USE OF SOFT COMPUTING TECHNIQUES FOR THE EVALUATION OF ENERGY PERFORMANCE OF EQUIPMENTS IN BUILDINGS

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ABSTRACT

The paper presents the use of pattern recognition and neural networks techniques for the evaluation of energy performance of equipments. Two methods were developed and validated using measurements of existing equipments.

INTRODUCTION

Soft computing is a collection of methodologies, which aim to exploit tolerance for imprecision, uncertainty and partial truth to achieve tractability, robustness and low solution cost (WFSC 2001). These techniques have been applied to some engineering problems as an alternative to the conventional approaches. The paper presents the application of two of these techniques for the evaluation of energy performance of equipments used in buildings.

APPLICATION NO.1

The breakdown of whole-house electricity consumption among the major end-uses can help to increase of homeowners' awareness about how the energy is used in the house and the potential impact of changing the people's behaviour (e.g., the frequency of usage of clothing washer, or the number and duration of hot showers) on the annual energy cost. Traditional load monitoring techniques can be described as intrusive techniques because the physical placement of sensors on individual appliances to gather end-use load data. Researchers have developed non-intrusive techniques of load monitoring as an alternative to long-term intrusive metering (Hart 1992, Norford 1996, Sharp 1994). Non-intrusive techniques of load monitoring are based on the analysis of appliance energy signatures. An appliance signature gives information about the operating state of an individual appliance, using the monitored whole-house electric demand. The main advantage of defining appliance signatures in terms of the whole-house load is that, afterwards, only a appliance single monitoring point in the house is required to gather end-use load data. The signature is assumed to remain constant for the life of the appliance provided that no modifications are made or malfunctions occur.

Farinaccio and Zmeureanu (1999) and Marceau and Zmeureanu (2000) developed two new rule-based pattern recognition approaches to disaggregate the total electricity consumption of a house into the major end-uses.

Although the two methods use different algorithms, their application has in common the following two phases: (1) a one-time training process required to tune the generic algorithms, to the characteristics of electric demand of each particular house under investigation; during this phase, the electric current is monitored at the main electric entrance of the house as well as at several appliances of interest such as the domestic hot water tank; and (2) the application phase, in which only the electric current at the main electric entrance is monitored.

PATTERN RECOGNITION APPROACH

The new approach is based on the top-down mental process of recognizing an object (Grey 1997), which in this case is the shape of variation of electric current, monitored at the main electric entrance of the house, during the operation of a particular appliance. The step-increase or decrease of the electric current, due to the activation or disactivation of an appliance, is a distinct feature which can be used for the preliminary recognition of objects. The pre-existing knowledge is used to generate a hypothesis about the object (e.g., the increase of electric current is due to the activation of a refrigerator). However, the hypothesis could be false for at least two reasons: (i) the signal is generated by the simultaneous operation of other appliances and not by a single appliance, and (ii) there are two or more appliances which can generate almost the same initial signal. Moreover the noise generated by the operation of several small appliances or by the variation of electric voltage in the utility lines could mask the real signal. In the following step, the hypothesis is tested, using additional features of each class of objects such as the variation of electric current in time or the frequency of activation. The hybrid combination strategy is preferred to connect the rules used for the recognition of objects: (i) some rules are applied sequentially, one after the another, to reduce the preliminary set of possible objects, and (ii) other rules are applied concurrently and independently, and their results are integrated using weighting factors.

The generic algorithms presented in this paper are developed from the analysis of electric current, monitored in a test house over a training period of one week. The house is heated by a central hot water system using oil as energy source. The monitoring equipment consisted of clamp-on sensors and data loggers to record the measurements, performed every 16 seconds. Since the electric demand (W) is better perceived by the readers, the energy signature is developed in terms of electric demand, using a constant voltage. This substitution does not affect the accuracy of results, mainly the evaluation of energy share, which is defined as the contribution of each appliance to the whole-house electricity consumption.

The algorithms are only based on monitored data and do not need information about the occupants' lifestyle and usage of appliances. Once the generic algorithms have been developed, they can be applied to other houses. However, some parameters used by the generic algorithms will have to be modified, through the training process, to fit the electric characteristics of appliances in each house.

