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An energy benchmarking model based on artificial neural network method with a case example for tropical climates

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SUMMARY

Energy benchmarking is an important step in evaluating a building's energy use and comparing it with similar buildings in similar climates. Depending on the benchmarking results, extra measures can be taken to reduce energy consumption when the subject building has been assessed to consume more than other similar buildings. This study presents the current state of energy benchmarking-related research and available tools. An artificial neural networks (ANN)-based benchmarking technique is presented as a highly effective method. The model specifically focuses on predicting a weighted energy use index (EUI) by taking into consideration various building variables, such as plug load density, lighting type and hours of operation, air conditioning equipment type and efficiency, etc. Data collected from laboratory, office and classroom-type buildings and mixed use buildings in Hawaii are used to present the ANN-based benchmarking technique. The developed model successfully predicted the benchmarking EUI for the buildings considered in the study. The model coefficient of correlation was 0.86 for the whole building benchmarking analysis, indicating a good correlation between the measured EUI and the ANN predictions. Additionally, the use of ANN benchmark model for predicting potential energy savings from retrofit projects was evaluated. Some of the benchmarking input variables were modified to reflect a potential energy savings from a retrofit project and the new input set was simulated with the ANN model. The preliminary results show that the developed ANN model can be used to predict energy savings from retrofit projects. Copyright © 2006 John Wiley & Sons, Ltd.

KEY WORDS: energy benchmarking; buildings; artificial neural network; energy conservation

1. INTRODUCTION

Energy benchmarking is an initial step in assuring energy-efficient buildings. In this method, the average energy performance of similar buildings in the same climate zone is compared and the ones with higher energy consumption identified. When the benchmarking indicates that a building has a higher energy consumption compared to similar buildings, it would necessitate further evaluation in order to identify as per the energy conservation opportunities (ECO).

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In energy benchmarking, the energy consumption is usually expressed in terms of energy use intensity (EUI), which is defined as energy use per square meter per year, or $\mathrm{k\,Wh\,m^{-2}\,yr^{-1}}$. The EUI provides normalized energy use assessment per year by building-floor area. This normalized measure is expected to yield a comparison base for different buildings' energy use, in turn, provide an indication for buildings where improvements need to be made.

Aside from the differences in methods, the main challenge in the benchmarking of existing buildings is the availability of sufficient statistical comparative data. The most common database used in existing-building benchmarking is the commercial building energy consumption surveys (CBECS). The CBECS data consists of statistical information collected on energy consumption, energy expenditures, and energy-related characteristics of commercial buildings in the United States. The survey has been conducted periodically since 1978 by the Energy Information Administration Division of the Department of Energy. In a more recent effort, California has developed a state-wide database called California's commercial end use survey (CEUS). The CEUS data was collected from California's utility companies. This database also serves as the main source to the Cal-Arch benchmarking tool.

Energy benchmarking has been in focus for many public and private organizations. Various researches have been done and benchmarking tools have been developed. Kinney and Piette (2002) have described the development of a California commercial building benchmarking tool Cal-Arch in their recent study. The Cal-Arch uses existing survey data from California's CEUS. In a recent study, Matson and Piette (2005) have provided review of energy benchmarking studies for commercial buildings. A stepwise linear regression method developed by Sharp (1996, 1998) is most commonly used in benchmarking buildings based on statistically weighted EUI. The Energy Star building benchmarking tool developed by the Environmental Protection Agency (EPA) and Department of Energy (DOE) is an example for stepwise linear regression method-based benchmarking. Details of the Energy Star Building and benchmarking can be followed from the article by Hicks and Von Neida (2000). In a study by Federspiel *et al.* (2002), a model-based benchmarking method especially suitable for laboratory buildings was developed. Additional discussion of laboratory benchmarking and practical considerations and limitations can be followed from Mathew *et al.* (2003).

This study presents a benchmarking method that utilizes artificial neural networks (ANN) in its computations. The ANN method offers better accuracy in its benchmarking prediction and flexibility through its computational structure when compared to what is available today. The foremost feature of ANN method is that the benchmarking algorithm renews itself as new building data is entered in the database. Whereas, the currently used linear regression, based on the statistical model in the EPA/DOE Energy Star benchmarking, requires determination of empirical constant coefficients manually each time the database is modified. An ANN benchmarking model was developed using mixed building data from tropical climate representing a case example, and its performance was evaluated.

2. ANN MODELLING

The review of the existing energy benchmarking studies indicates a need for improvements in benchmarking methods and databases. The up to date benchmarking models developed for existing buildings, use either a raw data visualization method (Kinney and Piette, 2002), a regression-based statistical modelling (Sharp, 1996, 1998), or a detailed idealized building energy modelling (Federspiel *et al*., 2002). The raw data visualization does not take into account the building envelope differences, building operation hours, or building occupancy and equipment density. While it gives a rough idea of building energy usage percentile, it is not an apple-to-apple comparison. The linear regression based statistical model requires the determination of empirical constant coefficients for each climate or regional division. This needs to be revised manually each time a new data set is entered into the database, or a new CBECS database is developed. There is ample room for development especially in this area which targets better modelling of the statistical data with advanced computational methods. The existing idealized building energy models are either developed for only a specific class of applications (Labs 21), or require cumbersome data entry (DOE-2.2). A generalized building energy model which simplifies interface development is required in this area.

ANN, representing non-parametric techniques for achieving arbitrarily complex functional mappings, are promising for wide applications in building-energy benchmarking. The foremost feature of ANN method is that the benchmarking algorithm will renew itself if a new building data is entered in the database. Additional advantages of ANN methods over other techniques, such as statistical methods and simulation, are: faster learning time, simplicity in analysis, beret accuracy in prediction and adaptability to changes in a buildings energy use. This study presents the first-time application of the ANN method in energy benchmarking.

The computational structure of ANN consists of an input layer, which accepts patterns from the environment and an output layer that shows response with regard to the environmental variables. There are also hidden layers which do not directly interact with the environment; rather, they enact the primary function of relating the input to the output. They consist of input weights, biases and transfer functions.

The neural network training process simply involves modification of weights until the predicted output is in close agreement with the actual output. Defined relations between the input layers, the hidden layers and the output layers determine a particular neural network model. Three types of networks used most commonly in ANN applications are feed forward networks, competitive networks and recurrent associative memory networks. Each network type may have different learning rules. The learning rules are described in broad categories of supervised learning, unsupervised learning and reinforcement (or graded) learning rules. Many studies on ANN theory have been published along with the development of the method. Zurada (1992) presents the theory of neural networks which can be followed by readers with different technical trainings. A practical description of ANN methods with sample applications are presented in Hagan *et al*. (1997). A study by Yalcintas and Akkurt (2005) presents use of ANN methods in building energy predictions and energy savings predictions due to building retrofits.

