Energy and Buildings 81 (2014) 152–160

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

Development of an energy prediction tool for commercial buildings using case-based reasoning

Danielle Monfet[a,*], Maria Corsi[b], Daniel Choinière[b], Elena Arkhipova[b]

[a] Department of Construction Engineering, École de technologie supérieure, 1100 rue Notre-Dame Ouest H3C 1K3, Montréal, Quebec, Canada
[b] CanmetENERGY, Natural Resources Canada, Varennes, Canada

ARTICLE INFO

Article history:
Received 4 April 2013
Received in revised form 24 May 2014
Accepted 10 June 2014
Available online 16 June 2014

Keywords:
Case-based reasoning
Energy demand prediction
Weather forecast

ABSTRACT

Building energy prediction is a key factor to assess the energy performance of commercial buildings, identify operation issues and propose better operating strategies based on the forecast information. Different models have been used to forecast energy demand in buildings, including whole building energy simulation, regression analysis, and black-box models (e.g., artificial neural networks). This paper presents a different approach to predict 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 3 h using weather forecasts. The results show that during occupancy, 7:00–18:00, the coefficient of variance of the root-mean-square-error (CV-RMSE) is below 13.2%, the normalized mean bias error (NMBE) is below 5.8% and the root-mean-square-error (RMSE) is below 14 kW. When the statistical criteria are calculated for all hours of the day, the CV-RMSE is 12.1%, the NMBE is 1.0% and the RMSE is 11 kW. The case study demonstrates that CBR can be used for energy demand prediction and could be implemented in building operation systems.

1. Introduction

Building energy prediction is an essential component for implementing load management strategies in buildings. Knowing the shape of the building's load curve as well as the possible occurrence of peak demand several hours or even 1 day ahead of time can allow building operators and energy managers to optimize the operation of building systems and reduce peak demand by modifying the control sequence. The concept of planning ahead is particularly important in High Performance Buildings and Net Zero Energy Buildings; these buildings are characterized by complex systems and often include renewable sources of energy and thermal storage. The intermittent nature of renewable energy supply emphasizes the need for tools and algorithms that effectively shape the demand by actively controlling the building systems to match the energy available through renewable energy [1].

The energy performance of buildings is often assessed by comparing the estimated or forecasted energy demand with actual measured values. In this context, the development of a model that provides sufficient information to characterize the performance of the building is required. Different methods have been used to forecast the energy use of commercial buildings: whole building energy simulation, regression analysis, and black-box models (e.g., artificial neural networks).

Some of the early work on commercial building energy prediction was a result of the two *Great Energy Predictor Shootout* competitions organized by ASHRAE. The objective of the first competition was to identify the most accurate methods to predict hourly energy use based on a limited amount of measured data by using empirical models [2]. Contestants were provided with a training data set to predict the hourly energy use. This data set included whole-building electricity power use (lights and receptacles), chilled water, hot water, and environmental data (ambient temperature, absolute humidity ratio, wind, and horizontal insolation). Three models provided the best predictions: the Bayesian non-linear model, the feed-forward multilayer perceptron and the neural network with pre- and post-processing [3]. The results from the three models had an average CV-RMSE and MBE below 0.205 and 0.146, which corresponds to values of 20.5% and 14.6% in percentage, respectively, for the prediction of whole building electricity use, chilled water load and heating water load.

The second competition required the development of the most effective model to simulate energy baselines for the purpose of evaluating energy savings from retrofits [4]. Two buildings that

* Corresponding author. Tel.: +1 514 396 8453; fax: +1 514 396 8584.
E-mail address: d_monfet@hotmail.com (D. Monfet).

http://dx.doi.org/10.1016/j.enbuild.2014.06.017
0378-7788/

had undergone retrofits were used as case studies. Contestants were provided data sets for pre- and post-retrofit periods for both buildings. Each file included independent variables (weather data and calendar time stamp) and corresponding dependent variables, such as whole-building energy use. The winner of the contest used a combination of 10 neural networks with two hidden layers of 25 units each [4]. The runner-up of the contest, in contrast to the other participants, used a non-neural-net-based statistical day type routine for weather-dependent independent variables and weekday–weekend day types, as well as hourly multiple regressions for the weather dependent data. The third place participant used a Bayesian non-linear regression with multiple hyper-parameters after removal of outliers. For all three models, the CV-RMSE and the MBE were below 0.20 and 0.35, which corresponds to 20% and 35% in percentage, respectively.

The results of the *Great Energy Predictor Shootout* competitions led to the development of other benchmark models used to identify variations in energy performance over time for particular buildings: examples of such models are presented in [5–12]. A review of methods for predicting building energy use, including statistical, neural networks, support vector machines and grey models, as well as their application in engineering, is also available [13].

