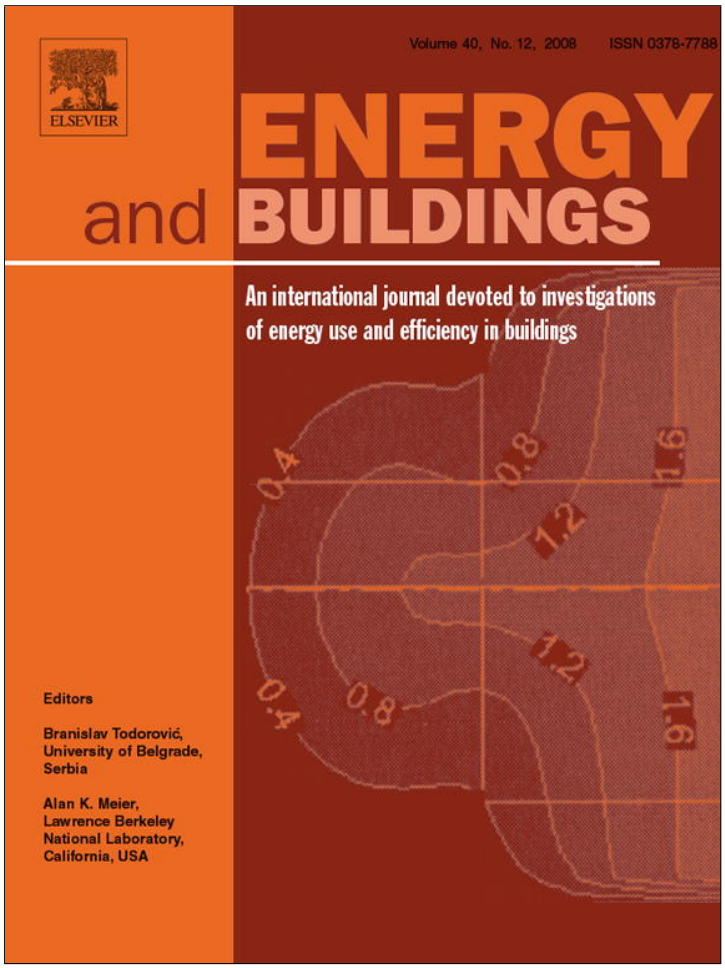

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Energy-savings predictions for building-equipment retrofits

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ABSTRACT

Energy-consumption data collected from two equipment-retrofit projects before and after the retrofits was used to develop a model that estimates energy savings from retrofit projects. The computation method used in the model is based on Artificial Neural Networks (ANN). The model integrates weather variables, specific equipment-usage and occupancy data, and building-operation schedules into the pre-retrofit energy-usage pattern. It then estimates the energy usage of the pre-retrofit equipment in the post-retrofit period by using weather data, occupancy, and building-operation schedules in the post-retrofit period. The difference between the recorded energy usage of the post-retrofit equipment and the predicted energy usage of the pre-retrofit equipment in the post-retrofit period is the estimate of energy savings. For the two retrofit projects used in the ANN model, the coefficient of correlation varied from 0.957 to 0.844; the root mean square error varied from 6.81% to 16.4%; and the mean absolute error varied from 5.31% to 9.95%. Additionally, the sensitivity of the model to the input variables was analyzed with one of the retrofit project data. Dry bulb temperature, wet bulb temperature, and time (representing building-occupancy and equipment-operation schedule) were determined as the most effective variables in the ANN model. The research and findings are presented in this paper.

1. Introduction

One particular application of energy-usage analyses for buildings is the estimation of the energy saved by an equipment replacement/retrofit. A reliable estimate of the energy savings from an equipment-retrofit project is important for utility companies, performance contractors, and building owners. The building owners use the information for decision-making. The utility companies use it to determine rebates awarded to the building owners. If performance contractors are involved in the equipment-retrofit project, an accurate prediction of energy savings is the main consideration in determining the construction fee and the profit range.

The main challenge in determining the energy savings from an equipment retrofit lies in identifying the data before and after a building's equipment has been replaced/retrofitted. The energy usage of building equipment is sensitive to variations in weather, internal building load (e.g., occupancy, lighting, and miscellaneous loads), and HVAC equipment-operation schedules. It is, therefore, difficult to compare the energy usage in the pre-retrofit and post-retrofit periods to determine the energy savings. This difficulty, along with limitations in the linear regression methods that are commonly used in processing measured data, causes large discrepancies between the estimated energy savings and the actual energy savings of an equipment retrofit. Thus, there is a significant need for a method that can accurately predict the energy saved by a retrofit.

The procedure for estimating the energy savings from a retrofit project should include the following steps: (i) measure the energy usage of the equipment to be replaced/retrofitted for a period of time, usually on the order of several weeks (pre-retrofit measurements); (ii) develop a model that relates the equipment energy usage to other relevant variables such as weather, building-occupancy, operation hours, etc.; (iii) measure the energy usage of the equipment after the equipment replacement/retrofit for a period of time, usually on the order of several weeks (post-retrofit measurements); (iv) use weather data and other building variables from the post-retrofit period with the pre-retrofit model to estimate the energy that would have been used if the original equipment had not been retrofitted; (v) the difference between the post-retrofit measurements and the pre-retrofit estimates for the post-retrofit period is the energy savings from the retrofit project.

In the literature, there are two groups of studies that aim to accurately estimate the energy savings from retrofit projects. The first group makes use of utility bill statistics to develop energy models for the whole building as a function of weather, occupancy, and other building variables [1]. The second group utilizes energy measurements before and after equipment retrofits to develop

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models based either on a statistical approach or on artificial neural networks, using hourly weather and other variables as input [2].

An example from the first group is PRIZM, a statistical model that processes year-long monthly billing data from a residential building or a small commercial buildings with consistent energy-usage characteristics to produce a weather-adjusted Normalized Annual Consumption (NAC) index [1,7]. The model assumes a constant rate of occupancy and electricity usage, with no seasonal variations. The program is run for pre-retrofit and post-retrofit periods to determine the savings from a retrofit project. The main principle of the program is the use of base reference temperatures (or balance-point temperatures) to compute heating and cooling degree days. The balance-point temperature is the temperature below which no building cooling is required (cooling degree day estimate, CDD) or above which no heating is required (heating degree day estimate, HDD). The balance-point temperature may vary by the energy periods. The method used in PRIZM is called the Variable Base Degree Day (VBDD) method, which takes into account the dependence of the balance-point temperature on building loads. Aside from the balance-point temperature, the model assumes constant energy usage for basic building-functions, such as refrigerator operation or water heating for each energy use period. This limits the applicability of the VBDD method to residential or small commercial buildings.