The data used for the benchmarking program in this study were collected in two phases. In the first phase, data collected from previous preliminary energy assessments (PEA) reports for over 60 buildings in Hawaii were evaluated. The building types evaluated include office, classroom, laboratory-type buildings, or mixed use buildings including any of the two or all office/classroom/laboratory activities. The data categories extracted from the PEA reports are listed in Tables I and II. Table I lists the general data on the building size, age, operation, and energy usage, as well as PEA estimates for lighting, air conditioning and plug loads end-use energy percentage distribution. Table II list survey questionnaire developed to estimate yearly electricity consumption for plug load, lighting and air conditioning end-uses.

Table I. General data on the building properties and operation.

Building general information	
Operation hours	Yearly electricity usage
Age	Percentage electricity used for
Square feet area	Lighting
	Air conditioning
	Plug loads

Table II. Building (A) plug load survey questionnaire, (B) lighting demand survey questionnaire, (C) air conditioning demand survey questionnaire.

(A)
1. COMPUTERS
   1 Few through the building
   2 Less than or equal to $1/40\,\mathrm{m}^2$
   3 Less than or equal to $1/30\,\mathrm{m}^2$
   4 Less than or equal to $1/20\,\mathrm{m}^2$
   5 Less than or equal to $1/10\,\mathrm{m}^2$
   6 Computer server facility serving a single building
   7 Computer server facility serving multiple buildings
2. FUME HOODS
   0 None exists
   1 Few through the building
   2 Less than or equal to $1/100\,\mathrm{m}^2$
   3 Less than or equal to $1/50\,\mathrm{m}^2$
   4 Less than or equal to $1/20\,\mathrm{m}^2$
3. OTHER EQUIPMENT
   0 None exists
   1 Few lab equipment including analysers, refrigerators, etc.
   2 Moderate lab equipment, light motorized equipment, moderate cooking equipment.
   3 High electricity demand lab testing equipment, moderate motorized equipment, heavy cooking equipment

(B)
1. Daily hours building lighted
2. Percentage floor area building lighted
3. Building internal lighting type
   1 High efficiency fluorescent lighting
   2 Low efficiency fluorescent lighting
   3 Low efficiency fluorescent and incondescent lighting
4. Building external lighting type
   1 Low lumen external lighting
   2 Medium lumen external lighting
   3 High lumen high efficiency external lighting
   4 High lumen low efficiency external lighting

(C)
1. Daily hours building air conditioned
2. Percentage floor area building air conditioned
3. Computer intensity rate (from (A) survey)
4. Internal lighting type (from (B) survey)

Table II. *Continued.*

5. Air conditioning equipment conditions	
1	Majority window AC uits
2	50/50 window units and DX split systems
3	Majority DX split systems
4	50/50 DX split systems and chilled water system
5	Majority chilled water system newer equipment variable flow conditions
6	Majority chilled water system newer equipment constant flow conditions
7	Majority chilled water system older equipment constant flow conditions
6. Building envelope, windows	
1	More than 40% glass
2	30–40% glass
3	20–30% glass
4	Less than 20% glass
7. Building envelope, solar window tinting/adjacent building shading	
1	Yes
2	No
8. Building envelope, wall type	
1	Concrate
2	Insulated frame
3	Non-insulated frame
9. Building envelope, roof insulation	
1	Yes
2	No

Answers to most of the survey questions in Table II existed in the PEA reports. Answers to questions such as 'building internal lighting type', 'air conditioning equipment type', 'floor percentage air conditioned' could be extracted from the PEA reports. However, answers to few questions were not tabulated explicitly in the reports, either because they were not required explicitly for the PEA analysis, or they required relative comparison among the buildings that were benchmarked. For example, computer density information required for plug load estimates was not available in the PEA report. For the purpose of this benchmarking study, the survey questions on the building equipment density and distribution (other than computer) required judgment for comparison with other buildings in the benchmarking group. Answers to such questions were estimated by the author, since the author either has actually conducted a PEA analysis on a particular building or was very familiar with the building. After gathering the information on the survey questions, several buildings in the benchmarking group were field verified for the accuracy of the estimates.

Figures 1 and 2 represent the total floor area and EUI distribution of the buildings used in the ANN modelling study. While the total building EUI clusters in the 1.5–4.5 $\mathrm{k\,Wh\,m^{-2}\,yr^{-1}}$ in Figure 2, the building square footage does not show any recognizable distribution pattern in Figure 1. This can be attributed to the mixed category use of the buildings in the benchmarking data.

The ANN model used in this study is based on Levenberg–Marquardt back-propagation algorithm. A three-layer feed-forward-type configuration including an input layer, hidden layer and an output layer was developed. Three separate ANN sub-models were developed for benchmarking the plug loads, lighting and HVAC end-use electricity. Those ANN sub-models were used to evaluate the survey questionnaire and prediction capacity in each category.

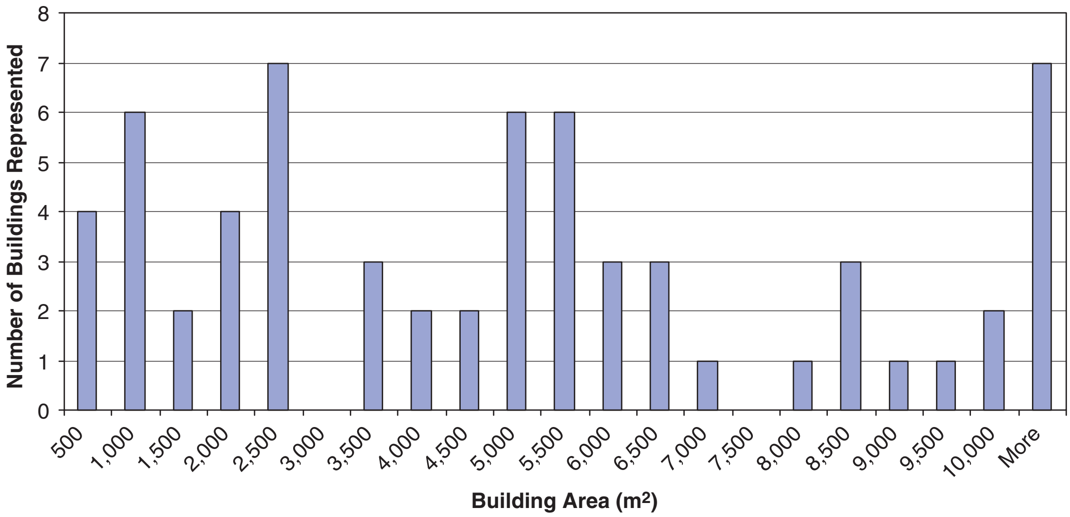

Figure 1. Building area distribution of the data used in the ANN benchmarking model.