The first pattern recognition approach is used to recognize the operation of DHW heater based on the total demand profile. The algorithm consists of three stages: (1) the detection of the activation (ON or start event) or disactivation (OFF or end event) of the appliance, by using its energy signature, (2) the estimation of the appliance's demand profile, and (3) the calculation of energy use.

The first stage of the algorithm consists of five pattern-recognition rules, which are used to identify start and end events from the monitored total demand profile. The first rule, or the *state change detection* rule, is applied to determine a preliminary set of possible start and end events based solely on the detection of a given step-increase or decrease in the total demand profile. The following three rules: the *profile vector norm* rule, the *number of data points* rule, and the *total demand* rule are then applied to each possible event. An aggregate score of the performance for these three rules is then attributed to each event. This aggregate score is then used to confirm or refute the occurrence of an event as recognized by the first rule. The *minimum score* rule is used to filter out the weak events from the data set of possible events, that is, those events with low aggregate scores. The remaining set of selected start and end events proceed to the second stage of the algorithm, which consists of three constraining rules: the *highest scoring event* rule, the *minimum ON and OFF interval* rule, and the *minimum total demand* rule. Unlike the first stage of the algorithm, where the rules try to match the variation in total demand with the characteristic increase of each appliance, the goal of these rules is to verify that the DHW ON periods estimated in the first stage of the algorithm are consistent with the frequency of appliance usage and the monitored data observed from the training period. Similar to the first rule, these rules are applied on a pass or fail basis. For example, an event is either confirmed as a start event or is recognized as a false start event, in which case, it is eliminated from the data set of possible start events. Consecutive start and end events are then linked together to obtain the sequence of activation periods of the DHW heater. Once the ON and OFF periods of the appliance are estimated, the DHW energy consumption for the duration of the day is then calculated.

The accuracy of the algorithm is assessed in terms of three performance indices: (i) daily DHW energy consumption, (ii) daily DHW demand profile, and (iii) daily energy share, that is the ratio of the DHW energy consumption to the whole-house energy consumption.

The error in estimating the daily DHW energy consumption, with respect to the monitored values, is under 7%. Only for four out of 19 days of testing, the error was between -10.5% and 15.9%.

Two statistics are used to evaluate the accuracy of the estimated DHW demand profile compared to the monitored profile: the coefficient of determination (R-squared) and the average error, which is calculated using the absolute values of errors for each individual cycle. For any given day, the estimated profile tracks the monitored profile fairly well. The average error varies between 11 W and 312 W, that is, 0.2 and 7% of the average electric demand of 4455 W, observed during the training period.

From the homeowner's point of view, the most useful result is the estimation of the energy share, that is, the contribution of this appliance to the whole-house energy consumption and cost. For any given day, the error in estimating the DHW heater energy share is between –5.1% and 5.5%. On a weekly basis, the average difference is below 2.5%.

APPLICATION NO.2

Energy Monitoring and Control Systems (EMCS) installed in buildings should allow for the comparison of monitored energy performance of HVAC equipments with the predicted performance. This comparison can help the building managers to detect abnormal operating conditions, due to failures or deterioration of the equipment efficiency, or unexpected changes due to people's habits. This function can also evaluate the cost-effectiveness of the equipment retrofit or replacement.
There are two elements preventing the implementation of such capabilities in the EMCS: (1) the increase of initial cost due to the type and number of sensors, which are required for the monitoring of relevant parameters, and (2) the complexity of application software, used to compare the monitored and predicted energy performance.

This paper presents a new approach, based on the artificial neural networks, to be implemented in the EMCS. It was developed and tested using measurements taken on two rooftop units installed about 15 years ago in Montreal. These units will be identified in the rest of paper as unit A, with a supply air flow rate of 3000 L/s, and unit B with 2400 L/s. The manufacturer's catalogue indicates the following operating characteristics at the design conditions: the total cooling capacity of 33.7 kW, the electric demand of 11.6 kW, and the Coefficient of Performance of 2.9.

Data was collected every 32 seconds during two cooling seasons (from July to September, 1997 and 1998), using five sensors for each unit: (1) one clamp-on probe for the electric current at the compressor and the fans of air-cooled condenser, and (2) four sensors for the temperature and relative humidity of air entering and leaving the cooling coil. The cooling load from the supply air flow rate and the enthalpy difference across the coil. Data was processed to obtain the daily values of parameters relevant to the performance of these two units, during the operation between 6:00 am and 6:00 pm. The corresponding daily average dry-bulb and dew-point air temperatures were calculated from the hourly values measured at the Dorval airport.

