Forecasting building occupancy: A comparative study of approaches

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ABSTRACT

This paper provides a sample of a LaTeX document which conforms to the formatting guidelines for ACM SIG Proceedings. It complements the document *Author's Guide to Preparing ACM SIG Proceedings Using LaTeX2$_\epsilon$ and BibTeX*. This source file has been written with the intention of being compiled under LaTeX2$_\epsilon$ and BibTeX.

The developers have tried to include every imaginable sort of "bells and whistles", such as a subtitle, footnotes on title, subtitle and authors, as well as in the text, and every optional component (e.g. Acknowledgments, Additional Authors, Appendices), not to mention examples of equations, theorems, tables and figures.

To make best use of this sample document, run it through LaTeX and BibTeX, and compare this source code with the printed output produced by the dvi file.

1. INTRODUCTION

According to the U.S. Department of Energy energy for heating and cooling accounts for approximately 35 - 45% [2] of the total expenditure within a building. With such a large investment of energy being used to regulate the temperature of a building, any possible areas of improvement in this area are heavily sought after. Knowledge of occupancy of people within a building are an important component to intelligent heating and air condition systems. True levels of occupancy are rarely known and as a results most buildings instead rely on existing systems such as carbon dioxide sensors or motion activated lights.

A number of other researchers have created local wireless network occupancy sensing devices using a combination of sensors. In this paper we explore the forecasting accuracy of multiple common time series forecasting models using a number of forecasting measurement metrics. Or occupancy is derived from infrared sensors densely placed around a building. The data is collected from two different types of buildings, one is an office building, the other a classroom and research building with different schedules of levels occupancy. We believe that this work will lead researchers to have a better idea of what forecasting algorithms will perform best under the specific conditions of our buildings.

The remainder of the paper is laid out as follows: Section 2 discusses the other work in this area including research from vehicle traffic systems. Section 3 discusses our forecasting models. In section 4 we introduce the datasets and give a brief description of the data collection method and the types of buildings from which the data was generated. Section 5 show the results of our forecasts and the paper concludes with a discussion of our conclusions and future work in section 6.

2. RELATED WORK

There has been considerable work in generating simulated models of occupancy [7, 3]. These simulations often involve agent based models where the concern is more with the accuracy of the models occupancy at any given time instead of the model's forecasting abilities. Agent based models also tend not to scale well to large buildings where the where large numbers of agents, rooms and interactions lead to non-trivial solutions.

Researchers have also created systems to attempt direct occupancy estimation using a combination of simple sensors and wireless motes. Agarwal, et. al [1] has created motes using a combination of an IR sensors reed switch place on a door to determine the likelihood that a room is occupied. This work is excellent for occupancy data acquisition, but little work was done on occupancy forecasting. Mamidi [6] and the University of Southern California have developed a building-level energy management system using a combination of motion detectors and environmental sensors. They compared their readings against a ground truth recorded by occupants using specifically monitored rooms. They used a variety of standard learning algorithms, including ensemble methods to accurately estimate the occupancy of a room. Work from both those these groups however seems to be more focused on occupancy estimation instead of forecasting.

Outside the world of building occupancy forecasting, there has been considerable work with counting vehicles on road ways. Forecasting for traffic roadways present many of the same challenges that buildings present. The data has clear
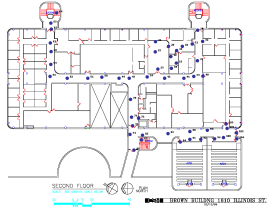
(a) Colorado School of Mines Brown building second floor
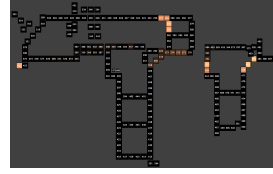
(b) Merl research lab 7th and 8th floor

Figure 1: Sensor locations for buildings

daily trends and is subject to large shifts in those trends based on environmental factors such as accidents or weather. Thus it seems pertinent to discuss any promising forecasting techniques used in the traffic domain along with the building domain.

