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Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks

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ABSTRACT

This study presents a methodology to forecast diurnal cooling load energy consumption for institutional buildings using data driven techniques. The cases for three institutional buildings are examined. A detailed analysis on their energy consumption data for two years shows that there is a high variation in diurnal energy consumption. This is largely attributed to the university scheduling and vacation periods. To reduce the degree of variation, the energy consumption data is divided into classes. These class numbers are then taken as inputs for the forecasting model which is developed using Artificial Neural Networks (ANN). The results show that the ANN is able to train and forecast the next day energy use based on five previous days' data with good accuracy. The model development, along with ANN architecture used in this case is discussed in detail. As a next step, the forecasted output is taken back as an input with a view to forecast the output of the following day. This step is repeated and the model exhibits an R^2 of more than 0.94 in forecasting the energy consumption for the next 20 days. It is also noted that such a methodology can be positively extended to other institutional buildings.

1. Introduction

University campuses have witnessed a marked increase in sustainable drive due to their impact on the environment and society at large. Most university campuses can be considered as medium to large size townships with numerous large scale facilities like residences, educational buildings, research centers, sports and recreation, etc. The reference to sustainability in higher education was first recognized in the Stockholm Declaration of 1972 [1]. It was followed by the Talloires Declaration in 1990 which was signed by 300 universities in over 40 countries [2]. Since then, many partnerships for campus sustainability have been established including C2E2 (Campus Consortium for Environmental Excellence), ACUPCC (American College & University Presidents Climate Commitment), ISCN (International Sustainable Campus Network), Higher Education's Commitment to Sustainability, etc., focusing on energy efficiency, conservation and management for colleges and universities. A comprehensive study on the approaches and management practices for campus sustainability can be found in the review article by Alshuwaikhat and Abubakar [3].

A survey on energy consumption and energy conservation measures for colleges and universities in Guangdong province by Zhou et al. [4] showed that campuses are among the major energy consumers. Along with shopping malls, office buildings and hotels, campus energy conservation enforcement would reduce CO_2 emissions up to 25%. It was also concluded that there exists a great difference in per unit energy consumption between different types of universities. This throws light on the different management strategies being followed across different universities. Chung and Rhee [5] investigated on the potential opportunities for energy conservation in university buildings in Seoul, Korea. They proposed a number of strategies for energy savings after a survey. It was found that the buildings' feature and occupants are the most important factors affecting energy use. The energy analyses of the seven surveyed buildings determined the potential for energy conservation in the range 6–29%. Another study by Gul and Patidar [6] on understanding the energy consumption and occupancy of a multi-purpose academic building shows the importance of understanding occupancy patterns for energy conservation. It was observed that the operational timings for the automated systems were not synchronized with the occupancy patterns. They proposed that an occupancy based energy consumption model can help facility managers to plan optimum schedules for the automatic systems to achieve significant amount of energy savings. Hence it is seen that

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institutional buildings present high variation with respect to occupancy schedules and energy management.

1.1. Importance of forecasting

In order to facilitate effective energy management in institutional buildings, an accurate energy forecasting model is essential. Such a building energy forecasting model can be of immense value to the building facility manager. It can provide a set of future boundary conditions and targets within which the building's energy consumption should ideally fall. It can also provide an initial check for facility managers and building automation systems to mark any discrepancy between expected and actual energy use. The forecasting algorithm can also be clubbed with smart sensors and control systems and equip them for future scenarios. A successful energy forecasting model can be combined with other building simulation models to generate useful operating variables. For example, the forecasted energy consumption can be used by a simulation model to identify and infer the occupancy and building operational data which can in turn be used to manage the building more effectively. This can help the building tenants and owners to be aware of future energy demand which can then be used as a criterion for investing into future energy conservation measures. For building energy data collection and cleaning, forecasting can deduce and impute any missing values.

1.2. Existing forecasting methodologies

Building energy forecasting has gained momentum due to the increase in building energy efficiency research. A large variety of building energy models have been identified for short, medium and long term energy forecasting [7,8]. The most popular models in recent times are machine learning models that accurately forecast the energy consumption based on previously recorded data. Recent review studies provide detailed accounts on existing forecasting models and their classification [9–11]. Although there are many such intelligent models, most of them are based on Artificial Neural Networks (ANN) and their developments [12–15].

Artificial Neural Networks (ANNs) are the most widely implemented methodologies in forecasting building energy consumption. Since the complexity of building energy system is very high due to several factors as mentioned previously, the ability of ANN in performing non-linear analysis is an advantage in executing buildings energy consumption forecasting. This section reviews some of the applications of ANN related to building energy forecasting and assesses the modeling methodologies including the type of network, input and output types and also the number of neurons in various layers of the network.

Aydinalp et al. [16] used ANN for estimating the energy consumption of appliance, lighting and space cooling in the residential sector. In the study, the application of ANN had shown its superiority in prediction when compared with an engineering model (building simulation model). The coefficient of determination (R^2) and the coefficient of variation (CV) for the ANN model were 0.909 and 2.094 respectively when compared to the simulation model which had the R^2 and CV as 0.780 and 3.463 respectively. In the following work two years later, Aydinalp et al. [17] used ANN to model space heating and domestic hot water energy consumption. The comparison between the ANN model and simulation model showed that both had good capability for prediction. However, the higher CV and lower R^2 value for simulation models indicated that the ANN model has better performance.

González and Zamarreño [18] used feedback ANN to predict short term electricity load. The feedback model that they used was part of the Ph.D. dissertation of Schenker [19]. This feedback network operates in such a way that part of the output is fed back as an input and the prediction error with respect to the measured output is used to train the network. The model produced good results for hourly load forecasting with the maximum Mean Absolute Percentage Error (MAPE) of 2.88. Furthermore, they suggested that there are three aspects of ANN that need to be quantified. They are the number of neurons in hidden layers, the optimum size of the data set and the training algorithm to be used.

Karatasou et al. [14] discussed the application of ANN in predicting building energy consumption in combination with statistical analysis. The modeling process is divided into three parts. These are the identification of all potential relevant inputs, selection of hidden units through an additive phase and removal of irrelevant inputs and hidden units through a subtractive phase. They used the methods described by Rivals and Personnaz [20] on selecting and constructing the ANN. The method comprises of an additive phase in which hidden neurons are added one by one till the condition number of the Jacobian matrix is below 10^8. The Jacobian matrix is a matrix containing the vector of network errors. In the subtractive phase, the redundant neurons and irrelevant inputs are removed separately using Fisher distribution statistical tests. Two ANN models were constructed and the first model had inputs of climatic variables and hour, day and week of the year. In the second model, past values of energy consumption at $t-1$, $t-2$ and $t-3$ were also considered.

ANN was used by Azadeh et al. [21] to forecast long term electricity consumption in energy intensive manufacturing industries in Iran. They used a feed forward neural network with error back propagation algorithm. The model had an input layer with 5 neurons corresponding to the 5 inputs, 3 neurons in the first hidden layer and 2 neurons in the second hidden layer and a final output layer with 1 neuron corresponding to the single output. The data used for training was from year 1979 to 1999 and that for testing was from year 2000 to 2003 respectively. The estimated results from the ANN model, a regression method an actual data were compared by a one-way analysis of variance (ANOVA). Following this, the Duncan's multiple range test is applied to determine the model with the closest mean to the actual data. It showed that the ANN has good forecasting accuracy for electricity usage. A similar study was performed by them for successfully forecasting monthly electricity consumption [22].

Another study on long term energy consumption prediction was performed by Ekonomou [23]. Here also a feed forward neural network was used with four neurons in the input layer, 1 output neuron in the output layer and 20 and 17 neurons respectively in the two hidden layers. Previous 13 years data (1992–2004) was used to train and validate the model and about 4 years recorded data from 2005 to 2008 was used to test the model. The predicted results by the neural network model were very close to the test values and much more accurate than those obtained by a linear regression model. In addition, the predicted results were found to be very similar to the ones obtained by a support vector machine model which the author also developed for result comparison.

