Evaluation of a case-based reasoning energy prediction tool for commercial buildings

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ABSTRACT

This paper presents the results of an energy predictor that predicts the energy demand of commercial buildings using Case-Based Reasoning (CBR). The proposed approach is evaluated using monitored data in a real office building located in Varennes, Québec. The energy demand is predicted at every hour for the following three hours using weather forecasts. The results show that during occupancy, 7:00 to 17:00, the coefficient of variance of the root-mean-square-error (CV-RMSE) is below 12.3%, the normalized mean bias error (NMBE) is below 1.3% and the root-mean-square-error (RMSE) is below 16.6 kW. When the statistical criteria are calculated for all hours of the day, the CV-RMSE is 13.9%, the NMBE is 2.7% and the RMSE is 17.9 kW. The case study demonstrates that CBR can be used for energy demand prediction and could be implemented in building operation systems.

INTRODUCTION

Building load management is often used to optimize the operation of building systems. This is achieved more easily if the peak demand and loads are known ahead of time using building energy prediction. Different techniques can be used to forecast the energy demand of the building such as whole building energy simulation, regression analysis, and black-box models (e.g., artificial neural networks). In this paper, Case-Based Reasoning (CBR), a machine-learning artificial intelligence technique, is used to predict the electricity demand of commercial buildings.

CBR is a problem solving technique that uses past experience, represented as “cases”, to identify and adapt solutions to new problems (Aamodt and Plaza 1994). It is characterized by four distinct processes: (1) retrieval of the most similar case or cases; (2) adaptation of the retrieved information and knowledge to solve the problem; (3) revision of the proposed solution; and (4) case accumulation, where information and knowledge are retained for future solutions (Lopez De Mantaras et al. 2005). Different techniques can be used to retrieve cases. In the proposed approach, the database of cases is scanned for cases having similar characteristics for variables that influence the dependent variable (energy demand). The contribution of each variable to the global case similarity is defined by its weight. The weights are selected based on the impact of each variable on the variable to be predicted. Using this approach, a prototype tool was developed to predict the energy demand of commercial buildings, which is currently installed in a real office building located in Varennes, Québec.

The initial implementation of the tool showed good agreement between the predicted energy demand and the measured values: the CV-RMSE were lower than 13.2%, the NMBE lower than 5.8% and the RMSE lower than 14 kW during occupancy, 7:00 to 18:00 (Monfet et al. 2013). Since then, lighting retrofits as well as major operation changes have occurred in the building. These changes require the identification of new weights to be selected for case retrieval. To re-select the weights, a new approach is evaluated and recommendations are presented.

BACKGROUND INFORMATION

CBR has been applied to several engineering applications; however, it has only been used in a few cases in the field of building environment. For example, CBR was used to select an appropriate neural network model to predict building energy consumption (Breekweg et al. 2000a, b). Similarly, it was used to evaluate thermal comfort by combining analytic and case-based approaches with knowledge-based expert system information (Kumar and Mahdavi 2001). CBR was used also in an approach to predict greenhouse gas emission level of housing units (Hong et al. 2012). For this case, CBR was used within cluster to identify similarities between housing units and a genetic algorithm was used to improve the performance of the CBR.

Different prediction accuracy criteria have also been proposed to evalute CBR approaches. Breekweg et al. (2000a) initially suggested that the CV-RMSE should be below 5% for energy prediction. However, energy predictions that were performed using a generalized neural network model with CBR as a learning technique for local training resulted in CV-RMSE of 10-11% with simulated data and around 20-25% with real building data, except for one building where the

CV-RMSE was below 5% (Breekweg et al. 2000b). The possible causes identified for the low prediction accuracies included inconsistency and high noise in the data set as well as system operating under manual mode.

ASHRAE (2002), on the other hand, recommends, for general model accuracy, the CV-RMSE and the NMBE to be within 30% and 10%, respectively on an hourly basis and 15% and 5% for monthly measurements, respectively.

