BUILDING ENERGY PREDICTION WITH ADAPTIVE ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

While most of the existing artificial neural networks (ANN) models for building energy prediction are static in nature, this paper evaluates the performance of adaptive ANN models that are capable of adapting themselves to unexpected pattern changes in the incoming data, and therefore can be used for the real-time on-line building energy prediction. Two adaptive ANN models are proposed and tested: accumulative training and sliding window training. The computational experiments presented in the paper use both simulated (synthetic) data and measured data.

INTRODUCTION

An accurate and reliable energy prediction scheme combined with an automated energy data collection system can help building managers identify maintenance problems and determine the best energy control strategies.

An automated energy prediction system can be built on top of a mathematical prediction model consisting of several parameters. The model parameters are estimated using existing data that typically include energy demand or consumption and temperature measurements recorded in the past. A variety of prediction models have been proposed in the literature that include time-series models, Fourier series models, regression models, Artificial Neural Network (ANN) models, and Fuzzy logic models. Each model type has its own features, advantages and disadvantages, and in addition, its performance varies from one application to another.

With the exception of a few ANN models, most of the surveyed literature focus on static prediction, a prediction scheme that involves a single prediction model that does not evolve over time: when the estimation of the model parameters is completed, the model is fixed; the most recently collected data is not used to update the model parameters. To obtain an accurate static model, a large volume of historical data is required to estimate the model parameters. The alternative approach is the use of a dynamic (adaptive) model that constantly updates model parameters based on newly available data. As the energy data collection process is automated, the entire process of retrieving new measurements, updating the model and making short-term energy prediction can be performed in 'real time' on-line.

This paper discusses the use of adaptive ANN models that are capable of adapting themselves to unexpected pattern changes in the incoming data, and therefore can be used for the real-time on-line building prediction (Yang 2004). With an adaptive ANN, the predictive model is retrained periodically with new environmental and operational data as they become available. Two adaptive models are proposed: an accumulative training technique and the sliding window training technique. With accumulative training, the set of training data is continuously augmented as newly collected measurements become available. With the sliding window training, the size of the set of data used for training remains constant. As new data are added to the training set, the oldest data is dropped from the training set.

LITERATURE REVIEW

Artificial Neural Networks (ANN) is a type of Artificial Intelligence technique that mimics the behavior of the human brain. It can approximate a nonlinear relationship between the input variables and the output of a complicated system. The main advantage of an ANN model is its self-learning capability. The use of ANN in building energy prediction has been investigated by many researchers (e.g., Anstett and Kreider 1993; Curtiss et al. 1994). They have been found to perform better than traditional methods such as regression models and time series models (Kawashima et al. 1995; Dhar et al. 1998).

However, most of the existing ANN models are ***static*** in nature, which means that the prediction model is set up in advance using historical data and does not change afterward, when new information become available. It is highly possible that such a model becomes invalid when new patterns emerge and more recent data becomes available. In this case, a dynamic prediction model that can adapt itself to such changes in the energy consumption pattern is desirable. This is especially true for short-term energy prediction.

Only a few dynamic prediction systems were found in the literature and all in the field of electric load forecasting for power system. They all used a sliding window approach in which the size of data set used for training is kept constant; however, the data set is periodically updated as the window moves forward in time (Djukanovic et al. 1995; Khotanzad et al. 1995; Mohammed et al. 1995; Charytoniuk and Chen 2000). These approaches have potentials in the area of building energy prediction.

ADAPTIVE ANN MODELS

In order to overcome the drawbacks of static prediction models, this research evaluates the performance of adaptive ANN models. Adaptive ANN models can be constantly updated as new environmental and operational data becomes available, and thus have an inherent self-revision capability to adapt to new conditions. Two adaptive ANN models are proposed: (1) the accumulative training, and (2) the sliding window training.

An ANN can be retrained periodically by a set of data augmented with newly collected measurements. This type of training strategy is referred to as ***accumulative training***. Accumulative training has the obvious advantage of being able to identify both the local (for example, daily) and the global (seasonal) trends of energy variation. Its main disadvantage lies in the fact that the larger the volume of data, the longer it takes for training the ANN. It is also likely that the latest changes in the accumulative training data set have smaller impact on the model training because their quantity is less compared to the older data.