Neto and Fiorelli [13] conducted a comparison between an EnergyPlus simulation model and ANN for building energy consumption forecasting for the administrative building in the University of Sao Paulo. They developed three different networks for all days, weekdays and weekends respectively. The input layer for the weekdays analysis network had 2 neurons corresponding to the 2 inputs of daily maximum and minimum external dry-bulb temperatures. The feed forward neural network used by them was based on the proposed algorithms by Freeman and Skapura [24]. The results show that the EnergyPlus consumption forecasts presented an error of ±13% for 80% of the tested database. On the other hand, the ANN model showed an average error of about 10% when different networks for working days and weekends are implemented.

Yokoyama et al. [25] used back-propagation ANN was to predict cooling demand for a commercial building. They proposed a global optimization method, called 'Modal Trimming Method', to identify model parameters [26]. The global optimization method can assess the effect of the numbers of neurons of the input and hidden layers on the accuracy of the prediction. The predicted cooling demand had a relative error of 8.2%. It was also found that by increasing the number of neurons in the input and hidden layers, the accuracy of predictions become lower. This is because the neural network with a large number of model parameters becomes excessively adaptable to learned data, thereby becoming inadaptable to unlearned, testing data.

Altan Dombaycı and Gölcü [27] developed an ANN model to predict daily mean ambient temperature in Turkey. They tested a number of feedforward neural networks with different number of neurons and the network with six neurons produced the best results. They used previous three years data (2003–2005) to train the network and recorded data for year 2006 to test the network. The predicted results were very accurate with a R^2 of more than 0.9888 for the testing dataset.

Rezaeian-Zadeh et al. [28] used multi-layer perceptron (MLP) and radial basis function (RBF) as two ANN methods to predict hourly air temperature. In all they developed four models (2 for MLP and 2 for RBF) with target output being the 24 h time series of air temperature in a day. Hence the output layer had 24 neurons. Each network for different number of neurons had been tested, in which the networks with six neurons produced the best result for this model. They used 255 daily maximum and minimum air temperature data as training data and 110 days data for testing. The models were tested across data from three different weather stations. The results show that the MLP model was consistent in accurate forecasting for all the three data sets. However, the RBF model with inputs as maximum and minimum air temperature ($T_{\min}(t)$ and $T_{\max}(t)$) along with their 1 h lag values ($T_{\min}(t-1), T_{\max}(t-1)$) was not accurate to predict hourly air temperature.

Wong et al. [29] applied ANN for predicting office building energy consumption in subtropical climates. The data was generated using EnergyPlus simulation and no actual data was used for the verification. The ANN used was the feedforward multi-layer perceptron model with 9 inputs and 4 outputs corresponding to the 4 output variables of daily electricity use for cooling, heating, lighting and total electricity consumption. The performance of ANN in this analysis was measured by using Nash–Sutcliffe Efficiency Coefficient (NSEC) where the value of 1 indicates a perfect match [30]. The NSEC for the ANN modeled cooling, heating, electric lighting and total building electricity use was 0.994, 0.940, 0.993, and 0.996, respectively.

These studies demonstrate the effectiveness of ANN modeling for energy forecasting. It is also inferred that to develop an accurate model, the selection of input variables and training algorithm are important. Another constraint seen is the variation in the dataset across different studies which show the importance of availability of recorded data. With this background, the objective of this study is to develop a building energy forecasting model for diurnal cooling load consumption for institutional buildings. It is intended that the model should take minimum computing time with a view to automate the real-time data analysis process in the future.

Table 1
Ground Floor Area (GFA) distribution for the three buildings.

Building	Air conditioned GFA (m^2)	Non-air conditioned GFA (m^2)	Total GFA (m^2)
A	4724	580	5304
B	3283	611	3894
C	7946	734	8680

2. Methodology

This study utilizes the energy data collected over a period ranging from one to two years for three institutional buildings in a university campus in Singapore. These buildings under study (referred to as building A, B and C) are part of the same school but vary in their respective functions. Building A mostly consists of offices, building B consists of offices and laboratories whereas building C consists of classrooms and seminar halls. The Ground Floor Area (GFA) distribution for each building is presented in Table 1. The diurnal energy consumption details for each building with their standard deviation are presented in Table 2. It is to be noted that the energy consumption is not directly proportional to the GFA. This is because each building has a different function as well varying operating schedules. Building A being the administration office has more fixed operating schedules than the other two buildings. Building B has laboratories and few server rooms that are small but running all day along. This building also has two large rooms for research students that are also utilized round the clock. Building C, on the other hand, mostly consists of design studios for under-graduate students and is also well utilized round the clock and has the highest consumption. This building has the largest floor area and highest occupancy. It is seen that for most cases, the standard deviation is of the order of 15–20%. For non-air conditioning load of building C, the standard deviation is high. This may be attributed to the diverse function of that building. This building is used for many studio related conferences and seminars throughout the year, leading to such high variability. On the other hand, buildings A and B have more offices and laboratories that lead to fixed operating schedules. This leads to lesser deviation in everyday energy consumption.

The annual energy consumption is found to be highly variable due to the operational characteristics of these buildings as discussed previously. As the objective of this study is to develop a fast and accurate forecasting model with a view to monitor and forecast real-time energy data in future, ANN is selected for the purpose of developing the forecasting model due to its quick computing time. The next section presents the research methodology in detail beginning with a discussion on the physical characteristics of the three buildings.

The energy data for these three buildings is obtained through the University's facility management office which collects energy data for all buildings in the campus at every 30 min interval. Chilled water energy meters or BTU meters (measures the energy content of liquid flow in BTU or British Thermal Units) are installed in every building. These meters record and transmit the readings to the facility management office through a wired network. These readings have been observed to contain two anomalies. The first is the presence of outliers and the second is the presence of gaps that

Table 2
Summary of load distribution in the three buildings.

Daily load	Air conditioning load (kWh)			Non-air conditioning load (kWh)		
Building	Max	Average	Std dev.	Max	Average	Std dev.
A	3543.5	2513	307.5	768	604	94.5
B	3463	2611.7	308	2432	2003.8	230.9
C	12,074	8414.5	1438.5	6606	3608.2	1049.9

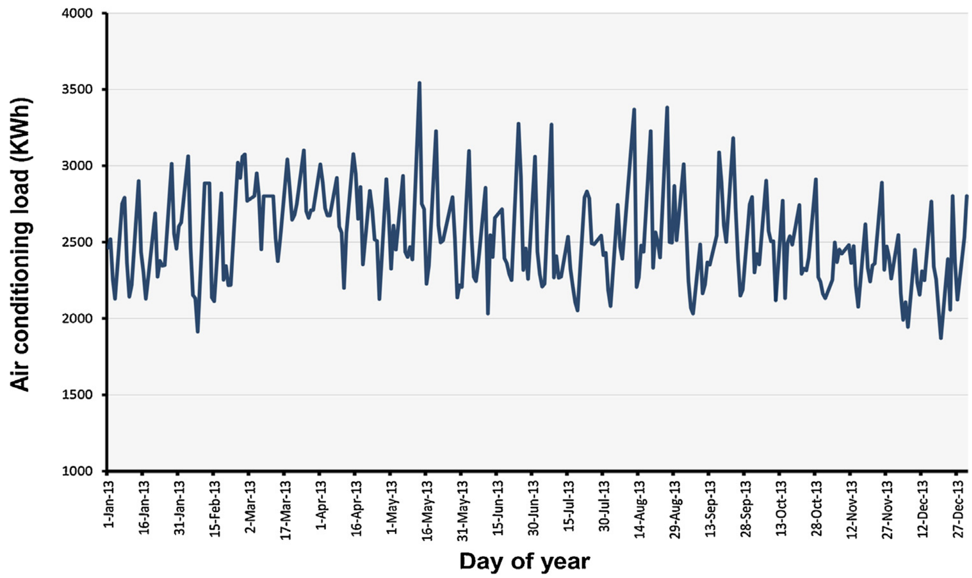


Fig. 1. Daily energy consumption variation for a period of one year for building A.