In this paper, three criteria are used to evaluate the performance of the case-based reasoning prediction: the coefficient of variance of the root-mean-square error (CV-RMSE), the normalized mean bias error (NMBE) and root-mean-square error (RMSE) as defined by Equations (1) to (3), respectively.

$$CV-RMSE=\frac{\sqrt{\frac{\sum_{i=1}^{n}\left(y_{data,i}-y_{pred,i}\right)^2}{n-p}}}{\bar{y}_{data}}\times 100 \qquad (1)$$

$$NMBE=\frac{\sum_{i=1}^{n}\left(y_{pred,i}-y_{data,i}\right)}{(n-p)\cdot\bar{y}_{data}} \qquad (2)$$

$$RMSE=\sqrt{\frac{\sum_{i=1}^{n}\left(y_{pred,i}-y_{data,i}\right)^2}{n}} \qquad (3)$$

where $y_{pred,i}$ is the predicted dependent variable value, $y_{data,i}$ is the data value of the dependent variable, $\bar{y}_{data}$ is the mean value of the dependent-variable test set, n is the number of records of data in the test set, and p is equal to 1.

DESCRIPTION OF THE CASE STUDY

The proposed CBR energy prediction tool, called energy predictor, is used to forecast the energy demand of the CanmetENERGY building, located in Varennes near Montréal, Québec. The building has a total floor area of 5300 m^2 (57 050 ft^2) and consists of two main sections of roughly equal size: (1) offices and conference rooms and (2) testing laboratories. The HVAC equipment consists of seven air handling units served by an air cooled chiller, ice storage, two fire tube gas boilers and one electric boiler. The chiller uses R-22 refrigerant with a shell and tube evaporator having a capacity of 120 tons. Two ice banks are available for ice storage that have a total capacity of 324 ton hours and generate ice at -5°C (23°F). The boilers operate during the heating season (October to early May). The electric boiler operates as the lead boiler and has a capacity of 200 kW (685 MBH); it is supplemented by the gas-fired boilers, having a capacity of 470 kW (1605 MBH) each.

The prediction is performed only for the offices and conference rooms, since the operation of the testing laboratories varies widely. The proposed CBR energy predictor is implemented within the monitoring and data acquisition system of the building under study.

BRIEF DESCRIPTION OF THE ENERGY PREDICTOR

The energy predictor was developed using case-based reasoning. At this stage, most of the development for the energy predictor has been on defining the case retrieval approach and adaptation process. No criteria have been defined to determine if new cases provide acceptable energy demand information and should be retained or not for case accumulation: new cases are automatically included in the library of cases. A brief description of each stage is presented. For a more detailed description of the tool refer to Monfet et al. (2013).

Case Retrieval

The approach undertaken for case retrieval scanned the database of cases having similar characteristics for variables that influence the dependent variable. To predict the total energy demand (dependent variable), the database of cases is scanned for cases having similar independent variables as presented in Table 1. Data for the previous three hours and available “forecastable” data for the next three hours are used to retrieve cases. The “forecastable” data include weather information, such as the outdoor air temperature and relative humidity. The weather forecasts are provided by the Canadian Meteorological Service for hourly data of the next 48 hours that are updated online every 6 hours.

Table 1
Variables and distance measurements for case retrieval

Input variables	d_{min}	d_{max}
Outdoor air temperature, °C	2.3	6
Outdoor air relative humidity, %	10	25
Day type[1]	0	1
Total building electricity demand, kW	20	75
Total electrical cooling demand, kW	10	50
Total electrical heating demand, kW	10	50
Total fan demand, kW	1	5
Representative interior zone temperature, °C	1.3	5
Ice making[2]	0	1

Notes
1. 0, 1, 2 for unoccupied, fully occupied, occupied after unoccupied day, respectively
2. -1 for ice bank discharge

