A Prediction Reference Model for Air Conditioning Systems in Commercial Buildings

Mahdis Mahdieh[*], Milad Mohammadi[†], Pooya Ehsani[‡]

School of Electrical Engineering, Stanford University

Abstract

Nearly 45% of the total energy of commercial buildings in U.S. is consumed on the air conditioning system. Machine learning techniques can be used to predict building A/C energy consumption to help with efficiently automating the air conditioning process. This study focuses on an in-depth analysis of Stanford Y2E2 building dataset to model the effect of each building sensor measurement on the A/C system energy consumption. By training different data models using a variety of supervised learning methods, we discovered that 3rd order polynomial support vector regression (SVR) model best predicts the building A/C system; however, all other trained models we studied generated acceptably low training error rates (smaller than 1.5%) and higher then 94% correlation with our labels. While linear regression is the simplest and least accurate model used in this study; it works well with a small training dataset and reaches the desirable accuracy faster than other models.

1. Introduction

According to the U.S. Energy Information Administration "Commercial Buildings Energy Consumption Survey" in 2003, 45% of the energy in commercial buildings is consumed on air conditioning as illustrated in Figure 1 [5].

The A/C system in Y2E2 building is managed by a fairly complex automated system, operating based on the present outside/inside atmospheric state of the building using numerous sensors for temperature, wind, solar energy, etc. Using this data the building consumes various levels of heating and cooling resources to maintain the building temperature at around 22°C with ± 2°C fluctuation.

We make use of some supervised learning algorithms to predict the amount of energy consumed to maintain the temperature at a desirable level. Because of the numerical and continuous characteristics of the dataset, we applied three different supervised learning algorithms including linear regression, support vector regression, and neural networks. Different parameter settings are used for each method to minimize the risk of overfitting and underfitting.

Resultant prediction models can give a clear insight on how the building facilities work and how various sensors and controllers perform in the building. Influence of each sensor data on the overall performance can be implied from the weight of corresponding feature in the prediction models. This can guide the building managers to find which sensors play a stronger role in determining the behavior of the building and which sensors can be eliminated for economizing the total cost. Moreover, if the weights of some sensors are unexpectedly different from their expected value, one may infer there is either a deficiency in the sensor performance or its location is not effectively provisioned. Furthermore, a prediction model for a building like Y2E2 can provide a predictive model that can be used in other campus building with similar structure.

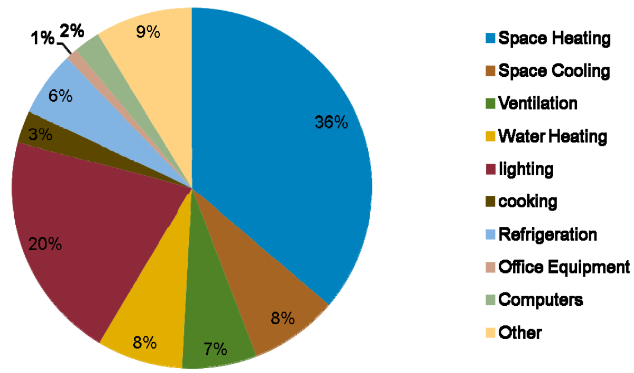

Figure 1: Space heating and cooling accounted for 45% of total energy use in 2003. From U.S. Energy Information Administration, Commercial Buildings Energy Consumption Survey, 2003 [5]

The remaining of this report is organized as follows. First we go through related works on machine learning applications in prediction of building energy consumption in section 2. We introduce our dataset in section 3 and also define the features and labels used to train all models. In section 4 we describe the three different supervised learning algorithms applied to the dataset. Finally, we discuss the results in section 5, followed by the conclusion in section 7.

2. Related Work

Energy and sustainability issues have raised a large number of academic research. Due to big success of machine learning and data mining approaches many have been convinced to apply those methods in the context of residential and commercial buildings energy consumption. While predicting values in residential and commercial buildings have outstanding differences, applied models on residential buildings in [4] give us insight on conventional and well-used models in this context. Dong *et. al.* in [3] apply support vector machines to predict

[*] mahdis@stanford.edu
[†] milad@cva.stanford.edu
[‡] pooya@stanford.edu

energy consumption of buildings in tropical regions where have similarity to weather conditions to the framework which we are studying, the Stanford campus. In addition, the authors in [2, 6] claim artificial neural networks achieve good results in predicting consumed energy in commercial buildings and offices.