Another study, by Sonderegger [3], has focused on developing a baseline equation that correlates past utility bills to observable building variables, such as occupancy, plug loads, lighting, vocational shutdowns, and weather data (mainly, daily outdoor dry bulb temperature), and projects the correlation into the future. The baseline equation estimates the electricity usage that would have occurred in the absence of the implemented energy-saving measures. The approach has specifically considered large buildings with varying occupancy and other electrical demands. Integration of variables such as occupancy, plug loads, lighting and vocational shutdowns, in addition to the main weather data, is what differentiates this model from PRIZM. In other words, Sonderegger has extended the VBDD model to integrate variables to account for non-weather-related building energy use with a two-step approach. First, the building's energy usage is regressed for the balance-point temperature. Then, a multivariable regression model is developed to include other factors that may influence the building's energy usage.

The limitation of the VBDD method in capturing the nonlinear relationship between the ambient temperature and the heating and cooling energy demand has lead to the development of a new model, called the four-parameter Change-Point (CP) model (or piecewise linear regression model). The CP model finds a linear relationship between the building's energy use and outdoor temperatures, both above and below an outdoor air change-point temperature. The CP model is strictly a function of weather variables. It does not include any other building variables such as occupancy and building hours [1]. Multivariable Regression (MVR) combined with CP, known as the CP–MVR method, estimates the building's energy use as function of weather variables (HDD and CDD) and other variables [1].

The data required as input for the above methods is relatively easy to access (HDD, CDD, monthly utility bills). However, to estimate the energy savings from a particular equipment retrofit, the entire building's energy usage is simulated. This reduces the accuracy of the energy-savings estimate for a retrofit project. Furthermore, the models are insufficient when the study building is large or has multiple functions (e.g., buildings with office space, residential units, restaurants, retail facilities, etc.). The energy usage of such a building is expected to be a complex function of climate, building envelope and other characteristics, building-occupancy and use, heating and air conditioning equipment type and schedule, and other equipment properties.

A more effective procedure for predicting the energy savings from a retrofit project, especially for large and complex facilities, is to measure the energy consumption of the particular equipment to be retrofitted before and after the retrofit, develop an energy model for the retrofit equipment, and compare the calculated pre-retrofit energy usage for the post-retrofit period to the measured post-retrofit energy use. Such models have been developed at limited capacities. Hourly weather data and other building variables are correlated to the measured energy usage of particular equipment. Multiple Linear Regression (MLR) models and nonlinear regression methods such as Artificial Neural Networks (ANN) are used for this type of model [2,4,8,9].

Typical inputs to ANN or MLR models include extensive hourly weather data and building operations data. Weather data may include dry bulb temperature, wet bulb temperature, relative humidity or dew point temperature, wind speed, and solar radiation. Building operations data may include building-occupancy rates, hours of operation, meals served in the case of a restaurant, computer usage in the case of an office building, heating and cooling schedule, weekday and weekend variations in building operation, etc. Advantages of the ANN methods over the MLR methods are: faster learning time, simplicity in analysis, better prediction accuracy, and ability to model fluctuations in a building's energy use.

ANN applications in energy-usage predictions for buildings and energy-savings predictions for retrofit projects are more recent than linear regression statistical modeling. Furthermore, ANN studies are still in the research stage, with few actual applications. In the study, Yalcintas and Akkurt [2] provided a review of ANN applications for energy-usage estimates for buildings and energy-savings estimates for retrofit projects. The studies reviewed used building energy data from various sources such as building-energy simulations, energy measurements from laboratory experimental equipment, and energy measurements for actual retrofit equipment. For a reliable ANN model, repeated energy measurements from retrofit equipment should be used to further develop the model. To the author's knowledge, no software product is available to predict the energy savings from a retrofit project using the ANN method with the above listed climate and building data. In contrast, several software products based on statistical analysis, such as ETracker and PRIZM, have already been used and recommended by various US and international agencies, organizations and schools (EPA, IPMVP, ASHRAE, Princeton University).

This study presents an ANN model developed to predict the energy savings from two retrofit projects that were carried out at hotels in Hawaii. The first project integrated Variable Frequency Drives (VFDs) on existing air-handling units and installed energy management systems in all guest rooms. The second project replaced an old cooling tower with a new, energy-efficient cooling tower. Actual electricity-usage measurements before and after the retrofit were used in the ANN models for both projects. Hourly weather data was used as input. The study also evaluated the importance of each input variable in the ANN model.

2. Artificial neural network modeling

The computational structure of ANN consists of an input layer, which accepts patterns from the environment, and an output layer, which shows the response of the model to the environmental variables. There are also hidden layers that do not interact directly with the environment; rather, their function is to relate the input to the output through the use of weights, biases and transfer functions. The neural network training process modifies the

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. Many studies on ANN theory have been published along with the development of the method. The theory of Neural Networks presented by Zurade [5], is accessible to readers with various technical training. A practical description of ANN methods with sample applications is presented by Hagan et al. [6].

The data used for the ANN model presented here consisted of hourly electricity measurements from the retrofitted equipment over a period of several weeks before and after the equipment retrofit, as well as hourly weather data obtained from the U.S. National Weather Service corresponding to the same periods. The first retrofit project involved the installation of an energy management system in hotel rooms and the integration of Variable Frequency Drives (VFDs) on existing air-handling units. The second retrofit project involved the replacement of an old cooling tower with a new, energy-efficient cooling tower. The hourly weather data included dry bulb temperature, dew point temperature, wind speed and direction, visibility, and air pressure, corresponding to the pre-retrofit and post-retrofit periods for both projects. The hour of the day was also recorded to account for variations in occupancy throughout a day. Table 1 lists the input and output variables used in the ANN model.