For most of the selected independent variables, the distance between two time series is defined according to the Weighted Euclidean (WE) distance. Using the normalized WE distance (Equation (4)), the similarity is determined between two time series: the similarity is set to 1 if the distance is less than a minimum threshold, d_{min}; if the distance is higher than d_{max}, then the similarity is set to 0. The similarity varies linearly between d_{min} and d_{max}. The values of d_{min} and d_{max} are selected based on expert knowledge for each variable (Table 1). Data for the three previous hours and forecast data for the next three hours are considered to select the most similar cases from the database.

$$W.E. = \frac{\sqrt{\sum_{i=1}^{n} w_i \left(x_i - y_i\right)^2}}{\sum_{i=1}^{n} w_i} \tag{4}$$

The global case similarity allows the ranking of the cases to identify the most similar cases to be used for case adaptation. The contribution of each variable to the global case similarity is defined by its weight. The weights are selected based on the impact of each variable on the variable to be predicted. For the case study, the weights were selected using Pearson product moment correlation coefficients between each pair of variables, determined using a commercial statistical software (STATGRAPHICS 2012). The Pearson product moment correlation coefficients range between -1 and +1 and measure the strength of the linear relationship between variables. The variables are correlated with the total building electricity demand at the next hour (t+1). The relative importance of each coefficient is used to determine the weights.

Case Adaptation

Once a sub-set of cases has been selected, it needs to be transformed into a solution for the current problem. From the set of retrieved similar cases, the most likely prediction is determined using equation (5).

$$P_t = \frac{\sum_{i=1}^{k} w_{s,i} \cdot \left(C_i\right)_t}{\sum_{i=1}^{k} w_{s,i}} \tag{5}$$

where P_t is the predicted value at time t, k is the number of cases retrieved, $(C_i)_t$ is the value from case i at time t, and $w_{s,i}$ is the weight of case i, which is equal to the similarity value of that case (*GS*). The prediction is updated every hour to improve its accuracy.

The energy predictor estimates the shape of the building's load curve for the next three hours as well as the possible occurrence of peak demand. This prediction allows building operators and energy managers to optimize the operation of building systems and reduce peak demand by modifying the control sequence.

WEIGHTS SELECTION FOR CASE RETRIEVAL

Different techniques such as contribution factor (Breekweg et al. 2000b), statistical analysis (Morcous 2002), and gradient descend method (Kim et al. 2004) have been discussed in the literature for the selection of the weights. In this study, the Pearson product moment correlations between each pair of variables was used to estimate the weights by using the relative importance of each coefficient to the total building electricity demand at the next hour (t+1). A similar approach was followed by Morcous (2000).

The initial testing of the energy predictor used a full year of data to identify the weights. This delays the implementation of the tool if no measured data are available at the time of installation. Therefore, a dynamic approach that can adapt itself to changes in the energy demand pattern is proposed. The approach consists of using an initial data set and to periodically re-calculate the value of the weights as new data become available (Figure 1). For example, the initial weights are identified using three data sets (no.1 to no.3). Once the weights are identified, the new monitored data sets (no.4 to no.6) are compared with the predicted values by the CBR energy predictor. The window is increased as new data are collected, and is composed now of four data sets (no.1 to no.4). The weights are re-calculated using the new enlarged data sets. The monitored data sets (no.5 to no.6) are compared with the values predicted by the CBR energy predictor with the new weights.

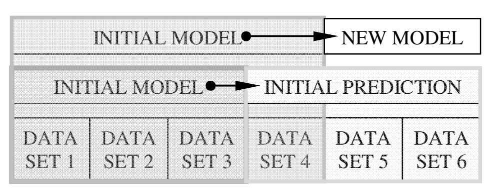

Figure 1. Schematic of the increase in dataset size

The new collected data are added in to the initial data set periodically (daily, weekly, bi-weekly or monthly), thus enlarging the quantity of data used to identify the weights. At the end of the year, for instance, the data set is large and covers the whole spectrum of operating and weather conditions.

