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Building lighting energy consumption prediction for supporting energy data analytics

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Abstract

Recent studies emphasized the importance of building energy consumption prediction for improved decision making. Data-driven models are being widely used for building energy consumption prediction. Among these, support vector machines (SVM) gained a lot of popularity due to its capability of handling non-linear problems. This paper presents an SVM-based lighting energy consumption prediction model for office buildings. For this study, an office building in Philadelphia, PA was instrumented and the required lighting energy consumption data to train the model were collected from this building. The developed model predicts daily lighting energy consumption based on two features: daily average sky cover and day type. The results showed that the developed model could be a good baseline model for predicting lighting energy consumption, which could be further extended by taking occupant behavior into account.

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Keywords: Data analytics; Machine Learning; Lighting energy consumption prediction; Support vector machines.

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1. Introduction

Energy is the lifeblood of modern societies. In the past decades, the world's energy consumption and associated CO_2 emissions have increased rapidly due to the increases in population and comfort demand of people. In this decade, the increases in energy consumption and associated CO_2 emissions are expected to continue due to similar reasons. Buildings are a significant consumer of the world's energy. The building sector is responsible for 39% and 40% of the energy consumption and 38% and 36% of the CO_2 emissions in the U.S. [1] and Europe [2], respectively. Buildings, therefore, offer a great potential for reducing the world's energy consumption and limiting the negative impacts caused by the use of non-renewable sources. On the other hand, people spend a significant portion of their time in buildings and they desire comfortable, healthy, and productive indoor environments. A recent study showed that the majority of residential and office building occupants attach high importance to thermal comfort, visual comfort, indoor air quality, health, personal productivity, energy cost saving, and environmental protection [3]. Improving building energy efficiency is one of the best strategies for reducing the energy consumption of buildings, while maintaining the comfort and well-being of the building occupants.

Accurate modelling and prediction of building energy consumption is crucial for enhanced decision making since it could facilitate building and grid design and operation. In this regard, predicting building energy consumption drew a lot of research attention in recent years. Building energy software tools (physical models), such as EnergyPlus and eQuest, are being widely used for energy consumption prediction. These tools are, however, very elaborate and therefore require a significant number of input parameters that are not always available to users. In order to predict energy consumption of buildings without many input parameters, data-driven models were developed. Data-driven approaches utilize historical input data (e.g., outdoor weather conditions, electricity consumption) for developing a prediction model.

There are numerous studies that developed data-driven energy consumption prediction models for buildings. These studies can be classified based on their learning algorithms, spatial scales, temporal granularities, types of energy consumption prediction, and types of dataset. Learning algorithms include support vector machines (SVM), artificial neural networks (ANN), decision trees, and other statistical algorithms. Spatial scales include building and region scales. Temporal granularities include short-term and long-term. Types of energy consumption prediction include overall, cooling, heating, and lighting energy consumption prediction. Types of datasets include simulated and real datasets. In this paper, the authors proposed a data-driven model for predicting lighting energy consumption. The rest of this paper is as follows. Section 2 provides a brief introduction on the related work and research gaps. Section 3 introduces the methodology and the proposed energy consumption prediction model. Section 4 presents and discusses the prediction results. Finally, section 5 summarizes the conclusions and future work.