Alternatively, the size of the training data set can be kept constant and new measurements are added while some of the oldest data are dropped from the training set. This approach can be graphically viewed as periodically sliding a time window across a time series of measurements to select the training data. This training strategy is referred to as ***sliding window training***. The relative small and constant size of the training data makes it possible to perform fast ANN re-training. The drawbacks of this approach are that the training data may only contain recent information, and the prediction result may not accurately reflect the annual or seasonal change in energy usage pattern. Also, determining the optimum window size ahead of time is difficult.

COMPUTATIONAL EXPERIMENTS USING SYNTHETIC DATA

This section contains the computational results based on a data set that was obtained from the simulation of an office building using the DOE 2.1E software. This data set is called synthetic data. The Laval office building, located in Montreal was built in 1972 (Zmeureanu et al. 1995). The building has a total floor area of 10,400 m^2 spread over a seven-floor office tower, an underground garage and a ground floor. There is a central Variable Air Volume system, which provides cooling in the summer and ventilation all year to the office spaces. Direct expansion cooling coils are connected to four condensing units, each equipped with two compressors with a refrigeration capacity of about 90 kW. The supply air temperature is controlled in terms of the outdoor air temperature. The system is also equipped with a dry-bulb temperature economizer system.

The simulated data associated with the Laval building is noise free: the building is assumed to operate under normal conditions, which do not change from week to week, and from season to season. In addition, there are no measuring errors, operation mistakes, faults or degradation of energy performance of equipments in time. Because the simulated data is generated from a well-behaved energy model defined in the simulation software (DOE 2.1E), it provides an ideal scenario under which the variation of the energy consumption is more "predictable". Performing experiments on this data set serves as the first step towards the understanding, developing and testing of a realistic ANN model.

Several experiments are performed on this data set. Because a static ANN model serves as the building block for a dynamic ANN, its construction and testing are described before the experiments associated with the dynamic models. Prior to present these results, the specific architecture of the ANN models used and the data processing are described. The prediction accuracy are measured by the coefficient of variation (CV) and the root mean square error (RMSE):

$$\mathrm{CV} = \frac{\sqrt{\dfrac{\sum_{t=1}^{n}[y_{pred}(t) - y_{data}(t)]^2}{n}}}{|\bar{y}_{data}|}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{n}[y_{pred}(t) - y_{data}(t)]^2}{n}}$$

Where n is the number of data, $y_{\mathrm{pred}}(t)$ is the predicted energy use at time t, $y_{\mathrm{data}}(t)$ is the measured energy use at time t, and $\bar{y}_{data}$ is the average of the measured data. Table 2, before the conclusion, summarizes the results of all the experiments.

ANN Architecture

The quantity predicted is the hourly electric demand of the chiller installed in the Laval building. The hourly data set consists of: outdoor dry-bulb temperature, Td(t); outdoor wet-bulb temperature, Tw(t); temperature of water leaving the chiller, Tl(t); and chiller electric demand (compressor and fans of the condensing unit), E(t). It is assumed that the electric demand of the chiller, at time t, is a function of some of the above mentioned environmental and operation variables collected at hours t-i, for i=1,2,…n. Those variables will become inputs to an ANN to predict the electric demand of the chiller at time t.

The ANN model used in the experiments consists of one hidden layer in addition to the input and output layers. The input layer contains n neurons used to feed n different inputs into the network (n is a variable because it varies with the experiments). The output layer contains one neuron from which the predicted chiller electric demand is extracted. The hidden layer consists of 2n+1 neurons. This three-layer ANN model was found to be sufficient for making a reasonably accurate prediction of the chiller electric demand for the Laval building.

The MATLAB ANN Toolbox is used to build, configure and train the network. The Toolbox offers several algorithms for training the network. All algorithms were tested in this study. When the data size is small, the Levenberg-Marquart (LM) algorithm appeared to be the fastest training algorithm (the mean square error of the ANN output approaches to zero at a quadratic rate). However, because the LM method must solve a linear system of equations in order to obtain the search direction, the computation becomes expensive when the number of input elements and the volume of the training data increase. Therefore, when the volume of the data is large, the standard gradient descent algorithm is used for training the ANN. Logistic sigmoid functions are used as the activation function in each neuron. In the output layer, a linear transfer function is used to allow the network to produce values outside of the range [-1, 1]. The training process is terminated when the mean square error (MSE) between the ANN output and the target values becomes less than 10^{-5}, or when a maximum of 500 epochs is reached. The initial weights and biases of the ANN are generated randomly.