In this study, the initial data set includes data from January to the end of March 2012. The database was then enlarged on a monthly basis to evaluate the impact of increasing the number of cases to determine the weights.

Table 2 presents the variation of the weights as well as the weights used previously in the energy predictor, prior to the changes that occurred in 2010 and 2011 (pre-retrofit weights). The results show that the most influential parameter is the previous total building electricity demand. Also, it is interesting to note that weights for the outdoor air temperature, the day type, the total heating demand and the total fan demand have varied slightly compared to the pre-retrofit period (Table 2). This is particularly true for the total fan demand that had an initial weight of 0.2 and has now a value of 0.6. At this stage, a full year of data was assumed to cover the full range of operating and weather conditions and the process of re-calculating the weights on a monthly basis was stopped. The next section presents the results obtained on a monthly basis as well as the prediction over the first three months of the year 2013.

RESULTS AND DISCUSSION

Two different sets of results are presented. First, the results of the monthly predictions for April to December 2012 where the weights, updated on a monthly basis, are presented. Secondly, the prediction made over the first three months of 2013 using the weights selected using a full year of data (data for 2012) are presented.

Predictions versus Measurements: 2012 Monthly Results

Table 3 presents the monthly statistical criteria calculated with hourly data for the first predicted hour. The CV-RMSE are lower than 23% except for the month of May. Before May, the outdoor air conditions were cooler; thus only a few cases corresponding to warmer weather conditions influenced the value of the weights. The predictions made at the first hour with the dynamically enlarged window after May are well within the recommended value for general model accuracy of CV-RMSE and NMBE to be within 30% and 10%, respectively (ASHRAE 2002). However, when the prediction is extended to the three-hour period, the CV-RMSE and NMBE are within the recommended accuracy for prediction made in July forward. Also, the percentage of predicted cases increases to 84% after July. Therefore, when the data acquisition begins in January for a climate similar to Montréal, at least six months of data are required to initialize the weights used in the energy predictor. However, these results must be interpreted with caution; a colder year – where warmer days only begin towards the end of June – might require an additional month of data to provide accurate predictions.

Table 2
Variation of weights for different size of initial database for input variables

Input variables	**01 to 03/12**	**01 to 04/12**	**01 to 05/12**	**01 to 06/12**	**01 to 07/12**	**01 to 08/12**	**01 to 09/12**	**01 to 10/12**	**01 to 11/12**	**01 to 12/12**	**Pre-retrofit**
Outdoor air temperature, °C	0.6	0.7	0.7	0.7	0.7	0.6	0.6	0.6	0.6	**0.7**	0.8
Outdoor air relative humidity, %	0.1	0.2	0.2	0.2	0.2	0.1	0.1	0.1	0.1	**0.2**	0.2
Day type	0.4	0.5	0.4	0.4	0.5	0.5	0.5	0.5	0.5	**0.4**	0.3
Total building electricity demand, kW	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	**1.0**	1.0
Total electrical cooling demand, kW	0.2	0.1	0.1	0.1	0.2	0.3	0.3	0.3	0.2	**0.1**	0.1
Total heating demand, kW	0.9	0.9	0.9	0.9	0.8	0.8	0.8	0.8	0.8	**0.8**	0.9
Total fan demand, kW	0.8	0.7	0.6	0.6	0.6	0.6	0.7	0.7	0.6	**0.6**	0.2
Representative interior zone temperature, °C	0.5	0.4	0.1	0.2	0.4	0.4	0.4	0.4	0.3	**0.4**	0.4
Ice making	0.1	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.2	**0.2**	0.2

Table 3
Prediction results for the first hour – 2012

Weights set	Predicted month	CV-RMSE, %	NMBE, %	RMSE, kW	% of cases predicted
01 to 03/2012	April	18.95	-2.40	15.9	64.1
01 to 04/2012	May	41.98	0.37	20.4	58.0
01 to 05/2012	June	22.89	3.54	12.7	82.5
01 to 06/2012	July	17.70	2.39	11.4	92.3
01 to 07/2012	August	15.40	2.74	10.5	96.6
01 to 08/2012	September	20.31	3.92	11.9	90.0
01 to 09/2012	October	19.18	3.84	15.3	84.5
01 to 10/2012	November	14.88	1.73	15.9	88.6
01 to 11/2012	December	13.40	2.78	14.4	89.0