2. Related Work and Research Gaps

Data-driven energy consumption prediction models are being widely used for building and grid design and operation. There are energy consumption prediction models available for building-scale and region-scale. The majority of these studies are focused on predicting overall, cooling, and heating building energy consumption. For example, Dong et al. [4] developed an SVM-based overall energy consumption prediction model. They predicted monthly electricity consumption based on mean outdoor dry-bulb temperature, relative humidity, and global solar radiation. The model was trained using three years' data of four office buildings in Singapore and tested on a year's data. The results showed that SVM can be employed for building energy consumption prediction. Li et al. [5] compared SVM and back propagation neural network (BPNN) on predicting hourly cooling load of an office building. DeST was used to generate five months' hourly cooling loads of an office building in China. The SVM and BPNN-based models were trained using a month's data. They tested the effectiveness of a set of input parameters and selected the following features: mean temperature of the current hour, mean temperature of the previous hour, mean temperature of the two hours ago, mean relative humidity of the current hour, mean solar radiation of the current hour, and mean solar radiation of the previous hour. The SVM-based model performed better than the BPNN-based model in predicting the hourly cooling load of the remaining four months. Li et al. [6] developed electricity consumption prediction models for residential buildings and compared the prediction performance of four learning algorithms including SVM, BPNN, radial basis function neural network (RNFNN), and general regression neural network (GRNN). The models predicted annual electricity consumption of residential buildings based on the mean heat transfer coefficients of the building walls, the mean thermal inert indexes of the building walls, the roof heat transfer coefficients, the building size coefficients, the absorption coefficients for solar radiation of the exterior walls, the eastern window-wall ratios, the western window-wall ratios, the southern window-wall ratios, the northern window-wall ratios, the mean window-wall ratios, the shading coefficients of the eastern windows, the shading coefficients of the western windows, the shading coefficients of the southern windows, the shading coefficients of the northern windows, and the integrated shading coefficients. The models were trained on 50 buildings and tested on 9 buildings. The results showed that SVM and GRNN can predict with lower error rates compared to BPNN and RBFNN. Massana et al. [7] developed prediction models for a university office building in Spain. They compared the performance of multiple linear regression, multilayer perceptron, and SVM in predicting the hourly loads of the building. They also assessed the contribution of outdoor weather, indoor environmental conditions, occupancy, and calendar data to the performance of electricity consumption prediction. The results showed that the SVM-based model that predicts based on temperature and occupancy is the best model, in terms of prediction error and computational cost. Xing-Ping and Rui [8] utilized SVM for predicting the annual electricity consumption of China. They compared multivariable SVM and univariable SVM. The gross domestic product per capita (PCGPD), heavy industry share, and efficiency improvement were the features for the multivariable SVM, while the previous year's electrical consumption was the only feature for the univariable SVM. The results showed that multivariable SVM performs better in terms of absolute proportional error.

Despite existing efforts, there is a lack of studies on predicting lighting loads. To the best of the authors' knowledge, only few studies (e.g., [9,10]) focused on lighting energy consumption prediction. Lighting accounts for 20% of the global electricity consumption [11]. It is also a significant heat source and therefore affects the cooling energy demand of buildings [10]. In general, one-third of the cooling energy consumption can be eliminated if a good synergy between natural light and solar heat can be achieved [10]. Predicting lighting energy consumption is essential for maintaining such a synergy and achieving energy saving. Furthermore, different building operation strategies, in terms of their lighting energy consumption, can be assessed using the models developed for predicting lighting energy consumption [9]. Lighting energy consumption prediction models, thus, require more attention to better understand the energy consumption of lighting systems and the interaction between cooling load and lighting.

3. Methodology

The objective of this paper is to develop a data-driven lighting energy consumption prediction model for buildings. In this regard, an SVM-based model was developed and validated using a dataset gathered from an office building in Philadelphia, PA. The model's parameters were then tuned up to maximize its performance. This section is organized as follows: Section 3.1 introduces the machine learning algorithm that was implemented. Section 3.2 provides the model features and the performance evaluation measure used in this study. Section 3.3 presents the building instrumented for this study, the data collection, and the algorithm implementation.

3.1. Machine learning algorithm

The SVM algorithm was selected because it can solve non-linear problems even with small amount of training data [12]. It is one of the most robust and accurate algorithms and has been listed in the top ten most influential data mining algorithms in the research community by the IEEE International Conference on Data Mining [13]. It was found to outperform other machine learning algorithms in numerous applications. In order to increase the computational efficiency of SVM, least squares support vector machines (LS-SVM) (e.g., [14]) and parallel support vector machines (e.g., [15]) were also implemented in the field of building energy consumption prediction.