3. Data Set

The Stanford Y2E2 building has 2375 sensors that report building energy system status and performance every minute. These sensors measure a variety of physical properties such as inside/outside temperature, air humidity, wind direction, plug loads, etc. This information is provided to the users through an online database system called SEEIT hosted by the university [1]. In this wealth of information, we were interested in predicting the A/C system energy consumption via numerous environmental properties affecting it.

The Y2E2 A/C system energy consumption mostly consists of the energy consumed on providing the cold water and hot steam coming into the building. The cold water and hot steam are provided by a central building in the university campus which is responsible for heat steam and cold water spreading out the flow to all campus buildings. The natural choice of a label for this study would be energy consumption of the building by the A/C system. However, since we do not have access to this data, the total heat exchange in time unit is linearly calculated based on the heat capacity relation from fluid dynamic; using the flow-rate which we recorded from the available data on SEEIT, we chose the following two labels:

- Building A/C cold water flow rate
- Building A/C hot steam flow rate

Selecting flow-rate and building learning models for predicting those labels is valuable in a number of application such as resource sharing and energy management on campus. If the model is capable of predicting future fluid consumption, managers can be informed about uncommon peaks in urgent situations like sudden temperature rises in advance in order to make appropriate provisioning. This can alleviate the issues like the heat wave incident in summer 2013 when the campus management shut off all commercial building A/C systems in order to sustain the A/C support to Stanford Hospital and a few other sensitive buildings.

Our studies of the existing datasets of the Y2E2 building sensors suggested potential correlations between the following building measurements and labels:

- Outside temperature/Humidity
- Outside wind speed/direction
- Building atrium automatic windows
- Inside temperature (Space air temperature)
- Hot/Chilled water (differential) temperature, pressure
- Solar energy radiation/diffuse

Figure 2 shows the changing trend of some of the features along with the labels. The first step was to select the right features from the list by computing the correlations and mutual

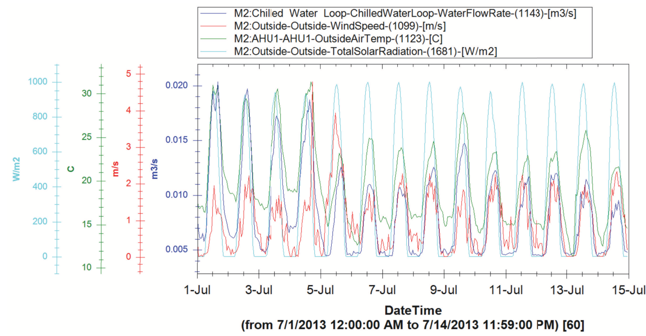

Figure 2: Strong correlation between different sensor measurements

information(MI). Most features are visually quite correlated with the labels. However, we found out some features are less correlated than perceived and some others are correlated with some time-shift; for example, the water-flow rate and inside temperature are correlated with a time-lag which is caused by the fact that chilled water changes the temperature after some time proportional to the diffusion rate of heat in air.

Table 1 lists some of the measured correlation and MI analysis between features and the cold water flow label in summer season. The time column suggests the time lag that maximizes the correlation and MI between each feature and the label.

Features	Corr	Max	Time	MI	Max	Time
OutTemp	0.96	0.96	0	1.56	1.60	0
WindSpeed	0.53	0.54	+0:45	0.91	0.95	+0:45
SpaceTemp	0.79	0.79	+0:30	1.26	1.28	+0:30
Humidity	0.54	0.55	+0:30	1.04	1.06	+0:45
SolarRad	0.72	0.83	-1:30	1.15	1.29	-1:30

Table 1: Summer Correlation and MI Analysis (Regarding to Cold water flow-rate). Time corresponds to the shift in data between the label and the measured feature in order to get the maximum correlation and mutual information. This table is generated from the data collected in July 2013.

