A NEURAL NETWORK MODELING APPROACH APPLIED TO ENERGY CONSERVATION RETROFITS

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ABSTRACT

This paper describes an artificial neural network- (ANN) modeling approach forpredicting the energv and demand savings resulting from energy conservation measure (ECM) retrofits in select buildings. Simulated data sequences were used to minimize the experimental uncertainty in the initial model, and to providê post period data for training. A university building was chosen to provide the data set for this study. The building was modeled and calibrated using the DOE-2.IE building energy analysis program. Following the retrofit implementations, year-long sequences of hourly consumption data were generated, along with the corresponding climate data. Multi-layer feedforward networks were developed for the building and each ECM cosidered The input parameters and the network architecture were selected to optimize-the training time and generalization. The initial results show that the ANN method successfuliv predicted the response from a loads,system, and plant level retrofit, given a time-dependênt (dynamic) prediction problem. This paper will report the performance of the model, its- usefulness as a reliable predictor of building energy consumption, and explore the possibility for continued work to develop a library of ANN ECM models.

INTRODUCTION

Forecasting building energy consumption is required to accurately determine the system efficiency changes resulting from energy conservation measures (ECMs), either for the design of new buildings, or following new retrofits. Continued interest in alternative methods of predicting the energy consumption of a building's heating, ventilating, and air-conditioning (HVAC) system has given rise to the application of a new set of tools based on the connectionist theory and approach. Artificial neural networks are one of these new tools which have been applied to a range of building energy processes.

While the application of neural networks to time-series prediction and system identification are not new, the specific application to building HVAC processes are fairly recent. Several studies have introduced new approaches to problems which in the past have relied on traditional concepts. Curtiss, Kreider, and Brandemuehl (1992) demonstrate how artificial neural networks can be applied to adaptive control of HVAC processes. A series of networks were used to first model the dynamic response of a heating coil, which was then linked to a second network designed to predict the optimum process control. The prediction of start-up time required by a controller for returning zones to the desired occupied temperature after night or weekend setback was shown by Miller and Seem (1991). Several studies have reported the prediction of building energy consumption using climate and building parameters, see Anstett and Kreider (1992) and Kissock (1994). Kreider and Haberl (1994), present several approaches used to successfully predict building energy use.

The objective for this study is to develop energy forecasting models of a building which has undergone energy conservation retrofits, using the simulated data sets from the DOE-2.1E building energy analysis program (Winkleman et.al 1993). Past studies have utilized monitored building data from pre- and post period retrofits, in order to determine the energy impact from these retrofits.

A new perspective is presented on the use of simulated data. given the key assumption that monitored building end-use data are available for a period of time before the retrofit. The method first uses a simulation to create the baseline energy consumption of the building; followed by the modeled retrofit performance. to give the response in energy and demand savings resulting from the retrofit. This response is a function of the modeled or measured building load. and climate parameters. A neural network can be trained to predict this response. Once trained. a combination of actual measured data from the building and local climate data could be input to the network to predict the response of the actual building. An interesting use for this technique would be the case where pre-retrofit end-use data are available. Assuming that a trained model for the retrofit type exists. then the monitored end-use data could used to estimate the response for the particular building The technique is not intended to replace other simulation methods. but could add confidence to other estimation techniques. as well as assist in the validation process. by combining engineering models with monitored load data.

The modeling by simulation is complex given the detailed building configuration data. and non-linear system response factors which are lumped into the analysis. Because of the complexity of the problem. the scope was limited to a specific building with its selected ECM retrofits. The data sets generated from the simulations were used to train the ANN model in order to characterize the dominant features and patterns resulting from the retrofits. The trained model is then given test sets consisting of data that were not included in the training. An important question about the trained model is—to what extent can the trained model extrapolate this response to other buildings and climates? An example of this might be the analysis of a different building with a similar HVAC system—or a similar building in another climate. This study considers one building. with two climate zones. The purpose of this paper is to provide a proof of concept for the method. and to lay the groundwork for future research which would investigate developing a library of trained ANN system models.