3.2. Model features and performance evaluation measure

The authors developed a prediction model that utilizes the following features: daily average sky cover and day type. Sky cover is the amount of opaque clouds and ranges from 0 to 1, where 0 indicates a clear sky and 1 indicates a completely covered sky. An increase in sky cover can increase the lighting energy consumption [16]. Day type denotes whether a day is a weekday or a weekend/holiday. Day type was used as a feature to indicate the approximate occupancy level. Generally, occupancy levels in an office building are expected to be high during weekdays and low during weekends and holidays.

The performance was evaluated using coefficient of variation (CV). CV is a performance criteria, provided by ASHRAE, for evaluating building energy consumption level prediction models. CV determines how much the overall prediction error varies with respect to the target's mean [14]. CV can be calculated using Eq. (1).

$$CV(\%) = \frac{\sqrt{\frac{\sum_{i=1}^{n}\left(y_{predict,i} - y_{data,i}\right)}{n-p}}}{\bar{y}_{data}} \times 100 \tag{1}$$

where $y_{predict,i}$ is the predicted energy consumption at day i, $y_{data,i}$ is the actual energy consumption at day i, $\bar{y}_{data}$ is the average energy consumption, n is the number of days in the dataset, and p is the total number of features in the model (e.g., day type).

3.3. Experimental setting, data collection, and algorithm implementation

The Philadelphia Business and Technology Center (PBTC) was employed for this study. PBTC is a 6-story building with an estimated total floor area of 40,000m^2. The fourth floor of the building was instrumented with various sensing devices and data loggers for empirical data collection. Three types of data are being collected: energy consumption data, indoor environmental condition data, and occupant behavior data. Energy consumption data include lighting, heating, cooling, and plug energy consumption data in 15 min intervals. Indoor environmental conditions include temperature, relative humidity, CO_2 concentration, particle concentration, and illuminance level data in 15 min intervals. Occupant behavior data include occupancy, turn on/off/adjust personal devices, turn on/off/adjust ceiling fan, turn on/off/adjust room air conditioning, adjust floor/ceiling/wall air ventilation, adjust thermostat, open/close doors, and open/close windows data. In addition, occupant feedback about their satisfaction levels with indoor environmental conditions are being collected via an occupant feedback app. The elevation and the floorplan of the designated area for the experiment are shown in Fig. 1.

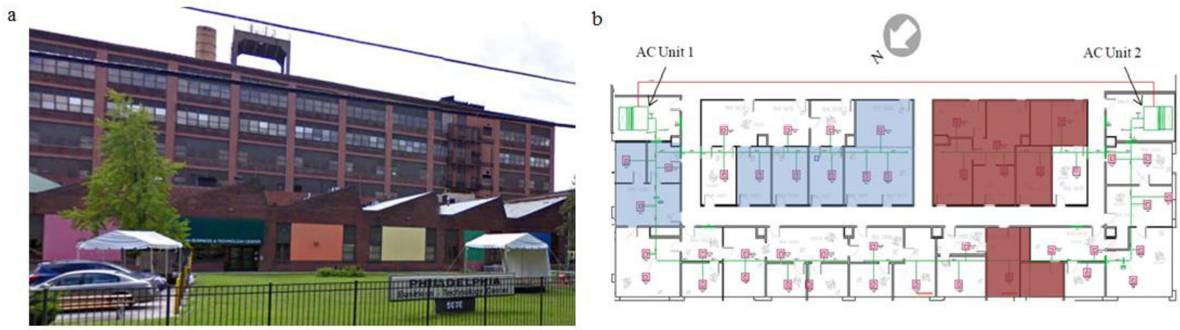

Fig. 1. (a) elevation; (b) floor layout, adapted from [17].

For this study, only the data that are related to lighting energy consumption were utilized. The used dataset, therefore, consisted of lighting energy consumption data in 15 min intervals, daily average sky cover of Philadelphia downloaded from the Philadelphia/Mount Holly Weather Forecast Office of National Weather Service Forecast Office, and day type. The authors utilized 60 days of data for this study. The data were cleaned, transformed to the format required by the learning algorithm, and normalized. Data cleaning included detecting/completing missing values and removing noisy data. After data cleaning, 37 days of data were left. Then, lighting energy consumption data were aggregated to daily energy consumption since sky cover data are daily. Finally, the data were normalized, transformed to the required format, and split into training and testing data. A set of 26 days of data was randomly selected from the 37 days of data and was used for model training. The rest of the data were used for testing.