often punctuate the data set. The outliers corresponding to zero meter reading are the weekend and public holiday energy consumption values when the air conditioning system is usually turned off. The missing values are imputed using the average between the previous and the next recorded data. Following this, the energy consumption data for every 30 min is extracted by taking the difference between the recorded meter data for each time stamp and the previous one. In this way, the energy consumption data for every 30 min is computed. The diurnal air conditioning energy consumption for each building is computed by adding the 30 min interval data for each day from 7:00 am to 9:00 pm. This time period is chosen because it is the operating period for the air-conditioning plant. Prior to this period and beyond it, the air conditioning is turned off and the recorded meter value is zero. Since this study focuses on the diurnal energy consumption analysis and forecasting, the outliers corresponding to zero values for weekends and public holidays are removed for analysis. In addition, the top 2.5 percentile and the bottom 2.5 percentile values are also removed and only the remaining middle 95 percentile values are taken for analysis and model development. The initial study involves analysis of one full year energy data. The advantage of studying annual variation is that it shows the range as well as the deviation in consumption for an entire year. It also throws light on seasonality effect, if any, on the energy usage pattern. The annual energy use for air conditioning load for the three buildings is presented in Figs. 1–3 respectively. Each figure shows the variation in air conditioning load through the year 2013. For a university campus, the energy consumption is usually higher during the instructional period as compared to the vacation period. The summer vacation period for the university is from the beginning of May to the end of July and that for winter is from end of November to mid-January.

2.1. Data analysis

In many studies, the energy forecasting model is developed by taking the outdoor climate indices as the dependent variables. González and Zamarreño [18] have developed forecasting models using machine learning tools where they take the ambient temperature, the current load and the hour and the day as inputs. Kwok et al. [31] have taken a number of climatic variables as inputs along with the occupancy area which is defined as the building floor area corresponding to occupancy scheduling as different areas in

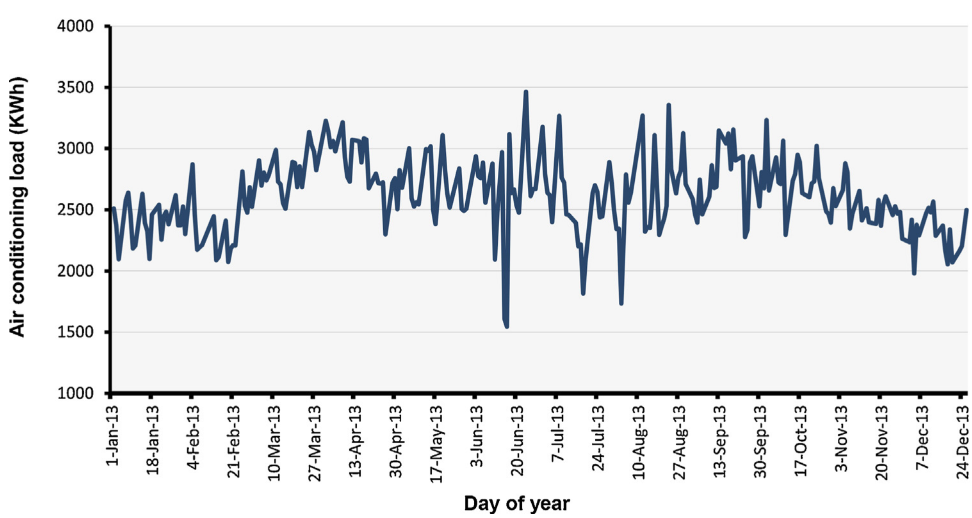


Fig. 2. Daily energy consumption variation for a period of one year for building B.

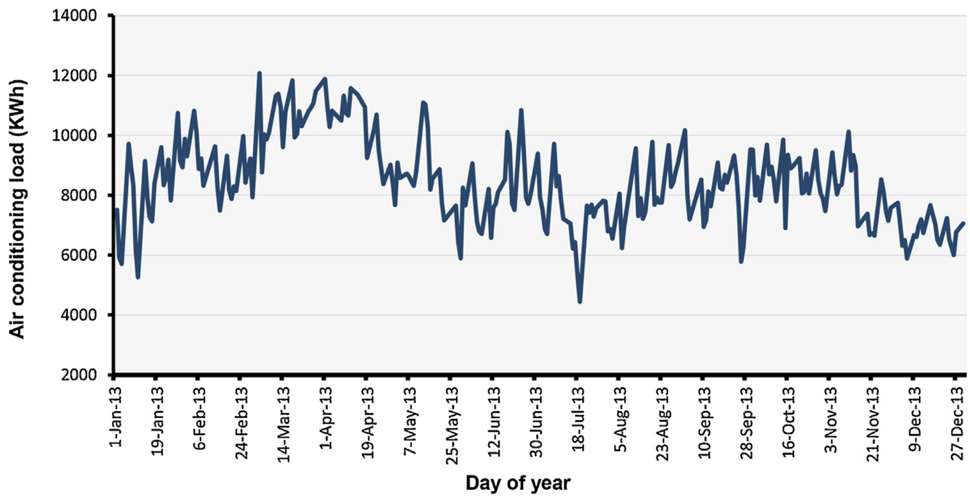


Fig. 3. Daily energy consumption variation for a period of one year for building C.

a building may have different operating schedules. Lazos et al. [32] have provided a review on building energy models that take climate and occupancy indices as input variables. It was found that for smaller building systems with limited optimization components, simple statistical processing of archived data or even external forecasts of temperature are sufficient for energy management. For larger and more dynamic building energy systems, it was found that the availability of accurate weather forecasts greatly enhances the savings potential. With this background, the influence of climatic variables on energy consumption is assessed by correlating the climate variables with energy use.

The climatic data is obtained from the National University of Singapore (NUS) weather station maintained by the Department of Geography, NUS. The station is located on the rooftop of building E2 (Faculty of Engineering) of the NUS Kent Ridge campus, near the south coast. At a height of about 90 m above sea level, it is the highest point in the region and therefore has clear exposure. The proximity of the station to all the other buildings in the Kent Ridge campus makes the data very suitable for climatic studies. The three outdoor climatic variables that were tested for any impact on the energy use were air temperature, relative humidity and solar radiation. Figs. 4–6 present the correlation of air conditioning load with the three climatic variables. The results of correlation show that neither of the variables have a good influence on air-conditioning energy consumption. Only the correlation with building A data is shown here. There is a possible trend with respect to outdoor air temperature but the correlation coefficient is extremely low. This clearly indicates that the air conditioning systems run almost independently of the outdoor conditions. This holds true for all three buildings. The air conditioning system installed in the three buildings is a chilled water VAV (Variable Air Volume) type. The VAV system functions with conditioned air being supplied at a constant temperature and varying airflow rates. The airflow rate is determined by the indoor ambient temperature. The rooms in these buildings contain thermostats with a default set-point temperature of 24 °C. These thermostats influence the airflow rates which in turn are controlled by the occupants. Since the occupancy variation is high in these institutional buildings, there is a high fluctuation in airflow demand. Therefore, the indoor conditions and occupancy are the key determinants for cooling load energy

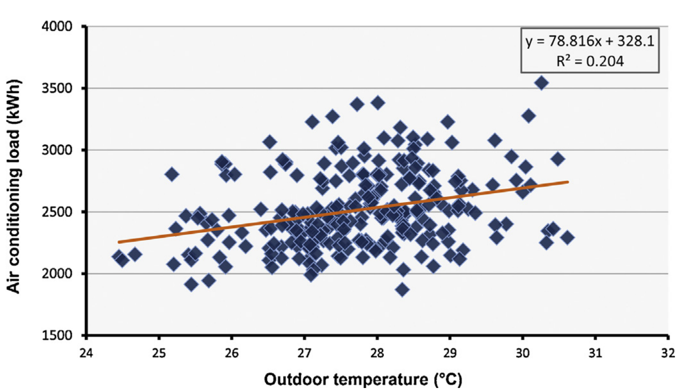


Fig. 4. Correlation of energy consumption with outdoor air temperature for building A.