The ANN model used in this study is based on the Levenberg–Marquardt back-propagation algorithm. A three-layer feed-forward configuration including an input layer, a hidden layer and an output layer was developed. The weather data was the input to the model, and the electricity measurement was the output. For both retrofit projects, the data was divided into two subsets. The first three-fourths of the data, making up the first subset, were used for ANN training and testing. The last fourth of the original data, making up the second subset, was used to evaluate the prediction capacity of the developed ANN model. The training data from the first subset was used for computing the ANN weights and biases, and the testing data, again from the first subset, was used to test the accuracy of the ANN model. Every fourth row in the first set was assigned for testing, and the rest of the data in the first subset was assigned for training. In the ANN model training process, the training continued until the sum of the squared errors in the Levenberg–Marquardt algorithm reached a steady level, at which point the training stopped, and the model was tested with the test data. The test set error was not used in computations during the training process; it was used only to evaluate the accuracy of the ANN model. A small error is an indication of an acceptable ANN model. After the model was established, its prediction capacity was evaluated by putting the second subset data into the model and comparing the model output with the actual electricity measurements.

MATLAB's 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 carried out so that the mean value of each variable was zero and the standard deviation was unity. The activation function used in the ANN model was a sigmoid function. To avoid over-fitting the data and to provide good generalization capability to the developed ANN algorithm, an automated regularization method was used. This automated regularization feature is built into the MATLAB Levenberg–Marquardt algorithm that is used for the ANN modeling in the study.

Table 1
The data used for initial ANN model construction

Variable	ANN model data	
	Input	Output
Time (h)	X	
Dry bulb temperature	X	
Dew point temperature	X	
Wind speed	X	
Wind direction	X	
Air pressure	X	
Visibility	X	
Retrofit equipment power consumption		X

3. Results and discussion

Case 1 retrofit project ANN model: the energy measurement data used in this study are from a hotel in Honolulu, Hawaii. The hotel had about 2250 guestrooms, as well as a number of restaurants, meeting rooms, and retail stores. The hotel was served with two 1400-ton capacity chillers. Only one chiller was operational most of the time, the second chiller serving as back-up. The particular retrofit project in the hotel consisted of installing energy management systems in the hotel rooms and integrating Variable Frequency Drives (VFDs) on the air-handling units. A number of air-handling units having varying fan motor sizes from 5 to 25 HP served the restaurants, meeting rooms and other common areas. Hotel rooms had fan coil units with cooling capacities ranging from 0.5 to 1.0 ton. The energy management system monitored the occupancy in the hotel rooms and the open/closed state of the balcony sliding doors. If the sliding doors were left open more than 5 min, the chilled water supply valve to the fan coil unit was turned off, and the fan cycle was left on. If no occupancy was sensed in the room for more than 30 min, the room temperature set point was increased to 87 F, from a normal occupancy set point of 75 F. Pre-retrofit and post-retrofit measurements were taken from the chiller plant for a total of about 3 weeks. Each measurement included hourly electricity demand (or kW) recordings. In addition to the chiller plant, the building saved energy from the air-handling unit operations with new VFDs. However, electricity measurements from the air-handling units were not available. Therefore, only the energy savings from the chiller plant were included in this analysis.

Case 2 retrofit project ANN model: this retrofit project was for another hotel building. The hotel was served with three 500-ton capacity chillers. Only two chillers were operational most of the time. The third chiller served as back-up. The particular retrofit project involved replacing two old cooling towers with new ones. The old cooling towers each had 50 HP constant speed fan motors. The new cooling towers had equal capacity fan motors; in addition, the fan motors were equipped with Variable Frequency Drives (VFDs). Electricity usage data was recorded from the old cooling towers for a 3-week-long pre-retrofit monitoring period, and from the new cooling towers for a 10-day-long post-retrofit monitoring period. Each measurement included hourly electricity demand (or kW) recordings.

Because of the sensitivity of the data presented, we have omitted any information that might reveal the identity of the facilities.

For both case studies, first, the ANN model for the pre-retrofit period was developed. The inputs to the model were the weather variables and the hour of the day, and the output was the electricity usage measured by the chiller (for Case 1) and cooling tower (for Case 2), as listed in Table 1. Different numbers of hidden layer nodes were tested during the development of the model. A three-node hidden layer provided the best predictions. A total of 393 sets of Case 1 data and 336 sets of Case 2 data were used for ANN training and testing. In addition, 113 sets of Case 1 data and 145 sets of Case 2 data, corresponding to a later time segment, were saved for evaluating the ANN model's prediction capability. Figs. 1 and 2 show Case 1 and Case 2 pre-retrofit and post-retrofit data.

The following error measurement parameters were used in evaluating the performance of the developed ANN model:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{1}$$

$$\mathrm{RMSPE} = \frac{\sqrt{1/n\left(\sum_{i=1}^{n}(y_i - x_i)^2\right)}}{\bar{y}} \tag{2}$$

$$R = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{3}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{x_i}\right| \tag{4}$$

In the above equations, RMSE is the root mean square error, RMSPE is the root mean square percentage error, R is the correlation coefficient, and MAPE is the mean absolute percentage error. The parameters x_i are the measured data, y_i are the ANN model predictions, n is the number of data points, $\bar{x}$ is the mean value of the measured data, and $\bar{y}$ is the mean value of the ANN model predictions.

Fig. 3 shows measured and predicted electricity usage for both training and test data for the Case 1 retrofit project in the pre-retrofit period. In this figure, the dashed line is the best linear regression relating the predicted electricity usage to the actual measurements. R is the correlation coefficient between the ANN outputs and actual measurements. A correlation coefficient closer to 1.0 is an indication of a successful ANN model. The coefficient of correlation for training and testing data are 0.957 and 0.912, respectively. The error measurement parameters are presented in Table 2.

Similarly, Fig. 4 shows measured and predicted electricity usage for training and testing data for the Case 2 retrofit project in the pre-retrofit period. The coefficients of correlation for training and testing data are 0.917 and 0.844, respectively. The error measurement parameters are presented in Table 2.

To evaluate the prediction capacity of the ANN model, a set of input data for a later time segment (still in the pre-retrofit time period) for the Case 1 retrofit project was fed into the developed ANN model. The ANN output was compared to the actual measurements. Figs. 5 and 6 show the results for the Case 1 and Case 2 retrofit projects, respectively. The coefficient of correlation between the predicted and measured values is 0.945 for the Case 1 retrofit project and 0.822 for the Case 2 retrofit project. The error measurement parameters for both Case 1 and Case 2 evaluation data are presented in Table 2.

