Regression based energy model and building energy saving literature review

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Contents

1 Motivation

The limited availability of fossile fuels [2, 41], the global warming, and other environmental challenges brought about the global effort of energy conservation: in the 12th 5-year plan, China set goals of reducing 16 percent energy, and 17 percent of carbon per unit GDP; “to move the United States toward greater energy independence and security”, U.S. EISA act was launched in 2007, requiring government agencies to reduce their energy consumptions by 30% till 2015; U.K. cut its average gas and electricity consumption by 25% throught increasing utility bills.

10 to 20 percent of energy cost could be saved by energy efficiency upgrades [35]. However, in order to accurately evaluate the effectiveness of these upgrades, difference in weather, occupancy, operation mode, etc, between pre and post retrofit needs to be accounted for. This requires an accurate baseline energy model [48].

In ASHRAE guideline 14, the ECM energy saving is estimated by projecting the pre-retrofit energy consumption into the post-retrofit period with a suitable regression model, and the saving is calculated as the actual projected pre-retrofit consumption under post-retrofit (weather) condition minus the post-retrofit consumption. The predictive power of the baseline energy model determines the accuracy of the ECM saving calculation. Such an energy baseline model could also be used in “determining retrofit savings, energy system fault diagnostics, acquiring physical insight into the operating patterns” [48], and “control strategy development, and on-line control applications” [48]

In addition to the predictive power, some baseline model also provides separate the whole building energy into different end uses such as heating, cooling, and baseload [10, 14, 23, 46]. This could be used in energy use benchmarking [10], identifying energy retrofit opportunities [10, 46], and encourage energy saving behaviors [46].

In this study, I will review a series of black-box or gray-box data-driven energy baseline methods, and compare their predictive performance of the aggregated consumption, and or the end-use consumption.

2 Background

In ASHRAE Handbook-Fundamentals, approaches to estimate building energy usage are broadly classified into forward and inverse method. A system contains three components: the input, the system structure, and the output [11]. The forward approach is given the input and the system structure to predict the output. It is based on the “engineering principles" and the model is a "physical description" of the building and its sub systems [11]. It is advantageous for evaluating the energy performance of the design and analysis stage but requires a lot of physical inputs. The inverse model approach aims to estimate the system parameters given the input and output. It is only applicable to existing systems with actual measured data. The inverse models are "more accurate predictors of future system performance than forward method" [11] because it captures more accurately the "as-built" system information, the data are more ready to get, and it is easier to be automated and thus is good for the analysis of large building portfolio [36]. The data-driven method is flexible as it could model both whole building, and equipment such as pumps, fans, chillers, and boilers [11]. As a result, the inverse models are receiving increasing attentions.

In literature, the topic is referred to as: whole building or building baseline models [9, 16, 25, 37, 48], weather-adjusted index of consumption [14], energy signature model [19, 36], inverse (energy) model [1, 26, 48], data-driven (energy) models [48], energy prediction model [9, 34, 47].

The models could be used for building load / demand / consumption forcasting [9, 19, 34, 38, 47], calculation of measured energy savings from energy conservation retrofits [11, 14, 17, 25, 26], evaluating building energy performance [1], building parameter estimation [19], energy end use disaggregation [10, 14, 46], assist the "identification of energy saving opportunities and recommend the types of energy efficiency measures" [10].

3 Related works: Models

paper	linear	piecewise	SVM	kernel	Gaussian process	Gaussian mixture	ANN	PAM	mean-week	day-time-temperature	LBNL	Decision Tree	PCA
Baselining methodology for facility-level monthly energy usepart 1: Theoretical aspects [37]	✓	✓											
PRISM: an introduction [14]	✓												
ENERGY STAR Score [32]	✓												
Comparisons of inverse modeling approaches for predicting building energy performance [48]		✓			✓	✓	✓						
Applying support vector machines to predict building energy consumption in tropical region [9]			✓										
Kernel regression for real-time building energy analysis [4]				✓									
Deep learning for estimating building energy consumption [34]							✓						
Evaluation of the Predictive Accuracy of Five Whole Building Baseline Models		✓						✓	✓	✓	✓		
Forecasting Energy Demand in Large Commercial Buildings Using Support Vector Machine Regression			✓										
A decision tree method for building energy demand modeling [47]												✓	
Statistical Modeling of Daily Energy Consumption in Commercial Buildings Using Multiple Regression and Principal Component Analysis [7]													✓
Principal component analysis in building energy efficiency rating system for apartment housings [24]													✓

Table 1: matrix of related works energy prediction baseline model

paper	linear	piecewise	contextual learning
Contextually Supervised Source Separation with Application to Energy Disaggregation [46]			✓
PRISM: an introduction [14]	✓		
LEAN Energy Analysis Using Regression Analysis to Assess Building Energy Performance [10]		✓	

Table 2: matrix of energy disaggregation baseline model

There are different aspect to categorize the models found in literature.

Based on the representation of outdoor temperature, the models are categorized as: mean temperature model, degree-day based model, and transformed hourly temperature (either with radio basis function, or with exponential weighting).

The mean temperature model could be sub-divided into 1p to 5p models based on the number of parameters involved. The degree-day models can be subdivided into constant-base degree day (CBDD) model and variable-base degree-day model (VBDD). The heating or cooling degree-day is calculated with respect to a certain temperature. This temperature is called "balance point temperature" [11], "base of the degree-day" [11], "break-even temperature" [14], or "reference temperature" [14, 14, 48]. It is defined as the outdoor temperature at which the heat loss equals to the internal and external heat gain, and no heating or cooling energy is needed [11]. CBDD uses a fixed balance point temperature for the heating or cooling degree-day calculation, which is usually 65F. As the balance point temperature is usually not the same for all buildings [14] and the selection of a proper balance point temperature could greatly affect the result of saving calculation, Fels et al. developed the VBDD model that chooses the balance point temperature with the highest R^2 [26].

