AN INVERSE MODEL TO PREDICT AND EVALUATE THE ENERGY PERFORMANCE OF LARGE COMMERCIAL AND INSTITUTIONAL BUILDINGS

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ABSTRACT

A new method for predicting and evaluating the energy performance of large commercial and institutional buildings is developed, as an alternative to using existing comprehensive energy simulation programs like DOE-2 and BLAST, or oversimplified tools like analyzing monthly utility bills. The steps are convenient and practical in their potential use by the energy analysts. The method mainly groups the Stepwise Multiple Linear Regression (SMLR) to empirically model the dynamic building thermal performance; Fourier Series to predict (extrapolate) internal loads; the Monte-Carlo Simulation to deal with the prediction of internal loads probabilistically; and a new approach in normalizing weather conditions. The method is capable of predicting the building energy performance in the pre-retrofit phase, identifies appropriate energy conservation measures, and estimates potential energy savings.

INTRODUCTION

A new method for analyzing the building energy performance and recommending necessary energy conservation measures is proposed. The method could be used by the utility companies and energy consultants, in the large commercial and institutional building sector, as an alternative to the use of microdynamic comprehensive simulation programs like DOE-2, or oversimplified tools like analyzing the monthly utility bills. Comprehensive simulation programs require a definition of extensive input parameters that are difficult to get in an existing and operating building. That problem necessitates the use of handbooks values, and blue prints information. Moreover, these simulations need to be calibrated by comparing their results with actual energy data (utility bills), to come as close as possible to the actual energy performance of the building. The new method promises to reduce the time that should be spent, had the comprehensive simulations been used. In addition, it will be easy to use by the energy consultants.

An Inverse Model developed from monitored data and used as an OFF-line predictive model, similarly to comprehensive simulation programs (DOE2, BLAST), should be capable of providing insights to improve the current building performance. Therefore the method behind the model should be able to breakdown the total energy consumption or the thermal energy consumption into end-uses. This will allow the energy analyst to prescribe appropriate energy conservation measures, by evaluating the impact of modifying a driving variable on the thermal or total energy consumption. The preliminary disaggregation of end-uses used as a first step in the proposed method, will help in focusing on the areas of high potentials of energy savings in the overall building energy performance. As a result, the model will predict the building energy performance under the current design and operation schemes, recommends appropriate energy conservation measures, predicts the performance under the recommended measures, and estimates the potential energy savings.

LITERATURE REVIEW

Building energy simulations are mostly used in the building design. However, these simulations were also used in applications required after the design phase of the building (assessing the energy performance of the as-built building, calculating the energy savings after retrofits, predicting energy consumption). In such applications (post-design) the simple inverse models showed to be more useful and yielding to more realistic results than the complex detailed models. The parameters that can be measured at a building are not enough to develop a simulation with detailed models (DOE-2, BLAST), yet they are sufficient for developing and using the inverse models. Inverse models can be classified, in an increasing degree of complexity, as follows: (1) Reference temperature and constant-base degree-days models (ASHRAE 1993); (2) Variable-base degree-days models

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(Fels 1986), and (Rabl and Rialhe 1992); (3) Bin methods models (ASHRAE 1993); (4) Correlation and regression models - regrouped by (Reddy 1989) in two groups: (a) Analogue models that adopt the thermal networks analogy, and (b) Grey-box models including: (i) Deterministic and Stochastic time series models (Seem and Braun 1991), and (ii) Time derivative models (Rabl 1988); and (5) Artificial intelligence models such as the Artificial Neural Networks and the Fuzzy Logic models.

LIMITATIONS OF EXISTING INVERSE MODELS

Existing Inverse Models showed limitations in their applicability. PSTAR and BEVA models (Subbarao 1985), (Subbarao et al. 1989), and (Balcomb et al. 1993) are applicable to residential buildings and test cells, and need the use of DOE-2 program to calculate certain parameters required by the models. PRISM (Fels 1986) is a steady state model (using the Degree-Days). PCA, MLR, and Change Point models (Reddy and Claridge 1994), and (Ruch and Claridge 1992), are used for fitting existing data. Therefore these models were not "predicting" in the real meaning of the term. Moreover, in these models, both training and prediction durations are not optimized. ARMA and other Box-Jenkins models (Seem and Braun 1991) are helpful for only short-term predictions, therefore they are widely used in thermal storage and predictive control applications. Thermal Networks models (Mathews et al. 1994) were only applied to model test cells, and single zone houses.

