The 6th IBPSA Canada Conference
La 6e conférence d'IBPSA – Canada
Winnipeg, May 19 – 20

EVALUATION OF DAILY ENERGY SIGNATURE MODELS FOR HOUSES HEATED AND OR COOLED BY ELECTRICITY: CASE OF OSHAWA, CANADA

Demba Ndiaye, Kamiel Gabriel

University of Ontario Institute of Technology
Oshawa, Ontario, Canada

ABSTRACT

Energy signature models are static identification models that can be used to normalize energy consumption with respect to weather, to predict the energy consumption, to estimate savings after building retrofits, or for building parameter estimations. In this paper, the main energy signature models available from the literature are tested using data on all-electric houses in the city of Oshawa (Canada). The models tested are: (i) a two-parameter model that can be used for all houses; (ii) a three-parameter model called PRISM that is appropriate for heated-only houses; and (iii) a five-parameter model called Extended PRISM that is usable with air-conditioned houses.

The results of the tests reveal that the PRISM-type models have a better prediction performance than the two-parameter model. Variants of the three models using the outdoor wet-bulb temperature in place of the outdoor dry-bulb temperature, or adding the solar gains as an explicit input to the model, are also tested. It is found that replacing the outdoor dry-bulb with the outdoor wet-bulb temperature in the calculation of the cooling degree-days for the extended PRISM model is advantageous.

The extended PRISM model is found to be the best predictor. However, it can be improved and an avenue for doing so is proposed.

INTRODUCTION

Identification models for buildings' energy consumption may be classified into dynamic and static models. Among the static models are the energy signature (ES) models. ES models are simple and efficient. In many cases, only billing data are needed to use them. ES models may be used to predict the energy consumption (Deeble and Probert, 1986) or to normalize the annual energy consumption of a building with respect to weather conditions (Fels, 1986). Daily ES models (which are based on daily average data) can be used to determine whether systems are being left on unnecessarily or are in need of maintenance by comparing the measured versus the predicted daily energy use (ASHRAE, 2005). In a general fashion, ES models add more reliability in the estimation of the energy savings after application of energy conservation measures (ECM) by separating weather-induced effects from ECM-induced effects (Zmeureanu, 1990). ES models may also be used for building parameter estimations (Hammarsten, 1987), although the estimates in this case may be highly biased (Hammarsten, 1987; Flouquet, 1992).

For example, Adderley et al. (1989) used an ES model to predict the energy behaviour of a hospital complex. Zmeureanu and Fazio (1991) developed energy signatures of office buildings to help analyse their energy performances. Sjögren et al. (2007) used the ES approach to evaluate the energy performance of multifamily buildings while using incomplete monthly data. Finally, Zmeureanu and Renaud (2008) developed a method based on the ES technique to estimate the potential impact of climate change on the heating energy use of existing houses.

In this paper, as a first step towards the development of an improved ES model (for houses air-conditioned or not) and its use to evaluate the energy behaviour of the housing stock in the city of Oshawa (Ontario, Canada), the main existing energy signature models and their variants (as found in the literature) are tested using electricity consumption data from sixteen houses in Oshawa.

ENERGY SIGNATURE MODELS

The energy balance of a house translates as follows (Adderley et al., 1988):

$$\begin{aligned}&\text{Rate of entering energy} = \\ &\text{Rate of leaving energy} + \\ &\text{Rate of stored energy}\end{aligned} \qquad (1)$$

In the heating period for instance, the first term of Equation 1 is the combination of:

- the energy provided by the heating system
- the solar gains
- the internal gains (people, appliances, equipment, …)

Under the same considerations, energy "leaves" the house as:

- conduction and radiation losses through the envelope
- ventilation (exhaust air) and infiltration losses
- energy in the fluids leaving through the drains (e.g. domestic hot water)

If the house is considered as being a single thermal zone (indoor temperature T_i assumed to be uniform throughout the heated space), then, under steady-state conditions, the energy balance equation reads:

$$Q + S_g + I_g = L(T_i - T_o) + C\frac{\Delta T_i}{\Delta t} + R \qquad (2)$$

where:

- Q: energy provided by the heating system (kWh)
- S_g: solar gains (kWh)
- I_g: internal gains (kWh)
- L: loss factor of the house (through the envelope, including infiltration) (kWh/K)
- T_o: average outdoor temperature (ºC)
- C: effective thermal capacitance of the house (kWh.s/K)
- Δt: time step (s)
- ΔT_i: indoor temperature variation during Δt (ºC)
- R: rejected heat (exhaust and drains) (kWh)

The thermal storage term in Equation 2 (second right hand term) may be neglected if the time step is large enough. For many houses, a time step of 1 day or longer can be considered large enough to neglect the thermal storage term (Hammarsten, 1987).