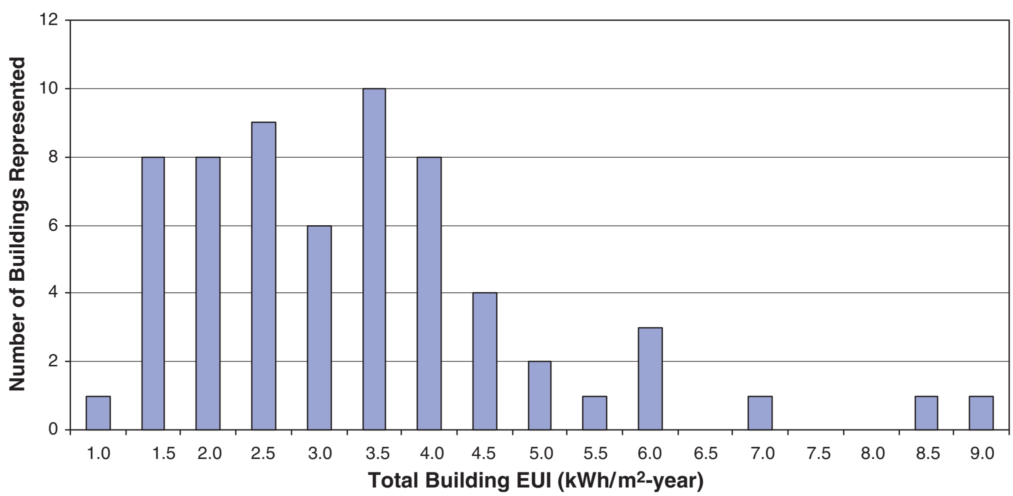

Figure 2. Total building EUI distributions of the data used in the ANN benchmarking model.

The sub-ANN models do not have any impact on the final ANN benchmarking model. The same Levenberg–Marquardt back-propagation algorithm was used in all models with varying input numbers.

The input to the ANN sub-model for the plug load EUI prediction is the three variables listed in the Table II(A), and presented numerically in Table III. The output of the model is the plug load EUI. The number of hidden layer nodes is five. Similarly, the input for the lighting EUI ANN sub-model is the four variables listed in Table II(B), and presented numerically in Table III. The output to the model is the lighting EUI, and the number of hidden layer elements

Table III. ANN benchmarking model input data.

Plug load input			Lighting input				HVAC input			
Computers	Fume hoods	Other equipment	Lighting hours	Floor percentage lighted	Internal lighting type	External lighting type	HVAC hours	Floor percentage air conditioned	HVAC equipment type	Output EUI
3	1	1	15	80	3	2	24	100	7	5.4
2	0	0	15	60	2	1	18	80	7	2.5
4	0	3	15	70	2	3	24	90	6	5.6
3	0	1	15	80	3	2	24	70	7	3.5
3	1	2	15	80	3	3	24	100	7	6.5
3	2	3	15	50	2	2	24	60	7	3.4
6	2	3	18	90	1	3	24	60	5	4.5
4	2	1	18	80	2	4	24	60	3	4.2
2	1	1	18	80	3	2	24	70	6	2.3
3	2	1	12	80	2	3	24	90	4	3.5
3	2	2	18	90	3	3	24	100	4	5.3
4	0	2	18	90	3	4	24	80	5	4.0
2	2	1	18	80	3	1	24	80	6	2.3
4	2	2	18	90	3	4	24	100	7	7.9
3	2	1	12	70	1	1	24	80	5	3.0
3	2	2	15	90	2	3	24	40	3	2.9
3	2	2	10	60	2	2	24	50	2	2.2
2	0	0	12	60	3	2	24	60	3	1.4
3	1	1	12	80	3	2	24	90	4	2.7
2	0	0	12	50	2	1	24	80	3	1.8
3	0	1	12	80	3	2	24	80	4	2.5
5	0	1	10	90	2	4	10	70	3	3.7
7	0	1	10	80	2	2	24	60	7	3.9
2	0	0	12	100	2	4	24	50	7	2.2
2	0	0	18	80	3	3	24	70	6	2.5
1	0	0	12	80	2	2	24	20	1	1.0
2	0	0	12	70	2	4	12	80	6	2.7
4	0	0	12	70	2	4	15	60	7	3.5
1	0	0	12	80	2	1	24	20	1	1.0
4	0	3	15	70	3	3	10	40	4	3.0
1	0	0	12	70	2	3	24	50	3	2.0
3	0	0	18	80	2	3	24	60	3	1.8
1	0	0	10	50	2	1	10	30	2	1.6
3	0	0	10	80	2	1	10	25	4	1.1
3	0	0	10	50	2	1	10	20	2	1.6
1	0	0	10	50	2	1	10	20	2	1.6
3	0	1	10	50	3	3	10	10	2	1.6
5	0	0	10	70	2	3	12	50	2	3.0
5	0	0	10	80	2	3	12	50	2	3.1
4	0	2	12	70	2	4	15	50	7	3.6
2	0	0	10	60	2	1	12	30	1	1.2
3	0	0	10	60	2	3	12	40	3	2.1
3	0	0	10	60	2	3	12	40	3	2.3
5	0	0	12	70	2	4	14	60	4	3.8
2	0	0	10	50	3	2	12	20	2	1.6
2	0	3	15	70	3	4	14	60	6	3.7
1	0	0	10	50	3	1	10	40	4	0.9
3	0	0	12	80	2	3	24	80	7	2.9
3	0	0	10	70	2	4	14	70	2	3.2