NEURAL NETWORKS APPROACH

The approach used for predicting the COP of existing rooftop units is based on the General Regression Neural Networks (Specht 1991). It was assumed that the information from the electric current at the compressor and the fans of air-cooled condenser can be used alone or coupled with another parameter to evaluate the COP.

This approach reduces the installation cost since only a minimum number of sensors is needed, and also during the operation it reduces the costs for re-calibration or replacement of sensors. The method has two components: (1) the learning component, in which the pattern of operation over a representative period is "learned," using data from the set of five sensors; and (2) the evaluation component, which predicts the COP by applying the "learned" pattern to the new operating conditions; during the evaluation period, a smaller number of sensors are needed.

The learning period of unit A is composed of 27 days of July, August and September, 1997. The unit A was tuned in June 1998, at the beginning of the new cooling season. The evaluation period is composed of nine days of July and August 1998. The daily average COP was 1.09 during the learning period and 1.68 during the evaluation period. In the case of unit B, the learning period is composed of 18 days of July and August 1997. The old expansion valve of unit B was replaced on August 28, 1997 with an experimental valve. The evaluation period is composed of eight days of September 1997. The daily average COP was 2.20 during the learning period and 1.86 during the evaluation period.

Several models were tested (Table 1). The base model, identified as no.1, uses data only from the monitoring of electric current at the compressor and the fans of the air-cooled condenser: the average (E_{avge}) and maximum (E_{max}) electric demand measured from 6:00 am to 6:00 pm, and the operation factor, which is the proportion of time the compressor runs. The models 2 to 12 were developed by adding to the base model other monitored data: (1) the average dry-bulb outdoor air temperature (T_{db}), (2) the average dew-point outdoor air temperature (T_{dp}); and (3) the average, maximum and minimum temperature of air leaving the cooling coil, respectively (T_{avge}, T_{max}, T_{min}).

Three types of methods were compared for learning the pattern of operation: (1) Multiple Linear Regression (MLR), (2) Backpropagation Neural Networks (BNN), and (3) General Regression Neural Networks (GRNN). Two commercial software packages were used: STATGRAPHICS (1989) for the MLR models, and NeuroShell 2 (1998) for the BNN and GRNN models. In the case of BNN and GRNN models, 80% of data available for learning was randomly selected for training the networks, and 20% for testing. The number of input parameters used by the BNN and GRNN models is equal to the number of relevant parameters presented in Table 1. For instance, the GRNN model 4 uses five input data. The BNN models use one hidden layer with seven nodes. All BNN models use the sigmoid [0,1] transfer function f(x) = 1/(1+exp(x)). The GRNN models use one hidden layer, on which the number of nodes is equal to the total number of patterns in the training and testing sets (27 sets for unit A, and 18 sets for unit B). The output layer has only one node, corresponding to the COP. The GRNN models use the linear [0,1] transfer function f(x) = x. A genetic adaptive algorithm is used to find the appropriate smoothing factor adjustment for each input.

RESULTS FROM THE LEARNING PERIOD

The fitness of each model for predicting the COP during the learning period was evaluated using three statistical indicators: the regression coefficient r^2, the standard error, and the mean absolute error (Table 1).

The three statistical indicators prove that all GRNN models perform well for both rooftop units, and much better than the MLR and BNN models. For instance, the standard error and r^2 of model 1 for unit B are, respectively, 0.063 and 0.993 (GRNN) compared with 0.135 and 0.671 (MLR), and 0.089 and 0.860 (BNN). It is important to note that the base model 1, which uses only measurements of electric current, performs well for both units (r^2 > 93%, and mean absolute error < 5%). Models 2 to 4 present a particular interest for this application, since they need one or two sensors for outdoor air temperature, which are already available in the EMCSs installed in some buildings.

RESULTS FROM THE EVALUATION PERIOD

The difference between the measured and predicted COP is used to evaluate the reduction of energy cost; negative values indicates the degradation of performance, hence the increase of energy cost. The calculations were performed by considering the rooftop units run 12 hours/day and 22 days/month, and using the following electricity rates: $11.72/kW plus $0.0372/kWh (HQ 1998).