Data processing

The data needs to be processed prior to the training of the ANN. It has been recognized in the literature that it is important to adopt a day-typing procedure to separate energy data with distinct load patterns into different prediction groups. Energy prediction can be made within each group instead of on the entire data set. An obvious separation can be drawn between weekdays and weekends (holidays). The Laval building operates from 7:30 a.m. to 11:00 p.m. Monday to Friday. Since the chiller is not used outside this interval, the non-working hours are removed from the data set since prediction is only to be made for the working hours. Without day-typing, the implementation is easier. However, the prediction errors increase if all data is included.

Static Prediction Models

Three experiments were carried out with static prediction models. The first experiment predicts the demand using time-lagged data by an hour (t-1). The second experiment tests various combinations of time-lagged data to improve the prediction. Seventy-five percent of data is used to train the ANN models, and twenty-five percent of data are set aside for testing. The second data set corresponds to the second week of each month.

Experiment no. 1 - Using (t-1) measurements as input

In the first experiment, h(t), Td(t-1), Tw(t-1) and Tl(t-1) are used as input variables to train the ANN to predict E(t). The variable h(t) indicates the hour for which to do the prediction. The training period is 11.4 seconds. The error between the predicted electric demand and the measured electric demand is defined by ***CV=0.16*** and ***RMSE = 25.46 kW***.

Experiment no. 2 – Using (t-1) measurements with up to (t-6) for temperatures as input

To improve the prediction accuracy, longer past history is included as additional input data to train the ANN model. Several combinations of time lagged input data, up to six hours delay, were tried and tested. The following combination of input variables provided the best results: h(t), Tl(t-1), and the last six hours for the wet-bulb temperature T_w (t-1 to t-6). The results are ***CV=0.15*** and ***RMSE = 22.0 kW***.

If the last six hours for the dry-bulb temperature T_d (t-1 to t-6) are added to the input vector, the results show that the inclusion of all past temperature measurements does not necessarily give the best performance: ***CV=0.22*** and ***RMSE=34.4 kW.***

Experiment no. 3 – Using up to (t-6) measurements as input and PCA to reduce the dimension of the input

The use of all available time-lagged measurements is not effective because of undesirable redundancy. The redundancy in the ANN input makes it difficult for the back-propagation algorithm to capture the optimal weights and biases for the desired ANN model. Thus, a meticulous selection of time-lagged data must be used to train the ANN model. However, in practice, it is not possible to try all possible combinations of lagged timed temperature measurements before a prediction is made. This problem can be eliminated by using the Principal Component Analysis (PCA) technique to select appropriate input data from h(t), $T_l(k-1)$, $T_d(t-k)$, $T_w(t-k)$, for k = 1, 2, …6.

The Principal Component Analysis (PCA) is a multivariate statistical analysis technique to assemble, synthesize and select relevant input variables among a large number of measurements (Feuston and Thurtell 1994). With PCA, the neural network input vector does not consist of the original input variables, but of linear combinations of these variables. The PCA technique reduces the dimensionality of data and removes redundancy by seeking clusters of data points that can be used to represent the main features of the data. This method is adopted in this study.

Six principal components that contribute to more than one percent of the variance of all past history data are retained. The training time is 9.9 seconds, and the results are reduced to ***CV=0.07*** and ***RMSE=11.4 kW***, respectively. The CV and RMSE values of the prediction obtained in this experiment are much better than the ones obtained without PCA..

Accumulative Training Adaptive Models

The previous static ANN model is modified to take advantage of new measurements that become available on a continuous basis. The first approach considered, called accumulative training, simply accumulates all the measurements collected up to time t, and retrain the ANN periodically using the entire set of measurements.

Data about temperatures and chiller electric demand from the month of June are set aside, and this portion of the data file is used to establish, through training, what is called a baseline ANN model for the chiller electric demand. The baseline ANN model is then used to predict the chiller electric demand associated with the first day of July. Once the prediction has been performed, the hourly temperature and electric demand measurements associated with the day being predicted is added to the initial data set allocated for the baseline training. This updated data set is used to retrain the ANN model for carrying out subsequent predictions. The weights and biases that emerge from the baseline model are used as the initial weights and biases during the retraining process. The experiments showed that retraining does not take as long as the baseline training because the weights and biases capture the nonlinear mapping between the input variables and the energy demand to be predicted. The results presented below compares the impact of different choices of input variables on the accuracy of the accumulative on-line prediction model.