If the time step is considered to be 1 day or longer, then Equation 2 becomes:

$$Q = Q_0 + L(T_i - T_o) \qquad (3)$$

where $Q_0 = R - S_g - I_g$.

Equation 3 is the energy signature of the house. Two main variants of this equation are in use in the literature. From now on, daily values will be considered (i.e. time step is 1 day).

First, the term LT_i may be included in Q_0, giving:

$$Q = Q'_0 - LT_o \qquad (4)$$

If the average efficiency of the heating system is η, then Equation 4 may be transformed to give:

$$E_h = a + bT_o \qquad (5)$$

where $E_h = Q/\eta$ (kWh) is the daily energy consumption of the heating system, a and b are regression parameters, and T_o is the daily average outdoor temperature. This model (Equation 5) was used, for instance, by Zmeureanu (1990), and will be designated

"Two-parameter model" in the remaining of the paper.

The inputs to this model are the total daily energy consumptions of the heating fuel for a given period (a 1-year period is better) and the daily average outdoor temperature for each day of the same period. Before applying the model, the base level of energy use (non-weather dependent energy use) must be determined, and the days corresponding to this level of energy use, eliminated from the further analysis. With these inputs, one can determine the two regression parameters. For analyses with subsequent years' data, these regression parameters may be assumed independent of the weather (Zmeureanu, 1990).

The second variant is the so-called PRISM model (Fels, 1986). The PRISM model is probably the most popular energy signature model. Introducing the average efficiency η of the heating system in Equation 3 leads to:

$$E_h = \frac{Q}{\eta} = \frac{Q_0}{\eta} + \frac{L}{\eta}T_i - \frac{L}{\eta}T_o = \beta\frac{Q_0}{L} + \beta T_i - \beta T_o = \beta(\tau - T_o) \quad (6)$$

where $\beta = L/\eta$, and $\tau = (Q_0/L) + T_i$ is the balance point temperature or reference temperature. The balance point temperature or reference temperature is the temperature above which any heating need is solely met by the free gains (net solar and internal gains). Above that value, $E_h = 0$. Usually, Q_0 is negative, leading to $\tau < T_i$. Note that in the two-parameter model, the reference temperature T_{ref} is determined from Equation 5 by setting $E_h = E_b$ (where E_b is the base level of energy use), giving:

$$T_{ref} = \frac{a - E_b}{-b} \quad (7)$$

If the heating fuel (electricity, natural gas, etc.) is used for other purposes such as domestic water heating, appliances, lighting, at a rate α, then the model becomes (Fels, 1986):

$$E = \alpha + \beta(\tau - T_o)^+ \quad (8)$$

where E (kWh) is the total daily consumption of the heating fuel in the house, and the "+" superscript indicates that only positive values of the difference $(\tau - T_o)$ are accounted for. Any other value is set to 0.

Equation 8 is the basic PRISM model. The inputs to the PRISM model are the total daily consumptions of the heating fuel for a given period and the daily average outdoor temperatures in the same period. Using these inputs, the regression parameters α and β are found for each guessed value of the reference temperature τ. The reference temperature is finally determined as the value for which the mean-squared error is minimized, or equivalently for which the R-square is the highest. The corresponding α and β are the best estimates of the regression parameters (Fels, 1986).

The basic PRISM model may be extended to account for houses heated and cooled with the same fuel, as follows (Stram and Fels, 1986):

$$E = \alpha + \beta_h(\tau_h - T_o)^+ + \beta_c(T_o - \tau_c)^+ \quad (9)$$

where the subscripts "h" and "c" refer respectively to "heating" and "cooling". The reference temperatures τ_h and τ_c are determined to be the values that lead to the minimum mean-squared error, or equivalently, to the maximum R-square. Normally, τ_c is greater than τ_h. We will refer to the model of Equation 9 as the extended PRISM model. See Figure 1 for a representation of the extended PRISM model.

Another possible extension to the PRISM model is to specifically account for the solar gains (see Hammarsten, 1987). In such case, the model would become:

$$E = \alpha + \beta\left(\tau - T_o\right)^{+} - S\,I \qquad (10)$$

where S is the solar aperture (m^2) and I is the daily total solar radiation (kWh/m^2).