Table III. *Continued.*

Plug load input			Lighting input				HVAC input			
Computers	Fume hoods	Other equipment	Lighting hours	Floor percentage lighted	Internal lighting type	External lighting type	HVAC hours	Floor percentage air conditioned	HVAC equipment type	Output EUI
3	0	0	15	60	2	3	14	80	4	2.8
3	0	0	10	80	2	3	14	80	3	3.3
1	0	0	10	50	2	1	14	70	3	1.1
1	0	0	10	70	2	1	14	70	2	1.4
1	0	0	10	70	2	2	14	70	2	1.7
5	0	0	18	100	2	4	24	80	7	2.9
4	0	0	18	100	2	4	24	80	7	2.4
6	0	0	18	100	1	4	24	60	5	3.3
2	0	1	18	100	2	3	24	80	7	2.3
3	0	0	18	100	2	3	24	80	4	1.3
2	2	2	18	90	2	3	24	100	4	5.1
2	2	2	15	100	2	4	24	90	7	4.3
2	2	3	15	100	3	4	24	100	7	8.0
3	1	0	18	100	2	3	24	80	5	1.9

is seven. Finally, the input for the HVAC EUI ANN sub-model is the first five variables listed in Table II(C), presented numerically in Table III (all 'HVAC input' columns, computers column under 'plug load input,' and internal lighting column under 'lighting input'). The output is the HVAC EUI, and the number of hidden layer elements is seven. The variables listed in the survey questions 6–9 in Table II(C) were not used in the HVAC ANN sub-model, since the variables had similar values, representing similarities in the building wall and window types and building external insulation. The questions 3 and 4 in Table II(C) were the internal lighting type and computer intensity rate. Both were available in Tables II(B) and II(A), respectively.

The final ANN benchmarking model input includes all variables listed in Tables II(A) and (B), and variables 1, 2 and 5 from Table II(C), resulting with a total of 10 input variables. The output to the model was the whole building total EUI. As can be seen from the input–output list, none of the partial EUIs for lighting, plug loads and HVAC end-use that were evaluated in the ANN sub-models are included in the final ANN benchmarking model. The number of hidden layer nodes for the ANN sub-models and final ANN benchmarking model is five.

The input data of the ANN benchmarking model is listed in Table III. For the ANN model, the data was divided into two subsets. The first subset is the training set, which is used for computing network weights and biases. The second subset is the testing set, which is used to test the accuracy of the ANN model. In this study, three-fourths of the data was used for training and remaining one-fourth was used for testing. The test set was composed by extracting every fourth input row from Table III starting with the second row. The remaining data in Table III was used as the ANN training set. In the training process, the training continues until the sum of squared errors and sum of square weights in the Levenberg–Marquardt algorithm reaches a steady level. When a steady level is reached, the training stops, and the model is tested with the test set. The test set error is not used in computations during the training process; it is used only to compare accuracy of the ANN model. A low error on the testing network is a good measure of an acceptable ANN model.

MATLAB neural network toolbox was used in developing the ANN model. A MATLAB normalization function was used to normalize the input and output values. The normalization was done such that the mean value of the data was zero and the standard deviation was unity. The activation function used in the ANN model was a sigmoid function. In order to avoid over-fitting of the data and to provide a good generalization capability to the developed ANN building energy prediction algorithm, an automated regularization method was used. The automated regularization feature is built into the MATLAB Levenberg–Marquardt algorithm that is used for the ANN modelling in the study.

3. RESULTS AND DISCUSSION

As mentioned earlier in Section 2, the ANN sub-models were developed to evaluate the accuracy and adequacy of the benchmarking survey questionnaire. Since energy distribution by end-use was already available from the PEA reports, they were used as output in the ANN sub-models, along with the survey questionnaire being the input to the sub-models.

The end-use EUIs from the plug load, lighting and HVAC predicted by the ANN sub-models for the test data, along with the actual EUIs calculated in the PEA reports, are shown graphically in Figures 3, 4 and 5, respectively. The data-points in the figures are of the test data used in the ANN models, which makes-up $\frac{1}{4}$th of the overall benchmarking data-points. The other $\frac{3}{4}$ of the data were used for training the ANN model. A description of test data and training data based on Table III is provided in the previous section. When a new data becomes available to benchmark with the ANN model, the input variables in the data is simply introduced to the model, and the model provided the estimate for the output EUI, using the network node weights that were determined during the model training phase. In the figures, the predictions are somehow closer to the actual measurements.

Figures 6, 7 and 8 show the correlation rate between the measured EUIs and ANN predicted EUIs for the same plug load, lighting and HVAC data presented in Table III for both test data

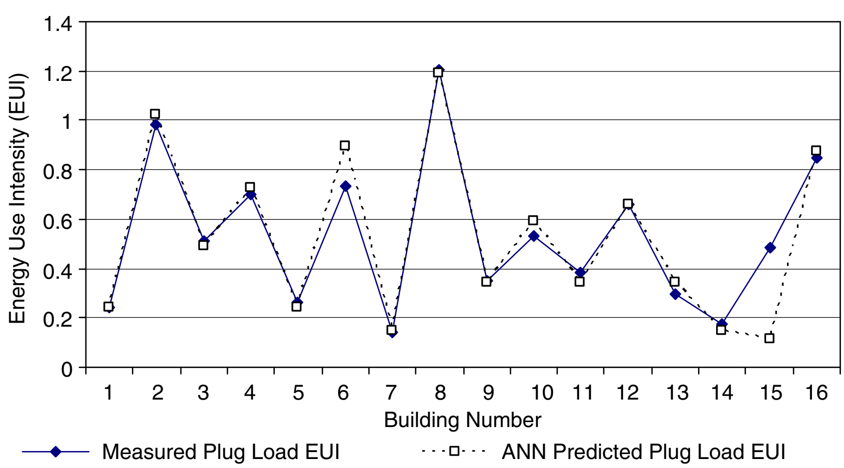

Figure 3. Comparison of ANN predicted plug load EUI to measured EUI.

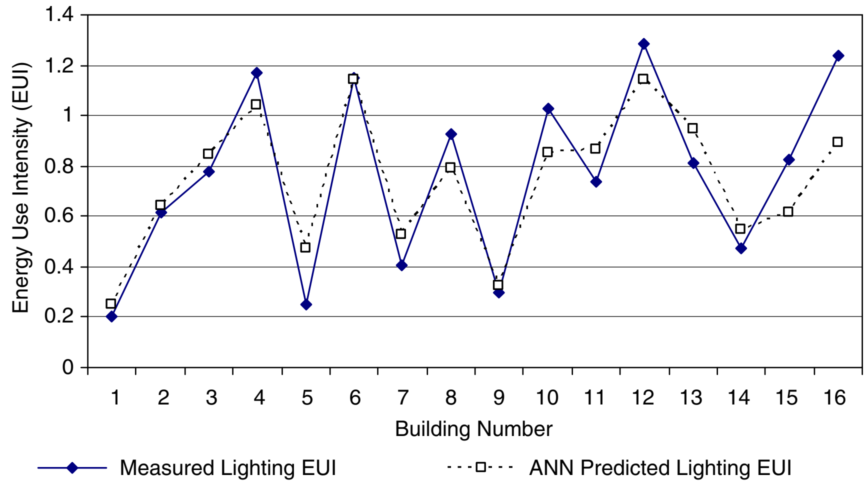

Figure 4. Comparison of ANN predicted lighting EUI to measured EUI.