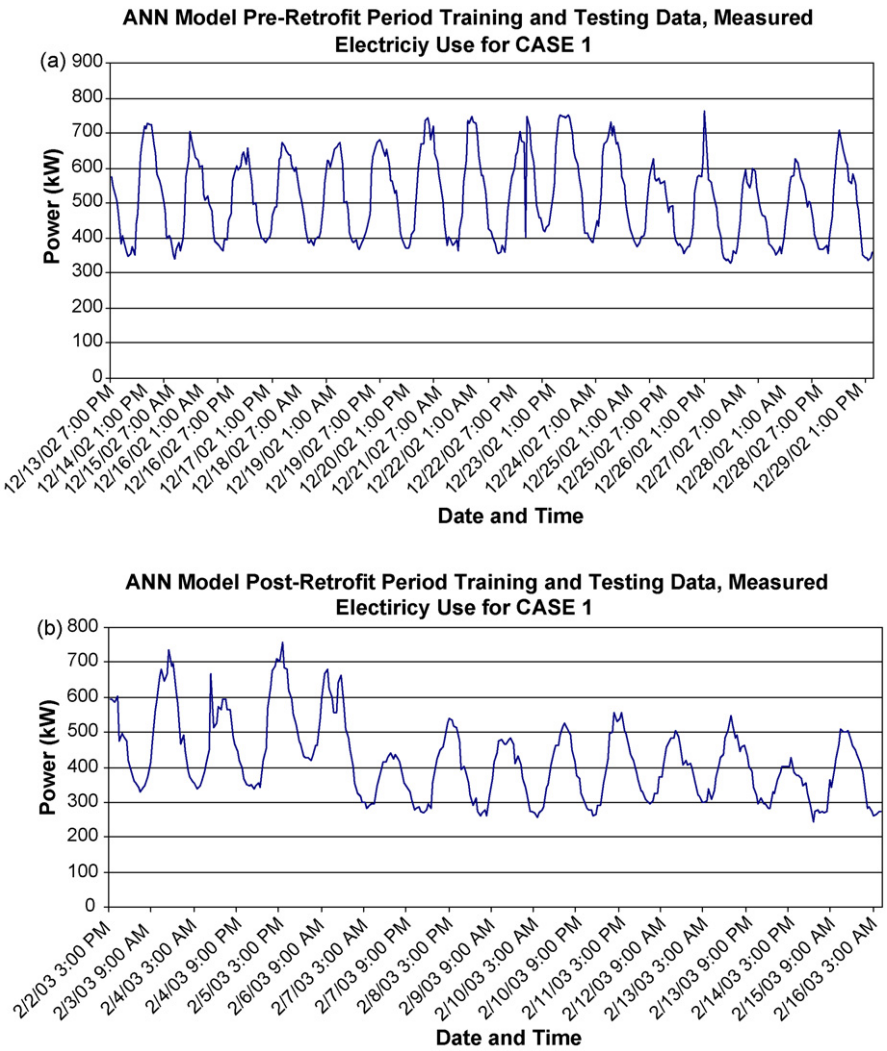

Fig. 1. (a) Training and testing data measured over the pre-retrofit period for the Case 1 retrofit project. (b) Training and testing data measured over the post-retrofit period for the Case 1 retrofit project.

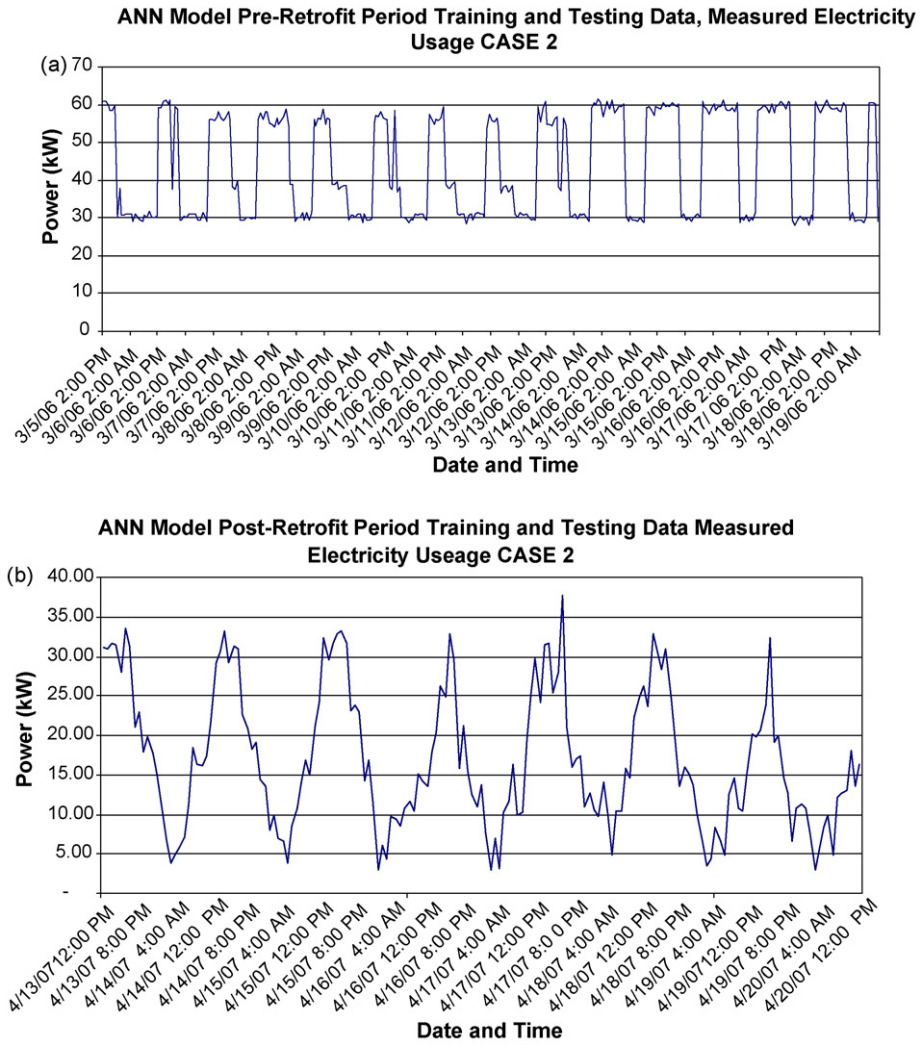

Fig. 2. (a) Training and testing data measured over the pre-retrofit period for the Case 2 retrofit project. (b) Training and testing data measured over the post-retrofit period for the Case 2 retrofit project.