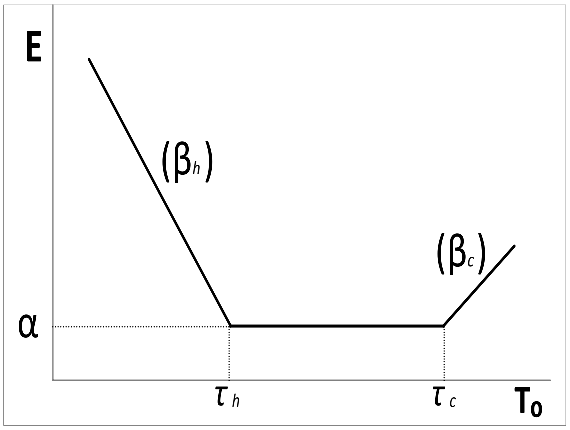

Figure 1 Graphic representation of the extended PRISM energy signature model

EXPERIMENTAL DATA

The data are from Phase II of the project "Investigating Energy Consumption Trends in Oshawa's Residential Dwellings". This project is conducted by University of Ontario Institute of Technology (UOIT, Oshawa, Ontario, Canada) and co-sponsored by Oshawa PUC Networks Inc. (OPUC), the local electricity distribution company, and by the Ontario Centre of Excellence for Energy. Phase II of the project involves the monitoring of the electricity consumption of about 270 houses in the Oshawa area using smart meters. One smart meter was installed in each home being monitored. Smart meters provided for each location the average hourly electric consumption, on a continuous basis. The uncertainty associated with smart meter readings is ±1%.

As, for various reasons, the data collection started at different dates and ended at different dates for the different houses equipped with smart meters, it was attempted to identify a full year period between the time of the first readings (February 2007) and the time of the last readings (July 2008) that would cover the maximum number of smart meters. That 1-year period is the reference year of smart meter readings. It has been identified to be the period from May 29, 2007 to May 28, 2008.

Since only electricity consumption data were collected, only all-electric houses (houses using only electricity as energy source) are investigated. From the available data, we identified seven all-electric houses that have no air conditioning, and nine all-electric houses that have air conditioning. In the following analyses, the houses are designated with their smart meter number. In summary, the data for each house are constituted by their daily electricity consumptions for each day of the 1-year period.

RESULTS AND DISCUSSIONS

In the present section, the two models, Two-parameter and PRISM, and their extensions are tested with data of the seven heated-only houses and of the nine air-conditioned houses. The daily average outdoor dry-bulb and wet-bulb temperatures for the period May 29, 2007 – May 28, 2008 for the Toronto Pearson weather station (Toronto airport) are used. For the solar radiation, no data are available for Oshawa or Toronto for the period May 29, 2007 – May 28, 2008 (Hampel, 2009). So it was decided to rely on the typical hourly values found for Toronto in a weather file used for building performance simulation purposes. The hourly values for each day were summed up to get the total daily solar radiations used here.

To test for the statistical significance of the individual regression parameters, the t-values (t-statistics) are used, with a confidence level of 95% (the most used level). The statistical significance of the regression itself is measured by the F-value, with a confidence level of 95%. The threshold for goodness of fit is set at R-square close to 0.80.

Two-parameter model applied to the heated-only houses

The model used is the model of Equation 5. Table 1 shows the results of the application of this model to the seven houses. Base consumption is determined to be the level that leads to the highest R-square.

Table 1 Results of the application of the two-parameter model to the heated-only houses' data

HOUSE	Base consumption (kWh)	a (kWh)	b (kWh/ºC)	R^2
64497	20	56.19	-1.21	0.583
79443	0	76.30	-3.23	0.872
79461	15	62.20	-2.06	0.785
79474	0	106.83	-1.29	0.206
79554	0	68.47	-2.34	0.625
79565	20	67.58	-1.66	0.657
79614	0	67.37	-2.29	0.755

All the regressions and all the parameters are statistically significant. It is noted that all the values for the parameter *b* are negative, meaning that this model translates into a decreasing function of the outdoor air temperature. The best R-square overall is obtained for house #79443 at 0.872. The worst fit is seen with house #79474 at only 0.206 for the R-square. The consumption for this house is almost flat. On further investigation, it is seen that this house has an electric pool heater. That might explain the relatively high consumption noted in the summer. Overall, only data for three of the houses may be considered well fit: these are houses #79443, #79461, and #79614. Globally, the performance of the model is weak, with only three "good" fits out of seven cases.

Two-parameter model applied to the air-conditioned houses

Similarly, the model of Equation 5 can be applied to air-conditioned houses. It is seen from the results that, as may be expected, the R-squares are generally better for the heated-only houses, compared to the air-conditioned houses. Overall, only data for house #79526 may be considered well fit, with a R-square at 0.846 (the best). Globally, the performance of the model is weak, with only one "good" fit out of nine cases.