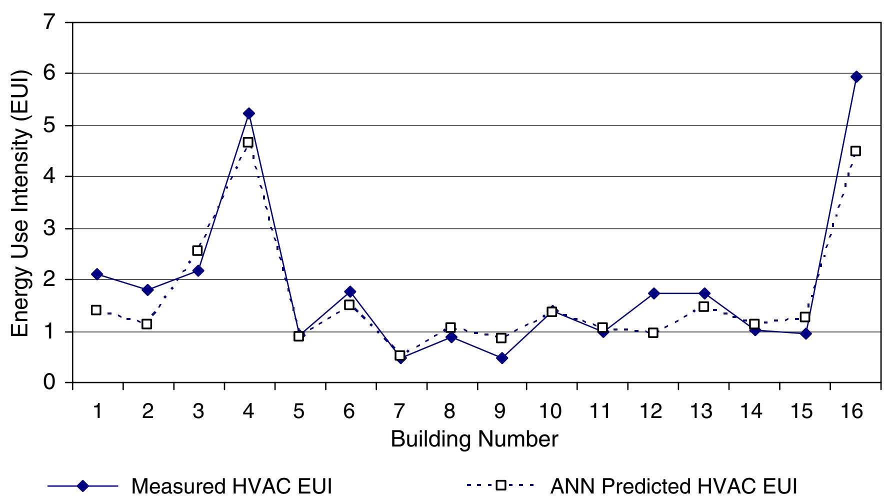

Figure 5. Comparison of ANN predicted HVAC EUI to measured EUI.

and training data. In Figures 6–8, '*A*' corresponds to the ANN predicted EUI and '*T*' corresponds to the target EUI (or the measured EUI data). The dash line is the best linear regression relating the predicted EUI to the target EUI. *R* in the figures is the correlation coefficient between the network outputs and targets. Correlation coefficient closer to 1.0 is an indication of a successful ANN model.

The test data in Figure 6, representing the plug load ANN model results, has a correlation coefficient of 0.95, which is a very good indication that the model will provide reliable prediction for a new set of survey questionnaire that the model has not seen before and EUI estimate is required. The lighting end-use ANN sub-model predictions were illustrated in Figure 7 for both

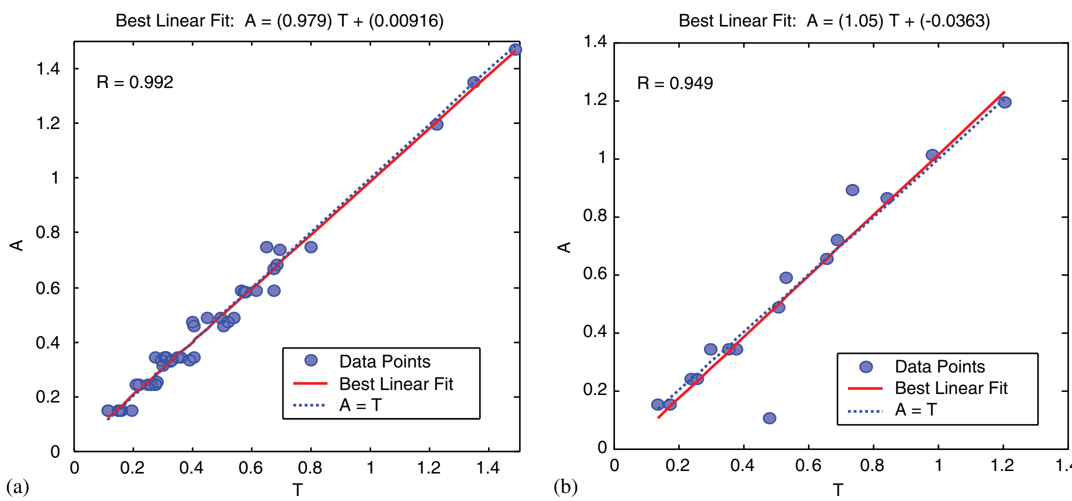

Figure 6. ANN model estimated plug load EUI (represented by A) compared against original EUI (represented by T): (a) Training data; and (b) testing data.

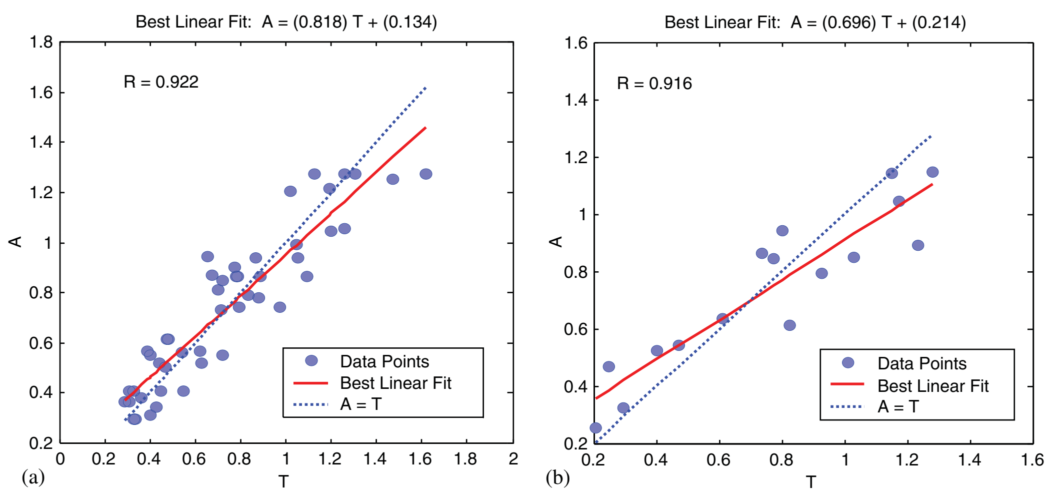

Figure 7. ANN model estimated lighting EUI (represented by A) compared against original EUI (represented by T): (a) Training data; and (b) testing data.

test data and training data. The test data in the figure has a coefficient of correlation $R = 0.92$. While it is still a good estimate of the EUIs, the input output correlation is not as good as the plug load estimates presented in Figure 6. This may be partly related to occupant interference with the lighting operations. Some occupants may leave the lights on when they leave the space and some may not, or some spaces may be used less frequently than the other spaces. Also, the survey questionnaire is aimed to capture general information on the lighting type and usage. It does not address specific questions on lighting intensity, efficiency and lighting 'on' times. The