MODELING APPROACH

Hourly building energy simulation programs such as DOE-2 are useful for evaluating the energy performance of commercial buildings. using long term average hourly weather data for the location under consideration. Input to DOE-2 consists of a detailed description of the building being analyzed: including. hourly scheduling of occupants. lighting. equipment. and thermostat settings. DOE-2 provides very accurate simulation of such building features as shading. fenestration. interior building mass. envelope building mass. and the dynamic response of differing heating and air conditioning system types and controls. The program can output hourly end-use consumption as well as a wide range of input and simulation parameters. In particular. long term average typical meteorological year (TMY) weather data. useful heating. cooling. and electrical loads. and system level parameters for the model predictors can be obtained.

The first step was to build a baseline model of the actual building using the DOE2.1E program. Before any confident predictions can be made on how a particular building or plant feature will perform when integrated into a real building. it is necessary to start with a calibrated model (where the term *model* refers to the simulation tool's representation of the feature). The building description was performed using walk-through audits. assisted by building plans and specifications. The building model was then calibrated with actual billing data. In an effort to provide a sampling of the possible retrofit implementation types. a loads. systems. and plant level retrofit were selected. to correspond with the differing levels of complexity involved in each. and to match the input structure of the program. The simulations were run for the baseline. and each of the retrofit implementations. The climate variables along with the base model consumption and plant loads were used as the independent predictor variables for the ANN model. The retrofit model consumption was subtracted from the base level consumption. to give the energy savings effect for the retrofit under consideration. The hourly energy savings becomes the dependent variable to be predicted by the ANN model. Figure 1 illustrates this process.

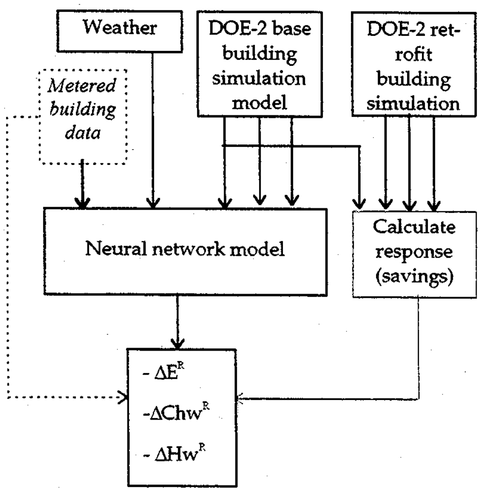

Figure 1. Ann Modeling Method.

Weather data, base level electrical consumption, E_b, chilled-water consumption, Chw_b, and hot-water consumption, Hw_b, are the outputs from the base case DOE-2 simulation. The next step is to simulate each retrofit implementation to get the post-retrofit consumption. The difference between the base-level and post-retrofit consumption are the target outputs. The superscript, ^{R} on each of the network outputs correspond to the particular retrofit which is under consideration.

BUILDING DESCRIPTION

The base case building selected is a four story university building which has 91,710-ft^2 (9,520-m^2) of floor area; characterized by sparsely insulated but massive stone construction. The site is oriented on an east-west axis, and is bordered on the north by a university building. The building geometry is rectangular, with the upper floors cantilevered above the main level. Clerestory windows provide some daylighting to the fourth floor offices. The building mechanical system is a dual-duct constant volume system, with three main air-handling units. Electricity, chilled water, and hot water are supplied by the campus central plant.

Table 1 provides a summary of the base building features.

Table 1. Baseline building summary

Business Building, University of Colorado	
Weather File	Chicago TMY
Total conditioned area	91,710-ft^2 (9,520-m^2)
Opaque wall R-value	0.281 Btu/hr·ft^2·°F (1.59 W/m^2·K)
Roof R-value	0.186 Btu/hr·ft^2·°F (1.05 W/m^2·K)
Floor R-value	0.471 Btu/hr·ft^2·°F (2.67 W/m^2·K)
Lighting system	Fluorescent F40-T12
<u>Windows</u>	
All orientations	Single Pane Clear
U-value	0.97 Btu/hr·ft^2·°F (5.50 W/m^2·K)
Shading coefficient	0.85
Window area	2846-ft^2 (264.4-m^2)
<u>Lighting Power Density</u>	
All areas weighted average	2.0 W/ ft^2 (21.5 W/m^2)
<u>Plug Load Density</u>	
Offices	1.0 W/ ft^2 (10.7 W/m^2)
Library	1.25 W/ ft^2 (2.7 W/m^2)
System type	Dual-Duct Constant Volume
Plant type	Central Steam and Chilled Water
HVAC schedule	AHU-1 24 hour operation
	AHU-2 8:00 a.m. - 6:00 a.m.
Cooling/Heating setpoint	74°F / 72°F (23.3°C / 22.2°C)
Outside sir supply flow	15 cfm/person (7 L/s/person)