Most of the methods are regression based. Based on the type of regression, the methods can be categorized into linear regression, segmented (piecewise) linear regression, Gaussian process regression model, Gaussian Mixture regression model [48], Kernel regression [4], SVM regression [9], ANN etc.. Linear regression models in the current context refer to the model with the form of (Equation 1) where y is the dependent variable, $\mathbf{x}$ is the independent (explanatory) variable vector, $\mathbf{w}$ is the model parameter vector, b is the intercept term, and ϵ is the error or noise. The VBDD or CBDD method falls into this category.

$$y = \mathbf{w}^T\mathbf{x} + b + \epsilon \tag{1}$$

The the ordinary least square method is commonly used to estimate the regression model parameters where the sum of the squared error is minimized [42]. The method assumes the data has iid Gaussian noise ($\epsilon \sim \mathcal{N}(0, \sigma^2)$), as it corresponds to the maximum likelihood estimate of the model parameters. However, the iid Gaussian assumption is violated as 1) the observed energy consumption cannot be negative, thus the error of the negative part is truncated [36]. The Tobit model is more suitable in this case [43]. Rabl and Rialhe observed a 10% difference in the slope term estimate between the least square method and the Tobit model method. Another approach to account for the non-Gaussian error is presented in [20].

Segmented or piecewise regression could refer to partitioning the independent variable into intervals and solve each segment with linear regression, or partitioning the independent variables [44]. The segmented regression in the current context refers to the former.

The change-point models is in this category, but it has an additional constraint: adjacent segments are continuous.

Kernel regression or kernel smoothing method makes prediction with a "weighted average of nearby data items, with the weights being controlled by a kernel function" [4]. Brown et al. presented a novel approach using kernel regression to predict hourly energy consumption.

SVM could be used in both classification and regression settings. The advantage of SVM includes 1) the Lagrangian dual is kernelizable, and thus has better guarantee to achieve a "smoother" solution that generalizes better to unseen data 2) through proper regularization, it could provide a sparse solution. Some examples include [9, 38].

A series of ANN based models are developed to predict hourly consumption during the ASHRAE "great energy predictor shootout" phase I [28] and II [18] competitions. Its goal is to find "the most effective empirical or inverse regression models for modelling hourly whole-building energy baselines for purposes of measuring savings from energy conservation retrofits" [18]. In phase I, 4-6 months of electricity hourly data and environmental data ("temperature, humidity, solar flux and wind" [30]) are given as inputs [4]. In phase II, "two sets of measured hourly pre-retrofit and post-retrofit data from buildings participating in a revolving loan program in Texas" are given as input [18]. Comparing with linear regression, the hidden layer provides it with more flexibility [30]. The winner for phase I is an ANN with the Automatic Relevance Determination prior (ARD) [30]. The winner for phase II is ANN with Walds test [8].

The output of the models can be "actual savings" or "normalized savings". The method developed by Kissock and adopted by ASHRAE guideline measures the "actual saving", which project the consumption of the baseline model to the post-retrofit period. The PRISM method and the one Energy Star uses [31] measures the normalized savings (NAC): the "annual energy consumption during a year of average weather condition" [37].

Based on whether the model contains the "time lag" term, they are classified as steady-state models, and dynamic models [11]. Steady-state models assumes "(i) the building is a linear system and (ii) the driving terms are periodic (and the interval for the data analysis. is a multiple of this period)" [36]. It is sufficient for the analysis on the daily or monthly level as most buildings have a operation cycle of 24 h [36]. For hourly or sub-hourly data, the assumption of the least square method will be violated, as the noise of consecutive measurements are not independent [19].

4 Model evaluation

This section discusses the issues and concerns about model evaluation in the following aspects.

4.1 Robustness to noise in the input data

We are concerned with the influence of the noise in the input data on the model estimate, thus one important factor is the robustness with respect to noisy input data. For example, hammarsten showed that random errors in degree-day input could result in a systematic lower estimate of the slope term [19]. Some model regularization techniques could reduce the impact of noisy input and make accurate predictions: Mackay used a ARD prior to reduce the impact of junk inputs [30], Dodier and Henze used Wald's test [8].

4.2 Predictive power and physically meaningful

Two main usage of the baseline models are 1) predicting energy consumption and 2) providing physical insights and suggest possible energy retrofit opportunities. Thus the predictive power and physically meaningful are two criteria for evaluating which is a suitable model.

The parameters of most black-box models tends to lack physical meanings, those of the calibrated simulation are based on the building physical conditions. The grey-box model with simplified building specification [4].

A model with high predictive power could produce more accurate estimate of the energy consumption. This is crucial in the ECM energy saving estimation. For model selection, the ASHRAE guideline 14 recommend the model with the best R^2 or $CV(RMSE)$. The following metrics are used to evaluate the predictive power of the model

Metric	definition	source
R^2		[11]
RMSE	Root Mean Squared Error	[11]
CV-RMSE	Coefficient of variance of RMSE	[4, 11]
NMBE	Net Mean Bias Error	[11]
Net Determination Bias	bias of the computation	[11]
SE	Standard Error	[19, 37]
PI	Confidence Interval (90%)	[37]
MAE	Mean Absolute Error	[46]
Cross Validation	"a model validation technique for assessing how the results of a statistical analysis will generalize to an independent data set" [45]	[4]
median absolute percentage error		[16]

Table 3: Model evaluation metric for predictive power

- cross validation: K-fold cross validation [6]

- SE: standard error of the coefficient. It "describes how much of the variance in the dependent variable is described by the model" [19]. It reflects "how accurately the regression model is able to identify the individual model coefficients" [37]. It is similar to the p value for the coefficients.