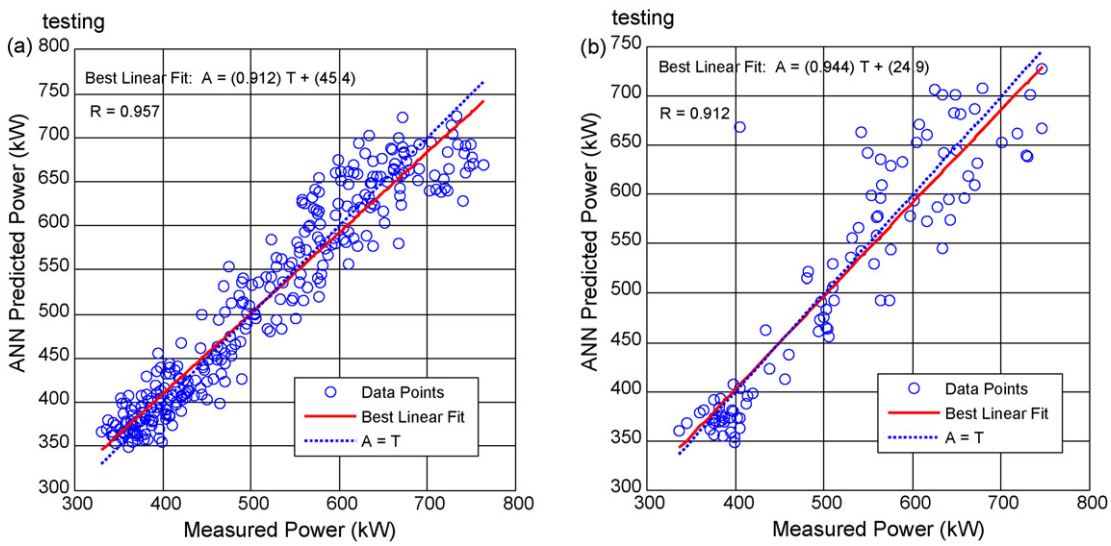

Fig. 3. Predicted vs. measured electricity usage over the pre-retrofit period for the Case 1 retrofit project: (a) training data, (b) testing data.

Table 2
ANN model testing, training and evaluation error measurement parameters for Case 1 and Case 2 retrofit projects with pre-retrofit data

	ANN model training				ANN model testing				ANN model evaluation			
	R	RMSE kW	RMSPE %	MEPA %	*R*	RMSE kW	RMSPE %	MEPA %	*R*	RMSE kW	RMSPE %	MEPA %
Case 1	0.957	34.92	6.81	5.31	0.912	49.27	9.48	6.85	0.945	52.23	9.68	8.11
Case 2	0.917	5.43	12.38	7.86	0.844	7.35	16.40	9.95	0.822	7.88	17.40	10.60

The goal in developing the ANN model for the pre-retrofit period was to estimate the hypothetical energy-consumption rate of the pre-retrofit equipment in the post-retrofit period. Therefore, in the next step, weather data for the post-retrofit period was used in the pre-retrofit model, and the energy-consumption rate was calculated assuming that the pre-retrofit equipment remained operational in the post-retrofit period. Figs. 7 and 8 show the predictions of the pre-retrofit model in the post-retrofit period and the actual measured electricity usage of the post-retrofit equipment, for the Case 1 and Case 2 retrofit projects, respectively. For Case 1, the average pre-retrofit equipment power during the post-retrofit period is 449 kW. The average post-retrofit equipment power during the same period is 388 kW. The difference of 53 kW, or 12%, is the average power savings from the retrofit project. For Case 2, the average pre-retrofit equipment power during the post-retrofit period is 42 kW. The average post-retrofit equipment power during the same period is 17 kW. The difference of 25 kW, or 60%, is the average power savings from the retrofit project.

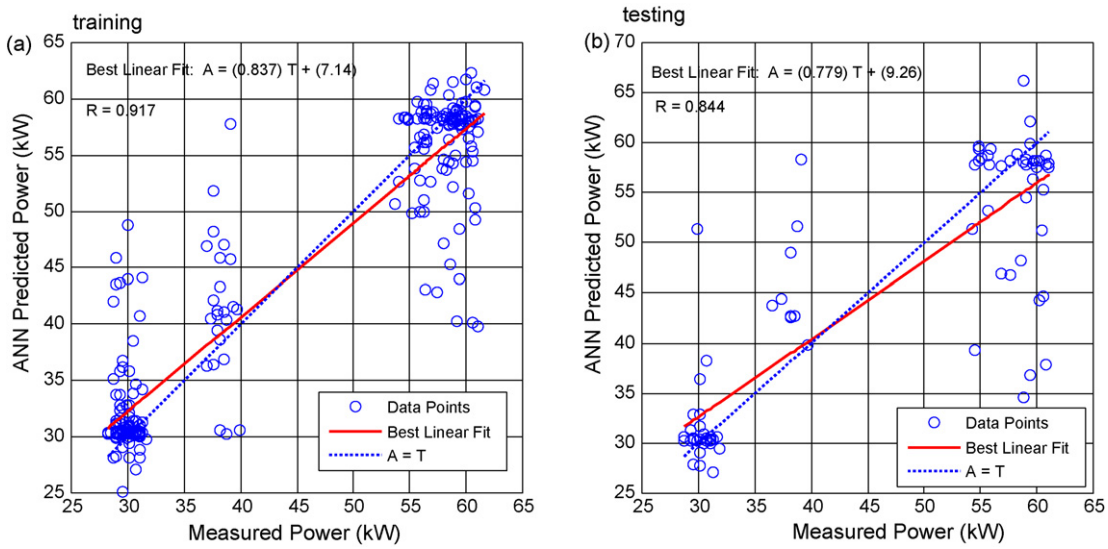

Fig. 4. Predicted vs. measured electricity usage over the pre-retrofit period for the Case 2 retrofit project: (a) training data, (b) testing data.