MODELING EVALUATION

In developing inverse models, various methods suitable for the analysis of large buildings energy performance were evaluated, using synthetic hourly data instead of measured data for the advantages of being fast, and working with well defined building descriptions. A synthetic hourly data (weather variables and consumptions) used to evaluate different inverse methods, and later in the case study, was generated by a DOE-2 simulation (Pasqualetto 1995), calibrated with utility bills, of an office building in Laval, Quebec, Canada. The building has 10410 m^2 total floor area. The building consists of an underground garage, a restaurant and a bank at the street level, and of seven office-space floors. Electricity is the only source for heating and cooling. The synthetic data is thus serving as measured data and will be simply called "measured data" hereafter. This measured data was divided in two sets designating the cooling season (April 15 - October 15) and the heating season (September 15 - May 1). This division of the data in two sets allows a better understanding of the system identification of the building, as the driving variables change between cooling and heating seasons. Accordingly, a model developed, for instance, in the cooling season may not perform accurately in predicting for the heating season and vice-versa. Future work will investigate the improvement that can be obtained by adding a third set of data for swinging seasons. In a second step, the heating season and the cooling season hourly data sets were divided into the following subsets: one and two weeks, and one, two, three, four, five, and six months for the heating season; and, one and two weeks, and one, two, three, four, and five months for the cooling season. By performing these subdivisions, inverse models are developed based on periods of measurements of different lengths to test their sensitivity to this factor which is of major importance when these models come to real use by the energy practitioners. In this paper, only the cooling season modeling is discussed.

The common driving variables considered in the cooling season are: the lighting load (LITE) in kWh/h, the office equipment load (EQUIP) in kWh/h, the domestic hot water load (DHW) in kWh/h, the total ventilation fans load (TOTVEN) in kWh/h, the ambient wet bulb temperature (WB) and dry bulb temperature (DB) in ^{o}C, the ambient enthalpy (ENTH) in kJ/kg, the solar radiation (SOLAR) in kW/m^2, the chiller consumption (CHILR) in kWh/h, the condenser consumption (CONDEN) in kWh/h, and two flag variables, (SCHED) indicating the day of the week, i.e., Sunday to Saturday (1 to 7), and (FLAG) having a value of (0) for weekdays and (1) for weekends and holidays. The “occupied/unoccupied” periods of the day were not considered as a flag variable since the response variable can sense the occupancy from other variables existing in the model, for instance, the internal uses. The total energy consumption during the cooling season (TOT), in kWh/h, is considered in this study as the response variable. However, (CHILR) and (CONDEN) can, themselves, be considered as response variables as a function of internal loads and weather conditions.

Three different methods of inverse models applicable to large buildings were evaluated: (1) the Stepwise Multiple Linear Regression technique (SMLR); (2) Fourier Series; and (3) AR/ARMA/ARIMA models. The SMLR is an improved Multiple Linear Regression technique where the entry of the variables into the model is controlled using either a forward or backward selection. The SMLR technique allows the variables to be entered and sequentially removed from the model if they become insignificant, until a significant set of regressors is read, and thus avoiding any multicollinearity between the regressors. This technique is helpful when building a model that has a large number of possible independent variables. The major advantage of the SMLR models, as compared with Fourier Series and ARIMA models, is that they allow the system identification of the building under study. The coefficients of these models, relating the regressors linearly, are combinations of efficiencies, losses, resistances and capacitances of the building structure, etc.. In the cooling SMLR modeling, 28 "meaningful" combinations of regressors were selected. Accordingly, 28 models were developed for the periods subsets of the cooling season. A thorough analysis was performed on the SMLR models, to identify the shortest period of required monitoring, and consequently its longest reliable period of prediction. The analysis consisted of calculating the Coefficient of Variance (CV) and the Mean Bias Error (MBE) of the predictions for all models. Predictions of all of these models were performed for periods ranging from one week to the full length of the cooling season. Models developed from two weeks of hourly values showed acceptable results.

APPROACH

After evaluating several methods of inverse models numerically, using synthetic data, a new method to predict and evaluate the energy performance of large commercial and institutional buildings for both pre- and post-retrofit periods was proposed.