Experiment no.4 - Accumulative training with time-lagged temperature measurements as input

The input to the ANN model consists of a combination of the past history temperature measurements $T_d(t-k)$, $T_w(t-k)$ and $T_l(t-1)$,where $1 \leq k \leq 6$. The output of the ANN is the chiller electric demand E(t). The PCA is applied to remove the redundancy in the input and only components that contribute to more than 1% to the variance are retained. Six principal components emerged as the input to the ANN after PCA has been applied.

The baseline model is modified and retrained daily by including the electric demand and temperature measurements collected on the previous day in the training data set. The value of MSE between the target and ANN training output converges to zero rapidly. The predicted chiller energy demand matches the actual usage reasonably well (Figure 1). The results obtained from testing are ***CV=0.15*** and ***RMSE = 28.3 kW***, respectively.

Experiment no. 5 - Accumulative training with time-lagged chiller energy usage as input

In this experiment, E(t-k) is added to the set of input variables. The ANN model is constructed and trained in a way similar to that carried out in Experiment no.4. The predicted electric demand matches the measurements reasonably well (***CV=0.17***, and ***RMSE=28.9 kW***). Since the CV and RMSE values obtained in Experiments no.4 and 5 are comparable to those obtained with static ANN models without PCA (Experiments no.1 and 2), one can conclude that the on-line model with accumulative training provides reasonable accuracy, when compared with static models.

Sliding Window Training Adaptive Models

The second adaptive approach, called sliding window training, maintains a fixed amount of training data by discarding old measurements while adding new measurements.

The training data consists of the temperature and electric demand measurements enclosed within the sliding window. The ANN model used in the sliding window approach has the same architecture as the one used in the accumulative prediction model.

Experiment no.6 – Training with sliding window using temperature data collected in previous hours

Experiments show that a window size of 20 working days provides a reasonable balance between accuracy and computational complexity per online prediction cycle (Table 1).

Table 1. Comparison of window sizes.

Window size	CV ( )	RMSE (kW)
10 days	0.25	45.5
20 days	0.40	8.05
30 days	0.20	3.00
40 days	0.46	82.0

Hence, all subsequent experiments use this window size. Measurements of temperature and electric demand associated with the first twenty days of June were selected as the initial set of training data. The prediction is made on a daily basis. Thus, once the initial training is completed and a prediction has been made for the electric demand on the twenty-first working day in June, the hourly temperature and electric demand measurements corresponding to the first working day of June are removed from the training data. The measurements of temperatures and electric demand associated with the twenty-first day are added into the training data and retraining is carried out. Consequently, the volume of training data does not change, and the selection window is shifted forward in time by one day. The results of the prediction are ***CV=0.40*** and ***RMSE = 8.05 kW***.

After PCA is applied to the initial set of time-lag temperature measurements to select principal components, six principal components emerged as the ANN input. However, the number of principal components may change when the sliding window is updated. More or fewer principal components may appear as daily training and prediction move forward. When the number of principal components associated with the new training data set is different from the one associated with the previous training data, one cannot restart from the ANN model obtained from previous training cycle. Weights and biases must be reinitialized randomly, and the training may take more time. The results obtained in this experiment are ***CV=0.15*** and ***RMSE = 27.7 kW***.

Experiment no.7 – Training with sliding window using temperature and electric demand measured in the previous hours as input

In this experiment, we investigate whether adding E(t-k) to the list of input variables: h(t), T_l(t-k), T_d(t-k), T_w(t-k), k = 1, 2, …6, can improve prediction accuracy. The PCA technique is used to remove the potential redundancy in the data. There is no clear improvement in prediction accuracy when E(t-k) is added. The results of the prediction are ***CV=0.16*** and ***RMSE = 27.78 kW***. Results from the on-line models using the sliding window training, applied to synthetic data, are as accurate as those obtained from the accumulative training.

COMPUTATION EXPERIMENTS USING MEASURED DATA

To evaluate the effectiveness of the proposed ANN models some computational experiments are performed with measured data from a real building. Measurements contain a number of anomalies that make it more challenging to produce highly accurate prediction results. The computational experiments present the typical difficulties encountered in developing an ANN model to predict the energy demand in a real building.

This section contains the results of using the proposed ANN techniques to predict the chiller electric demand of the building housing the CANMET Energy Technology Center located in Varennes, Quebec, Canada. Because the original data provided in this experiment is not prepared in a format that can be directly used by the MATLAB code developed in this research, the raw data was first preprocessed and converted into the desired format. During the process of conversion, several problems associated with the completeness and fidelity of the data were discovered. Problems encountered and methodologies for addressing these problems are described below, before discussing the ANN architecture, experiments and results.