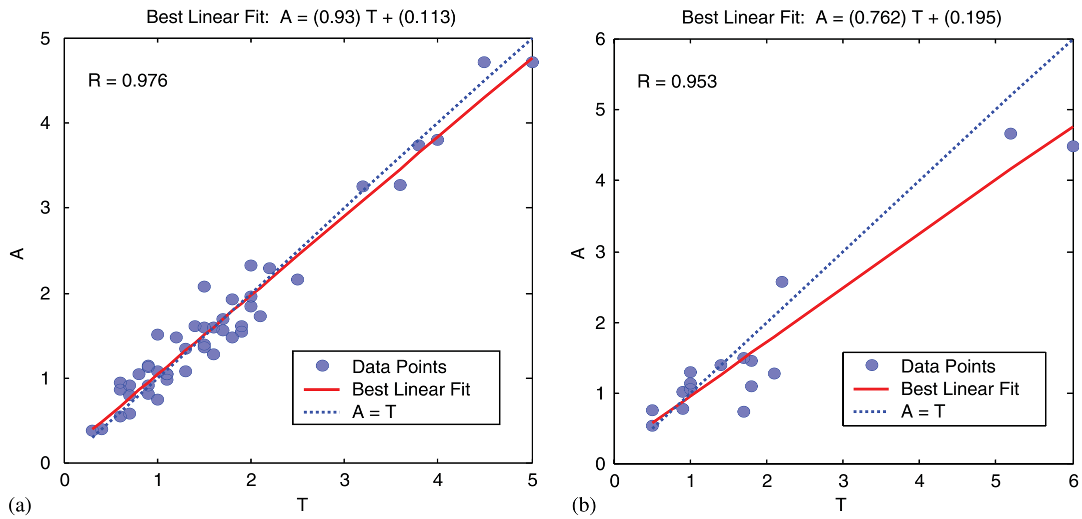

Figure 8. ANN model estimated HVAC EUI (represented by *A*) compared against measured EUI (represented by *T*): (a) Training data; and (b) testing data.

model accuracy may be improved if more detailed questions were added into the survey questionnaire, such as percentage distribution lighting by efficiency and intensity. However, it is usually difficult to find correct answers to such detailed questions during a general survey.

The HVAC end-use ANN sub-model results for both test data and training data are illustrated in Figure 8. The figure shows a coefficient of correlation of 0.95 for the test data. Having the HVAC correlation coefficient equal or higher than that of the lighting and plug load was a surprise, since estimating HVAC end-use EUI can be even more difficult than estimating the lighting end-use EUI. The determinants of HVAC energy usage is not only dependent on equipment efficiency and controls, but is also dependent on plug loads, lighting, human occupancy, HVAC designer's specifications and any alterations or renovations on the building.

The ANN sub-models for the end-use EUIs provided reasonable predictions illustrating the acceptability of the survey data for the total energy benchmarking. In the next step, the ANN benchmarking was developed with the input and output data in Table III. The details of the ANN model development was provided in the previous section. Here, we present the model results. Figure 9 present the comparison of the EUIs predicted by the ANN model vs the actual EUIs determined from the PEA reports for the test data. Figure 10 shows whole building ANN model energy use prediction for both test data and training data. The model coefficient of correlation is 0.86 based on the test data, indicating good correlation between the input variables and the output total EUI. If a new survey data with unknown EUI is inputted to the model, the model can predict the EUI of the survey building.

Another way of using this ANN benchmarking model is to estimate approximate energy savings from an energy efficiency upgrade of a building. The building upgrade may be energy-efficient lighting retrofits, air conditioning retrofits, or improvements in building envelope. This is a new concept in energy benchmarking. To the author's knowledge, currently there is no study that investigates the use of energy benchmarking models in building energy savings estimates due to an energy-efficient building retrofit. In order to test the idea, the survey data from several

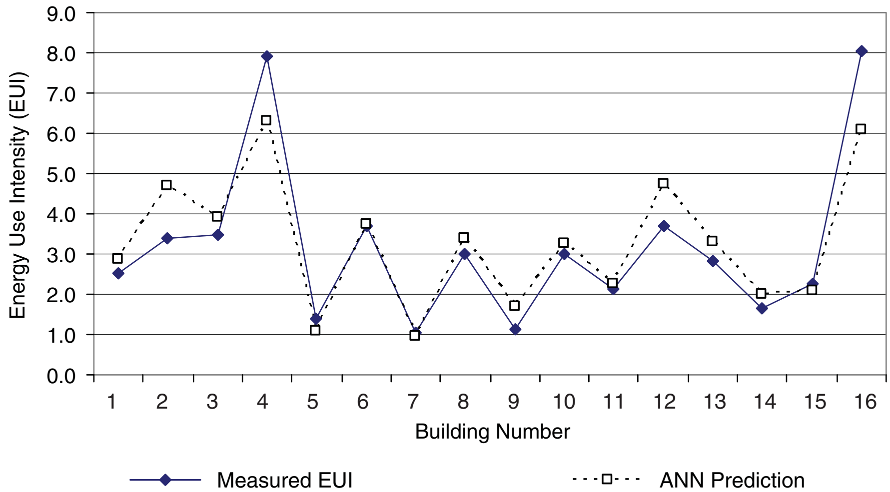

Figure 9. Comparison of ANN predicted whole building EUI to measured EUI.

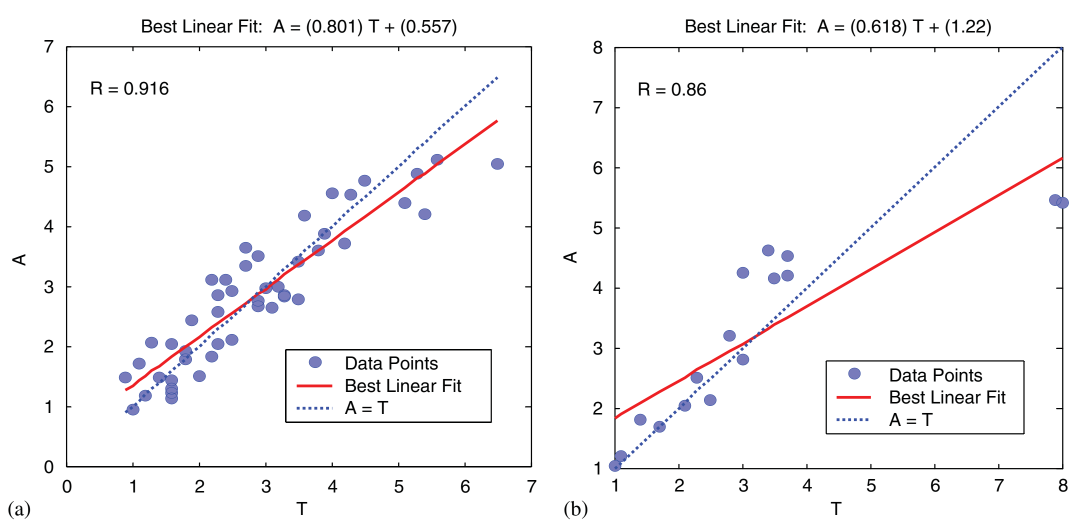

Figure 10. ANN model estimated whole building EUI (represented by A) compared against measured EUI (represented by T): (a) Training data; and (b) testing data.

