8
CMS	1.1892	0.1193	73.474	0.47	29.4	0.6022	0.3042	81.310	0.16	61.7	0.2055	0.0068	56.109	0.20	47.0	0.4347	0.1555	79.350	0.21	70.2
OES	1.6086	0.0156	53.014	0.35	12.2	0.2748	0.018	60.295	0.17	74.7	0.3927	-0.0015	44.464	0.01	49.6	0.3226	0.0247	70.622	0.16	74.7
WMS	2.0112	0.0312	62.813	0.45	12.2	0.4308	0.1218	84.703	0.05	86.5	0.4205	0.0523	76.028	0.24	52.7	0.4241	0.1343	84.703	0.06	81.4
PES	1.5900	0.0354	61.835	0.61	12.5	0.4533	0.1459	83.764	0.11	82.3	0.3477	0.0014	52.355	0.02	32.0	0.4164	0.1544	83.764	0.14	78.1
MES	2.1524	0.0403	66.723	0.44	12.9	0.4739	0.2568	83.764	0.16	98.0	0.3424	0.0108	72.521	0.06	48.2	0.4277	0.2665	83.764	0.19	96.8

Table A2. ***Monthly Model Coefficient & Goodness-of-fit Indices Using Different Modeling Approaches for the Ten Primary and Secondary schools in Texas***

	From 9-month 3-P Regression Models FY94 (FY93 for Sims)			From Multiple Liner Regression Models FY94 (FY93 for Sims)				Proposed Method FY94 (FY93 for Sims)		
School Name	a_{oc}(W/ft²)	**b**	c_{in}(°F)	c_{final}(°F)	a_0(W/ft²)	a_1(W/ft²)	b_m	**CV**	**APE (%)**	**Note**
SES	1.0395	0.0575	60.083	63.9	0.3720	1.2170	0.0600	11.167	-0.185	good daily and monthly model
DMS	1.1025	0.0931	61.174	61.5	0.6207	0.7737	0.0985	13.797	1.801	daily and monthly model are not good
SHS	0.6698	0.0247	60.504	45.0	0.1410	0.5516	0.0165	6.281	15.372	daily model is worse
VHS	0.7442	0.0289	61.008	61.0	0.2513	0.8108	0.0273	6.657	0.016	daily model is worse
NHS	0.9539	0.0348	50.505	56.0	0.1573	1.4160	0.0413	11.185	-0.030	daily model is worse
CMS	0.9007	0.0635	70.587	74.0	0.0279	1.4033	0.1156	14.163	0.005	daily and monthly model are not good
OES	1.1664	0.0290	65.164	67.0	0.2576	1.5171	0.0227	5.856	0.012	daily model is worse
WMS	1.3850	0.0367	63.011	68.0	-0.1668	2.6091	0.0346	7.042	0.001	daily model is worse
PES	1.1329	0.0328	61.935	67.0	0.0322	1.8722	0.0325	6.402	-0.027	daily model is worse
MES	1.4132	0.0336	60.860	67.0	0.1650	2.1305	0.0347	8.303	-0.018	daily model is worse

Table A3. ***Monthly Model Goodness-of-fit Indices Using Different Modeling Approaches for the Ten Primary and Secondary schools in Texas for FY95 & FY96***

	Proposed Method FY95 & FY96		Landman's Method FY95 & FY96	
School Nam	**CV**	**APE (%)**	**CV**	**APE (%)**
SES	6.720	2.290	8.623	3.210
DMS	12.215	1.173	21.251	-0.587
SHS	5.858	-1.347	11.037	-2.157
VHS	8.489	-3.368	15.943	-4.466
NHS	7.806	0.475	20.974	-13.13
CMS	8.643	1.396	17.827	-0.817
OES	3.187	0.199	24.607	-10.067
WMS	13.789	4.077	59.598	29.605
PES	17.479	6.801	26.980	-2.914
MES	25.172	10.043	28.693	10.818

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