BASELINE POWER ESTIMATION

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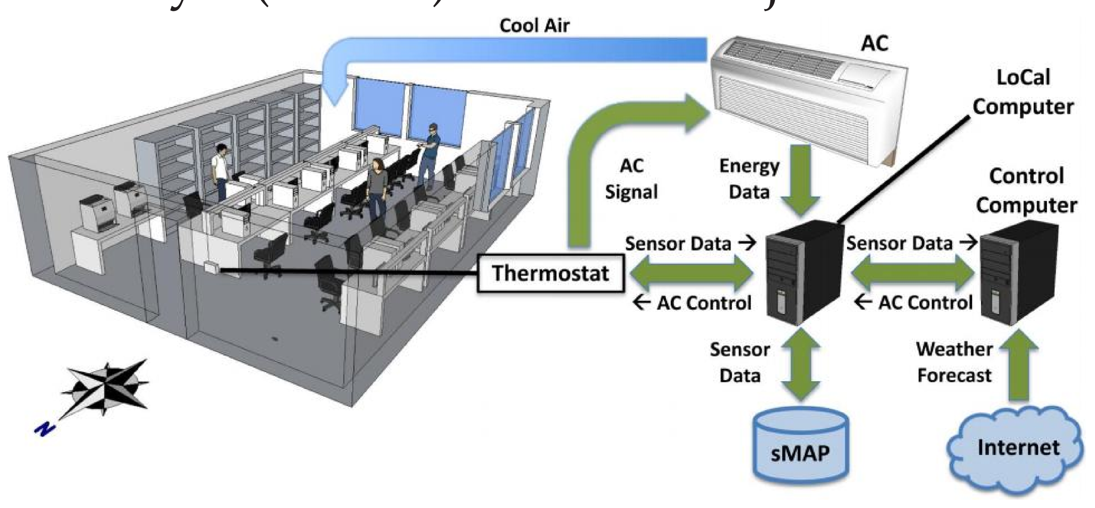
INTRODUCTION

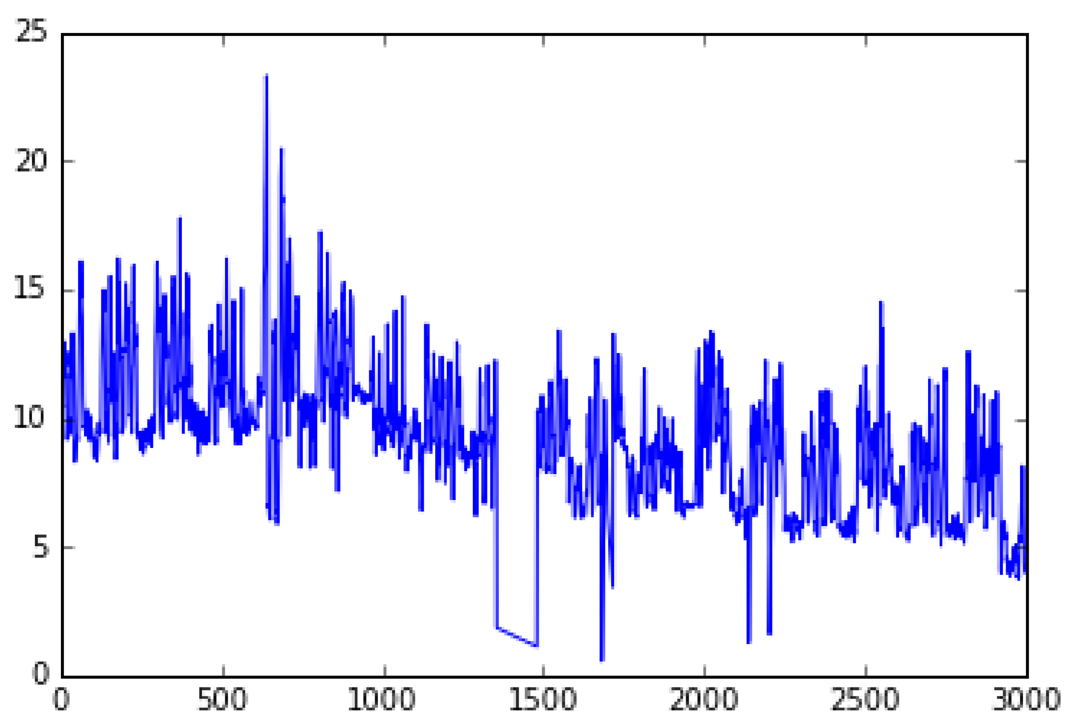
Energy usage control for commercial buildings can reduce peak power consumption and stabilize overall power grid consumption by intelligently applying inputs to individual buildings. However, in order to apply intelligent control, an accurate tool is needed for calculating baseline power consumption. This value is difficult to predict to an hourly degree of accuracy without requiring building specific equipment. We propose a generalization of thermodynamic linear models and time series forecasting to estimate the conditional dependence on prior power use observations specific to a building. We apply the EM algorithm to explore the conditional dependence between time steps without propagating errors that is caused by iterative prediction.