The new method consists of two stages:

Stage I:

Stage I (Figure 1) is a preliminary study of the energy performance of the building. It starts with a site visit. *Interviews* with the owner and the facility staff will be conducted. *Utility bills, logbooks* (if *EMCS*'s do not exist), and *one-time measurements* will be considered. *Visual inspection* of the end-uses should be performed, to determine the *state* (age, quality, etc..) and the *Plate power ratings* of the existing equipments (chillers, pumps, air handlers, fans, etc..). Finally, an access to the *building plans* and *specification documents* (design values) can shed additional light on the preliminary study. After obtaining the available data, a disaggregation of the billed monthly total energy consumption is conducted. First, the billed monthly energy consumption for the whole year is displayed graphically, to determine the weather-dependent and base-load consumption. The disaggregated energy consumption will be determined using design power densities and capacities, hours of operation, schedule multipliers, design COP's, and correction factors (Mei 1994). The preliminary disaggregation allows focusing on the real potentials for energy savings in the building, by comparing the disaggregation results with values of a similar target building, using previous studies, and energy standards. If the building under study is found to be complying with energy efficient building requirements, a report can be produced to document the findings. If the building is not complying with the energy standards, and falling behind energy efficient buildings, *Stage II* of the method should be utilized. However, the results of the preliminary study (cost level of the ECM’s) should be discussed with the building owner for approval.

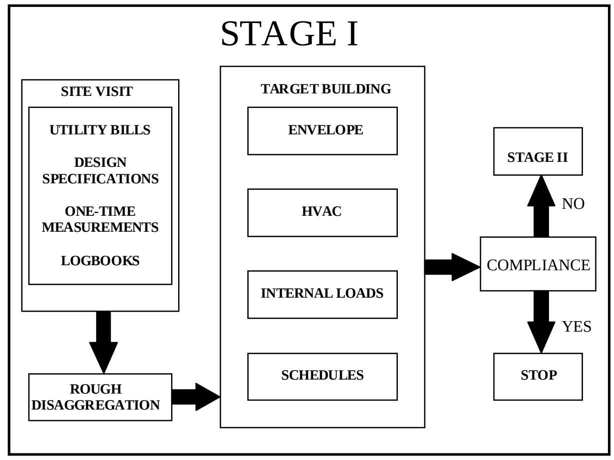

Figure 1 Stage I of the proposed method.

Stage II:

Stage II of the method (Figure 2) is where the short-term measurements, along with the predictions and the analysis are performed. Following the steps of *Stage II*, long-term predictions will be obtained from short-term measurements. According to the types of energy source used in the building, the analyses can be performed on the whole year, the cooling season, or the heating season bases. In any case, the first step in *Stage II* is the in-situ measurements. These variables, along with the timing and duration of the predictions, and the cost level of the ECM to be considered, are dictated from *Stage I* results. Variables to monitor, typically, include internal loads, thermal loads, and weather conditions. Based on normalized weather conditions, the temperature variation during the whole year or for a certain season, for a certain location will be studied in order to define the *ranges* for that variation. These ranges along with the schedule of operation of the chiller, for instance, help in the timing consideration of the measurements to be performed, to cover the whole range of the temperature variation.

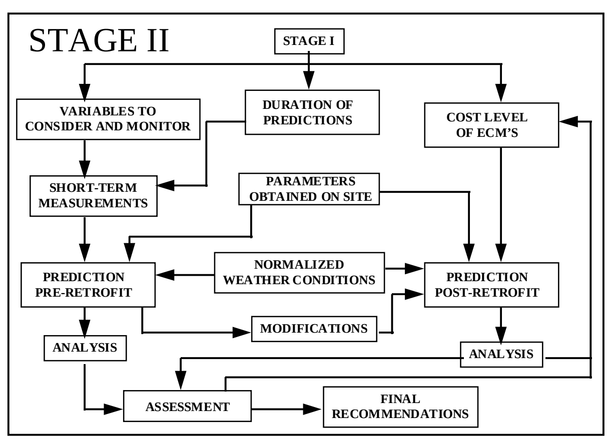

Figure 2 Stage II of the proposed method.

Prediction method for the pre-retrofit phase

The prediction procedure in *Stage II* for the pre-retrofit phase (Figure 3), is performed following the steps listed below:

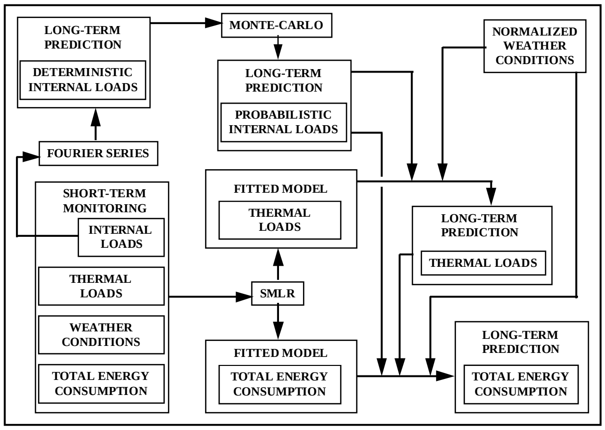

Figure 3 The pre-retrofit prediction procedure in Stage II of the proposed method.