of the buildings in the Table III were changed to reflect energy-efficient upgrades. Then, the new data was inputted into the ANN benchmarking program, and the EUI estimates were obtained as the ANN output. More specifically, three different building retrofits that could save energy were evaluated. Those retrofits were: (1) building interior lighting retrofits with energy-efficient alternatives, (2) building exterior lighting retrofits with energy-efficient alternatives, (3) air conditioning upgrades. No upgrades for the plug load data were possible, since it was difficult to categorize the potential energy savings upgrades on the plug loads. The selected original survey data for the purpose, which is same as the test data used in the ANN model development, is listed in Table IV.

For the building internal lighting retrofits, the data in the internal lighting column of Table IV was replaced with '1', which represents high efficiency fluorescent lighting. Then the modified data was introduced to the already developed ANN model to obtain the new EUI estimates. The resulting EUI estimates from the retrofits along with the original ANN prediction are shown in Figure 11. As can be followed from the figure, the EUI prediction after the retrofit is usually less then before the retrofit. However, the reduction in EUI is not proportional in all cases reflecting either higher energy savings or potential error factor in the method.

Similarly, for the building external lighting retrofits, the data in the external lighting column of Table IV was replaced with '1', representing low electricity consumption for external lighting. The modified data was introduced to the ANN model and new EUI estimates were obtained. Figure 12 shows the resulting EUI estimates. In this case also, the EUI predictions after the retrofit are usually less than before the retrofit. However, the reduction in EUI is not proportional in all cases reflecting either higher energy savings or potential error factor in the method.

Finally, high-efficiency central plant cooling method was selected for the HVAC retrofits, which was represented by '5' in Table IV. In the table '7' is the most energy-consuming item, and '1' is the least energy-consuming item. '1' represents window air conditioning units. It is not an energy-efficient air conditioning alternative, but because a window air conditioner is turned on or off frequently by the user, its energy consumption is less when compared to even the most energy-efficient central cooling system. Also, if a building is air conditioned by a window unit

Table IV. Data extracted from Table III for predicting energy savings from a building retrofit using the ANN benchmarking model.

Plug load input			Lighting input				HVAC input		
Computers	Fume hoods	Other equipment	Lighting hours	Floor percentage lighted	Internal lighting type	External lighting type	HVAC hours	Floor percentage air conditioned	HVAC equipment type
2	0	0	15	60	2	1	18	80	7
3	2	3	15	50	2	2	24	60	7
3	2	1	12	80	2	3	24	90	4
4	2	2	18	90	3	4	24	100	7
2	0	0	12	60	3	2	24	60	3
5	0	1	10	90	2	4	10	70	3
1	0	0	12	80	2	2	24	20	1
4	0	3	15	70	3	3	10	40	4
3	0	0	10	80	2	1	10	25	4
5	0	0	10	70	2	3	12	50	2
3	0	0	10	60	2	3	12	40	3
2	0	3	15	70	3	4	14	60	6
3	0	0	15	60	2	3	14	80	4
1	0	0	10	70	2	2	14	70	2
2	0	1	18	100	2	3	24	80	7
2	2	3	15	100	3	4	24	100	7

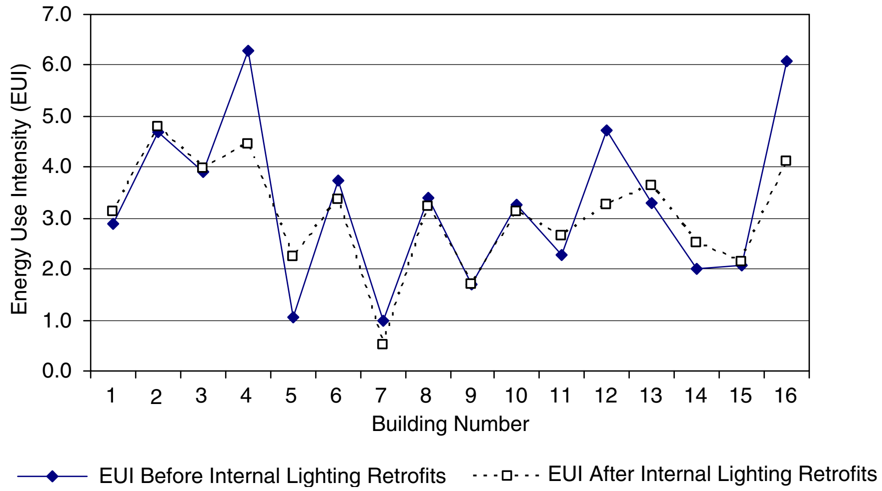

Figure 11. Energy savings prediction from a building internal lighting retrofit by using ANN benchmarking model.

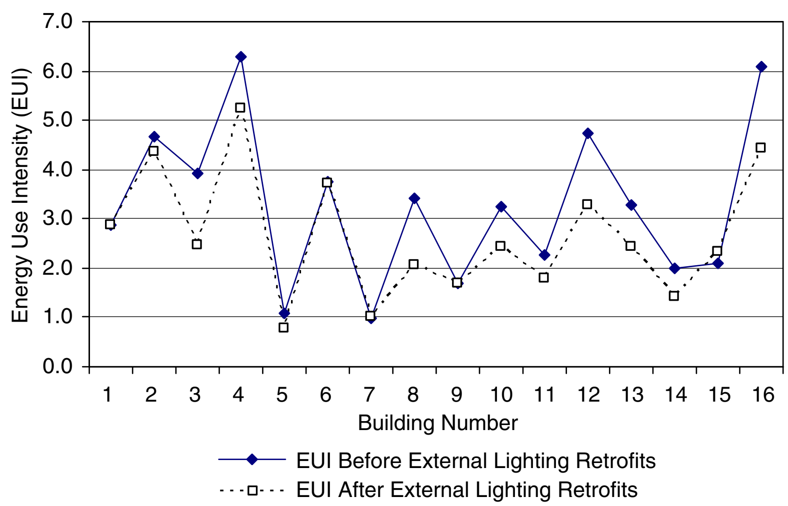

Figure 12. Energy savings prediction from a building external lighting retrofit by using ANN benchmarking model.