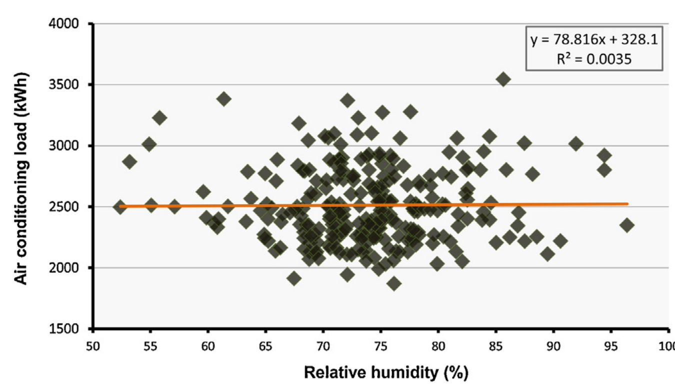


Fig. 5. Correlation of energy consumption with relative humidity for building A.

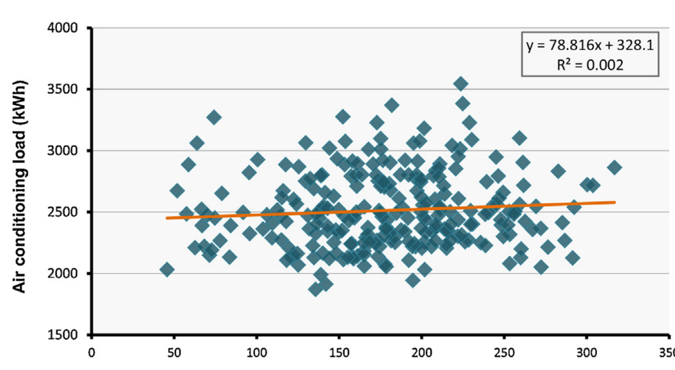


Fig. 6. Correlation of energy consumption with solar radiation for building A.

Table 3
R^2 values for the three buildings with respect to the three climatic variables.

Building	R^2		
	Air temperature	Humidity	Solar radiation
A	0.204	0.003	0.002
B	0.242	0.002	0.121
C	0.09	0.001	0.003

consumption in these buildings. In addition, there is not much variation in the outdoor climatic conditions for Singapore [33]. Table 3 shows the correlation R^2 values for the three buildings with respect to the three climatic variables. From the point of view of energy efficiency, an air conditioning system that varies with the outdoor conditions is considered better. With respect to humidity and solar radiation, there is no clear trend and the plot is significantly scattered, generating very low correlation coefficient values. It may be therefore concluded that the outdoor climatic condition has little effect on the energy consumption and these variables may be of no significant effect in model development.

3. ANN model development

Artificial neural networks are based on mimicking the function of the human brain. This concept was first introduced by McCulloch and Pitts [34] in 1943 where they studied the capabilities of the interconnection of basic components based on the model of a neuron. Morris and Hebb [35] presented the adoption laws involved in neural systems. Rosenblatt [36] devised the basic architecture of a neural network and coined the name 'perceptron' concerning the functioning of a single neuron. There was a halt in this field after Minsky and Papert [37] performed a detailed analysis on the limitations of the perceptron model. However, with the work of Hopfield in 1980s, there was a revival in interest in this field which has continued till today. Currently, the applications of ANN are well acknowledged in a number of disciplines, particularly for nonlinear modeling. The basic element in ANN is the artificial neuron that are aligned in layers and connected to neurons in other layers through links. These links are known as the synaptic weights and one of the objectives of the training process is to derive these weights. The activation of a neuron is determined by the summation of the weighted inputs and can be mathematically denoted as in Eq. (1):

$$O = f\left(\sum (w_{ij}x_j)\right) \tag{1}$$

Here, O is the output of the neuron, x_j is the input to that neuron, w_{ij} is the weight of the connection of the input to the neuron and f is the transfer function. The transfer function used in neural networks is usually the Sigmoidal function which has the following form (2):

$$S(t) = \frac{1}{1 + e^{-t}} \tag{2}$$

This selection makes it a differentiable real function that is defined for all real input values. This also has a positive derivative at each point which is immensely useful to calculate the connection weights. The output of a neuron is passed to the neuron in the next layer through these weights and so the output of this neuron in the next layer can be represented in a very simple form as in Eq. (3), where, O_l is the output of the neuron in the next layer and w_{jl} is the weight connecting the previous neuron to the neuron in this next layer:

$$O_l = f\left(\sum \left(w_{jl} f\left(\sum (w_{ij}x_j)\right)\right)\right) \tag{3}$$

The learning process in an ANN involves determining the weight vectors. There are various algorithms that are used for this purpose. The aim of the training process is to minimize the squared error between the predicted and the measured outputs (4). E is minimized by the gradient descent method which involves computing the partial derivative of E with respect to each weight in the network. The most popular training algorithm is the backpropagation algorithm and its details can be found in the work of Rumelhart et al. [38]:

$$E = \sum \frac{1}{2}\left(O_p - O_m\right)^2 \tag{4}$$

Here, E is the total error, O_p is the predicted output and O_m is the measured or desired output.

As observed in the previous section, the climatic variables have a poor influence on energy consumption of the three buildings under study. In addition, the occupancy data for these buildings is not readily available. Moreover, the cluster of these three buildings has many openings for occupants to enter and exit, and is also used as a transit to reach other buildings in the campus. This makes it very difficult to keep a count of the number of occupants actually present. Combined with this, the presence of open study areas also invites students and visitors to use this facility from the fringes. All such factors make it difficult to measure an exact occupancy count. For these reasons, the focus is given to investigate on the internal energy consumption pattern based on the collected energy data. Each building is assessed individually for its internal energy consumption patterns. To begin with, the energy data of air conditioning load for building B is analyzed in detail. The average daily cooling energy consumption for this building is 1885.56 kWh with a standard deviation of 1153.97 kWh. Another consideration made here is that the scale of data analyzed is on the yearly level. For this, the total cooling energy consumption for each day is taken as an assessment element. Therefore, every day represents one value of total energy consumption. Moreover, the weekend energy data is excluded from this analysis as the building is officially closed during these times. Excluding the weekend and public holidays, there are about 250 data points (one for each day) and each value corresponds to the total cooling energy consumption value for that day.

As a typical feedforward ANN, the network used in this study consists of an input layer, a hidden layer and an output layer. The number of inputs corresponds to the number of neurons in the input layer. In the same way, the output corresponds to the neuron in the output layer. The number of neurons in the hidden layer, however, is determined by certain rules which differs from case to case. One of such rule is to fix the number of hidden neurons as an average between the input and output neurons. In other cases, trial and error method is used to fix the number of hidden neurons. In this study, the trial and error method is adopted to perform a sensitivity analysis to determine the number of neurons in the hidden layer. It is seen that the number of neurons in the hidden layer when fixed to 20 generates accurate results without consuming much time. With a view to automate the prediction process as part of the next phase in this project, the number of hidden neurons is fixed at 20 to accelerate the computing time. The results discussed here are based on the ANN architecture presented in Fig. 7.