1. Develop a SMLR model for the total electricity consumption (dependent variable) from the hourly values of the monitored dependent and independent variables . The internal predictiveness of the SMLR model is assessed with the R^2_{adj} value, and the residual errors, the SEE (standard error of estimation) and the MAE (mean absolute error). The prediction regression model has the following general form:

TOT = a + b(DB) + c(WB) + d(ENTH) + e(SOLAR) + f(LITE) + g(TOTVEN) + h(DHW) + i(EQUIP) + j(CHILR) + k(SCHED) + l(FLAG) **(1)**

2. Develop a SMLR model for the thermal loads, function of internal loads and weather conditions (for instance, the chiller electricity consumption and the cooling load) from the same measurements. The regression models will be similar to the following form:

CHILR = a + b(DB) + c(WB) + d(ENTH) + e(SOLAR) + f(LITE) + g(TOTVEN) + h(EQUIP) + i(SCHED) + j(FLAG) **(2)**

and

COOLOAD = a + b(DB) + c(WB) + d(ENTH) + e(SOLAR) + f(LITE) + g(TOTVEN) + h(EQUIP) + i(SCHED) + j(FLAG) **(3)**

In order to obtain long-term predictions for the thermal loads (*chiller consumption, and cooling load*) covering, for instance, the whole cooling season's weather conditions variations, measurements of the same variables but during a different period should be performed. As many additional SMLR models for the thermal loads, will be developed as required.

3. Develop a Fourier Series model for each of the *internal loads* **(**domestic hot water load, office equipment load, lighting load, ventilation fans load, etc..). Those internal loads are first assumed to remain *invariable* from a week to another during the operation of the building. This assumption is based on the well determined schedules of the building systems. The Fourier Series model will have the following form:

$$Y_F = Mean(y_t) + \sum_{i=1}^{n} a_i \cos(2\pi f_{Fi} t) + \sum_{i=1}^{n} b_i \sin(2\pi f_{Fi} t)$$

(4)

$$a_i = \frac{2}{m} \sum_{t=1}^{m} y_t \cos(2\pi f_{Fi} t) \quad \textbf{(5)}$$

$$b_i = \frac{2}{m} \sum_{t=1}^{m} y_t \sin(2\pi f_{Fi} t) \quad \textbf{(6)}$$

where:

Y_F: is the simulated Fourier Series of the internal load

n: designates the number of peaks in the periodogram (in the frequency domain)

m: is the length of the original time series

y_t: is the original time series of the internal load (in the time domain)

f_{Fi}: is the Fourier frequency of the corresponding peak in the periodogram

t: is the hour (1 to m)

Mean: is the mean value of the time series of the internal load (in the time domain).

The internal predictiveness of the models is assessed with the residual errors, the coefficient of variance (CV) and the mean bias error (MBE):

$$CV = \frac{\sqrt{\left(\sum_{i=1}^{n} (y_{pred_i} - y_{meas_i})^2\right)}}{n.y'_{meas}} \quad \textbf{(7)}$$

$$MBE = \frac{\sum_{i=1}^{n} (y_{pred_i} - y_{meas_i})}{n.y'_{meas}} \quad \textbf{(8)}$$

where:

$y_{pred\,i}$: is the predicted value

$y_{meas\,i}$: is the measured value

n: is the length of the time series

y'_{meas}: is the mean of the whole measured observations in the time series.

Obtain the long-term predictions (whole cooling season, for instance) for internal loads using equation (4) above; i.e., assign values for the variable *t* (the hour) from *one* till the total number of hours *m* during the season. The Fourier Series for the whole season will be, as such, obtained.

4. To account for the uncertainty that actually exists in the internal loads consumption, but which was not considered when these loads were predicted in a deterministic way in step (3) above , the Monte-Carlo simulation is run for each of the internal loads to obtain probabilistic results following certain probability density functions, and covering a range that is likely to occur. The description of the Monte-Carlo simulation is not included in this paper, and is left for future work in the case study.