The energy conservation retrofits considered were: (1) Lighting efficiency retrofit, (2) Variable air volume retrofit, and (3) combination variable-speed chiller drive and thermal storage system. The first retrofit is an internal load reduction measure. The lighting efficiency retrofit assumes changing a portion of the fluorescent lighting system to high efficiency T-8 lamps and electronic ballasts. The variable-air-volume (VAV) retrofit is a system level measure. The supply fans have a variable-speed drive attached allowing supply cfm to vary with the load, with the minimum stop setting at 30% of full flow. The plant level retrofit assumes a centrifugal chiller equipped with an adjustable-frequency drive (AFD) on the compressor motor. The performance curve fits are bi-quadratic equations for the chiller capacity, energy input ratio (EIR), and the EIR as a function of the part load ratio (PLR). The curve fits are related to the following inputs: the capacity is a function of the chilled water temperature, and the entering condenser water temperature; the efficiency is adjusted for changes in chilled water and condensing temperatures, as well as the PLR. The curve fits were obtained from work done by Roberts (1992). In addition to the AFD, the chiller also serves a chilled water storage tank. The chiller charges the tanks at night. Stored chilled water is released from 12 p.m. to 5 p.m. simulating an on-peak period for a time-of-day electric rate schedule. The chiller provides off-peak cooling and supplements the tank during the on-peak period if necessary. Table 2 summarizes the retrofit implementations.

Table 2. Building ECM retrofits

Loads - R1	Lighting efficiency retrofit	T-8 lamps - electronic ballasts
Systems - R2	Variable-air-volume retrofit	VFD fan drive
Plant - R3	Variable-speed-drive, chiller/thermal storage retrofit	VSD compressor - thermal storage tank

PARAMETER SELECTION

An important task in the ANN approach to the energy prediction process is data handling and selection of the appropriate independent variables to be used in defining the dependent variable of interest. It is desired that the selected variables be readily available and useful predictors. Building energy consumption is known to be highly correlated with climatic variables. The independent climate variables chosen were, ambient dry-bulb temperature (°F), ambient wet-bulb (°F), and total horizontal solar radiation (Btu/hr·ft^2). The desired outputs are hourly values of: the whole building hourly electrical consumption (kW), chilled water consumption (MMBtu), and the hot water consumption (MMBtu). Since electrical consumption, heating loads, and cooling loads are directly output from the simulation, the base model levels of each were input as predictors for the change (in these same variables) resulting from the retrofit implementations. Another criteria in the selection process was the need to select variables which could be obtained from monitored data in the field for use as input to the trained network. Given a set of training samples, $\{x_1(\tau), x_2(\tau), x_3(\tau), \ldots, x_n(\tau)\}$, and an associated series of predictions, $y_i(\tau)$, where each $x_i(\tau)$ and $y_i(\tau)$ are the independent predictors and the resulting target predictions occurring at time (τ) for each prediction (i). The resulting expression for the building energy consumption and loads prediction has the form given in Eq. 1.

$$y_i(\tau) = f\{x_1(\tau), x_2(\tau), x_3(\tau), \ldots, x_n(\tau)\} \quad 1)$$

Where:

$$y_i(\tau) = \{\Delta Wbe, \Delta Chw, \Delta Hw, r$$

$$x_n(\tau) = \{t_s, T_{db}, T_{wb}, Q_s, Wbe_b, Chw_b, Hw_b$$

NEURAL NETWORKS

There are many different implementations of ANN's. The implementation used in this analysis is a variation on the back-propagation algorithm popularized by Rumelhart and McClelland (1986). For a detailed introduction on the origins and theory of back-propagation refer to Werbos (1974). Artificial neural networks are an alternative approach to traditional modeling and statistical methods. Some of the more traditional applications include classification, noise reduction, and time-series prediction. ANN's have inherent advantages over other methods under the following conditions. When the data; are "fuzzy", ill-defined, have hidden patterns embedded, exhibit nonlinearity, or chaotic behavior. Additional features of ANN's are their powerful function-approximation capability.