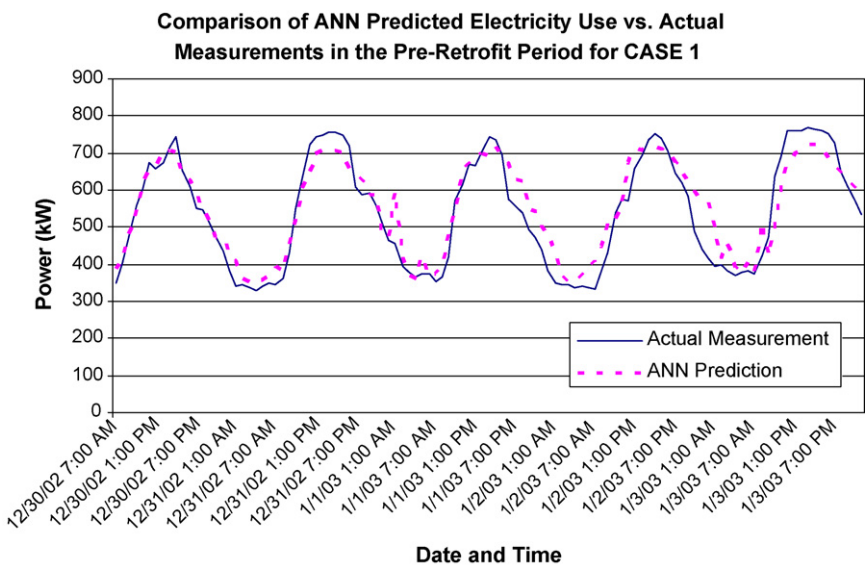

Fig. 5. Comparison of predicted electricity usage and actual measurements in the pre-retrofit period for the Case 1 retrofit project evaluation data.

Another way to estimate the energy savings from the retrofit project would be to apply the reverse method; i.e., develop an ANN model using weather data and energy measurements from the post-retrofit period, and calculate the hypothetical energy usage of the post-retrofit equipment in the pre-retrofit period. Since the weather variables are different in the pre-retrofit and post-retrofit periods, the energy savings calculated by the direct and reverse methods are not expected to be the same. Nonetheless, the order of magnitude of the calculated energy savings should be the same. In addition, instead of relying on just the estimate from the direct analysis, one can take the average of the estimates from both direct and reverse analyses. Fig. 9 shows the output of the post-retrofit model in the pre-retrofit period, and the actual measured electricity usage of the pre-retrofit equipment, for the Case 1 retrofit project. The average post-retrofit equipment power usage during this period is 504 kW. From the measurements, the average pre-retrofit equipment power usage during the same period is 539 kW. The difference of 35 kW is the average power that would have been saved if the post-retrofit equipment had been in place during the pre-retrofit energy measurement period. Fig. 10 shows the same comparison for the Case 2 retrofit project. The average post-retrofit equipment power usage during this period is 23 kW. From the measurements, the average pre-retrofit equipment power usage during the same period is 45 kW. The difference of 22 kW is the potential energy savings.

The two energy-savings estimates for Case 2, shown in Figs. 8 and 10, are relatively close. This is expected, since the pre-retrofit and post-retrofit periods for Case 2 are in the same season (approximately 1 year apart). In contrast, the two energy-savings estimates for Case 1, shown in Figs. 7 and 9, are different. This is also expected, since the pre-retrofit and post-retrofit periods belong to different seasons. Nonetheless, since the energy savings from a retrofit project are much larger than climate dependent energy-usage variations, using either of the two energy-savings estimates, or the average of the two, still yields an approximate estimate of energy savings from the Case 1 equipment-retrofit

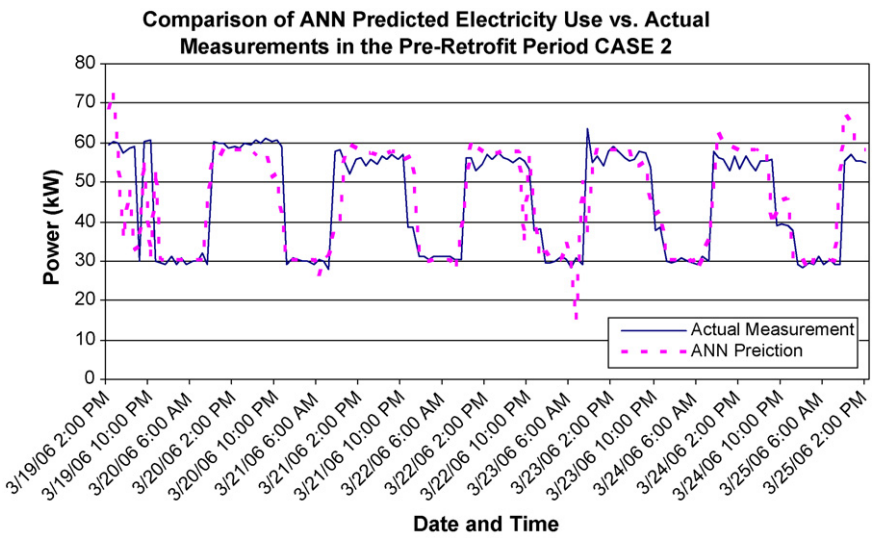

Fig. 6. Comparison of predicted electricity usage and actual measurements in the pre-retrofit period for the Case 2 retrofit project evaluation data.

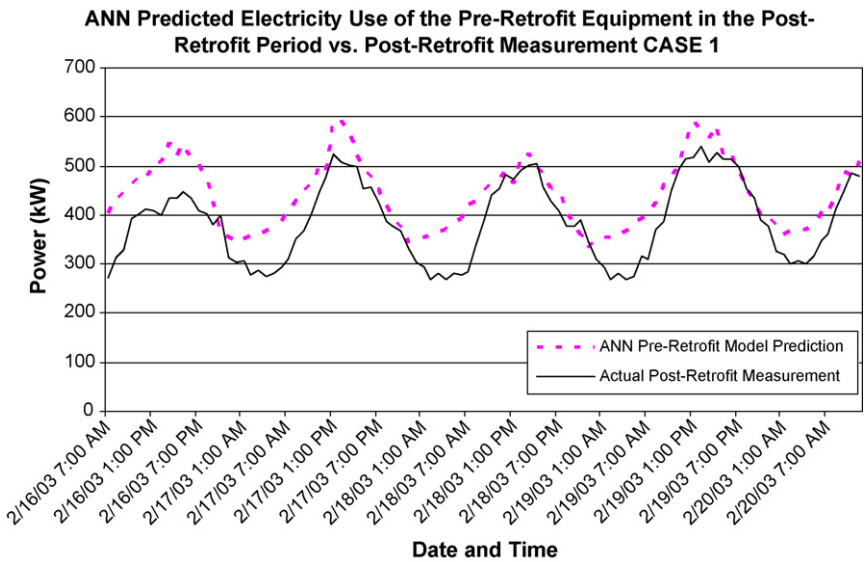

Fig. 7. ANN predicted electricity usage of the pre-retrofit equipment in the post-retrofit period in comparison to post-retrofit measurements, showing the energy savings for the Case 1 retrofit project.