5. Use a weather normalization approach to solve two obstacles. First, the obstacle of providing long-term hourly weather conditions predictions (whole season), which is not possible; and second, using the same weather conditions (normalized) for the analysis in both pre- and post-retrofit phases. The approach consists of using weather records of a certain location for a period of ten to fifteen years. For each hour in the year (8760 hours), the mean and standard deviation of each variable (in the weather conditions) will be calculated. Three time series of each variable will be obtained: (1) the time series using the mean value; (2) the time series using the mean value plus one standard deviation; and (3) the time series using the mean value minus one standard deviation. These three time series will represent the range where the weather variables are likely to fall.

6. The values of the internal loads and weather conditions variables obtained in steps (4) and (5) respectively are used in the models of step (2) above, to obtain the long-term predictions for the thermal loads, by respecting the ranges of the typical meteorological year in terms of temperature variation. Thus, the long-term prediction (whole cooling season) for the thermal load (chiller consumption) will be obtained.

7. Use the results obtained in steps (4), (5), and (6) in the model of step (1) to obtain the long-term prediction of the total electricity consumption (TOT).

Prediction method for the post-retrofit phase

Stage I will determine the cost level of the ECM's. The proposed method deals with three ECM's cost levels: (1) *No Cost ECM's*, (2) *Low Cost ECM's*, and (3) *High Cost ECM's*. No Cost ECM's may include modifications in the schedules of lighting, ventilation, chiller, domestic hot water; cycling of fans and chiller, temperatures setpoints and setbacks, free cooling (night flushing), ventilation requirements, domestic hot water supply temperature, domestic hot water flow rate, and other modifications. Low Cost ECM's may include changing the lighting type or reducing the lighting load. High Cost ECM's may include changing the boiler, the chiller, the ventilation fans, and the pumps. The NO Cost ECM's can be dealt with, by asking the building operator to run the building for one day under the new scenario, while monitoring the same variables monitored in the initial scenario (pre-retrofit). New models for this post-retrofit "simulated" phase will be developed by extrapolating the results of the "experimental day" for the whole season, and the savings will be calculated. However, a limitation of the new method arises when operation restrictions prevent such experimental scenarios. The Low Cost ECM's like reducing the lighting consumption, will be dealt with by modifying analytically the time series for the lighting consumption (for example reducing the hourly values by 30%). The reduced values will be used to obtain the resulting time series of the thermal loads that will be affected (for example, the cooling load resulting in the chiller energy consumption). Eventually the resulting total electricity consumption will be obtained, and the savings can be calculated. For the High Cost ECM's , the predictions of an end-use of interest, where a potential for energy savings exists, are modified following a procedure described below, to obtain the building energy performance under a post-retrofit scenario. For instance the energy performance of *boilers, pumps, fans, chillers*, can be dealt with in a similar manner. In actual cases, an installed chiller, is replaced by a new chiller with a higher design COP, and part-load efficiency; boilers are replaced with new products with higher efficiencies; pumps and fans motors are replaced with variable-speed, more efficient products. The basic thermodynamic functions governing the operation of boilers, pumps, fans and chillers should be considered. Variables in these functions should be used in a practical way; i.e., where they can be derived or obtained directly by in-situ measurements. For instance for the chiller:

Electricity Input = Cooling Load / COP, *(kWh/h)*

Cooling Load = 4.17 . Q . ΔT_{CHW}, *(kWh/h)* **(9)**

Thus,

Electricity Input = (4.17 . Q . ΔT_{CHW}) / COP, *(kWh/h)* **(10)**

where: Q: is chilled water flow rate, *(L/s)*
ΔT_{CHW}: is the chilled water temperature difference across the evaporator, (^{0}C).

For an existing chiller the *design Capacity* and *COP* are known. The operating hourly capacity (cooling load) and the operating electricity consumption can be monitored (equations (9) and (10)). Thus, the operating COP (hourly values) can be obtained. Finally, a Part-Load multiplying factor F can be obtained as follows:

$$F = COP_{operating} / COP_{design} \quad \textbf{(11)}$$

In a similar approach, for a proposed chiller the *design capacity* and *COP* are obtained from the manufacturer. Part-load performance data can be also obtained in terms of percentage design capacity (Part-Load Ratio (PLR)) vs. percentage Power Input (%PI).