DATA

Our data consists of historic data collected from the Berkeley Retrofitted and Inexpensive HVAC Testbed for Energy Efficiency (BRITE) at Sutardja Dai Hall.



Similar to previous work, we utilize the past year's measured power data, of dimension $(3000, 6)$.



We also utilize regional weather data collected from forecast.io, of dimension $(3000, 6)$ representing 3000 hours of forecast data.

REFERENCES

[1] E. Eirola, A. Lendasse Gaussian Mixture Models for Time Series Modelling, Forecasting, and Interpolation

[2] Q. Hu, F. Oldewurtel. Model Identification of Commercial Building HVAC Systems during Regular Operation - Empirical Results and Challenges In *ACC '16*

[3] A. Aswani, N. Master, J. Taneja, A. Kriouskov, D. Culler, C. Tomlin. Energy-Efficient Building HVAC Control Using Hybrid System LBMPC In *NMPC '12*

WEATHER MATCHING APPROACH

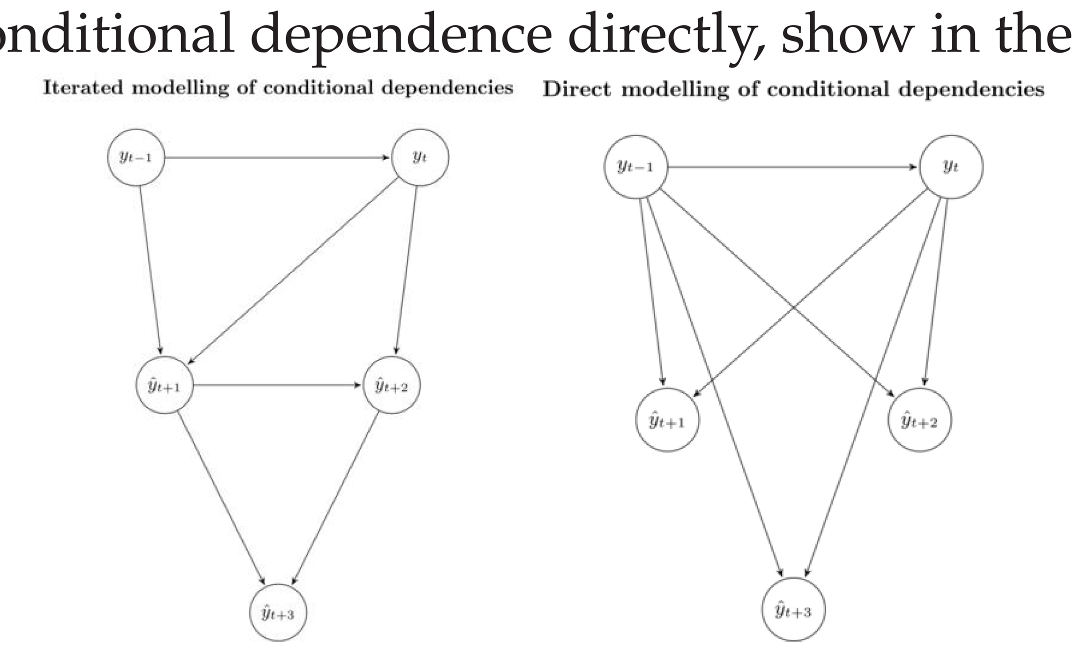
Weather forecast data is readily available at a region-wide level and can be used to estimate general seasonal trends (such as people's heating usage habits and the sunrise and sunset time dictating when people use their lights). The weather data is pulled in data forecast.io, and then we set up an optimization problem $Ax = y$ in which A is our tracked differences in weather data between the current day and historical observed ones, x is each of their weights, and y is the expected difference in power readings.

EXPECTATION MAXIMIZATION APPROACH

Now, we aim to reduce our error even further by taking into account the temporal relationship between the past day's power readings and future ones. More generally, we can perform time series forecasting using a slice of the last n hours $z_0, z_1, z_2, ..., z_{n-2}, z_{n-1}$

Using this, we can create our design matrix X where each row is such a slice.