Data Processing

The data set contains measurements between 12:00 P.M. June 21, 2002 and 12:00 A.M. March 27, 2003, and between 11:00 A.M. May 8, 2003 and 0:00 A.M. July 10, 2003. The objective of this study is to predict the chiller electric demand E(t), in kW, at a particular time t. Variables listed in Table 2 are initially identified to be the independent variables that can potentially affect the variation of E(t). A closer examination of data reveals that not all variables listed in the data file are measured at every hour. Furthermore, the number of available measurements is different from one variable to another. The number of hourly measurements for some variables is roughly 50% of the total number of hours between the beginning and ending period of the measurements due to problems related to data collection. The low quality of the raw data makes it difficult to design, train and test an accurate ANN model. However, this situation could occur in a monitoring system installed in buildings. Therefore, the challenge is to develop, in the absence of complete information, an ANN model able to provide reasonably accurate on-line predictions of electric demand.

The prediction of chiller electric demand is made only when at least one compressor is turned on (indicated by SCi(t) = 1 for i=1,2…6). As a result, both training and testing are only performed using measurements associated with non-zero SCi(t) values.

ANN architecture

The ANN models used here are similar to the ones used to predict the chiller electric demand using synthetic data. The initial weights and biases of the ANN are generated randomly. Whenever possible, the Levenberg-Marquardt (LM) algorithm is specified to train the network. When the number of input elements or the volume of the data is large, the standard gradient descent algorithm is used for training the ANN.

Static prediction of chiller electric demand

An experiment is first carried out with a static prediction model to assess the accuracy of ANN to predict the chiller electric demand at time t demand using time-lagged data as input.

Experiment no.8 – Static prediction model using time-lagged measurements as input

In this experiment, an ANN model is developed that predicts E(t) based on measurements collected in previous hours. About 80% of the nonzero measurements data between September, 2002 and May, 2003 are reserved for training. The PCA is used to reduce the dimension of the input and to remove redundancy in the data. Six principal components that contribute to more than 1% of the total variation are retained. Training time is 5.7 seconds. The MSE of the ANN output at the end of the training process is around 10^{-2}. The overall accuracy of this ANN model is satisfactory: ***CV=0.26*** and ***RMSE=4.28 kW***.

Accumulative training adaptive model

An experiment was carried out to test the accumulative training ANN model.

Experiment no.9 - Prediction using SCi(t-1)

In this experiment, the chiller related variables, measured between September 2002 and May 2003, are selected for baseline training. The volume of the training data is small (it corresponds to 130 hours). After the baseline training, the initial ANN model is used to predict the chiller electric usage for the next 24 hours. In this accumulatively trained on-line model, the ANN is updated daily by adding measurements that become available on the day chiller energy is to be predicted into the training data set. The results are ***CV=2.53*** and ***RMSE=13.29 kW***.

Sliding window training adaptive model

An experiment was carried out to test the sliding window training ANN model. Like in Experiment no.9, the chiller related variables measured between September 2002 and May 2003, are set aside for baseline training. Once the baseline training is completed, the initial ANN model is used to predict the chiller electric usage for the next 24 hours. The ANN is updated daily by adding new measurements into the training data set and deleting some previous measurements from the training set. Only data recorded during the hours during which a chiller is on are added to the training data set.

Experiment 10 - Prediction using SCi(t-1)

The difference between the predicted and measured data becomes large: ***CV=0.26*** and ***RMSE=12.88 kW***. The drawback with this approach is that the prediction assumes that if in the last hour the chiller was ON, it will be ON in the next hour. So when the chiller is turned off, the system will miss it by one hour since it assumes it is ON based on the previous hour. Only in the following hour will the system finally "sees" it as OFF and then works properly. The prediction of the ON/OFF status of the chiller is always lagged by one hour. One way to address this would be to develop another ANN that would predict when the chiller will be turned ON or OFF. This could not be achieved at the moment due to the lack of data.