Based on the correlation and MI information, we excluded wind direction, automatic windows states, and diffuse solar radiation from our feature sets. For the features that were correlated with our labels with a time-shift, we also added the shifted features to the feature set. Surprisingly, adding the shifted features ended up not significantly improving the results in any of the models.

Because of the obvious difference in the feature-label relation in different seasons, we chose to train different models for summer (Jul 1st, 2013 to Aug 1st, 2013) and winter (Jan 1st, 2012 to Feb 1st, 2012) seasons. This model can be expanded to all 12 months of the year and can be made even more accurate by combining data from several years.

4. Prediction Methodology

Y2E2 building sensors are recording continuous numerical values. Because of these characteristics of features and labels, we were to use regression learning algorithms. We applied three different supervised algorithms on the dataset, including linear regression, support vector regression(SVR), and neural networks. Different parameter settings are used in each method to find the one with minimum train and test error which also minimizes the risk of overfitting and underfitting.

In this section we introduce each method and it's parameter settings in more details. Linear regression method is discussed in part 4.1, while SVR and neural networks are explained in part 4.2.

4.1. Linear Regression

The first regression method to apply on the Y2E2 building was the linear regression algorithm. It gave a clear vision about the data characteristics and helped us to adjust our features and training size such that our model is neither overfitted nor underfitited.

We then evaluated the effect of various bandwidth parameters, τ, on the prediction accuracy of the weighted linear regression. Our conclusion was due to the high correlation of the label with the input features, different bandwidth values result only in marginal changes in the prediction outcome. Thus, in this work, we choose to report our results for the unweighted linear regression model.

4.1.1. Model Training :

The training model was applied to 2600 elements from the input set selected randomly. The test set consists of 300 randomly selected elements from the remaing part of the input set.

4.2. SVR and Neural Networks

The authors in [3,6] have claimed that more sophisticated models like Support Vector Regression and Neural Network work well for the same framework of commercial buildings energy prediction. Thus we decided to evaluate the performance of other prediction models as well as linear regression, including ν-SVR, ε-SVR and Neural Networks.

4.2.1. Model Training / Optimization :

Working with complex SVR models can be tricky, as the influential parameters and kernel should be chosen carefully to result in the optimal solution. Misplacing the parameters or choosing sophisticated kernels could easily yield in overfitting. Various models were built and compared using different level of kernelization. In addition, in each try 10% of the training data was used as validation set to quiz if the model was suffering from high variance and overfitting. Resultant validation error was investigated to compare the accuracy and to find the optimal point of the effective parameters for each model, such as (C, ν) for ν-SVR, (C, ε) for ε-SVR, (b, γ) for kernelized SVR ans N as the number of hidden nodes in Neural Network. This step is visualized for cold water flow rate in July as an example in Figure 3, while a similar process has been done for other prediction models as well.

5. Results and Discussion

To have a fair comparison over various prediction models, unique train and test sets were applied to all models and corresponding errors were computed. Squared difference of predicted and measured values normalized by the set size was chosen as the error metric. Figure 4 depicts the comparison results of built models for July 2013 dataset.

We assume any error value lower then 1.5% is acceptable. In this study, as shown in Figure 4, all methods match our expected error rate by a large margin. A related observation from the comparison chart is the same error percentage for linear regression and linear SVR. It aligns with the expectation since the gist of the linear SVR is nothing but linear regression with an acceptable margin. On the other hand, applying 3^{rd} order polynomial or radial basis kernel resulted in higher accuracy. It implies linearity of data sets in a higher dimension.

The error rates in this figure also imply an interesting fact about the neural network model; this model achieves the least training error among all other models, despite its relatively higher validation and test errors. One may infer that neural network is overfitted and may not have the acceptable performance in the context of our study.

Figures 5 and 6 illustrate the average trends of hot steam and cold water flow rates over 24 hours in one month. They show both linear regression and 3^{rd} order polynomial kernel ν-SVR, as the accurate non-linear model, track the average monthly flow rates closely. The SVR tracks the measured labels more precisely, indicating the more accurate prediction by this model. However, the computation time of SVR is noticeably higher than linear regression, making linear regression a more practical technique for this application. To formulate the accuracy by other metric, we computed the correlation of the measured labels and predicted values of both models. We observed higher than 94% correlation for all models and training sets.