The classic time series Auto Regressive Moving Average Model (ARMA) or derivations on its form (ARIMA, SARIMA, VARMA, etc) have been used in numerous papers on forecasting. The results on this class of models seem mixed. William's [8] showed promising short term forecasting results using Seasonal ARIMA models on traffic sets from London and Atlanta. Hong [4] , while again demonstrating the feasibility of Seasonal ARIMA models to traffic forecasting, achieved better results combining genetic algorithms and simulated annealing.

Zheng [10] used a bayesian combination of time delayed neural networks to achieve better forecasting accuracy than each neural network alone. This demonstrates the feasibility of both a bayesian combined approach and the use of time delayed neural networks for traffic forecasting. The problem with these forecasting approaches is that they focus only on short term forecasts, typically one time step into the future (often 15 minutes). While this forecast horizon may be applicable to traffic forecasting, pre-heating and cooling systems can utilized occupancy forecast up to 24 hours into the future [5].

3. OCCUPANCY DATA

Our datasets come from two sources. The first is Mitsubishi's MERL dataset [9]. Data is collected here from a collection of roughly 150 passive infrared sensors place densely throughout the 7th and 8th floor of a research building. The sensors sensors are place roughly two meters apart on the ceilings creating a dense sensing area with little non-sensed space. Readings are taken at the milisecond level, but due to the sensors settling times the interdetection time of motion is roughly 1.5 seconds. The data was collected for years and there are roughly 53 million sensor readings. This building similar to most office buildings with a number of personal offices along with labs and conference rooms. Employees have roughly set schedules and holdiays are observed as normal.

The second dataset is from the Colorado School of Mines (CITE) Brown building. Data is collected from 50 passive IR sensors mounted on the ceiling of the second floor. The density of the sensor placement depends on the location within the building. Outside auditorium is a dense collection of sen-

Figure 2: Passive infrared motion detector

sors place every meter. Throughout the rest of the building the sensors are placed roughly every 5 meters. Data was collected for one academic school year 2008 to 2009 with readings at the one second resolution. This building operates much differently than the MERL dataset as classes provide motion on a rigid schedule during the day. Also as students have exams and projects, late night motion is sporadic based on the time of year.

4. FORECASTING MODELS

For comparison we select from some of the most common models used for time series forecasting. This section gives a brief introduction to each of these forecasting models.

To introduce some notation the data used for these models comes from a set of M binary infrared sensors. Each of these sensors may sense a person's motion at some time t. This leaves us with a dataset of the form $\{d_a^{(s)}\}$ with s in the set of all sensors S and a is the time of the sensor activation over some time span A_{span}.

This data is this aggregated into blocks of 10 minute intervals. Each block is the sum of all sensor activation for its unit of time. This leaves us with a dataset of the form $\{y_t^{(s)}\}$ where the total number of blocks of time are T.

4.1 Seasonal ARIMA Model

The Auto Regressive Moving Average Model (ARMA) or derivations on its form (ARIMA, SARIMA, VARMA, etc) have been used in numerous papers on forecasting with applications ranging from economics to vehicle traffic systems [8, 4].

An ARMA model of with a number of ϕ and θ parameters, represented by p and q respectively is defined as:

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_p y_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - ... - \theta_q e_{t-q}$$

(1)

where $\{y_t\}$ denotes the observed time series and $\{e_t\}$ represents an unobserved white noise series. We abbreviate the model name to ARMA(p, q). This approach involves training a set of parameters to fit a regression model based on a fixed number of historic readings. ARMA based approaches are useful for their capability to predict further than one measured time instance in the future.