- standard deviation of the noise [19] An example of daily vs weekly data comparison is shown in [19], demonstrating the R^2 by itself is not sufficient to evaluate the model with different time step and the difference in standard deviation of the noise needs to be adjusted: in the example, the weekly model have higher R^2 than the daily model, but that's a result of decreased variance of the data [19]. If the daily model predicted aggregated monthly consumption is actually more accurate than the monthly model prediction [19].

- Coefficient of determination or R^2: it evaluates how well a model fits the data [37].

$$1 - \frac{\sum_i (y_i - \bar{y})^2}{\sum_i (y_i - \hat{y}_i)^2} \tag{2}$$

- CV-RMSE: evaluates the mean variation in the data that is not explained by the model [37].

$$CV - RMSE = \frac{RMSE}{\bar{y}} \cdot 100$$

- NDB: The term "bias" used here is different from that in statistics (which is guaranteed to be zero by doing regression). net determination bias. In ASHRAE standard, the "Net determination bias should be no more than 0.5% for regression models for whole-building and retrofit isolation approaches", later in the standard, it says the net determination bias should be less than "0.005%". Also, it seems that NDB could be negative.

$$NDB = \frac{\sum (y_i - \hat{y}_i)}{\sum y_i}$$

  [21].

- PI: confidence interval, by convention use the 90% level [37]. However, in 3P change point model, the residual on different side of the change points are found to be un-equal for a lot of cases (non-uniform model residual problem) [37], so the PI is not suitable for 3P change point.

To apply the model to energy audit, the physical meaningfulness is an important part. ANN has good prediction power, but its parameters are meaningless regarding the building's physical condition. There are also cases when the model only corresponds to the physically condition at times. For example, in the case of simultaneous heating and cooling, the base load could be over-estimated [36]. In the following example, the solid line is the total consumption (steam), and the true heating and cooling balance point temperature (estimated with sub-meter data) are the dashed line. This example demonstrated that the model estimated "breakpoint temperature" might not correspond to the true balance point temperature with actual physical meaning.

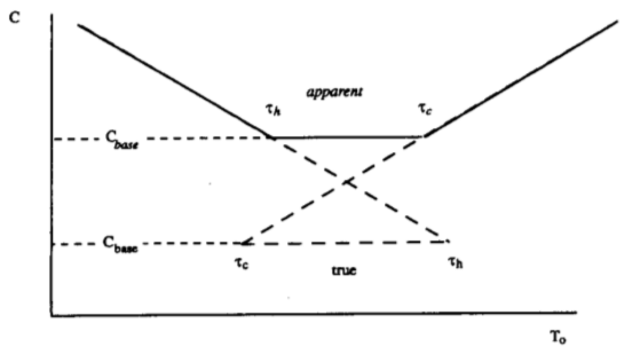

Figure 1: The true balance point vs the apparent [36]

4.3 Performance under small training data set

There are a lot of cases in which we do not have enough training data points for the baseline period: two consecutive retrofit are close in time and we want to evaluate the incremental saving from one retrofit to another; predicting energy consumption for a new building. Thus the performance under small amount of data could be another metric to evaluate models.

5 Related work: Packages / software tool

This section reviews the method, input, output, time-interval and other features of available software or packages that produces baseline models.

tool	author	methods	input	output	time step	source
E-Tracker	Kelly Kissock et al.	4p or 5p change point model	meter reading date, electricity and thermal energy consumption, peak electrical demand, average daily outdoor temperatures	saving, baseline model parameters, R^2, CV-RMSE	monthly	[27]
PRISM	Fels et al.	VBDD	one year utility bill, average daily temperature	R^2, CV-RMSE of NAC	monthly	[14]
ECAM	William Koran	linear (2p) and 3-6p change-point	energy data, temperature of closest weather station, or TMY3	Projected Baseline Energy (pre), Measured Energy (post), Energy Saving (avoided consumption), CV-RMSE, NDB, 95% confidence interval of the output, pre and post period NAC	daily or hourly	[39]
First View	NBI	unknown	utility bill, building characteristics	LEAN plot, "spectrum plot"	monthly	[23]

Table 4: tools

- E-Tracker The portfolio manager energy star uses a method based on the E-tracker [31].

  The flowing are the screen shots of the software with its sample input data. From the tool, it seems the 4p model implemented by this model does not rule out the case of the model with left side slope up and right side slope down.