system, usually a small portion of the building square footage is provided with air conditioning. Whereas, a central air conditioning system usually covers a larger floor area than the window unit. Therefore, in this retrofit analysis '1' could not be selected as an energy conservation alternative. The alternative '5' was the possible energy conservation retrofit alternative in the HVAC EUI estimates. Figure 13 shows the resulting ANN prediction for EUI after the retrofit and comparison with the original prediction. The prediction for this case was somehow different

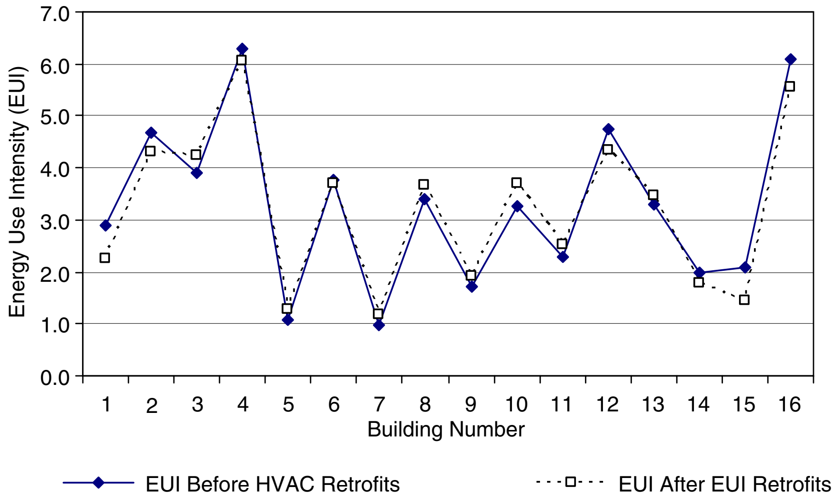

Figure 13. Energy savings prediction from a building HVAC retrofit by using ANN benchmarking model.

than the previous two cases: While the EUI decreased for some data-points in the figure, it increased on some others indicating the energy usage increased from the retrofit. This was a reasonable prediction because of the differences of HVAC systems as discussed.

The energy savings prediction capability of the ANN benchmarking program illustrated here is based on the model simulation only. Further validation either through building energy modelling or actual cases should be evaluated to prove the accountability of the prediction results, when the ANN benchmarking program is intended to be used for energy savings predictions due to a building retrofit.

4. CONCLUSIONS

Evaluating a building's energy usage efficiency by a benchmarking method is the least expansive method when time and cost is concerned. Within its current capabilities, an energy benchmarking method does not provide detailed results about the building's energy usage characteristics when compared to a PEA method or an energy feasibility analysis. However, the method serves well for identifying a building with higher energy consumption when compared to similar buildings in its category (office, hospital, school, hotel, etc.). For the future, the energy benchmarking concept may expand to provide detailed evaluation of a buildings energy usage and potential savings through retrofits based on sufficient data and content of survey questionnaire. The study presented here may serve in the development of the future benchmarking concept. Specifically, the ANN-based analysis approach presented here brings flexibility in data processing and modelling. The concept of the energy savings prediction through the benchmarking model is introduced for the first time in this study.

The data used in the model was collected by reviewing existing energy audit reports for over 60 buildings. Large variations existed in the data inputs including the building square footages, building ages, plug load densities, lighting densities and building ventilation requirements and air conditioning. Air conditioning was the primary consuming component of the buildings' electricity. Also, the dataset was specific to the Hawaiian tropical climate, where the variations between the seasons are at minimum and most of the building equipment operates throughout the year. Compared to data from other parts of the U.S. or other non-tropical countries, potential energy recording errors/deviations were at minimum in the data used here. The ANN model was quite successful which had a correlation coefficient of 0.92 for the whole building EUI prediction.

This study also presents the potential use of benchmarking method for energy savings prediction due to a building's energy efficiency upgrades. Several energy-efficient upgrades were identified including building internal and external lighting replacement with energy-efficient alternatives, and HVAC upgrades. Benchmarking data for the buildings in the ANN test set were revised with the corresponding numerical data representing the upgrades. The whole building EUIs after the building upgrades were predicted with the ANN model. While results showed decrease in EUIs in general, it was not possible to measure the accuracy of the prediction, since no actual data was available to compare the predictions. Overall, the study presents potential use of ANN methods in energy benchmarking. The model can be extended to predict energy savings due to a building's energy-efficient upgrades. The further studies on the ANN benchmarking concept includes use of larger databases such as CBECS or CEUS, and testing the energy savings predictions through benchmarking methods with actual data.

REFERENCES

Federspiel C, Zhang Q, Arens E. 2002. Model-based benchmarking with applications to laboratory buildings. *Energy and Buildings* **34**(3):203–214.

Hagan MT, Demuth HB, Beale MH. 1997. *Neural Network Design*. PWS Publishing Co.: Boston, MA.

Hicks TW, Von Neida B. 2000. An evaluation of America's first ENERGY STAR buildings: the class of 1999. *Proceedings of the ACEEE 2003 Summer Study on Energy Efficiency in Buildings,* vol. 4, 177–185.

Kinney S, Piette MA. 2002. Development of California commercial building energy benchmarking database. *Information and Electronic Technologies*, vol. 7, 109–120.

Mathew P, Sartor D, Van Geet O, Reilly S. 2003. Rating energy efficiency and sustainability in laboratories: results and lessons from the Labs21 program. *Proceedings of the ACEEE 2003 Summer Study on Energy Efficiency in Buildings,* vol. 4, 321–329.

Matson N, Piette MA. 2005. Review of California and national methods for energy-performance benchmarking for commercial buildings. *California Energy Commission, Public Interest Energy Research Program, LBNL No. 57364.*

Sharp T. 1996. Energy benchmarking in commercial office buildings. *Proceedings of the ACEEE 1996 Summer Study on Energy Efficiency in Buildings,* vol. 4, 321–329.

Sharp T. 1998. Benchmarking energy use in schools. *Proceedings of the ACEEE 1998 Summer Study on Energy Efficiency in Building,* vol. 3, 305–316.

Yalcintas M, Akkurt S. 2005. Artificial neural networks applications in building energy predictions and a case study for tropical climates. *International Journal of Energy Research* **29**:891–901.

Zurada MJ. 1992. *Introduction to artificial neural systems*. PWS Publishing Company: Boston, MA, U.S.A.