An n value of 48 hours covers the span of two days. We then use the idea that certain types of days can be modeled as Gaussian mixtures and fit our training data using EM to obtain the mean and covariance matrices of K such mixtures. This allows us to take the last dayś measurements as the 24 first hours, and determine the conditional expectation of the following 24 hours. We then take the probability of the current day fitting into each of the Gaussian mixtures and use them as weights for their respective means. The weighted sum of these next 24 hours then gives us the next day's predicted values. This allows us to model the conditional dependence directly, show in the bottom right image.



$$t_{ik} = \frac{\pi_k \mathcal{N}(\boldsymbol{x}_i^P \mid \boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)}{\sum_{j=1}^{K} \pi_j \mathcal{N}(\boldsymbol{x}_i^P \mid \boldsymbol{\mu}_j, \boldsymbol{\Sigma}_j)},$$

$$\boldsymbol{\mu}_k = \begin{bmatrix} \boldsymbol{\mu}_k^P \\ \boldsymbol{\mu}_k^F \end{bmatrix}, \quad \boldsymbol{\Sigma}_k = \begin{bmatrix} \boldsymbol{\Sigma}_k^{PP} & \boldsymbol{\Sigma}_k^{PF} \\ \boldsymbol{\Sigma}_k^{FP} & \boldsymbol{\Sigma}_k^{FF} \end{bmatrix}.$$

$$\tilde{\boldsymbol{y}}_{ik} = \boldsymbol{\mu}_k^F + \boldsymbol{\Sigma}_k^{FP} (\boldsymbol{\Sigma}_k^{PP})^{-1} (\boldsymbol{x}_i^P - \boldsymbol{\mu}_k^P)$$

$$\hat{\boldsymbol{y}}_i = \sum_{k=1}^{K} t_{ik} \tilde{\boldsymbol{y}}_{ik}.$$

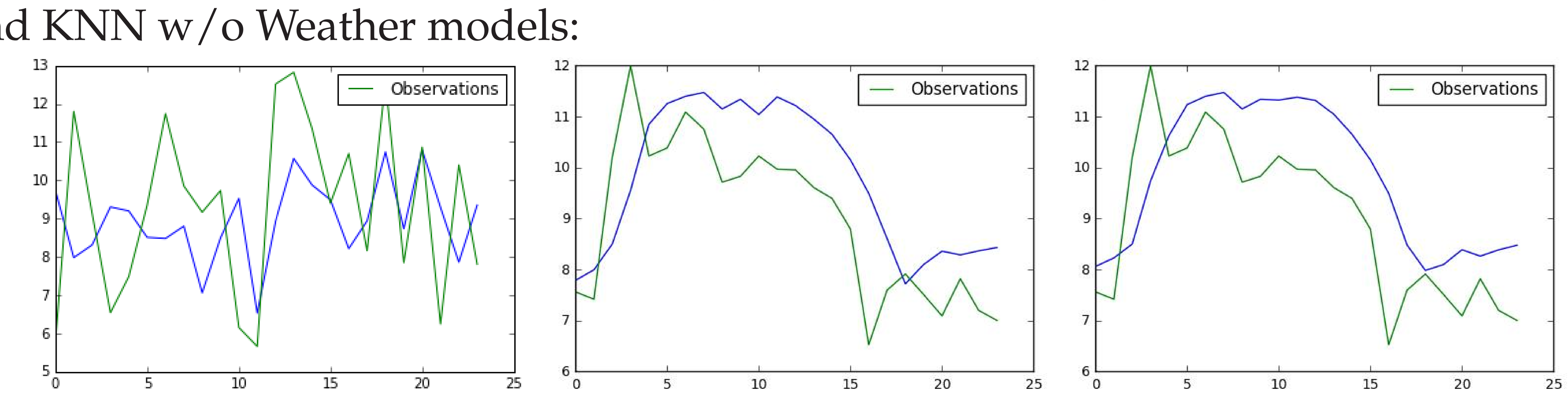
K-NEAREST NEIGHBORS AND RECURRENT NN APPROACH

First, let's take a l Let yt denote the value of the time series at time point t, then we assume that

yt+1=f(yt,âĂę,ytâĹŠn+1)+Ïţt, yt+1=f(yt,âĂę,ytâĹŠn+1)+Ïţt, for some autoregressive order nn and where ÏţtÏţt represents some noise at time tt and ff is an arbitrary and unknown function. The goal is to learn this function ff from the data and obtain forecasts for t+ht+h, where hâĹĹ1,âĂę,HhâĹĹ1,âĂę,H. Hence, we are interested in predicting the next HH data points, not just the HH-th data point, given the history of the time series.

RESULTS

Predicted and observed power usage across a 24-hour period for EM, KNN w/ Weather, and KNN w/o Weather models:



Lasso	EM	K-Means w/ Weather
12.461124	2.41236	1.25888

K-Means w/o Weather	RNN w/ Weather	RNN w/o Weather
1.256917	1.18180	1.107