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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 multipurpose 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.