The three different layers are connected to each other through adaptable synaptic weights. The first step in a neural network analysis is the training step which involves modification of the synaptic weights until the predicted output is close to the measured actual output. Once the training is completed, there is a defined set of relationship between the neurons across various layers. This relationship can be used for predicting new outputs with new set of input data. For simple representation, an ANN with five input neurons and 20 hidden neurons is represented as 4–20. This 4–20 architecture is used as the basic structure for energy prediction. A sensitivity analysis is performed to test the prediction accuracy

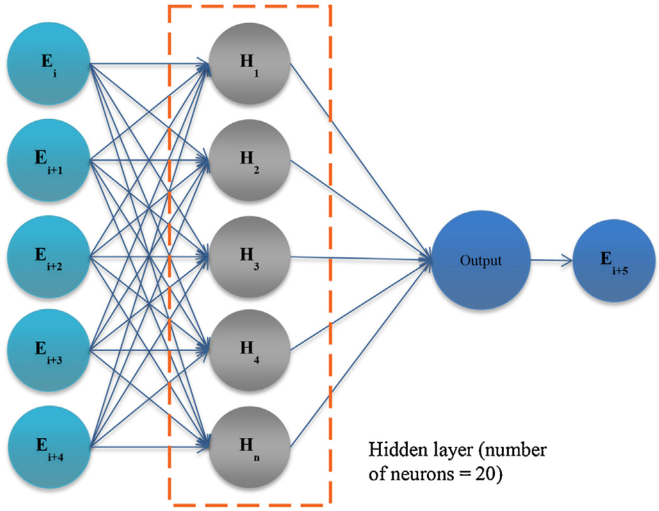


Fig. 7. The ANN used for this study. Inputs E_i, E_{i+1}, E_{i+2}, E_{i+3}, E_{i+4} are energy data for five consecutive days and E_{i+5} is the output for the next day (sixth day in this case). H_1, H_2, H_3, H_4 and H_n are neurons in the hidden layers.

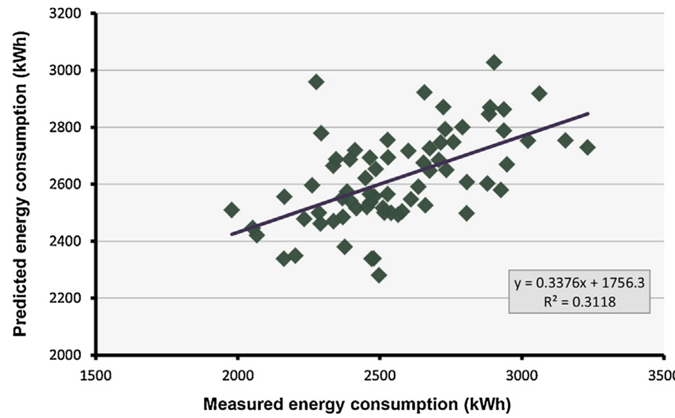


Fig. 9. Results of predicted output with five previous days' crisp energy consumption value as inputs.

by adding more hidden layers. Few of the ANN architecture tested were 5–20, 5–20–20 and 5–20–50. It was however observed that the 5–20 network is the best given the quick computing time as compared to the other networks. The training algorithm used is the Bayesian regularization algorithm ('trainbr') in MATLAB. The Bayesian regularization minimizes a linear combination of squared errors and weights. It modifies this linear combination so that the resultant trained network has good generalization qualities. More discussion on this algorithm can be found in Mackay [39] and Dan Foresee and Hagan [40].

3.1. Energy classes

As seen by the annual distribution of energy consumption for the three buildings, it is very difficult to develop a forecasting model based on the crisp energy consumption values. This is because the time series distribution of diurnal cooling energy consumption is highly variable and the model takes into account the previous consumption patterns. A box-and-whisker plot study for the 12 months shows the extent of this high variation (Fig. 8). For each month, the large spacing between the boxes shows high degree of dispersion and skewness in the data set. Such a distribution may be regarded close to a random distribution. ANN being good in nonlinear modeling is able to generate a fairly accurate model based on crisp energy consumption values. The weights generated between the neurons of different layers are very rigid. Such a model is highly specific to the training data set and performs poorly for the testing data set. Therefore is it very difficult to generalize such a model to new or test data sets. This problem exists because the criterion to train the model is not the same as the criterion to judge the efficacy of the model. Hence, the model begins to 'memorize the training data rather than 'learning' from it. Fig. 9 shows the low R^2 between the predicted and measured crisp energy consumption values for the testing data set for one year data of building B. A detailed study on the variation of diurnal energy consumption levels is presented in the next section.

To overcome this problem of high variation, the level of information in the energy consumption values is reduced to certain defined classes. In all, the data is equally divided into five classes and later distributed as 25 class numbers. The two year energy consumption data for building B is considered and the first 20 percentile data in ascending order is regarded as Class 1. These are assigned as 'very low' energy consumption levels. Similarly, the values in the next 20 percentile are assigned as 'low' energy consumption levels and so on. Following this, the class values are distributed as class numbers corresponding to the day of the week. This is done to differentiate between different days in the week and avoid overlaps between energy class levels of one day and another. Tables 4 and 5 show the division of data into classes and class numbers. For example, class number '1' implies Mondays with low energy consumption, whereas, class number '18' implies Thursdays with average energy

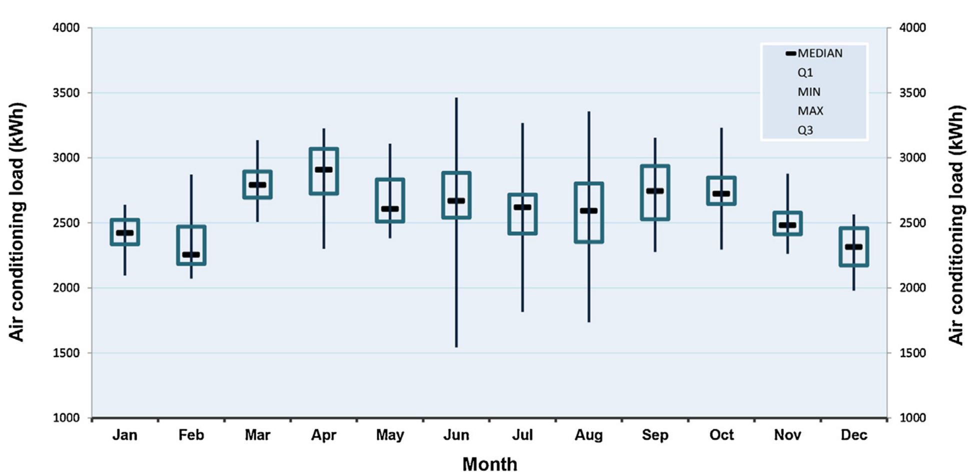


Fig. 8. Box-and-Whisker plot of annual energy consumption data for cooling load for building B.

Table 4
Division of data into 5 energy classes.

Class	Significance	Class range (kWh)	Range width (kWh)
1	Very low	<2392.6	–
2	Low	2392.6–2533.3	140.7
3	Medium	2533.3–2688.2	154.8
4	High	2688.2–2885.2	197
5	Very high	>2885.2	–

Table 5
Assigning class numbers for each day of week.

Energy class	1	2	3	4	5
Class numbers					
Monday	1	2	3	4	5
Tuesday	6	7	8	9	10
Wednesday	11	12	13	14	15
Thursday	16	17	18	19	20
Friday	21	22	23	24	25

consumption. The class division would enable better understanding of the energy use sequence and also take contain the high variation to a reduced level. In terms of building management, the predicted class numbers are much simpler to comprehend and understand. From the view point of facility managers, these aid in distinct visualization of the energy consumption ranges that a building is expected to operate within. This leads to easier formulation of energy management strategies. On the other hand, such a class division would also support control systems in programming for future energy consumption scenarios. From the programming viewpoint, class or cluster numbers corresponding to certain ranges are very effective. This also makes the computing faster by operating in defined bands or ranges. Once the class numbers are assigned, they form the input variables for the ANN model. The model is designed to take five days' energy class data as inputs and predict the energy class value for the next day. Although there are five classes into which the daily energy consumption is divided, there are 25 class numbers considering the weekdays from Monday to Friday. The number of class divisions also determines the range width of energy consumption levels for that class. For example, dividing the data equally into 20 classes produces the class range as given in Table 6. The lower the class number, the higher is the class range. This technique of dividing the energy data into class numbers can be extended to obtain predictions close to the crisp values. This can be done by increasing the class numbers. More on

Table 6
Table showing class ranges corresponding to the division into 20 classes.