DATA PRE-PROCESSING

The simulated data sets which were generated consisted of 8760 hourly values. The data sets were reduced to 4000 data points providing a statistical representation of an entire year of operation. The neural network requires that the data are scaled within some "reasonable" range. Pre-processing functions are used to normalize inputs. This prevents inputs with large magnitudes from swamping out other, equally important, but smaller, inputs. The inputs to the network were normalized using the Mean/Standard deviation transform. Each input is handled independently and is modified by subtracting the mean for that input, μ and dividing by the standard deviation for that input. The formula is as follows:

$$x_i' = (x_i - \mu) / \sigma \quad 10)$$

Most ANN implementations assume that the output neurons have the same activation function as the hidden neurons, typically the logistic function. The network considered for this analysis uses the *linear* function or $f(x) = x$, for the output neurons. Sigmoid functions tend to emphasize output values near the intermediate range and can produce low predicted values near the upper limits and high values near the lower limit, leading to a compressed output range. A discussion of the advantages and limitations of using the linear output function can be found in Masters (1994).

The architecture that produced the best results for this problem was a four-layer network, having two hidden layers with six neurons each. The selection of the number of layers and neurons in a network is an important task. Picking too many can overfit the network, and picking too few can reduce the network's ability to map the target outputs. The selection was done empirically using past experience, and by carefully checking the training/testing error curves, and output response.

TRAINING AND TESTING RESULTS

In the following, the ANN methodology for predicting the energy consumption savings will be described using network statistics, and graphical comparisons of the predicted and target outputs. Table 3 shows the architecture used and the number of training iterations for each network considered. The common parameters used to initialize these networks are shown in Table 4. Table 5 provides the total energy savings obtained (for the period), and the percent difference, from the predicted and actual retrofits. For each retrofit, three desired outputs exist, each having its own individual network. Typically, increased accuracy can be obtained by using single output networks although multiple output networks have been used. Most of the test sets use the Chicago, Illinois weather data, with the exception of the test sets starting with (P) which indicate Phoenix, Arizona weather data. The performance of the networks are characterized by the testing mean square error, MSE, the correlation coefficient, R^2, and the coefficient of variation, CV, which is described in Eq. 11.

$$CV \equiv \frac{\sqrt{\sum_{i=1}^{n}\left(y_{p,i}-y_{a,i}\right)^2}}{n} \tag{11}$$

Table 6 provides the test set periods, and statistics for each retrofit considered. The test sets are taken from three snapshot periods corresponding to a "Winter", "Summer", and "Fall" season. An important feature to remember when considering the statistics for periods in which zero or negligible changes in the output have occurred is that the resulting values do not give a good indication of how well the model has performed. In this case, a more effective approach may be to assess the networks ability to predict this zero savings by looking at graphical results. The graphical results from the test sets are depicted in Figures 4a through 5c.

DISCUSSION

A typical one week testing set is used to determine the performance of the ANN for each retrofit measure. This week was not part of the training set used to determine the weights of the ANNs. In most instances, the retrofit response showed the most variation in the "Summer" season. In the following: whole building electrical, chilled water, and hot water "consumption" will be referred to as Wbec, Chwc, and Hwc respectively. A sample of the results discussed in the following.

Figure 4a shows the predicted and actual Chwc savings for the lighting retrofit, during a week in June. The prediction of Wbec is accurate as expected since most of the electrical load is a scheduled response. The total and peak savings are very close to the actual savings with all predicted outputs within a few percent of the target savings.