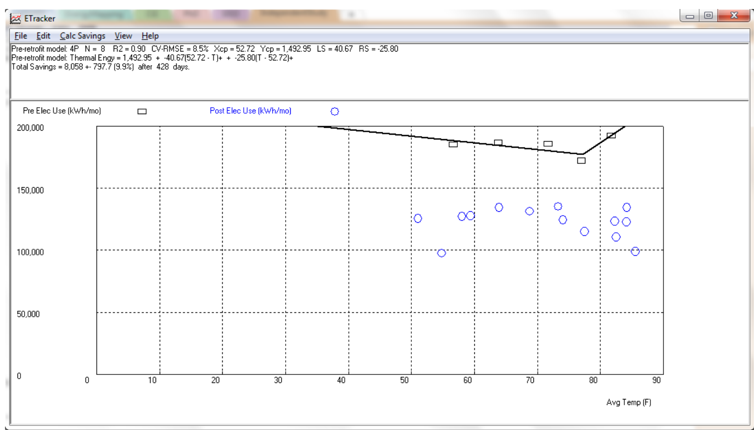

Figure 2: E-tracker electric baseline model

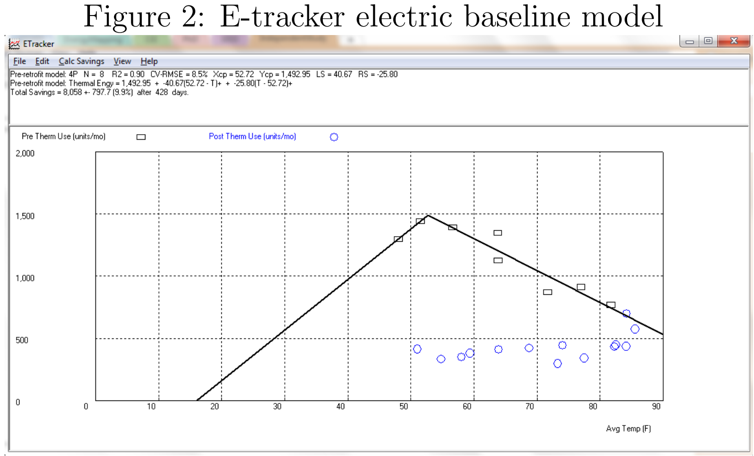

Figure 3: E-tracker gas baseline model

- First View: from the description in [22], the input is described as "monthly utility bills and a few building characteristics", and from [23], the method to calculate the baseload, heating, cooling load are not clear, or does not seem to be likely what the tool is actually doing. They claimed the electric base load is "calculated as the sum of lighting, plug loads, year-round fans and pumps, consistent process loads and electric water heating", but this seems to be impossible, unless they ask users to directly input the consumption of those components. The heating and cooling load is calculated from "analyzing the estimated internal gains, overall heat transfer coefficient, and modeled equipment efficiencies of a building". Gas base load is calculated by from "summer gas use". The method of separating different end use described in the First View document does not appear in other literature I've read so far.

  In addition to creating a LEAN energy plot of heating, cooling, base gas and base electric plot, they also provides a "spectrum" of energy signature plot (energy consumption vs temperature). There's no documentation about how it is computed.

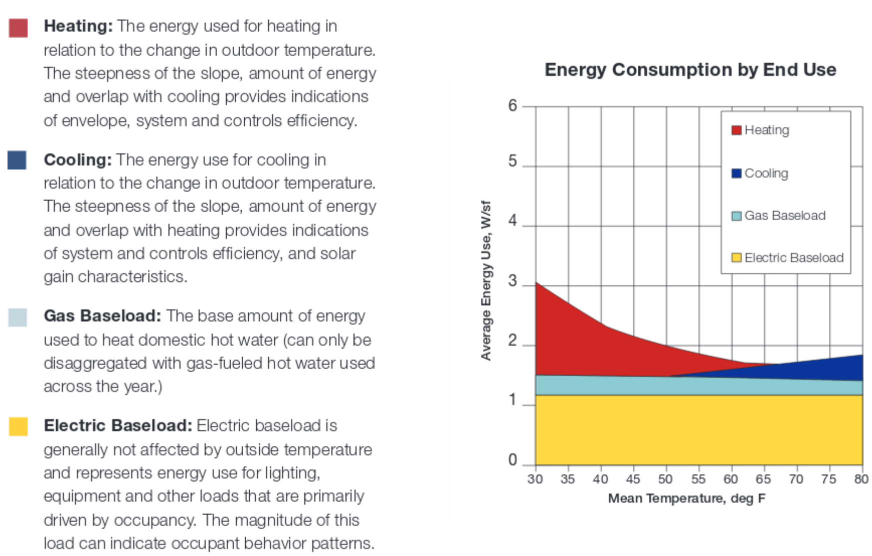

Figure 4: First View LEAN plot [23]

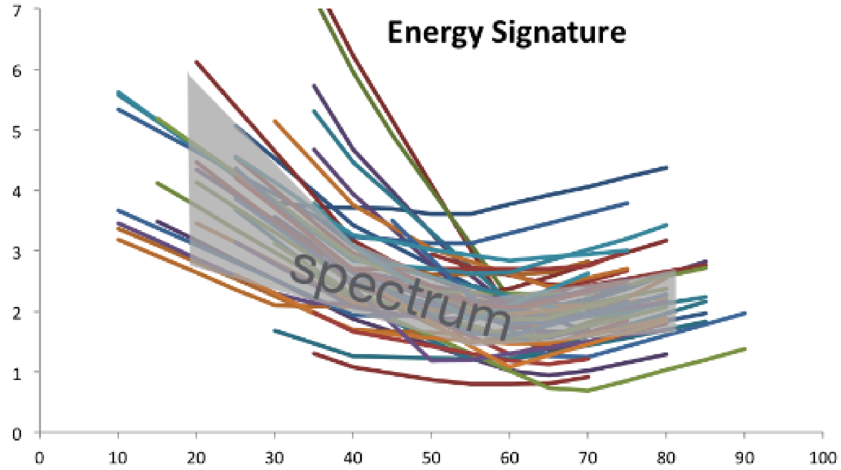

Figure 5: First View Spectrum Plot

6 Summary of individual papers

6.1 A Critical Appraisal of Energy-Signature Models [19]

Energy Signature (ES) are parameters in a energy-balance model. ES can describe the energy performance. Other equivalent terms include Equivalent Thermal Parameter (ETP), and Building Element Vector Analysis (BEVA).