Figures 7 and 8 show the train and test error rates for linear regression in January and July. All error rates reach below the acceptable error rate of 1.5% with relatively small training set sizes. The small training set size for predicting flow-rate makes our prediction scheme quite attractive in practice. The low error rates in these graphs also suggest our prediction models are well fitted for this application.

6. Conclusion

Three prediction models, SVR, neural networks, liner-regression were built for prediction of cold water and hot steam flow-rates in commercial buildings. Although currently there are individual models for each season, the prediction systems can be combined by introducing time as a new feature

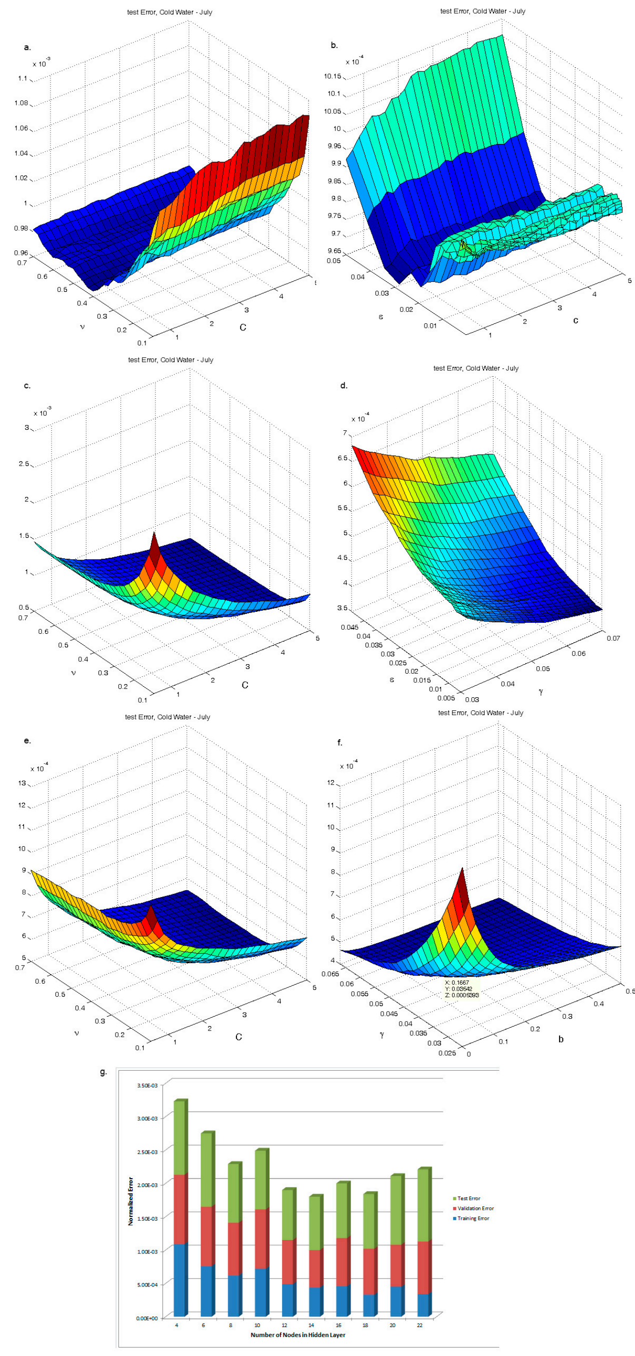

Figure 3: Trend of Validation Error while the effective parameters are swept. a: C, ν for linear ν-SVR. b: C, ε for linear ε-SVR. c: C, ν for 3^{rd} order polynomial kernel ν-SVR. d: C, ε for 3^{rd} order polynomial kernel ε-SVR. e-f: C, ν, b, γ for radial basis kernel ν-SVR. g: Number of intermediate nodes in hidden layer for neural network.