project. A method that includes long-term meteorological data, such as TMY2 data, can yield more accurate predictions. In such a study, ANN models would be developed for both pre-retrofit and post-retrofit periods. Then the energy usage of both pre-retrofit and post-retrofit equipments would be calculated for 1 year's TMY2 climate data. The difference between the calculated energy usages would give 1-year's energy savings from the retrofit project.

The overall energy savings for the Case 1 retrofit project is estimated to be about 385,000 kW h/year. This was calculated by the averaging the 35 and 53 kW power savings that were calculated using the two methods. Similarly, the overall energy savings for the Case 2 retrofit project is estimated to be about 206,000 kW h/year. This was calculated by the averaging the 22 and 25 kW power savings that were calculated using the two methods.

An analysis of the sensitivity of the ANN model predictions to the weather variables was also performed. Originally, a total of seven weather variables were used in developing the ANN model, as listed in Table 1. To determine which variables had more influence on the model, two approaches were followed: (1) different ANN models were developed using only six of the variables out of the original seven, each time removing a different variable from the input set. (2) Based on the observations made using the first approach, the input variables were ordered by their influence in the model. Different ANN models were then developed, each time removing one variable from the input data set permanently, following the order of the influence identified using the fist approach. Post-retrofit measurements and corresponding weather data for the Case 1 retrofit project were used for the sensitivity analysis. Coefficients of correlation calculated for the ANN training data were used to evaluate sensitivity.

Tables 3 and 4 list ANN model inputs and corresponding coefficients of correlation for each analysis, using the first and second approaches, respectively. Removing one input variable at a

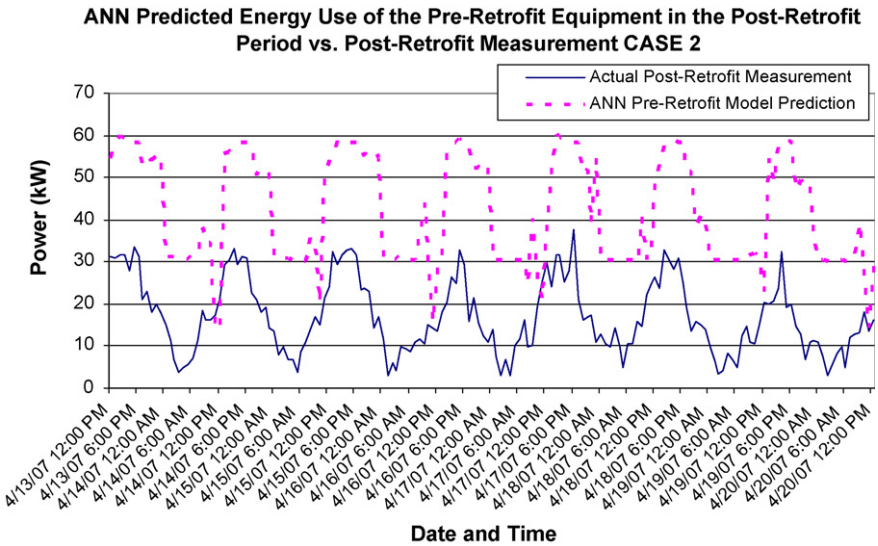

Fig. 8. ANN predicted electricity usage of the pre-retrofit equipment in the post-retrofit period in comparison to post-retrofit measurements, showing the energy savings for the Case 2 retrofit project.

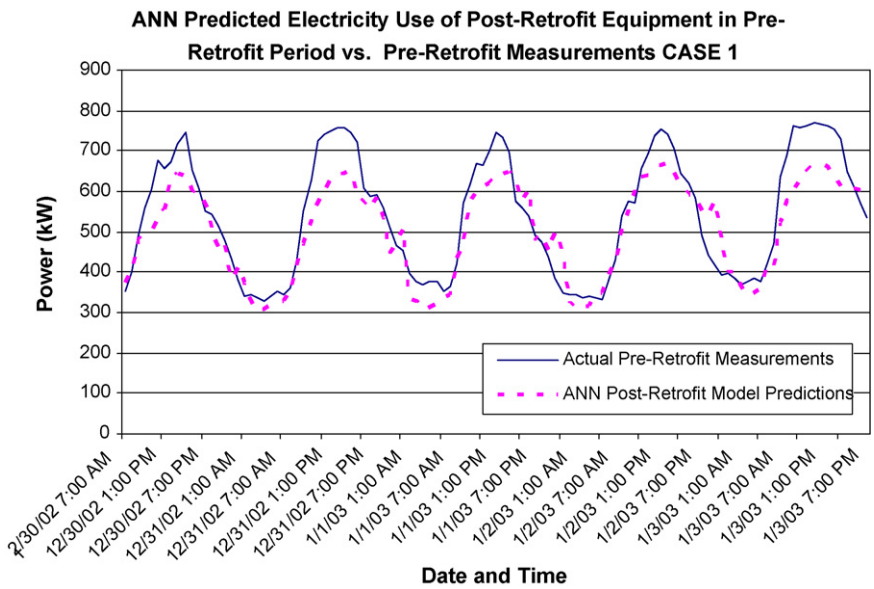

Fig. 9. ANN predicted electricity usage of the post-retrofit equipment in the pre-retrofit period in comparison to pre-retrofit measurements, showing the energy savings for the Case 1.