Predictions versus Measurements: 2013 Results

The weights identified with a full year of data – year 2012 – were used to forecast the energy demand every hour for the next three hours for the first three months of 2013, from January 1 to April 3. Table 4 presents the statistical criteria calculated at each prediction hour over the three months, while Table 5 presents the statistical criteria during occupancy. The occupancy period considered in the case study are 7:00 to 17:00 Eastern Standard Time (EST) and 8:00 to 18:00 Eastern Daylight Time (EDT), when it is recommended to reduce the electricity demand of the building.

The prediction results are in fair agreement with the measured values with CV-RMSE and NMBE lower than 13.9% and 2.7%, respectively. The RMSE is around 10% of the average total electricity demand of the building. During occupancy, the CV-RMSE is 10.5% for prediction made at time t+1, while being lower than 12.3% over a three-hour prediction period. These values are well within the values recommended by ASHRAE (ASHRAE 2002).

Table 4
Prediction results – January to April 2013

	CV-RMSE %	NMBE %	RMSE kW	% of cases predicted
+ 1 hour	12.31	2.72	16.6	89.0
+ 2 hour	13.57	2.55	17.5	89.1
+3 hour	13.88	2.39	17.9	89.1

Table 5
Prediction results during occupancy – January to April 2013

	CV-RMSE %	NMBE %	RMSE kW	% of cases predicted
+ 1 hour	10.53	1.06	15.2	87.7
+ 2 hour	11.65	1.26	16.2	87.9
+3 hour	12.33	1.13	16.6	87.9

Figure 2 presents the CV-RMSE on an hourly basis. For most occupied hour, from 7:00 to 17:00, the CV-RMSE is around 10%, while being below 20% for all hours.

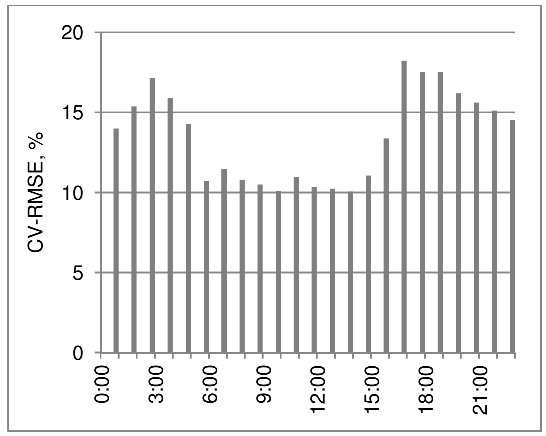

Figure 2. CV-RMSE for hourly prediction: January to April 2013

The results obtained in 2013 for all hours and occupied hours are slightly better than the CV-RMSE of 20-25% reported in the previous study when real building data were used to predict the energy use based on a neural network model combined with CBR (Breekweg 2000a).

Figure 3 to Figure 5 present the predicted electricity demand and measured values for three days: 19 January, 21 February and 20 March 2013. For 19 January (Figure 3), the whole building electric demand varies slightly throughout the day: there is no noticeable electricity demand peak and the energy predictor estimates provide enough information for the building operator to modify the operation of the system if required.

The shape of the predicted energy demand is close to the measured value on 21 February 2013 (Figure 4). The electricity demand is relatively constant during occupancy and decreases at around 18:00. However, it rises again at around 21:00 to maintain the minimum building air temperature at night.