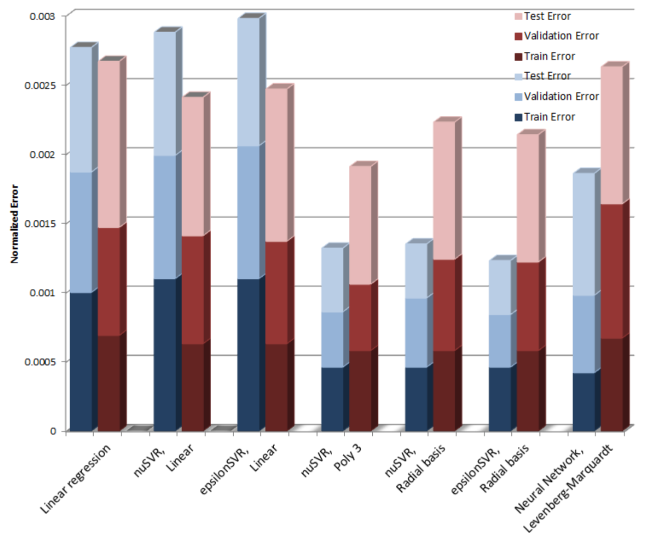

Figure 4: Normalized Test, Validation, and Train errors for various SVR and linear regression trained models. Blue and red stacks correspond to models for cold water and hot steam flow-rate respectively. (July 2013 dataset)

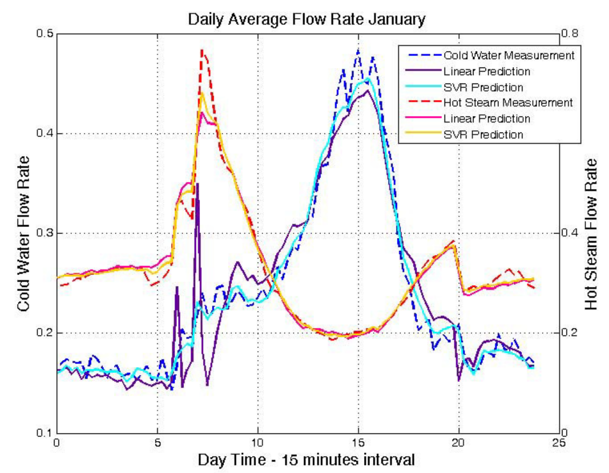

Figure 5: Y2E2 building hot steam and cold water flow-rates in 24 hours (on 15 minute intervals) in January 2013. The two dashed graphs illustrate the average of flow-rate daily measurements in this months. The solid lines illustrate linear regression and SVR predictions for both flow-rates.

to accumulate the results and improve the prediction accuracy. All our prediction models generated acceptably low training error rates (smaller than 1.5%) and higher then 94% correlation with the labels. While linear regression is the simplest and least accurate model used in this study; it works well with a small training dataset and reaches the desirable accuracy faster than other models.

Our prediction model can be used in predicting the flow-rate of similar buildings on campus that do not have such suffisticated sensor infrastructure for adjusting its A/C system. Furthermore, computed weights can assist building managers

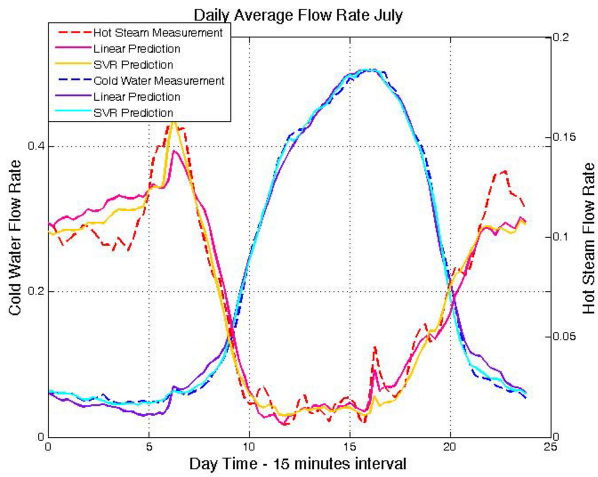

Figure 6: Y2E2 building hot steam and cold water flow-rates in 24 hours (on 15 minute intervals) in July 2013. The two dashed graphs illustrate the average of flow-rate daily measurements in this months. The solid lines illustrate linear regression and SVR predictions for both flow-rates.