Basic PRISM model applied to the heated-only houses

The model is given by Equation 8. Reference temperatures from 13 to 21 ºC are tried, with variation steps of 0.5 ºC. The results are shown in Table 2.

Table 2 Results of the application of the basic PRISM model to the heated-only houses' data

HOUSE	Reference temperature (ºC)	α (kWh)	β (kWh/ºC)	R^2
64497	13.0	31.59	1.88	0.656
79443	16.5	10.74	4.01	0.916
79461	13.0	16.41	3.40	0.901
79474	13.0	80.81	2.09	0.271
79554	19.0	18.63	2.65	0.643
79565	18.0	29.56	2.10	0.692
79614	13.0	23.77	3.32	0.798

All the regressions and all the parameters of all the houses are statistically significant. As with the application of the two-parameter model, House #79443 get the best fit, with a R-square at 0.916 (see Figure 2), and House #79474 get the worst fit, with a R-square at 0.271. By direct comparison with the two-parameter model, it can be seen that the PRISM model does a better prediction job for all houses. However, the performance of the model is also weak, with only three "good" fits out of seven cases.

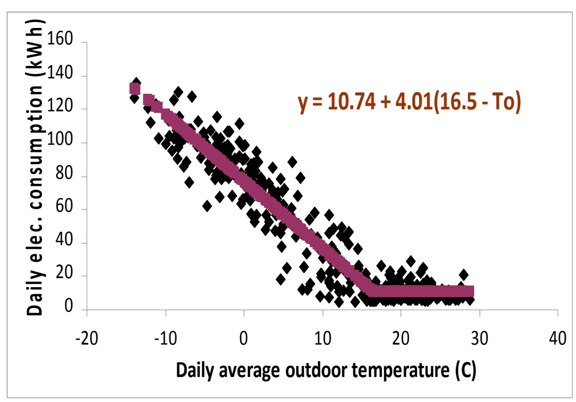

Figure 2 Best fit for data regression from the basic PRISM model for heated-only houses: house #79443

Basic PRISM model applied to the air-conditioned houses

Compared to the two-parameter model, there is, except in one case (House #79450), an improvement in the R-squares. Here, the model realizes four "good" fits out of nine cases. It is expected that the extended PRISM give better results.

Extended PRISM model applied to the air-conditioned houses

The extended PRISM model is given by Equation 9. Values from 14 to 20 ºC, with variation step of 1 ºC, are chosen for the reference temperature for heating τ_h. Values from 18 to 25 ºC, with variation step of 1 ºC, are chosen for the reference temperature for cooling τ_c. With the constraint that $\tau_h \le \tau_c$, that leads to a total of 53 combinations (τ_h, τ_c) to examine.

Although all the regressions are statistically significant, the β_c-parameter for three of the houses (#79526, #79613, and #79615) are not significant. For these three houses, the basic PRISM model better applies. The reference temperatures for heating vary from 14 to 19 ºC, while those for cooling vary from 18 to 24 ºC. Base consumptions (α) vary from 17 to 64 kWh per day, with a median at 25 kWh and an average at 30 kWh. As with the two-parameter model, the best fit is for house #79526 at $R^2 = 0.880$, and the worst for house #79450 at $R^2 = 0.021$. However, the performance of the extended PRISM model is better than the one of the two-parameter model, as it realizes four "good" fits out of the nine cases.

Explicit solar input added to the models

Regardless of the model, it is found that this addition does not improve them.

On another hand, it has been hypothesized that adding or replacing the outdoor dry-bulb with the outdoor wet-bulb temperature might improve the fit of the data for air-conditioned houses (Zmeureanu, 1990). In the two following sections, we apply modified two-parameter and extended PRISM models to the air-conditioned houses' data.

Modified Two-parameter model applied to the air-conditioned houses

The model we apply is the following:

$$E_h = a + bT_{o,DB} + cT_{o,WB} \qquad (11)$$

A slight improvement in the R-squares, mainly due to the addition of another variable, is noted. The c-parameter is not statistically significant in four out of the nine cases. In other four cases where the c-parameter is significant, the b-parameter is not. The replacement of T_{DB} with T_{WB} should lead to results identical to the basic two-parameter model.

Modified Extended PRISM model applied to the air-conditioned houses

The model is given by Equation 15. The modification is the replacement of the dry-bulb temperature by the wet-bulb temperature in calculating the cooling degree days.

$$E = \alpha + \beta_h (\tau_h - T_{o,DB})^+ + \beta_c (T_{o,WB} - \tau_c)^+ \qquad (12)$$

Here, all the regressions and all the parameters for all the houses are statistically significant. Although the improvement in the R-squares is minor, a decisive benefit in replacing the dry-bulb temperature with the wet-bulb temperature in the extended PRISM model is that all the β_c-parameters become statistically significant.