For the VAV retrofit, Figure 4b The Hwc responded as expected, requiring an increase in hot water consumption due to less fan heat added to the air-stream.

For the ASD chiller drive/thermal storage retrofit, Figure 4c, the Wbec dynamic response shows an increase in the evening (thermal storage system charging) and a decrease during the day when the tanks are discharging and the ASD chiller is able to ramp down due to a decrease in load. The daytime peaks were predicted well, while some of the evening charging peaks were missed. This is evident when looking at the integrated savings prediction in table 5.

Figures 5a through 5c are from testing the network trained with the Chicago building loads and weather, with the loads and weather produced by a simulation using the Phoenix location. The loads retrofit network predicted the peak occurrences (with the exception of the evening ramp down) and the integrated savings well for the Wbec, and the Chwc (Figure 5a). The systems level retrofit did not predict the dynamic response of the Wbec as well, although the integrated savings were close. The same holds true for the Chwc and the Hwc (Figure 5b). For the plant level retrofit, the the peak Wbec and total savings were not predicted as well as for the trained weather file (Figure 5c), but followed the expected pattern.

ACKNOWLEDGMENTS

The authors would like to thank Jim Garrick for his support in developing the methodology for this study.

CONCLUSIONS

The results show that ANNs can be used to determine energy savings from retrofits using available building loads and local climatic data for limited cases. The ability of the network to extrapolate to other climates shows promise, although further research is necessary to develop more specific predictors for the systems and plant retrofits. It is clear that more information is necessary to define the system dynamics involved. This could be in the form of scheduling indicators, building configurational data, and control variables which may give the network more information about non-standard operation and variability not presently accounted for.

Future work should concentrate on improving the selection of predictors to the model. Other efforts will involve the input of actual monitored building and climate data into the trained networks in order to test the method in a "real" building, and to help in the validation process. Additional work could investigate the development of a generic library of trained, system retrofit models, which could be tested on a range of actual building data sets.

Table 3. Neural network configuration

Network	Batch size	inputs	H1	H2	Outputs	N_{it}
R1-el	4000	7	5	5	1	409
R1-cw	4000	7	5	5	1	500
R1-hw	4000	7	5	5	1	500
R2-el	4000	7	5	5	1	649
R2-cw	4000	7	5	5	1	243
R2-hw	4000	7	5	5	1	212
R3-el	4000	7	5	5	1	2500
R3-cw	4000	7	5	5	1	85
R3-hw	4000	7	5	5	1	100

Notes:
N_{it} : Number of iterations for ANN training
H1: E.g.: Number of units in hidden layer 1

Table 4. Neural network common parameters

Error Type	Transfer function Hidden	Transfer Function Output	Learning rate (η)
MSE	Sigmoid	Linear	0.001
Weights decay (ε)	Max Step size (μ)	Shrink factor (δ)	Input Normalization
1.0e-5	1.25	0.444	Mean/stdev

Table 5. Total retrofit savings for test period

Test Set	Wbe Predicted Savings (kWh)	Wbe Actual Savings (kWh)	Cw Predicted Savings (Mbtu)	Cw Actual Savings (Mbtu)	Hw Predicted Savings (MMBtu)	Hw Actual Savings (MMBtu)
CT1L	2320.7	2315.3	0.1	0.0	-7.5	-7.6
CT2L	2335.5	2347.0	3.9	3.8	-0.3	-0.6
CT3L	2318.8	2317.0	0.0	0.0	-6.7	-7.1
CT1S	18431.4	18690.6	-1.7	0.0	-51.7	-51.9
CT2S	16010.6	15391.1	12.2	22.0	-7.9	-6.6
CT3S	18431.4	18662.7	-1.7	-0.2	-51.7	-51.9
CT1P	-31.6	0.0	-178.6	0.0	0.2	0.0
CT2P	1620.9	51.1	1298.7	-526.9	0.0	0.0
CT3P	2.6	0.0	-210.7	0.0	0.0	0.0
PT2L	2645.3	2347.0	1.5	1.2	-0.1	-0.6
PT2S	15674.8	17424.1	75.8	60.0	-4.2	0.2
PT2P	7614.3	4843.7	4935.4	254.0	0.0	0.0

