Detecting Occupancy Patterns of Smart Buildings for Efficient Energy Management

INTRODUCTION

In 2011, the US building sector accounted for 41% of the total energy consumed, outperforming the transportation and industrial sectors by 28% and 31%, respectively. [3] Prior studies show that occupancy pattern detection can reduce the energy consumption of lighting by 50% [9] and air conditioning by 20% [5]. The prediction of occupancy patterns is particularly important in *Heating Ventilation and Air Conditioning* (HVAC) control systems because the process of reaching the appropriate temperature is time consuming and costly. The objective of this study is to develop an AI-based model that predicts the occupancy pattern of a commercial building (i.e., *Mitsubishi Electric Research Laboratory* (MERL)) in order to anticipate the optimal temperature for the HVAC system two hours from the present.

RELATED WORK

Researchers have used various methods to model the occupancy pattern of buildings. Erickson et al. developed an agent-based model that simulated occupancies by modeling the behavior of individuals. [6] They also proposed a multivariate Gaussian model that calculates the probability of a particular state at a given time. To model the temporal dynamics of occupancy, Erickson et al. used an inhomogeneous Markov Chain method, by which they achieved 42% annual energy savings. [4] They expanded their study by comparing the performance of three Markov Chain algorithms: Closest Distance Markov Chain, Moving Window Markov Chain, and Blended Markov Chain and showed that the Blended Markov Chain outperformed the others. [7] Unfortunately, the models developed in most of these studies use time constrained datasets (e.g., 79 days, 110 days [1]) and are not entirely generalizable. Our research, however, will model the occupancy pattern over the long term (730 days) using temporal, spatial, and seasonal variance. In addition, although the MERL dataset has been used in few research studies (e.g., how social networks move through a building by examining the spatial and temporal accumulators [2]), none have researched the significance of meteorological or seasonal data on those spatial and temporal values.

PROJECT DESCRIPTION

The goal of this project is to build several predictive models in various zones of the Mitsubishi Electric building. In Project 1, we examined the MERL dataset using GMM/EM and Regression Analysis. The results using GMM/EM were promising, however we identified areas for further improvement, such as modeling many hidden factors (e.g. weather conditions) that effect the accuracy of the Occupancy Prediction Model. In Project 2, we will examine Hidden Markov Models for two main reasons. First, there are hidden unknown factors in the model, such as weather. Second, the state is not directly visible, but the output, dependent on the state, is visible. We also examine a method that generalizes HMM by factoring the state space called Dynamic Bayesian Nets (DBN). Table 1 summarizes the advantages and disadvantages of HMM and DBN.

Table 1: Preliminary Evaluation of different Modeling Methodologies [8]

Method	Pro	Con
HMM	Works well on the classification of large temporal datasets and have been used successfully in the area of human behavior modeling. HMMs are simpler to train and to do inference with, handle continuous data, and impose less computational burden than DBN	The accuracy of the classifier is dependent upon the number of states and variables.
DBN	Recognizing appropriate dependencies and independencies between variables is easy and it is good for modeling noisy data. They handle uncertainty and incomplete datasets very well and can learn dependencies between variables that were assumed independent in HMMs	Calculation is NP-hard and dependent upon the quality of the model. Accuracy of inference by DBNs seems to be less sensitive than HMMs to loss of access to sets of observations

By investigating *Hidden Markov Models* (HMM) and *Dynamic Bayesian Nets* (DBN) over five minute cycles of the entire MERL dataset, we are going to identify the most appropriate modeling framework as applicable to the energy requirements of a commercial building. We will evaluate these methods on their accuracy of predicting the occupancy patterns for the different sections in the building over a 2-hour window.

METHODS OF EVALUATION

From Project 1, we observed the patterns vary significantly over different seasons, holidays, and workdays. The training sets and evaluation models will therefore be chosen differently in Project 2. We will compare the maximum, minimum, average and most probable occupancies to our test data using two evaluation metrics based on range and variance. The range metric evaluates whether the test data successfully falls between the maximum and minimum occupancy values of the model predicted. The variance metric evaluates how different the most likely occupancy predicted compares to the test data. The K-fold cross-validation method (K=10) will be used to test the model. The cumulative average prediction precision will be our final result.

To evaluate the practical impact of our model, we compare the results of energy simulation analysis for two different models. The first model uses the static building occupancy profile recommended by building codes. The second model, however, uses our dynamic occupancy pattern to estimate the energy consumption of the building. This comparison will demonstrate how much energy we can save.

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