The Part-load multiplying factor F for the proposed chiller is calculated as follows:

$$COP_{design} = Capacity_{design} / \text{Power Input}_{design} \quad \textbf{(12)}$$

$COP_{operating}$ = (PLR . $Capacity_{design}$) / (%PI . Power $Input_{design}$)

$$COP_{operating} = (PLR / \%PI) . COP_{design} \qquad \textbf{(13)}$$

Thus,

$$F = COP_{operating} / COP_{design} = PLR / \%PI \qquad \textbf{(14)}$$

In this manner F can be obtained for different ranges of PLR (0 to 100%) with data available from manufacturers.

The following steps can be followed to estimate the performance of a new chiller:

1. Get the PLR vs. %PI data from the manufacturer at the *ARI standard conditions* (entering condenser water temperature 85F at 100% PLR to 60F at 0% PLR; decreasing by 2.5F at each 10% decrease in the PLR). This data will be used to derive the F factor of the new chiller as function of part load ratio and entering condenser water temperature.

2. Calculate the time series of the part load ratio (PLR) of the existing chiller, by dividing the operating capacity time series (predicted for the whole cooling season) by the design capacity value.

3. Construct the F time series of the new chiller corresponding to the existing chiller PLR time series (recall that F of the new chiller was determined for various ranges of PLR (0 to 100%)).

4. Multiply the obtained F time series by COP_{design} of the new chiller, thus obtain the part-load $COP_{operating}$ of the new chiller.

5. Divide the operating capacity (cooling load) time series, which remains constant for the pre- and the post-retrofit periods, by the $COP_{operating}$ time series of the new chiller, thus, obtain the hourly operating Power Input (electricity consumption) of the new chiller.

6. Use the time series of the new chiller electricity consumption in the model of the total electricity consumption, along with the time series of the rest of the variables (remaining unchanged), and thus, obtain the hourly time series of the total electricity consumption for the post-retrofit period.

7. Obtain the predicted energy savings by calculating the difference in the hourly values of the chiller and total electricity consumption between the pre- and the post-retrofit periods.

CASE STUDY

A case study applying the new method was conducted using the synthetic data that was used for evaluating different inverse methods. The synthetic data served as measured data. To determine the periods needed for measurements, it is necessary to look at the variation in the ambient dry bulb temperatures during a specific season. The range of the ambient dry bulb temperature weekly average variation during the cooling season (April 15 - October 15) is 18^0C; lowest temperature is 5^0C and highest is 23^0C. The variation range is divided by two, and consequently two ranges of temperatures were defined: 5 to 14^0C and 14 to 23^0C. The periods lying in these ranges are as follows: April 15 - May 12 and September 16 - October 15 are the low temperature periods (5 - 14^0C), and May 13 - September 15 is the high temperature period. The monitoring is done for two weeks in the low temperature periods (April 15-28) and for two weeks in the high temperature period (July 15-28). Using two weeks of monitored data for developing the prediction models was justified based on the analysis performed on the CV and MBE values of the predictions of all possible SMLR models for various durations within the cooling season.

Pre-retrofit phase

The steps described in the approach above are performed and the following results are obtained:

1. A SMLR model is developed for the hourly total electricity consumption (kW) (dependent variable) from the two weeks hourly values of the monitored dependent and independent variables in the middle of the cooling season (July 15-28). Another model for the low temperature period (April 15-28) is not required due to the fact that the energy performance of the building considered is internally dominated (internal loads form 83% of total electricity use). The SMLR technique keeps only the significant set of regressors in the model. The following model is obtained:

TOT = -7.1406 + 1.0166(LITE) + 1.0537(EQUIP) + 1.0162(DHW) + 1.0122(TOTVEN) + 1.0101(CHILR) - 0.2869(DB) + 0.1698(ENTH) + 0.0090(SOLAR) **(1.a)**

with: R^2_{adj} = 99.99%
SEE = 2.14
MAE = 1.74

2. The SMLR model of the chiller electricity consumption developed from the July 15-28 two weeks data was:

CHILR = -111.0125 + 0.9826(TOTVEN) + 0.7115(LITE) + 3.9279(DB) - 12.4238(FLAG) **(2.a)**

with: R^2_{adj} = 94.43%
SEE = 20.12
MAE = 14.44

The SMLR model of the cooling load developed from the July 15-28 two weeks data was:

COOLOAD = -232.1634 -21.8955(WB) + 6.2278(DB) + 7.6060(ENTH)+1.3719(LITE)+3.4487(DHW)+1.0401(TOTVEN)-21.4688(FLAG)-109.9194(ONOFF) **(3.a)**

with: R^2_{adj} = 96%
SEE = 41.96
MAE = 30.82

The SMLR model of the chiller electricity consumption developed from the April 15-28 two weeks data was:

CHILR = -44.0807 + 20.5445(ONOFF) + 3.4119(DB) + 0.0068(SOLAR) - 0.3430(TOTVEN) **(2.b)**

with: R^2_{adj} = 71.85%

SEE = 8.67

MAE = 6.43

The SMLR model of the cooling load developed from the April 15-28 two weeks data was:

COOLOAD = -388.8537 - 21.5686(WB) + 9.5142(DB) + 10.4068(ENTH) + 0.0171(SOLAR) + 0.7884(TOTVEN) + 51.5252(ONOFF) **(3.b)**

with: R^2_{adj} = 71.22%

SEE = 23.15

MAE = 17.06

3. A Fourier Series model for each of the internal loads is developed using equation (4) above. Long-term predictions are obtained for the whole cooling season for internal loads. The Fourier Series for the whole season is, as such, obtained. Tables 1, 2, 3 and 4 show the parameters of the Fourier models for the domestic hot water, office equipment, ventilation fans, and lighting electricity consumption respectively. The Monte-Carlo approach was not included in this case study.

Harmonic Number	Harmonic Index (i)	Fourier Series Coefficients		Fourier Frequency
		a_i	b_i	f_i
1	3	-4.0261	4.5066	0.00595
2	5	0.453	4.0027	0.0119
3	7	1.104	0.792	0.01786
4	9	-1.2106	0.2712	0.02381
5	11	-1.5019	2.7075	0.02976
6	13	1.2769	3.621	0.03571
7	15	-8.1329	-3.3704	0.04167
8	17	2.2222	-1.0961	0.04762
9	19	0.31186	-1.1989	0.05357
10	29	-1.3863	-1.7315	0.08333
11	31	1.0401	0.026	0.08929
12	43	1.00503	1.67265	0.125
13	57	-0.2872	1.62455	0.16667
14	85	0.6676	-0.6557	0.25
Time Series Mean:	M=15.114 kWh/h			

Table 1 Fourier Series parameters for the Domestic Hot Water electricity consumption.

Harmonic Number	Harmonic Index (i)	Fourier Series Coefficients		Fourier Frequency
		a_i	b_i	f_i
1	3	-4.9317	5.8352	0.00595
2	5	0.8504	5.0497	0.0119
3	11	-1.3505	3.8372	0.02976
4	13	2.66509	4.4918	0.03571
5	15	0.8549	-9.1079	0.04167
6	17	2.8725	-2.458	0.04762
7	29	7.4964	-1.3811	0.08333
8	43	6.1599	6.2574	0.125
9	57	-5.2857	0.0528	0.16667
10	71	-3.8181	1.2006	0.20833
11	85	5.3249	-0.1418	0.25
12	99	-4.3134	-6.3965	0.29167
13	127	3.2412	5.0333	0.375
14	141	3.0695	-1.0262	0.41667
Time Series Mean:	M= 56.015 kWh/h			

Table 2 Fourier Series parameters for the Office Equipment electricity consumption.

Harmonic Number	Harmonic Index (i)	Fourier Series Coefficients		Fourier Frequency
		a_i	b_i	f_i
1	3	-12.746	20.7055	0.00595
2	5	4.409	21.1679	0.0119
3	7	6.4607	8.54851	0.01786
4	9	-5.2997	5.4758	0.02381
5	11	-9.74	14.225	0.02976
6	13	-1.097	17.4261	0.03571
7	15	-29.485	-17.235	0.04167
8	17	4.551	-1.3558	0.04762
9	29	-2.7305	-14.224	0.08333
10	31	5.0142	0.79821	0.08929
11	33	4.47724	-2.3084	0.09524
12	57	-6.7604	4.28419	0.16667
13	71	-6.5146	-1.2825	0.20833
14	99	0.64978	5.05189	0.29267
Time Series Mean:	M= 39.736 kWh/h			

Table 3 Fourier Series parameters for the Ventilation Fans electricity consumption.