Class	Class range (kWh)	Range width (kWh)
1	<1977.5	–
2	1997.5–2097	119.6
3	2097.1–2192.1	95.0
4	2192.1–2251.9	59.8
5	2251.9–2339.9	88.0
6	2339.9–2392.6	52.8
7	2392.6–2438.4	45.7
8	2438.4–2508.8	70.4
9	2508.8–2582.7	73.9
10	2582.7–2635.4	52.8
11	2635.4–2688.2	52.8
12	2688.2–2765.6	77.4
13	2765.6–2853.6	88.0
14	2853.6–2906.4	52.8
15	2906.4–2976.7	70.4
16	2976.7–3033.0	56.3
17	3033.0–3110.4	77.4
18	3110.4–3205.4	95.0
19	3205.4–3304.0	98.5
20	>3304	–

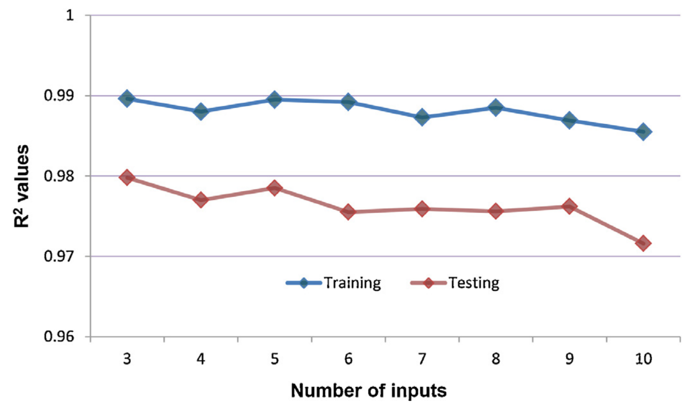


Fig. 10. Variation in prediction R^2 values with change in number of inputs.

the results obtained by increasing the class divisions is presented in Section 4.

The number of inputs used to develop the ANN forecasting model is also examined. In an attempt to make the model recursive, the output element is fed back as an input and the successive predicted output is generated. The details of this method are discussed in the next section. Fig. 10 shows the variation of R^2 values for next day prediction of energy consumption with five class inputs against the change in the number of inputs. It shows that the best results are obtained by fixing the number of inputs to three and five. However, it is observed that in order to make the model recursive, the model with five inputs performs the best and is selected for further analysis.

As the first step is pattern analysis, a sequence study is performed. For this, the energy consumption value at each day is analyzed with respect to the energy consumption value of the day that follows. The number of similar class numbers that follow a particular day are counted and represented through a matrix. Table 7 shows that matrix with the '$i+1$'th day on the X-axis and the 'i'th day on the Y-axis. Therefore the bottom row of this matrix implies the class numbers that usually follow a Monday with low energy consumption. As evident, the bottom row only takes values in columns 6–10 which correspond to the energy classes for Tuesday. The number in the box shows the frequency count. This matrix gives an understanding of the relationship between an energy class followed by another. For example, with this matrix it is possible to determine the number of times a low energy Wednesday is followed by very low, low, average, high or very high energy consumption Thursdays. After establishing these counts, the class numbers are fed into the ANN with the objective to predict the subsequent day's energy consumption class number with energy consumption class number for previous five days as inputs.

4. Results and discussion

The result of the ANN using the class number values shows significant improvement in the prediction accuracy. With previous five day's measured energy class as inputs, the model shows an accuracy of 0.9794 between the measured and predicted data class for the next day. Such high prediction rate is attributed to the improved clarity of the data set that is fed to the ANN for training. Rather than providing crisp energy consumption values, the class number represent a better way of classifying energy data and make it easier to comprehend the existing pattern of energy use from one day to another. Fig. 11 shows the plot with measured and predicted class values for building B. It is observed that the slope of the line is also close to 1. As a next step, the output is re-fed into the input and the viability of the model is determined. It is observed that

Table 7
Frequency count for class values for 'i'th day followed by the values of '$i+1$'th day.

		Monday					Tuesday					Wednesday					Thursday					Friday				
Class values on i^{th} day		**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**
Friday	25					4																				
	24	1				5																				
	23			1	2	8																				
	22		2	3	1	5																				
	21	2	2	4	5	1																				
Thursday	20																							2	1	1
	19																					1		4	5	3
	18																					1	5	2		
	17																					4	5	2		
	16																					8	1	1		
Wednesday	15																1	1		2	3					
	14																	1		4	1					
	13																	4	3	5						
	12																2	4	4	3						
	11																6	3								
Tuesday	10												1	1	1	6										
	9												3	6	3											
	8												3	4	1	1										
	7											2	2	2												
	6											7	3		1											
Monday	5						3		5	10	7															
	4						1	3	2	2	1															
	3						3	1	2	1	1															
	2						3	1																		
	1						2	1																		
		Class values on $(i+1)^{th}$ day																								

this model with class number values as inputs can predict energy consumption with significant improvement in prediction accuracies. As the ANN modeling is based on the connections between input and output layers, it is observed that the model prediction is improved by classifying the energy data into classes and class numbers. This is attributed to the benefits of the first level of classification that is already been considered while dividing the data into classes. With this, the ANN simply constructs the weights around the relationship between the input and output layers in terms of the class number they belong to.

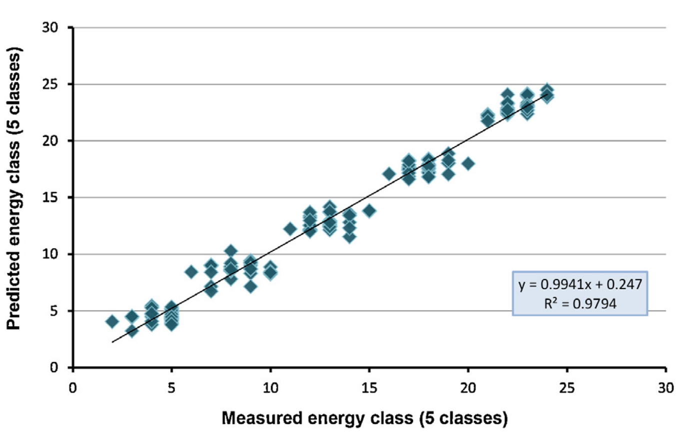


Fig. 11. Results with previous five days energy class values as inputs and the sixth day class value as output.

4.1. Change in class divisions

The results of the ANN model show that there is no much change in the prediction accuracy by changing the number of classes. For a class division of 20, the R^2 value for predicting next day energy consumption is 0.9712 (Fig. 12), compared to the R^2 value of 0.9745 which was obtained for a class division of five. This indicates that the class division can be increased, thereby compressing the class range and taking the prediction values close to the crisp values. This is beneficial for making predictions that are desired to be close to crisp values of energy consumption. Such prediction may be beneficial while predicting variables like ambient air temperature etc. However, when dealing with building energy consumption data on the diurnal level, it may be difficult to predict the precise value of energy consumption because of the high variability in the energy

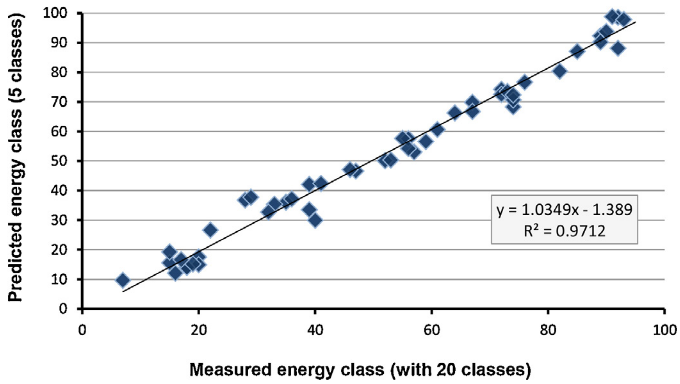


Fig. 12. Prediction results with 20 class divisions.