The model was trained using LIBSVM 3.20 package. The authors tested different kernels and algorithm parameters to improve the prediction performance. As a result, the following parameters were chosen: nu-SVR (type of SVM), linear kernel (kernel type), and 500 (cost).

4. Results, Discussion, and Limitations

As shown in Fig 2, the predicted results of the model, on the testing dataset, showed good fitness with the actual energy consumption. The model achieved 6.83% CV. This performance can further be improved by taking occupant behavior into account, because occupant behavior has a very dominant impact on lighting energy consumption. Lighting use is significantly affected by occupant behavior and actions [18]. For example, 500 lux is the recommended illuminance level for office buildings [19] and occupants are expected to decrease their use of artificial lights [20]. However, Yun et al. [18] showed that there are no statistically significant relationships between outdoor illuminance and artificial lighting use patterns.

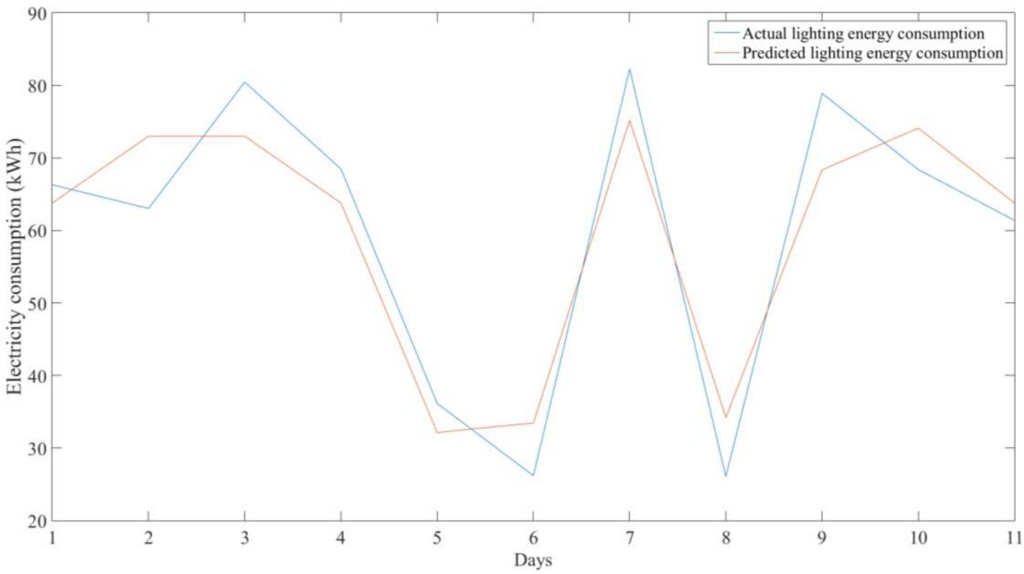

Fig. 2 Prediction results.

The authors acknowledge that the results of this study may not be enough to demonstrate the applicability of the proposed model given the limited number of features and amount of data. In order to validate the effectiveness of the proposed model, further experiments should be conducted on different buildings and locations, and over longer periods.

5. Conclusion and Future Work

In this paper, the authors introduced a data-driven model for predicting lighting energy consumption of buildings. The proposed model used SVM as the learning algorithm. Daily average sky cover and day type were utilized as the features. The model was trained and tested on a data set that was collected from an office building in Philadelphia, PA. The prediction results showed that the proposed model has the potential to be successfully used for lighting energy consumption prediction.

In future work, the authors will test the proposed model on different buildings and in different locations and will further improve the model, if/as needed. Currently the authors are conducting a set of empirical energy studies in residential and office buildings to capture energy use behavior of building occupants. Later on, energy use behavior of building occupants will be incorporated in the model. The authors aim to improve the performance of the proposed model by taking the energy use behavior of building occupants into account. The authors are also planning to extend this model to sub-hourly, hourly, and monthly lighting energy consumption prediction.

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