The paper reviewed some energy signature (ES) models. Static ES models could be used in cases with time-step at least one day. The author define the ES model to be a set of parameters that describe the energy performance of a building in an energy-balance model.

Models reviewed are:

- static two-parameter: assuming constant / stable indoor temperature

$$Q = Q_0 - LT_o \tag{3}$$

- static two-parameter with indoor and outdoor temperature

$$Q = Q_0 - L(T_i - T_o) \tag{4}$$

- dynamic model with lag term (the same variable in previous N time steps), I is solar radiation, Q_0 is the constant power loss or gain, Q is power.

$$\sum_{k=0}^{N} a_k T_i(t-k) + \sum_{k=0}^{N} b_k T_o(t-k) + \sum_{k=0}^{N} c_k I(t-k) - \sum_{k=0}^{N} d_k Q(t-k) = Q_0 \tag{5}$$

input variables:

- environment: outside air temperature (T_o), indoor temperature, solar radiation (T_i), solar aperture (S).

- energy: power

6.2 A BIN METHOD FOR CALCULATING ENERGY CONSERVATION RETROFIT SAVINGS IN COMMERCIAL BUILDINGS [17]

The author pointed out that even if change-point models accounted for some non-linear relationship between temperature and energy consumption, there are buildings that change-point models do not fit well. The paper aims to improve the existing model and presented a method of using "hourly bin" to calculate retrofit energy savings, the result is tested in two buildings.

Required data include: at least nine months pre-retrofit hourly energy data, and hourly temperature data. Energy data include electricity, AHU electricity, chilled water, hot water energy consumption.

A box-whisker-mean plot is used: it is similar to the box plot, except that the high and low end of the whiskers are the 90th and the 10th percentile (or the authors might have remembered it wrong). The method splits the energy into two types: weather independent and weather dependent, for the former, the x axis is time of the day; for the latter, the x axis is the outdoor air temperature.

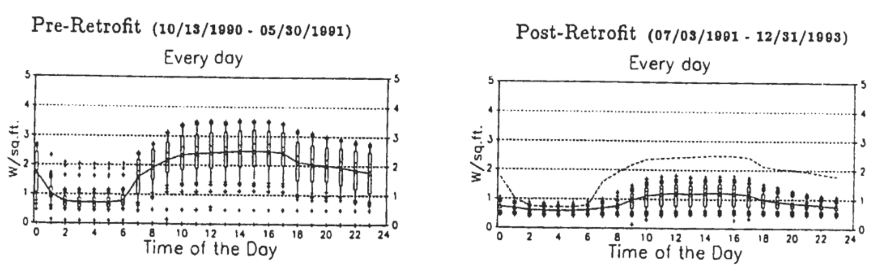

Figure 6: weather independent energy model

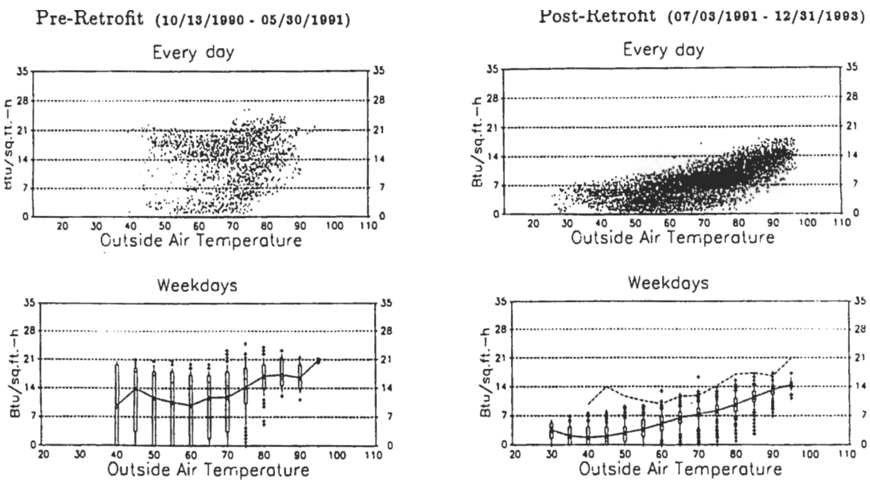

Figure 7: weather dependent energy model

The saving is determined with Equation 6. $E_{pre_{i,j}}$ is the pre-retrofit model predicted post-retrofit use for model i hour j in the non-weather dependent case, temperature bin j for the weather dependent case.

$$\sum_{i=1}^{n}\sum_{j=1}^{m}(E_{pre_{i,j}} - E_{post_{i,j}}) \tag{6}$$

In the non-weather dependent (schedule dependent) case. The saving is determined by comparing the hourly average consumption for each model in pre-retrofit period, and post-retrofit period. Outliers are removed as follows: when a day has entire 24h consumption below the 10th percentile or above the 90th percentile.

A separate model (indexed by i) is fit to a different operation mode for both cases. Bins are selected so that the interquartile range is below a threshold (?? is this reasonable). The models are evaluated with R^2, Coefficient of Variance, and Mean Bias Error. Althrough, it seems the authors are mainly selling the fact that the bin method have lower Coefficient of Variance, without mentioning that they have higher Mean Bias Error. The bin method captures better the non-linear relationship [17](my opinion: each bin is a small piecewise linear with slope being 0), and the authors suggest that bin method should be applied if the change-point models have large error.