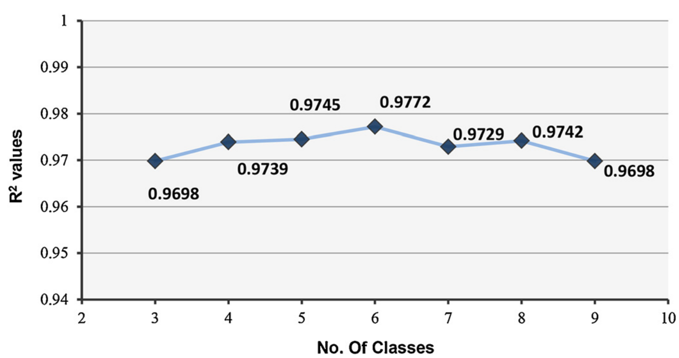


Fig. 13. Variation in prediction R^2 values with change in class divisions.

data. The class division therefore compresses the data and provides a class or range of energy consumption values that are desired for the predicted day. From the point of view of the facility manager, such an energy consumption range simpler to deal with as compared to crisp values.

Fig. 13 shows the variation in prediction R^2 values with change in class divisions. This is tested on one year energy consumption data (air conditioning data) for building B. It shows that the range of variation of prediction accuracy (R^2 values) is between 0.96 and 0.98. The ANN model used remains the same in all cases and the numbers of input, hidden and output neurons remain unchanged. In addition, the Bayesian regularization training algorithm is also the same in all cases. The consistency in the prediction accuracies is because there is no change in the ANN architecture when the data class divisions are changed. It is to be noted that only the range of input values differ and not the number of inputs. For example, in case of 5 class divisions, the range of inputs is from 1 to 25 (class numbers), whereas in case of 20 class divisions, the range of inputs is from 1 to 100. The change in range of inputs does not affect the ANN architecture and ANN is able to train itself in the same way with different input ranges. This shows that the functioning of ANN with class divisions as inputs is highly efficient as there is no much impact by changing the classes.

4.2. Lengths of forecasting output

In this section, the model is tested in its ability to take the predicted output as input and make further predictions. Fig. 14 shows the graphical representation for this. To perform such an analysis, the ANN model is first trained using five inputs. The data used is the two year air conditioning energy consumption data for building B. It is divided in the ratio of 3:2 for the purpose of training and testing respectively. Once the model is trained and tested, it is deemed ready to make further predictions. The predicted energy consumption for the sixth day is then taken as an input along with the previous four consecutive days. This makes the number of inputs to the model as five again, with four measured and one predicted energy consumption values. This is termed as case 1. The same method is applied further to generate subsequent cases. The result of such a cyclic prediction is presented in Fig. 15. The results show that the ANN model is able to predict with good accuracy for the next 22 cases. This is equivalent to predicting next 20 days of energy consumption by just using the first five days measured values as inputs. The R^2 values gradually decrease and reach a point of stability after case 22. The same method is applied on the energy consumption data for building A and C and the results obtained are similar to the results of building B. Figs. 16 and 17 shows the decrease in R^2 values for building A and C respectively as the prediction cases are increased.

The ability to predict the energy consumption for the next 20 days (three weeks) using the measured values for just five previous days is a significant step forward. This can help facility managers and building owners to prepare weekly energy usage plans and also to be equipped with predicted energy demands. The weekly forecast can also aid in implementing saving measures and compare the savings with the predicted values. Such a weekly prediction is also useful in mapping and planning the occupancy schedule, thus paving way for enhanced building energy management. The ANN model predictions can also be combined to other energy modeling platforms and energy simulation softwares like the Energy Plus. Such a link can be explored to generate other energy consumption variables based on the predicted energy consumption values by the ANN model. Although the predicted energy consumption is in terms of class values, this allows a certain range for facility managers to operate and manage energy use. Hence, the class divisions provide a better understanding of the energy use pattern.

4.3. Error analysis

The accuracy obtained in the ANN model predictions is followed by an error analysis. An example with building B is presented here. The error is measured as the difference between the measured and

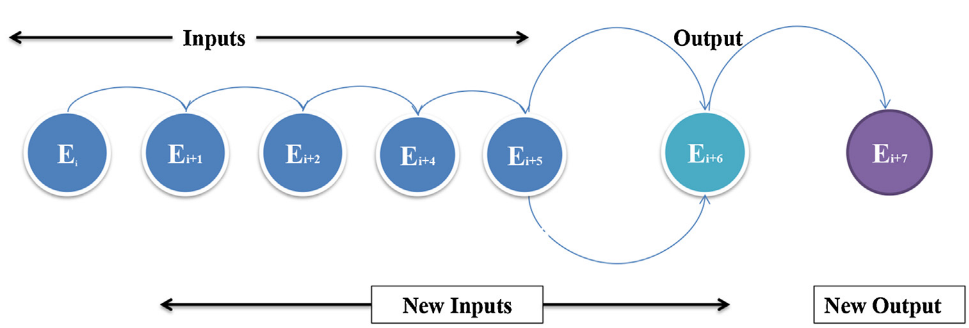


Fig. 14. Graphical representation of the input configuration for ANN model to be tested for lengths of prediction.

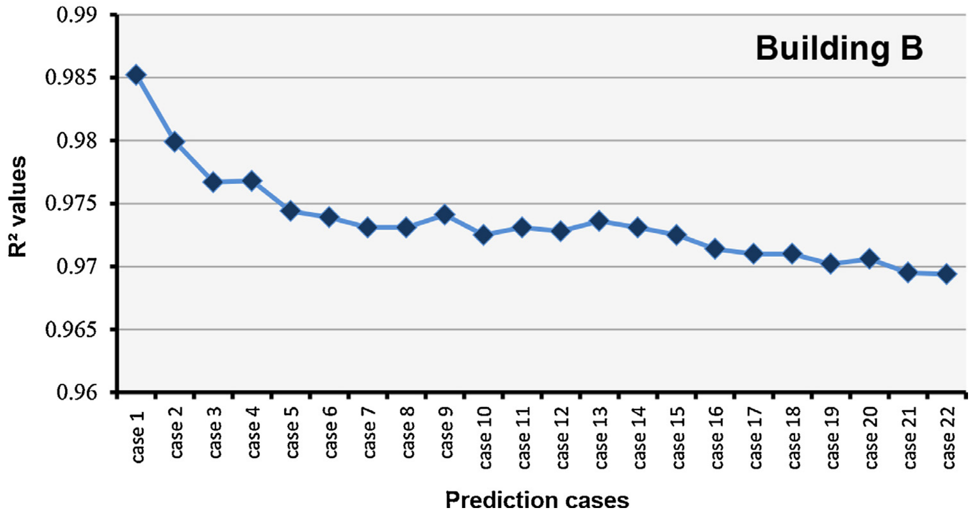


Fig. 15. R^2 values for subsequent prediction cases to test the recursive ANN model for building B.