Table 6. Test set statistics

Network	Test Set	Test Period	(CV)	R^2	MSE_{tst}
R1-el	CT1EL	Feb 20-27	0.11	0.99	0.2127
R1-el	CT2EL	Jun 8-14	0.16	0.99	0.0025
R1-el	CT3EL	Nov 14-20	0.09	0.99	0.0082
R1-cw	CT1CL	Feb 20-27	N/A	0.0	0.4008
R1-cw	CT2CL	Jun 8-14	2	0.97	0.0081
R1-cw	CT3CL	Nov 14-20	N/A	0.0	0.0103
R1-hw	CT1HL	Feb 20-27	1.01	0.83	0.2362
R1-hw	CT2HL	Jun 8-14	17	0.0	0.0023
R1-hw	CT3HL	Nov 14-20	1	0.73	0.0094
R2-el	CT1ES	Feb 20-27	0.27	0.0	17.04
R2-el	CT2ES	Jun 8-14	1	0.45	0.0150
R2-el	CT3ES	Nov 14-20	0.24	0.38	0.0297
R2-cw	CT1CS	Feb 20-27	N/A	0.0	15.7
R2-cw	CT2CS	Jun 8-14	11	0.0	0.0760
R2-cw	CT3CS	Nov 14-20	70	0.0	0.0463
R2-hw	CT1HS	Feb 20-27	1	0.50	4.837
R2-hw	CT2HS	Jun 8-14	6	0.60	0.0150
R2-hw	CT3HS	Nov 14-20	1	0.50	0.0297
R3-el	CT1EP	Feb 20-27	N/A	0.99	1.668
R3-el	CT2EP	Jun 20-27	8.03	0.72	40.89
R3-el	CT3EP	Nov 20-27	N/A	0.99	0.0074
R3-cw	CT1CP	Feb 20-27	N/A	0.0	1.668
R3-cw	CT2CP	Jun 20-27	0.71	0.63	37.94
R3-cw	CT3CP	Nov 20-27	N/A	0.0	0.0076
R3-hw	CT1HP	Feb 20-27	N/A	0.66	1.668
R3-hw	CT2HP	Jun 20-27	N/A	0.67	48.14
R3-hw	CT3HP	Nov 20-27	N/A	0.67	0.0076
R1-el	PT2EL	Jun 20-27	0.92	0.99	17.2
R1-chw	PT2CL	Jun 20-27	10	0.0	0.005
R1-hw	PT2HL	Jun 20-27	16	0.67	0.022
R2-el	PT2ES	Jun 20-27	0.90	0.58	17.04
R2-chw	PT2CS	Jun 20-27	1.76	0.80	0.115
R2-hw	PT2HS	Jun 20-27	131.9	0.66	0.276
R3-el	PT2EP	Jun 20-27	74	0.53	66.98
R3-chw	PT2CP	Jun 20-27	190	0.49	0.0632
R3-hw	PT2HP	Jun 20-27	N/A	0.67	0.188

Notes: N/A: Not applicable due to zero target values (cannot divide by zero)
CT1EL:E.g.: (CT1) Chicago-test-set1 (E) Electric consumption (L) Loads retrofit
CT1CS: E.g.: (CT1) (C) Chilled water consumption (S) Systems retrofit
CT1HP: E.g.: (CT1) (H) Hot water consumption (P) Plant retrofit
R1-cw:E.g.: (R) retrofit (1) Loads,(chw) chilled water consumption