Due to our traffic data having periodic trends and a non stationary mean, it is advantageous to use a seasonal ARIMA model. An ARIMA model can handle non stationary means while periodic trends are handled by the seasonal component of the model. The seasonal ARIMA model is defined as:

$$\phi_p(B)\Phi_p(B^{season})\nabla^d\nabla_s^D y_t = \theta_q(B)\Theta_Q(B^{season})e_t \quad (2)$$

where B is the backshift operator, $a_t \sim N(0, \sigma^2)$ is a white noise process, ∇_j^i is the seasonal difference operator, and ϕ, Φ, θ, Θ are trainable parameters. We represent seasonal ARIMA models as $ARIMA(p, d, q)(P, D, Q)_s$ where p is the number of autoregressive terms, d is the number of differences and q is the number of moving average terms. P, D, and Q all correspond to the seasonal equivalents of p, d, and q. The parameter s is the seasonality of the model.

Forecasting from this model is performed by iteratively forward feeding values of the model into itself. Since the set of residuals e from a properly trained seasonal ARIMA model is described by a white noise gaussian distribution (TODO PUT NORMAL DIST HERE), we can assume the residual for the current time is always 0.

$$\phi_p(B)\Phi_p(B^{season})\nabla^d\nabla_s^D y_{t+1} = \theta_{q-1}(B)\Theta_{Q-1}(B^{season})e_t \tag{3}$$

4.2 Historic Average
This model is simply the per day average of readings at each time step. For certain types of data this model is has been shown to be more accurate than seasonal ARIMA forecasting. If the data has a strong historical correlation, average forecasts may be most accurate. Certainly average forecasts have the advantage of being extremly computationally fast and having a forecast accuracy that does not depend on forecasting horizon. This result will be shown later.

4.3 Bayesian Combined Forecasting
$$p_k^{(t)} = p(k|x_{1:t}) = \frac{p_k^{t-1} \cdot err(x_t - h_k(x^{1:t-1})}{\sum_{j=1}^K p_j^{t-1} \cdot err(x^{(t)} - h_j(x_{1:t-1})} \quad (4)$$

where $p(Z = k|x)$ is the probability of model k given data x, K is the total number of models, h_k is the forecast from model k, and $err()$ is the probability mass function of the forecasting error for model k.

4.4 NARX
4.5 Time Delayed Neural Networks
4.6 Random Walk
5. RESULTS
SHOW RESULTS HERE

6. CONCLUSION
7. REFERENCES

[1] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng. Occupancy-driven energy management for smart building automation. In *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building - BuildSys '10*, page 1, New York, New York, USA, 2010. ACM Press.

[2] U. DOE. Building Energy Databook, 2010.

[3] R. Goldstein, A. Tessier, and A. Khan. Schedule-calibrated occupant behavior simulation. In *Proceedings of the 2010 Spring Simulation Multiconference on - SpringSim '10*, page 1, New York, New York, USA, 2010. ACM Press.

[4] W.-C. Hong, Y. Dong, F. Zheng, and S. Y. Wei. Hybrid evolutionary algorithms in a SVR traffic flow forecasting model. *Applied Mathematics and Computation*, 217(15):6733–6747, Apr. 2011.

[5] Y. Ma, F. Borrelli, and B. Hencey. Model predictive control for the operation of building cooling systems. In *America Control Conference*, 2010.

[6] S. Mamidi, Y. Chang, and R. Maheswaran. Improving building energy efficiency with a network of sensing, learning and prediction agents. In *International Conference on Autonomous Agents and Multi Agent Systems. AAMAS 2012*, 2012.

[7] J. Page, D. Robinson, N. Morel, and J.-L. Scartezzini. A generalised stochastich model for the simulation of occupant presence. *Energy and Buildings*, 40:83–98, 2008.

[8] B. M. Williams and L. a. Hoel. Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results. *Journal of Transportation Engineering*, 129(6):664, 2003.

[9] C. Wren, Y. Ivanov, D. Leigh, and J. Westbues. The MERL motion detector dataset: 2007 workshop on massive datasets. In *ICMI Workshop on Massive Datasets*, 2007.

[10] W. Zheng, D.-H. Lee, and Q. Shi. Short-Term Freeway Traffic Flow Prediction: Bayesian Combined Neural Network Approach. *Journal of Transportation Engineering*, 132(2):114, 2006.