The authors pointed out that the limitation of the method is that it cannot extrapolate into un-observed temperature ranges, the number of parameters in the Coefficient of Variation calculation is not resolved (?? then how are they calculated in this paper).

The method is illustrated with two buildings: it is benchmarked against the daily change-point model

end use	ZEC	EDP
AHU	1 parameter	
Cooling	2 parameter	4 parameter
Heating	2 parameter	4 parameter
Lighting Equipment		1 parameter
Motor Control		1 parameter

Table 5: zecedb

input variables:

- time: day type (every-day, weekday, weedend), hour of day
- environment: hourly temperature

6.3 Statistical Modeling of Daily Energy Consumption in Commercial Buildings Using Multiple Regression and Principal Component Analysis [7]

6.4 Principal component analysis in building energy efficiency rating system for apartment housings [24]

6.5 LEAN Energy Analysis Using Regression Analysis to Assess Building Energy Performance [10]

The paper reviewed the Lean Energy Analysis method for building energy performance assessment. The regression model used in the Lean Energy Analysis could also be used in energy prediction, saving calculation, and tracking building energy performance. In the regression model, the independent variable could include weather, occupancy, and utilization factors ("square footage, school days, or production quantity").

The paper wrote "The savings represent the difference between the energy predicted by the model (for post-retrofit conditions) and the actual measured energy usage." This is wrong, both the pre and post consumption are "predicted" by the model, the saving is calculated by the difference of both of the predicted value (NAC).

6.6 Climate and weather (portfolio manager) [31]

The document explains how Energy Star Portfolio Manager evaluates a buildings energy performance by accounting for the changing weather and the difference in climate.

The “weather” refers to the variation by time in one location, and “climate” refers to the variation (of average condition) by location. “Weather normalization” thus could evaluate the performance of a building over time, but cannot compare different buildings. To compare the performance of different buildings, one should use the energy star score.

6.7 ENERGY STAR Score [32]

The energy star score compares the target building with “other buildings nationwide that have the same primary use” from the Commercial Building Energy Consumption Survey (CBECS) [13]. They are not based on buildings entered into the Portfolio Manager. The peer group is selected based on building type, program (e.g. operation time), data limitation, and analytical filters. A ordinary least square regression model is produced to predict the energy use based on its business activities: number of operation hours, weather in HDD and CDD with base temperature 65F (They are still using this ??). The dependent variable is source EUI, and the independent variables are “operating hours, number of workers, and climate” [32].

6.8 PRISM: an introduction [14]

This paper documents the PRinceton Scorekeeping Method (PRISM) method. The inputs are utility bill (requires at least one year), and average daily temperature. The outputs are Normalized Annual Consumption (NAC) of pre and post retrofit period, and R^2 of NACs. The NAC is the energy consumption under average weather conditions. It is computed with the formula (α is the base load, β is the slope, $H_0(\tau)$ is the degree day under average weather with base temperature τ).

$$\text{NAC} = 365\alpha + \beta H_0(\tau) \tag{7}$$

The authors claims the advantage of the PRISM model is 1) it is physically interpretable, 2) its NAC is “extremely well determined” (strange wording) 3) it is accurate (might not be true any more) 4) it has error estimation output 5) it could generalize to all fuel types and all building types.

“The PRISM method is a statistical procedure for calculating changes in energy consumption over time” [14]. It is not developed for energy prediction, but rather a statement of the past (since it is projecting to a average condition, which is not a real future condition). It is a steady-state model with no time input.

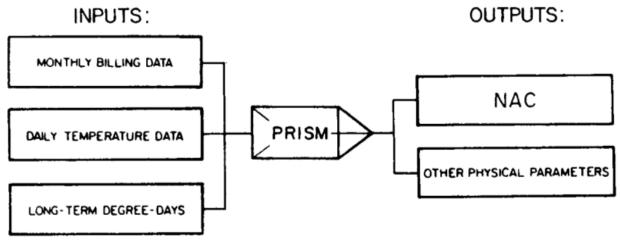

Figure 8: Prism flow diagram

The model have three physically meaningful output: base-load reflects the consumption of appliances, reference temperature reflects the setpoint temperature, slope reflects the "lossiness" of the house (heat-loss rate in the heating model). The reference temperature is affected by the indoor temperature setpoint.

The model assumes a proportional increase in heating energy consumption when the temperature is below some threshold. The reference temperature is chosen so that the energy-degree day plot is closest to a straight line, with the highest R^2 or the least mean squared error.

6.9 Baselining methodology for facility-level monthly energy use-part 1: Theoretical aspects [37]

The paper proposed a baseline methodology for ECM saving calculation and "determine progress toward any preset energy-efficiency goals" calculation at the facility level. The paper compared the performance of two software packages: PRISM by Fels et al. (using VBDD), and EModel by Kissock et al. (using simple regression with Monthly Mean Temperature);discussed the baseline year selection rule; and proposed statistical methods for evaluating uncertainties.

The paper listed a few building energy conservation programs supported by Executive Order 12902 (reducing 30% energy per gross square foot from 1985 to 2005): Federal Energy Management Program (FEMP), Rebuild America, and Energy Star. The paper is part of the the Model Energy Installation Program (MEIP).

The author summarized potential influential variables of building energy consumption: 1) climate, 2) conditioned area, 3) occupancy, 4) non-ECM related load, 5) ECM related load. The paper only normalizes for 1) and 2) and uses baseline selection rule to isolate the effect of 5).