Experiment	CV	RMSE [kW]
Static models using synthetic data		
No. 1	0.16	25.46
No. 2	0.15	22.0
No. 2 with 6 T_d	0.22	34.4
No. 3 (PCA)	0.07	11.4
Accumulative training with synthetic data		
No. 4 (PCA)	0.15	28.3
No. 5 (PCA)	0.17	28.9
Sliding window training with synthetic data		
No. 6	0.40	8.05
No. 6 (PCA)	0.15	27.7
No. 7 (PCA)	0.16	27.8
Static models using measured data		
No. 8 (PCA)	0.26	4.28
Accumulative training with measured data		
No. 9 (PCA)	2.53	13.29
Sliding window training with measured data		
No. 10 (PCA)	0.26	12.88

Table 2. Statistical indices for each experiment

CONCLUSION

Most of the surveyed literature focused on using static ANN models to predict energy demand at time t, when all independent parameters are known at the same time t. Although this modeling approach has serious drawbacks for the on-line prediction, it is presented in this paper for the sake of comparison. With synthetic, noise-free data the training time is between 10 and 11 s, and the Coefficient of Variance (CV) is between 0.07 and 0.16. The static models applied to real measurements lead to lower accuracy (CV=0.23-0.26) than in the case of synthetic data (CV=0.07-0.16). This is due to the lower quality of available input data, the smaller amount of data, and the complex operation strategies of chillers in the existing building, compared to the simulated one. Therefore, one can expect that the adaptive models would have an even lower accuracy. This is not always the case, as presented below.

Two types of adaptive ANN training schemes are presented in this paper. In the case of synthetic data, the accumulative training technique appears to have an equal performance with the sliding window training approach in terms of CV (0.15-0.17). In the case of real measurements, the sliding window technique gives better results, compared with the accumulative training, if the Coefficient of Variance is used as an indicator: CV of 0.26, compared with 2.53 (for accumulative training).

Future research work will use another institutional building, having a larger volume of operational data over several years, to estimate the optimal window size for the sliding window training approach. Other architectures and types of neural networks, such as recurrent neural networks, will also be considered.

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REFERENCES

Anstett M., Kreider J.F., 1993. Application Of Neural Networking Models To Predict Energy Use. ASHRAE Transactions 99 (1), 505-517.

Charytoniuk W., Chen M.S., 2000. Very Short- Term Load Forecasting Using ANN. IEEE Transactions on Power Systems 15 (1), 263-268.

Curtiss P.S., Kreider J.F., Brandemuehl M.J., 1994. Energy Management in Central HVAC Plants Using Neural Networks. ASHRAE Transactions 100 (1), 476-493.

Djukanovic M.R.S., Babic B., Sobajic D.J., Pao Y.H., 1995. A neural-based short term load forecasting using moving window procedure. Electric Power & Energy System 17 (6), 391-397.

Dhar A., Reddy T.A., Claridge D.E., 1998. Modeling Hourly Energy Use in Commercial Buildings With Fourier Series Functional Form. ASME Journal of Solar Energy Engineering 120 (3), 217-223.

Feuston B., Thurtell J., 1994. Generalized Non-linear Regression with Ensemble of Neural Nets. ASHRAE Transactions 100 (2), 1075-1080.

Kawashima M., Dorgan. C.E., Mitchell. J., 1995. Hourly Thermal Load Prediction for The Next 24 Hours by ARIMA, EWMA, LR, and an ANN. ASHRAE Transactions.101 (1), 186-200.

Khotanzad A., Hwang R.C., Abaye A., Maratukulam A.D., 1995. An adaptive modular ANN hourly load forecaster and its implementation at electric utilities. IEEE Transactions on Power System 10 (3), 1716- 1722.

Mohammed O., Park D., Merchant R., Dinh T., Tong C., Azeem A., Farah J., Drake C., 1995. Practice experience with an ANN short-term load forecasting system. IEEE Transactions on Power Systems 10 (1), 254-265.

Yang J., 2004. On-Line Building Energy Prediction Using ANN, M.A.Sc. Thesis, Dept. of Building Civil and Env. Eng., Concordia University.

Zmeureanu R., Pasqualetto L., Bilas F., 1995. Comparison of cost and energy savings in an existing large building as predicted by three simulation programs. Proceedings of the IBPSA Building Simulation ’95 Conf., Editors: J.W. Mitchell and W.A. Beckman. Madison, 485-492.