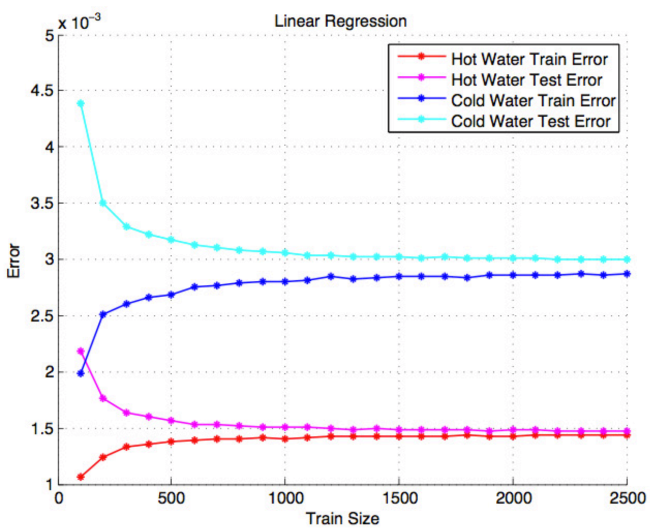

Figure 7: Training error and test error rates versus training set size for linear regression model for hot steam and cold water flow-rates in January 2013

to find the most and least influential measurements, and economize the overall sensor assembly and maintenance cost.

Acknowledgement

We would like to thank Professor John Kunz, Scott Gould, and Gerry Hamilton for their insightful advises and helps in collecting Y2E2 building data and processing them as well as the CS 229 course staff for their support during the course of this project.

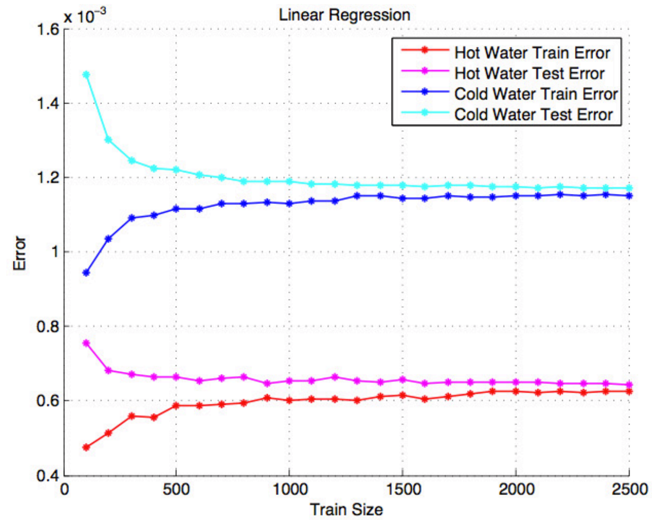

Figure 8: Training error and test error rates versus training set size for linear regression model for hot steam and cold water flow-rates in July 2013

References

[1] "Seeit: Y2e2 building sensor database software," http://stanford.edu/class/cee243/Labs/SEEITV2.0.4Setup.msi, accessed October 5th, 2013.

[2] A. E. Ben-Nakhi and M. A. Mahmoud, "Energy conservation in buildings through efficient a/c control using neural networks," *Applied Energy*, vol. 73, no. 1, pp. 5–23, 2002.

[3] B. Dong, C. Cao, and S. E. Lee, "Applying support vector machines to predict building energy consumption in tropical region," *Energy and Buildings*, vol. 37, no. 5, pp. 545–553, 2005.

[4] R. E. Edwards, J. New, and L. E. Parker, "Predicting future hourly residential electrical consumption: A machine learning case study," *Energy and Buildings*, vol. 49, pp. 591–603, 2012.

[5] B. Hojjati and S. H. Wade, "Us commercial buildings energy consumption and intensity trends: A decomposition approach."

[6] S. Wong, K. K. Wan, and T. N. Lam, "Artificial neural networks for energy analysis of office buildings with daylighting," *Applied Energy*, vol. 87, no. 2, pp. 551–557, 2010.