The input variables are outdoor dry-bulb temperature (claimed to be the most influential independent variable), and monthly utility bills. The method provides the error band for both the monthly and the annual level, and a solution for un-known utility reading dates. One reason for not including occupancy in the model is that it is usually not measured well.

The model evaluation / selection measure (goodness of fit) used are R^2 and CV-RMSE. R^2 describes the variation in the dependent explained by the model. It indicates "how well the model fits the data". CV-RMSE (in %) is a form of normalized $RMSE$. It is suitable if the aim is to calculate the energy saving. The formula of CV-RMSE here and in the ASHRAE standard has $n-p$ (n: sample size, p: number of parameters) in the denominator, but I'm not sure if this is appropriate, same with standard deviation. The author argues that the criteria of $R^2 > 0.1$ and CV-RMSE $< 7\%$ be deemed "good" models proposed by Fels et al. is arbitrary. There should not be a strict cutoff. The criteria used in this paper is also arbitrary: CV-RMSE less than 5%, 10%, 20% are considered excellent, good, and mediocre, CV-RMSE $> 20\%$ is considered poor. Standard error (SE) measures "how accurately the regression model is able to identify the individual model coefficients".

For the VBDD method, it is most suitable for single-zone buildings (residential, or small commercial). The inputs of the associated package are monthly utility bill, and daily average outdoor temperature and outputs normalized annual consumption (NAC), the energy consumption under average weather conditions, and R^2. The saving is calculated by $NAC_{pre} - NAC_{post}$, the model is in the form of Equation 8($DD(\tau)$ is either heating or cooling degree day), and Equation 9 ($_h$ for heating, $_c$ for cooling). The Y are monthly mean daily energy, not monthly total energy.

$$Y = \alpha + \beta \cdot DD(\tau) \tag{8}$$

$$Y = \alpha + \beta_h \cdot DD(\tau_h) + \beta_c \cdot DD(\tau_h) \tag{9}$$

For the Simple Regression Models Using Monthly Mean Temperature (MMT), the author emphasized that the temperature should be during the same period as the billing period, not the calendar month. The 1 to 5 parameter models are:

$$Y = \bar{T} \tag{10}$$

$$Y = \alpha + \beta \cdot T \tag{11}$$

$$Y = Y_{cp} + RS \cdot (T - X_{CP})^{+} \tag{12}$$

$$Y = Y_{cp} + LS \cdot (T - X_{CP})^- \tag{13}$$

$$Y = Y_{cp} + RS \cdot (T - X_{CP})^+ + LS \cdot (T - X_{CP})^- \tag{14}$$

$$Y = Y_{cp} + RS \cdot (T - X_{CP,h})^+ + LS \cdot (T - X_{CP,c})^- \tag{15}$$

The form of the 3 to 5 parameter enforces the different pieces to be continuous. The package by Kissock et al. implemented these models better suitable for hourly or daily data for commercial buildings, but could be used on monthly data (suitable for hourly is doubtful). [17] is to be further read to checked for the implementation details of the package. The inputs to the package are: monthly mean daily temperature, and the monthly utility bill.

The author discussed the uncertainty of the MMT models. The standard approaches for computing the 90% confidence band for the (non-segmented) linear regression does not apply to 3 to 5 parameter change point models, because they are not linear. The authors also found that the residuals for a 3P MMT model have different variance on different sides of the change point. The authors claimed the standard testing method for the MMT models are too complicated to be feasible, but this needs to be further checked. They propose to compute a separate 90% confidence band for different segments in the piecewise regression regression. Although the description of X_0 is confusing. The annual confidence interval equals the average of the monthly ones.

The author pointed out the uncertainty of bill reading date could result in some inaccuracy in the saving estimate, and proposed a method to estimate the approximate reading date: computing a model for each potential utility bill reading time and choose the best model with low CV-RMSE. Although since the reading dates of one month influence the calculation of adjacent months, one would probably want to optimize for the aggregated CV-RMSE for all months, instead of just one month.

6.10 Comparisons of inverse modeling approaches for predicting building energy performance [48]

The paper reviewed four major data-driven energy baseline models for building energy prediction, in the context of ECM saving calculation. The application of such models include "determining retrofit savings, energy system fault diagnostics, and acquiring physical insight into the operating patterns" [48], "control strategy development, and on-line control applications" [48].

The author briefly listed some existing data-driven baseline methods including: constant base degree day method, variable-base degree day method, degree-hour method for heating and cooling energy demand prediction, the bin model (compares pre and post retrofit average hourly energy consumption for the 24 hour of the day), ANN models, generalized fourier series model, support vector machine regression model Pulse Adaptive Model, change-point model, LBNL model, mean-week-model, day-time-temperature-model, decision tree method.

Gaussian Process Regression method, Gaussian Mixture Regression Model, are proposed and are compared with change-point regression model and an ANN based model.

The four methods are tested on an office building data to predict the hot water energy consumption with R^2, RMSE, CV-RMSE. For the hourly prediction, the data from 2012-1-1 to 2012-2-24 is selected as the training set, and the data from 2011-12-8 to 2011-12-31 is used as the test set. For the daily prediction, 2012-1-1 to 2012-12-5 is selected as the training set, and the 2011-8-11 to 2011-12-31 is the test set. The rational for the selection of the size of training set is not mentioned.