There is more variation in energy demand on 20 March 2013 (Figure 5). Two demand peaks occurred: (1) between 7:00 and 10:00 at the beginning of the work day, and (2) one at 16:00. The magnitude of the first peak was well estimated by the energy predictor while its duration underestimated. For the second peak, the value was slightly underestimated. In order to proceed with a deeper understanding of the discrepancies, additional information such as occupancy level is required.

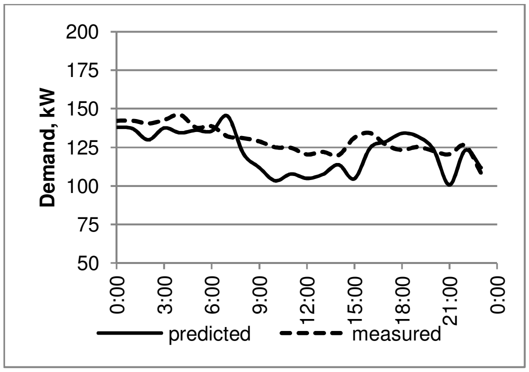

Figure 3. Predicted versus whole building electric demand: 19 January 2013

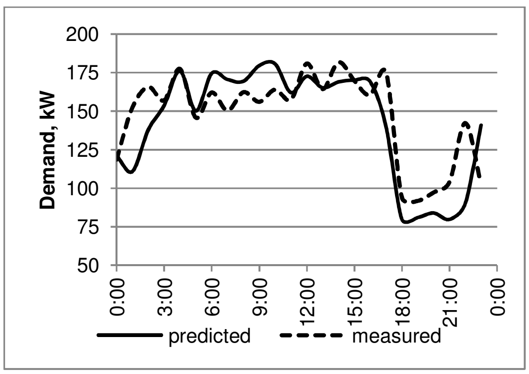

Figure 4. Predicted versus whole building electric demand: 21 February 2013

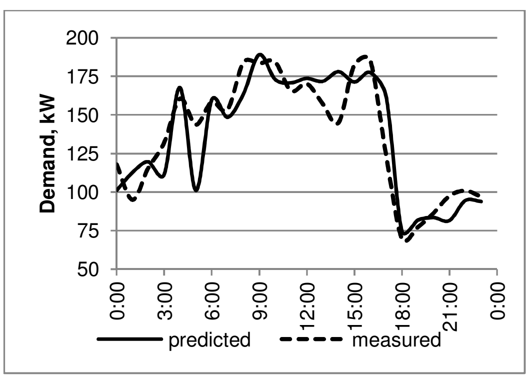

Figure 5. Predicted versus whole building electric demand: 20 March 2013

CONCLUSIONS

In this paper, an energy predictor prototype tool based on the use of CBR to predict the energy demand in commercial building was tested. A dynamically augmented dataset approach was proposed for the selection of the weights. The results showed that for the building under study, where the energy predictor is installed, six months of data – form January to the end of June – were required to obtained accurate predictions over the remaining of the year. Once a full year of data was available to identify the weights, the weights remained the same to predict the energy demand for the first three months of 2013. For the 2013 data sets, the CV-RMSE varies between 12-14 % and the NMBE is lower than 3%. These results are well within the recommended values by ASHRAE of 30% for CV-RMSE and 10% for NMBE (ASHREA 2002). Also, when compared to the CV-RMSE of 20-25% reported in previous study (Breekweg 2000a), the results obtained with the proposed approach are slightly better, especially during occupancy, when reducing the electricity demand is recommended.

The approach presented in this paper is based on data monitored in a real building where inconsistency may occur due to manual operation and noise in the data set. Also, the evaluation of changes in weights with the dynamically augmented approach is the first step towards improving the robustness of the CBR energy predictor. Additional research is required to identify if the time at which recording of the measured data has an influence on the amount of data required to identify the weights. Furthermore, a comparison between different techniques for the identification of the weights value might lead to improve accuracy. As a final remark, the proposed CBR energy predictor show promising results for its use as a tool to implement load management strategies in buildings. This is becoming more important with the rise in complexity of the building systems as well as the integration of renewable energy.

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