From the tests undertaken, it is found that the basic PRISM model for heated-only houses and the extended PRISM model for air-conditioned houses give the best results. However, their performances are relatively weak. For example, the extended PRISM model realized only four "good" fits out of the nine cases it was applied to. So it is necessary to improve them. For example, considering the extended PRISM model (see Figure 1), between τ_h and τ_c, the model assumes a straight line. However, the data between these two reference temperatures can have any profile: adding for instance another reference temperature that lies between τ_h and τ_c may help improve the fit. It is also worth considering the replacement of the dry-bulb temperature with the wet-bulb temperature in calculating the cooling degree days for the extended PRISM model.

CONCLUSION

Three main daily energy signature models were identified: a two-parameter model, a three-parameter model (basic PRISM) and a five-parameter model (extended PRISM). The two-parameter model may be used for both heated-only and air-conditioned houses. The basic PRISM model is most appropriate for heated-only houses, while the extended PRISM model may take in charge air-conditioned houses.

These models were tested using regressions on data from sixteen all-electric houses: seven heated-only houses and nine air-conditioned houses. These houses are located in the city of Oshawa, and the data are available under the form of hourly electricity consumption for a full 1-year period (May 29, 2007 – May 28, 2008). It was found that:

- the performance of the two-parameter model when applied to heated-only houses is weak as only three "good" fits out of the seven cases were observed
- the two-parameter model realizes even a worst score when applied to air-conditioned houses: only one "good" fit out of the nine cases
- the basic PRISM model obtains also only three "good" fits when applied to heated-only houses, even if it realizes better R-squares than the two-parameter model in the same conditions
- the extended PRISM model gets a better performance on the air-conditioned houses than the two-parameter model; however, its performance remains weak: four "good" fits out of the nine cases.

It has been hypothesized that adding explicitly the solar input in the model, or replacing the dry-bulb temperature with the wet-bulb temperature for models applied to air-conditioned houses, might help improve the regressions. From our tests, replacing the dry-bulb with the wet-bulb temperature in calculating the cooling degree days for the extended PRISM model was found beneficial. However, no significant effect of undertaking the other modifications was found.

ACKNOWLEDGEMENTS

Ontario Centre of Excellence for Energy (OCE) sponsors this research.

REFERENCES

Adderley A.E., O'Callaghan P.W. and Probert S.D. (1988), 'Energy-Saving Options', *Applied Energy*, 30 269-279.

Adderley A.E., O'Callaghan P.W. and Probert S.D. (1989), 'Energy-Signature Characteristic of a Hospital', *Applied Energy*, 34 125-153.

ASHRAE (2005) *ASHRAE Handbook - Fundamentals*, American Society of Heating, Refrigerating, and Air-conditioning Engineers, Atlanta, GA, U.S.A.

Deeble V.C. and Probert S.D. (1986), 'Straight-Line Correlations for Annual Energy-Consumption Predictions?', *Applied Energy*, 25 23-39.

Fels M.F. (1986), 'PRISM: An Introduction', *Energy and Buildings*, 9 5-18.

Flouquet F. (1992), 'Local Weather Correlations and Bias in Building Parameter Estimates from Energy-Signature Models', *Energy and Buildings*, 19 113-123.

Hammarsten S. (1987), 'A Critical Appraisal of Energy-Signature Models', *Applied Energy*, 26 97-110.

Hampel C. (2009), *E-mail correspondence*, Ontario Climate Center, Environment Canada.

Sjögren J.-U., Andersson S. and Olofsson T. (2007), 'An Approach to Evaluate the Energy Performance of Buildings Based on Incomplete Monthly Data', *Energy and Buildings*, 39 945-953.

Stram D.O. and Fels M.F. (1986), 'The Applicability of PRISM to Electric Heating and Cooling', *Energy and Buildings*, 9 101-110.

Zmeureanu R. (1990), 'Assessment of the Energy Savings due to the Building Retrofit', *Building and Environment*, 25 2 95-103.

Zmeureanu R. and Fazio P. (1991), 'Analysis of the Energy Performance of Office Buildings in Montreal in 1988', *Energy and Buildings*, 17 63-74.

Zmeureanu R. and Renaud G. (2008), 'Estimation of Potential Impact of Climate Change on the Heating Energy Use of Existing Houses', *Energy Policy*, 36 303-310.