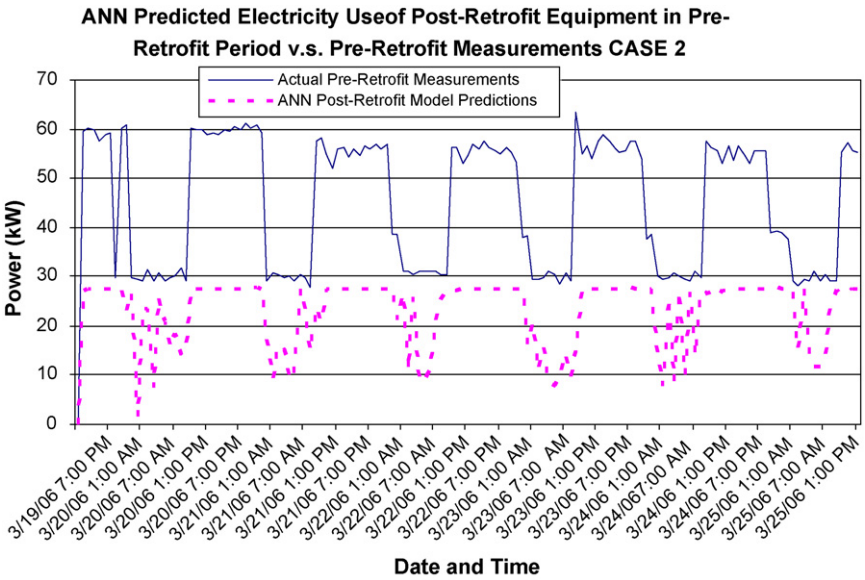

Fig. 10. ANN predicted electricity usage of the post-retrofit equipment in the pre-retrofit period in comparison to pre-retrofit measurements showing the energy savings for the Case 2.

time has provided insight on the sensitivity of the model to each variable. Removing variables from the input permanently, hence reducing the number of inputs for each successive ANN model, has provided additional insight for prioritizing the inputs in case data on certain variables is unavailable. Table 4 emphasizes the importance of dew point temperature in the ANN model (by the psychometrics chart, instead of dew point temperature, wet bulb temperature or relative humidity may also be used). When dew point temperature is used as an input variable in addition to time and dry bulb temperature (Model 5), the coefficient of correlation is 0.931. On the other hand, when dew point temperature is removed and only time and dry bulb temperature are used as input variables (Model 6), the coefficient of correlation is 0.864. Additionally, the time variable, though not included in the climate data, is a significant variable in the ANN model, as can be seen in both Tables 3 and 4. This is because building-occupancy and other variables related to building operations are related to the hour of the day.

Table 3
ANN model sensitivity analysis and corresponding error measurement parameters using the first approach with Case 1 retrofit project post-retrofit data

ANN model no	Input*	ANN model training				ANN model testing			
		R	RMSE kW	RMSPE %	MEPA %	*R*	RMSE kW	RMSPE %	MEPA %
1	t, db, dw, ws, wd, ap, v	0.943	37.86	8.62	6.85	0.951	34.99	8.02	6.45
2	t, db, dw, ws, wd, ap	0.942	37.89	8.63	6.86	0.951	35.17	8.06	6.51
3	t, db, dw, ws, wd, v	0.939	38.98	8.88	7.13	0.949	36.13	8.28	6.67
4	t, db, dw, ws, ap, v	0.942	38.01	8.66	6.89	0.950	35.47	8.13	6.40
5	t, db, dw, wd, ap, v	0.929	41.84	9.53	7.70	0.940	38.80	8.89	7.12
6	t, db, ws, wd, ap, v	0.902	48.94	11.15	8.94	0.906	47.88	10.97	8.81
7	t, dw, ws, wd, ap, v	0.897	50.12	11.41	8.55	0.918	44.82	10.28	7.93
8	db, dw, ws, wd, ap, v	0.901	49.40	11.25	9.62	0.897	50.57	11.59	10.25

* t: time, db: dry bulb temperature, dw: dew point temperature, ws: wind speed, wd: wind direction, ap: air pressure, v: visibility.

Table 4
ANN model sensitivity analysis and corresponding coefficient of correlations using the second approach with Case 1 retrofit project post-retrofit data

ANN model no	Input*	ANN model training				ANN model testing			
		R	RMSE kW	RMSPE %	MEPA %	*R*	RMSE kW	RMSPE %	MEPA %
1	t, db, dw, ws, wd, ap, v	0.943	37.86	8.62	6.85	0.951	34.99	8.02	6.45
2	t, db, dw, ws, wd, ap	0.942	37.89	8.63	6.86	0.951	35.17	8.06	6.51
3	t, db, dw, ws, ap	0.929	42.03	9.57	7.62	0.935	40.17	9.20	7.42
4	t, db, dw, ws	0.936	39.94	9.10	7.25	0.944	37.47	8.59	6.69
5	t, db, dw	0.931	41.35	9.42	7.46	0.940	38.67	8.86	7.28
6	t, db	0.864	56.98	12.98	10.34	0.874	54.93	12.58	10.38
7	t, dw	0.886	52.61	11.98	8.99	0.908	47.48	10.88	8.02
8	db, dw	0.871	55.70	12.68	10.83	0.868	56.39	12.92	10.28
9	db	0.811	66.36	15.11	12.92	0.812	66.25	15.18	12.91

* t: time, db: dry bulb temperature, dw: dew point temperature, ws: wind speed, wd: wind direction, ap: air pressure, v: visibility.

4. Conclusions

This study evaluates the tools currently available for predicting energy savings from retrofit projects, and focuses on model development based on the ANN method. The nonlinear modeling capabilities and simplicity of use of ANN methods make these methods more popular for estimating energy savings from retrofit projects than multi-linear regression methods. The ANN model developed in this study is based on the Levenberg–Marquardt back-propagation algorithm. The retrofit projects included installing energy management systems in the guest rooms of a hotel and VFDs on the air-handling units in one case study, and replacing an old cooling tower with a new cooling tower in the second case study. Pre-retrofit and post-retrofit energy measurements were recorded from the chiller plant. The coefficient of correlation of the ANN models for pre-retrofit and post-retrofit periods varied from 0.957 to 0.844. The root mean square percentage error varied from 6.81% to 16.4%, and the mean absolute percentage error varied from 5.31% to 9.95%. Additional research on this topic may include analyzing the ANN model with typical meteorological years' weather data (such as TMY2 data), testing the method with different retrofit projects, enhancing prediction capability for longer periods of time, and analyzing sensitivity when the effects of several variables are combined.

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