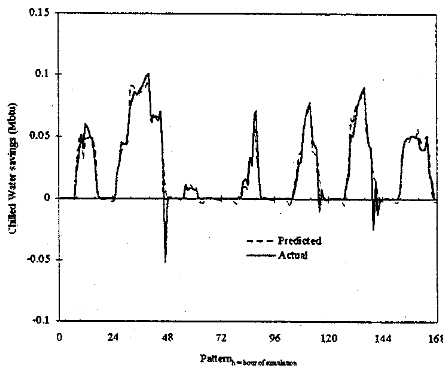

Figure 4a Chw, Lighting retrofit, Test-set (CT2CL) June 8-14

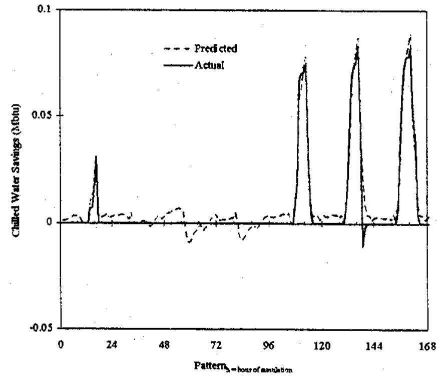

Figure 5a Chw, Lighting retrofit, Test-set (PT2CL) Jul 20-27

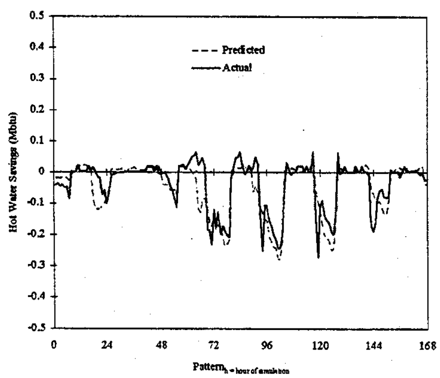

Figure 4b Hw, VAV retrofit, Test-set (CT2HS) June 8-14

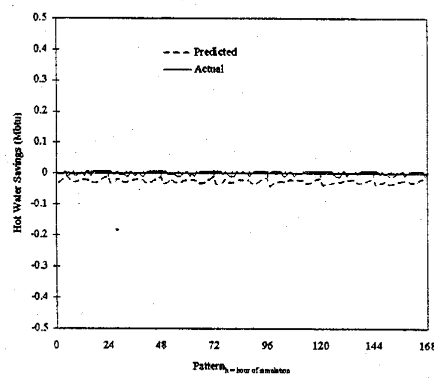

Figure 5b Hw, VAV retrofit, Test-set (PT2HS) June 8-14

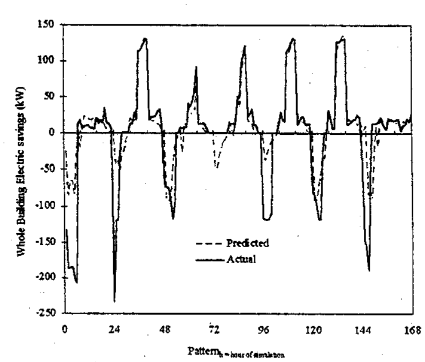

Figure 4c Wbe, ASD/TS retrofit, Test-set (CT2EP) July 20-27

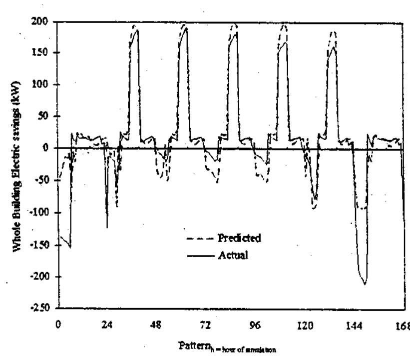

Figure 5c Wbe, ASD/TS retrofit, Test-set (PT2EP) Jun 1-7

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NOMENCLATURE

$\Delta Wbe_{,r}$ change in whole building electric usage from retrofit *(kW)*

$\Delta Chw_{,r}$ change in chilled water use from retrofit *(Mbtu)*

$\Delta Hw_{,r}$ change in hot water usage from retrofit *(Mbtu)*

t_s time, *(hour of simulation)*

T_{db} outdoor dry-bulb temperature *(°F)*

T_{wb} outdoor wet-bulb temperature *(°F)*

Q_s total solar horizontal radiation *(Btu/hr-ft²)*

Wbe_b whole building electric from base model *(kW)*

Chw_b whole building chilled water from base model *(kW)*

Hw_b whole building hot water from base model *(kW)*

x_i' scaled value for input (*i*)

x_i real valued input (*i*)

μ mean value for all x to be normalized (can be each column, or all x)

σ standard deviation for all x to be normalized