This paper presents the application of Case-Based Reasoning (CBR), an Artificial Intelligence technique, to predict the energy use of commercial buildings. CBR is a problem solving technique that uses past experience, represented as "cases", to identify and adapt solutions to new problems [14]. The cases are stored and accumulated in a case library. Case-based reasoning attempts to match the problem to be solved (the "current case") with past cases and adapts the retrieved cases to present a solution to the current problem [15].

Few papers have been published on the use of CBR to predict energy demand in buildings. Breekweg et al. [16,17] introduced CBR in a general framework to select an appropriate neural network model to predict building energy consumption. CBR was not used directly for energy forecasting; rather, it was used as a learning technique for local training of the model. Other examples where CBR was used for building environment applications include a thermal comfort field study where analytic and case-based approaches were combined with knowledge-based expert system information [18], and decision-tree methods that used data to identify the outcome of future problems [19,20]. CBR was also used in combination with a decision-tree for the development of a decision support model to compare and analyze levels of greenhouse gas emissions in residential buildings [21]. The approach undertaken included the use of decision-trees and a database of 324 buildings to create clusters of multi-family housing units based on the effect of independent variables on the gas energy consumption. Then, CBR was used within each cluster to identify similarities between housing units to predict the greenhouse gas emission level. A genetic algorithm was used to improve the performance of the CBR that led to prediction accuracy greater than 93%.

The few examples available in the literature for the use of CBR as an energy prediction approach in buildings show great potential. In this paper, the CBR approach is described in Section 2, including the reasoning structure used for energy prediction. Section 3 describes the testing of the proposed approach using synthetic data. Section 4 presents modifications required for the implementation of the method in a real building and discusses the results obtained. Conclusions and prospects for future research are presented in Section 5.

2. Development of the CBR energy predictor

On-line energy prediction uses a series of pre-recorded or measured data to forecast instantaneous energy demand for the next few hours. Energy demand typically holds a non-linear relationship with respect to time, weather conditions and building characteristics, making an accurate prediction of energy demand challenging. The accuracy of the prediction depends heavily on the quality of the input data as well as the prediction model describing the interaction between various independent input factors and the energy output. Furthermore, due to the dynamic nature of energy demand, an adaptive prediction model capable of automatically adjusting the non-linear mapping between the input and output is highly desirable.

Artificial neural networks (ANN) have been shown to be among the best methods for short-term prediction of energy demand. However, case-based reasoning was selected as the energy prediction method for the work presented in this paper because of its significant advantages over ANN. The knowledge of a CBR system can be updated more easily, because the update only consists in adding new cases to the case library or in modifying existing cases, while updating the knowledge of an ANN requires the system to be retrained. Solutions proposed by a CBR system can be more easily understood, because the reasoning is embedded in the retrieved cases, whereas an ANN acts as a 'black box' and provides an output with no justification or explanation. A CBR system can handle a large number of features per case, while an ANN may have difficulties in handling a large number of features (i.e., input and output) in the training and testing. A CBR system can also handle missing information. Missing information in the current problem or in the cases stored in the case library does not prevent the CBR from producing answers. However, an ANN requires a training set that is complete and sound and the input to the system also needs to be complete.

Different examples are available in the literature that highlights the advantages of CBR compared to ANN. For instance, the CBR approach has been compared to ANN for predicting the deterioration of highway bridges [22]. It was found that CBR provided 77% correct predictions compared to ANN, which provided 33% correct predictions at the same level of accuracy. It was also found that updating the CBR model was easier than updating the ANN model. Another study compared CBR and ANN in predicting the outcome of construction litigation [23]. The CBR provided 83% of correct predictions compared to 67% for ANN. Construction cost estimating models based on regression analysis, neural networks (NN), and case-based reasoning were compared and showed that the NN model provided the most accurate prediction with Mean Absolute Error Rate (MAER) of 2.97 compared to 6.95 and 4.81 for the regression and CBR models, respectively [24]. However, the study also concluded that the CBR model was easier to update than the other models.

2.1. General description of the CBR energy predictor

Case-based reasoning falls under the machine-learning artificial intelligence techniques. It has been used in various scientific fields for different applications, such as planning, design, diagnostic, explanation, and interpretive tasks. It achieves much of its knowledge through the accumulation of new cases and the assignment of indices [25].

Case-based reasoning 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 [26]. The CBR process is illustrated in Fig. 1.

Different approaches are available for each of the four CBR processes. Sections 2.1.1 and 2.1.2 present, in general form, the approaches undertaken for case retrieval and adaptation in order to predict the energy demand of commercial buildings using CBR.