Harmonic Number	Harmonic Index (i)	Fourier Series Coefficients		Fourier Frequency
		a_i	b_i	f_i
1	3	-19.062	19.904	0.00595
2	5	0.7913	18.4224	0.0119
3	7	4.6923	4.1765	0.01786
4	9	-5.7009	0.482	0.02381
5	11	-9.1393	11.2734	0.02976
6	13	2.28612	18.1745	0.03571
7	15	-36.156	-26.342	0.04167
8	17	12.3744	-1.9723	0.04762
9	19	3.76152	-5.4241	0.05357
10	29	-2.666	-6.7875	0.08333
11	41	4.6875	-1.7839	0.11905
12	43	-4.3313	11.2669	0.125
13	57	-4.7469	3.2678	0.16667
14	71	5.0369	0.77861	0.20833
Time Series Mean:	M= 85.784 kWh/h			

Table 4 Fourier Series parameters for the Lighting electricity consumption.

4. A Typical Meteorological Year of weather conditions for Montreal (neighbor city of Laval) was used in the predictions instead of the proposed weather normalization approach.

5. The values of the internal loads and weather conditions variables obtained in steps (3) and (4) respectively are used in the models (2) and (3) above, and the long-term predictions (whole cooling season) for the thermal loads (chiller electricity consumption) are obtained, by using the appropriate model for the periods corresponding to each range of the weather variation.

6. Results obtained in steps (3), (4), and (5) are used in model (1) and the long-term prediction (whole cooling season) of the total electricity consumption (TOT) is obtained.

Post-retrofit phase

In the case study, replacing the old chiller of the building with a new one was considered as a high potential for energy savings since the chiller consumption forms 17% of the total electricity consumption of that building. A new chiller with an Electric Input Ratio (EIR) value of 0.169 was considered to replace the old chiller having an EIR

value of 0.366. The new chiller data was obtained from a manufacturer. Another reason in considering the chiller replacement is to test the capability of the proposed method to accommodate the prediction of the building energy performance under a high-cost ECM. The post-retrofit prediction steps described in the approach above were applied, and finally the predicted energy savings are calculated. Table 5 shows the results of the predicted total and chiller electricity consumption in the pre- and post-retrofit periods. It is worth mentioning that the error in the predictions of the total electricity consumption in the post-retrofit period were higher than in the pre-retrofit period.
This feature was expected since the predictions for the post-retrofit period are based on the predictions for the pre-retrofit period, therefore endorsing the errors involved in the pre-retrofit predictions. Also, it is noted that the whole predictions, for the whole cooling season in the pre-retrofit, and later, in the post-retrofit period are based on four weeks of measurements in the pre-retrofit period *only*. The prediction errors for the total electricity consumption were below 7%, whereas those for the chiller electricity consumption were below 23%; results within the limits accepted in the prediction of the energy performance. It is noted that the savings occurred in the chiller consumption should be reflected in same savings values in the total electricity consumption, because replacing the chiller was the only ECM considered in the study. This feature appeared to be correct in the case of the predictions with the proposed method, with savings of 124,000 kWh in the consumption. It should be mentioned that for validating the post retrofit predictions of the model, these predictions were compared with a modified version of the synthetic data, obtained by changing the Electric Input Ratio (EIR) value of the chiller from 0.366 to 0.169 in the input file of the original DOE-2 simulation..

		Measurements (kWh)	Predictions (kWh)	Prediction Error (%)
Total Electricity Consumption	Pre-Retrofit	1,079,982	1,125,051	4.17
	Post-Retrofit	935,246	1,000,768	7.01
	Savings	144,736	124,283	-14.13
	Percent Savings	13.4	11.05	
Chiller Consumption	Pre-Retrofit	187,757	230,371	22.7
	Post-Retrofit	95,588	107,331	12.28
	Savings	92,169	123,040	33.49
	Percent Savings	49,09	53.41	

Table 5 Prediction results of the Total Electricity and Chiller Consumptions for the Pre-retrofit and Post-retrofit periods.

CONCLUSION

The SMLR technique was used to develop the total energy consumption model that was able to predict the energy performance for the whole cooling season in a pre-retrofit and a post-retrofit phase, based on four weeks of monitored data in the pre-retrofit phase. This technique was assisted by using Fourier Series models and normalized weather data. The limitation of performing short-term measurements to obtain long-term predictions was challenged for the first time as the conducted literature survey shows, and the results showed to be acceptable (prediction error between 4% and 23%). In the proposed method, the modelling for day-types (weekdays, weekends, holidays, etc..) was avoided by adding time indicator (flag) variables, and thus reducing the time and effort in the modeling, otherwise required. Performing short-term measurements reduces the time and effort to be provided by the energy analyst who is using the proposed method.
The predicted energy savings can be verified with utility bills, or with the technique described in the North-American Energy M & V Protocol (1996), which accounts for weather variations and changes in the building operation from a year to another.

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