The unit B experienced a change of the COP from 2.20 to 1.86. The models did not face conditions which are significantly different from those of the learning period, and as a result the difference between the predictions of COP, given by all models, is small (Table 2). The GRNN model 1, using only the measurements of electric current, provides a good evaluation of the expected COP of 1.94 compared with the measured COP of 1.86. The addition of other sensors increases the initial cost, without increasing significantly the accuracy of prediction. For instance, the model 12 which uses all parameters leads to the largest error (predicted COP of 2.1compared with the measured COP 0f 1.86). On the other hand, the three statistical indicators show that the model 12 is the best fit to the learning data. More important is the evaluation of the reduction/increase of energy cost due to the replacement of valve. The model 1 predicts an increase of energy cost of $3.3/month, while the model 12c predicts $7.9/month, a difference of $4.6/month or $13.8 for the cooling season. The increase of initial cost for the installation of three additional sensors (the dry-bulb outdoor temperature, the dew-point outdoor temperature, and the leaving air temperature) is not justified by the value of information obtained, that is $13.8/summer.

The COP of unit A significantly increased from 1.09 to 1.68, due to the tuning of June 1998. The models appear to be very sensitive to the new conditions, and their predictions are different (Table 2). For instance, the base model 1 predicts COP = 0.77, while model 2, which uses in addition the dry-bulb outdoor temperature, predicts COP = 1.17, compared with the measured COP of 1.68. The measurements of electric current alone do not provide enough information to the GRNN model to accurately predict the COP and the energy savings. The addition of a sensor for the dry-bulb outdoor air temperature improves significantly the accuracy of predictions from COP = 0.77 to 1.17.

In the case when no significant changes of operation or failures occur, the GRNN model can predict the COP using only the measurements of electric current. Otherwise, two sensors are needed, one for the electric current, and another for the dry-bulb outdoor air temperature. If the EMCS system installed in the building already monitors the weather conditions, this information can be retrieved and therefore only the electric current must be monitored.

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Table 1. Evaluation of the fitness of Genaral Regression Neural Network models to predict the COP during the "learning" period. All models contain E_{avge}, E_{max} and $time_{ON}$. First line is for unit A, and second line for unit B.

Model	Other parameters					r^2	standard error	mean absolute error
	T_{db}	T_{dp}	T_{avge}	T_{max}	T_{min}			
1						0.931 0.933	0.077 0.063	0.047 0.040
2	x					0.968 0.886	0.055 0.077	0.023 0.060
3		x				0.980 0.993	0.045 0.025	0.017 0.007
4	x	x				0.973 0.989	0.045 0.032	0.021 0.011
5			x			0.890 0.933	0.095 0.063	0.071 0.041
6			x	x	x	0.984 0.998	0.032 0.020	0.015 0.003
7				x	x	0.975 0.967	0.045 0.045	0.023 0.025
8	x		x			0.988 0.885	0.032 0.077	0.012 0.060
9		x	x			0.973 0.983	0.045 0.032	0.018 0.022
10	x	x	x			0.988 0.993	0.032 0.020	0.012 0.006
11	x		x	x	x	0.990 0.922	0.032 0.071	0.014 0.041
12	x	x	x	x	x	0.990 0.995	0.032 0.020	0.013 0.012

Table 2. Use of the GRNN model to estimate the reduction of energy cost savings during the evaluation. First line is for unit A and second line for unit B.

Model	Measured post-retrofit COP	Predicted post-retrofit COP (based on the pre-retrofit pattern)	Reduction of energy cost [CAN$/month]
1	1.68 1.86	0.77 1.94	65.0 -3.3
2		1.17 1.92	26.0 -2.7
3		0.84 1.91	55.0 -2.4
4		1.24 2.02	22.0 -5.7
5		0.85 1.94	54.0 -3.3
6		0.83 1.89	56.0 -1.8
7		0.81 1.89	59.0 -1.8
8		1.31 1.91	18.0 -2.4
9		0.93 2.05	45.0 -6.5
10		1.31 1.89	18.0 -1.8
11		1.30 1.85	19.0 -0.4
12		1.27 2.10	21.0 -7.9