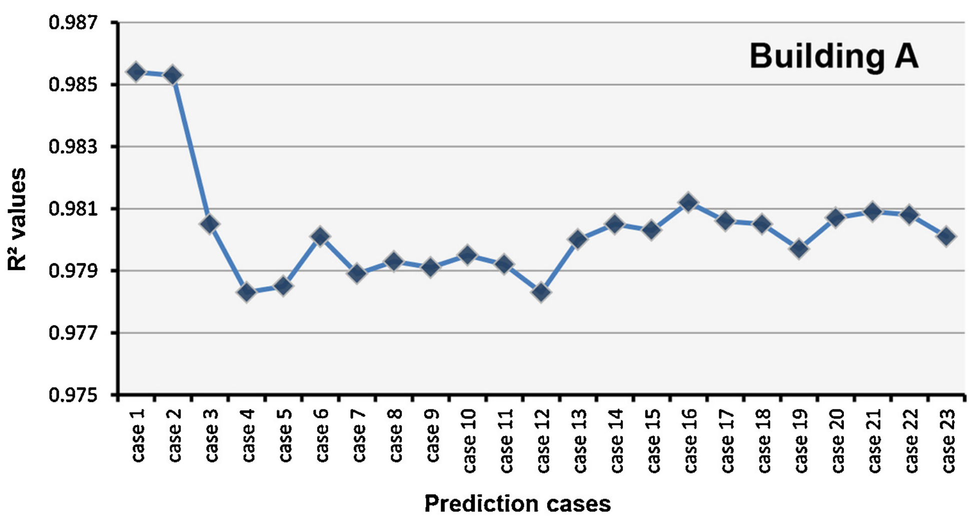


Fig. 16. R^2 values for subsequent prediction cases to test the recursive ANN model for building A.

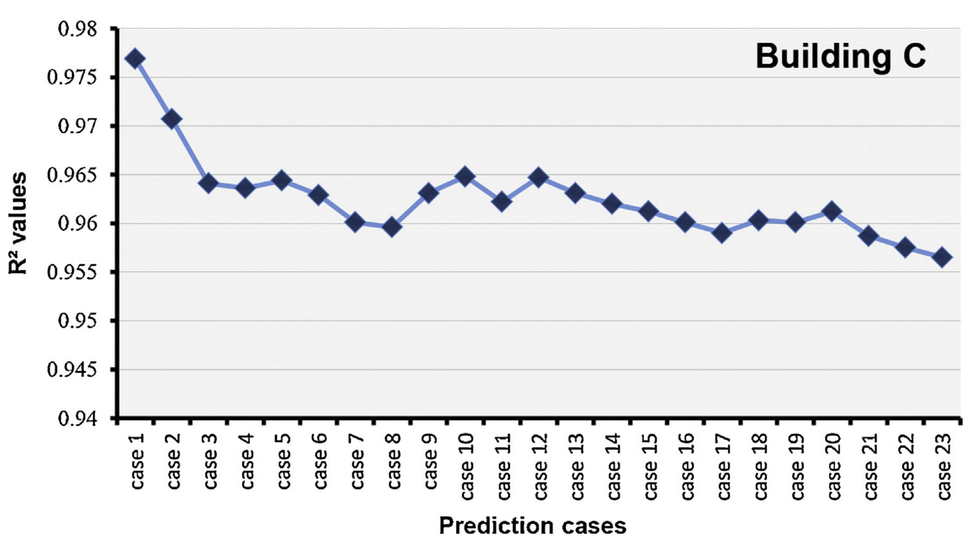
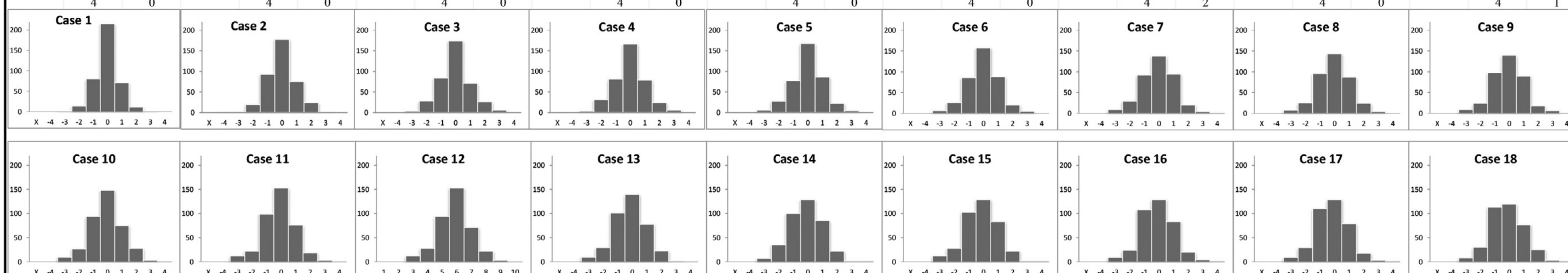


Fig. 17. R^2 values for subsequent prediction cases to test the recursive ANN model for building C.

ΔE	Case 1 Count	Case 2 Count	Case 3 Count	Case 4 Count	Case 5 Count	Case 6 Count	Case 7 Count	Case 8 Count	Case 9 Count
-4	0	1	0	0	0	0	0	0	0
-3	2	2	4	4	6	7	9	8	9
-2	14	20	28	31	27	26	29	25	24
-1	80	93	84	81	77	86	92	96	98
0	215	178	174	167	168	158	138	144	140
1	71	75	71	79	86	88	95	87	90
2	11	24	26	24	22	20	20	24	18
3	2	1	6	6	5	5	4	4	7
4	0	0	0	0	0	0	2	0	1



ΔE	Case 10 Count	Case 11 Count	Case 12 Count	Case 13 Count	Case 14 Count	Case 15 Count	Case 16 Count	Case 17 Count	Case 18 Count
-4	0	0	0	0	0	0	0	0	0
-3	10	12	12	10	7	12	9	9	8
-2	27	22	28	29	35	28	24	29	30
-1	94	99	94	101	100	103	108	110	113
0	148	153	153	139	129	129	129	129	120
1	75	76	71	78	85	83	83	79	77
2	28	19	22	23	22	22	20	18	25
3	3	3	3	2	2	2	4	3	3
4	1	1	1	1	2	2	2	2	2

Fig. A1. Error analysis for the ANN model for predicting energy consumption classes for the next 20 days for building B.

the predicted class values. For example, if the measured class value is 1 and the predicted class value is 2, then the error in this case will be 1. Based on this, a zero error will correspond to the case when the model predicts the class values same as the measured class value. For the case 1 prediction by the ANN model for building B, the number of errors corresponding to zero value is 215 (out of 395). The number of error in the ± 1 range is 151. A detailed graphical representation of the same is presented in Appendix A for all the 22 cases for building B. The same analysis is done on buildings A and C. For building C, the number of errors corresponding to zero value is 98 (out of 196). It is to be noted that for building C, the quality of the collected data is not as good as that in building B. Therefore, the total data set comprises of data for only 196 days for building C as compared to 395 for building B. For this reason, the ANN model training is not the same between these two models. The ANN usually performs better when the training data set is large as in the case of building B, when compared to building C. The results for building A however, are very similar to that of building B.

5. Conclusions

This study presents a new method to develop a forecasting model while dealing with highly variable energy consumption data of institutional buildings. This high variability can be dealt by dividing the data into classes and class numbers as presented in this study. The forecasting accuracy is high by taking these class numbers as inputs for an ANN model. A feedforward ANN with 'Bayesian regularization' training algorithm is found to be most effective and quick in computing as compared to other training algorithms with these class numbers as inputs. It is also seen that a class division of five is most suitable for condensing the high variability and for successive predictions.

This study demonstrated that it is possible to predict many days in succession without changing any of the model parameters. From the viewpoint of facility managers and control systems, such an output is very relevant to formulate day-to-day energy management strategies. It can provide a range of energy consumption values within which the building's energy use must ideally fall for the next coming days. The length of predictions that can be made using this method is close to 21 days with R^2 values gradually decreasing from 0.9852 to 0.9694.

Most of the previous studies either focused on short term energy forecasting with data gathered every 10–30 min time interval or long term forecasting with yearly data analysis. This study, on the other hand, takes diurnal variation into account with a view to aid facility managers and control systems. This also paves way in future to develop this model further and generalize it for a wider selection of institutional buildings.

This paper is an elaborate extension of the paper presented in 'ISHVAC-COBEE' Conference in Tianjin between July 12th and 15th (2015) and published in Procedia Engineering [41].

Appendix A.

Error analysis for the ANN model for predicting energy consumption for the next 20 days for building B (Fig. A1).

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