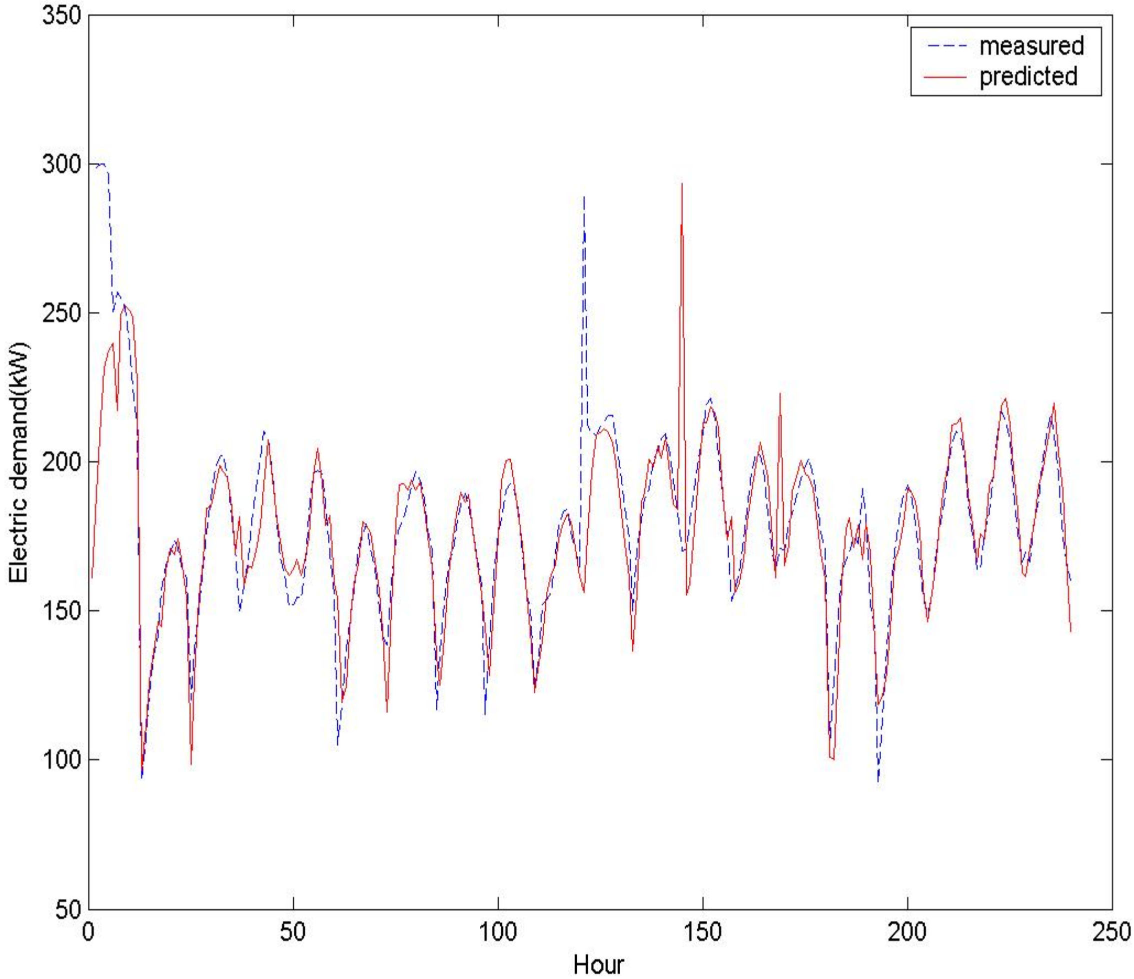

Figure 1. Comparison between the predicted chiller electric demand and synthetic data using an on-line model with accumulative training and time-lagged temperature measurements (Experiment no.4).

Table 3. Input and output variables at time t related to the chiller electric demand.

VARIABLE	DESCRIPTION
SC1(t)	On/off status of compressor 1
SC2(t)	On/off status of compressor 2
SC3(t)	On/off status of compressor 3
SC4(t)	On/off status of compressor 4
SC5(t)	On/off status of compressor 5
SC6(t)	On/off status of compressor 6
Te(t)	Temperature of the water entering the ice tank
Tev(t)	Temperature of the water entering the evaporator
Tlv(t)	Temperature of the water leaving the evaporator
Hum(t)	Outdoor relative humidity
TOD(t)	Outdoor temperature
SV1(t)	Is the chilled water prepared in the ice tanks? (yes/no)
SV2(t)	Percentage of chilled water prepared in the ice tanks
HD(t)	Holiday indicator
WS(t)	Weekday schedule
CR(t)	Electric current used by the chiller