The input is the dry-bulb temperature. The author also have tested adding HVAC hour of operation, and horizontal heat flux are also tried out, but claimed that these two additional variables did not have much impact and were thus dropped from the model. (It is not clear how this step is conducted, seems to lack a solid procedure, the author should leave those variables in the regression and use regularization terms to automatically set their weights to be very small or to be zero. Or maybe using PCA to pre-processing the data)

A three parameter change-point model was learned for both the daily and hourly model. However, the equation (10) and the plot (figure 7) does not match, as the intercept in the plot does not match that of the equation: the function in equation (10) is not continuous, while the plot is. unless the unit for power demand is also a different from the equation (the equation seems to have used degree F and plot used degree C, which is confusing). This implicit assumption will needs further researching on.

For the change-point model, the author explained the algorithm for finding the change point, and commented that the method is "good for its simplicity, robustness and accuracy". However, this claim does not have any evidence presented here, especially robustness and accuracy.

The author discovered that for the change point model, the hourly model have more "error" and provided the following explanation: "hourly building behavior usually has instant large energy flow demands, which cannot be respond immediately by the HVAC system due to relatively high system inertia"... "This system inertia could contribute to the error in the training data set".

The description of the Gaussian process and Gaussian mixture process models are very confusing, I need further readings other than this paper in order to understand this part more.

In the conclusion section, the author claims that ANN model is the worst because "ANN model needs sufficient training data in order to accurately capture the relationship". However, they haven't provided justification of this, one could have tested the influence of the size of training data on the performance on the test data. Also, since there are so many different implementations of ANN, it could be the case that the authors just implemented a bad one. Also not sure why the author thinks GMM is the best: GMM is the best in hourly models, but GPM is actually the best in daily models.

Also in the conclusion, the author wrote, "all models except the ANN model (CV-RMSE of 32.35%)" meets the ASHRAE standard. It is wrong, because we want "CV-RMSE" to be small, not large, it should be ANN does NOT meet the standard and other models do.

Some terms are used in-correctly: "non-negative definite" should be "positive semidefinite", "priori" should be "prior", in table 6, the model abbreviations are different from those that are used in the text ("GMM" changed to "GMR", "GPM" changed to "GPR")

The author cited that the requirement in ASHRAE guideline are as Table 6 follows, but I searched, the 22%, 5%, 7% are not there. the places with 10%:

- "The computer model shall have an NMBE of 5% and a CV(RMSE) of 15% relative to monthly calibration data. If hourly calibration data are used, these requirements shall be 10% and 30%, respectively." (but this is under the "Whole-Building Calibrated Simulation Performance Path" though, which is not relevant here)

- "baseline model shall have a maximum CV(RMSE) of 20% for energy use and 30% for demand quantities when less than 12 months worth of postretrofit data are avail- able for computing savings. These requirements are 25% and 35%, respectively, when 12 to 60 months of data will be used in computing savings. When more than 60 months of data will be available, these requirements are 30% and 40%, respectively" (this is the relevant one)

	Monthly	Daily	Hourly
CV-RMSE	15%	22%	30%
NMBE	5%	7%	10%

Table 6: ASHRAE guideline 14 requirement of model error (wrong) [48]

6.11 Applying support vector machines to predict building energy consumption in tropical region [9]

The paper presented an approach of kernelized SVM regression on building load forcasting and a general discussion of the feasibility and parameter estimation approaches of the SVM model. The input variables include monthly outdoor dry-bulb temperature, relative humidity, global solar radiation, and monthly utility bill. The utility bills are collected from survey data, and the weather data are received from the Singapore National Environment Agency.

The paper defined the landlord energy consumption as the energy used in central ventilation and air-conditioning system, vertical transportation, and lighting. The authors argues that the landlord energy should be used in ECM saving calculation instead of the whole building. The fact that landlord energy consumption has non-linear components motivates this study of the non-linear models for energy consumption estimation.

The primal objective function form of SVM can be expressed as:

$$\frac{1}{2}\left\|w\right\|^2 + C\sum_{i=1}^{n} L_\epsilon(y_i, \hat{y}_i) \tag{16}$$

$$L_\epsilon = \begin{cases} |y_i - \hat{y}_i| - \epsilon & \text{if } |y_i - \hat{y}_i| > 0 \\ 0 & \text{otherwise} \end{cases} \tag{17}$$

The $L(y_i, \hat{y}_i)$ is the the ϵ insensitive loss function. The Lagrangian dual of the SVM regression is kernelizable, and could be more probable to achieve large margin in the higher dimensional ϕ space, thus prevents over-fitting. It also models the non-linear component in the regression model. The loss function is measuring the structural risk, which corresponds to "an upper bound of the generalization error". The author pointed out that input should be scaled to $[-1, 1]$ or $[0, 1]$ before applying SVM or ANN. This could reduce numerical error, and balance the influence of different variables.

The parameters C and ϵ in the objective function are selected with 3-fold cross validation (selecting γ, a one-time search method [5] (searching for C, and ϵ), and stepwise search (a more efficient variation of the grid search for C and ϵ). In the classification setting, C represent the trade-off between allowing large margin, and the amount of mis-classification. Larger C will more strictly penalize mis-classification, and small C will favors large margin. In the regression setting, C controls the tradeoff between model complexity and "model complexity and the degree to which deviations larger than ϵ are tolerated". Larger ϵ corresponds to sparser solution but could also harm the accuracy. Each building has its own set of parameter values. Brown et al. commented that "their technique lacks a continuous optimization framework for kernel bandwidths and cannot generalize to large training sets" [4].

The method is tested on 4 randomly selected commercial office buildings from the central area of Singapore in CV-RMSE, and error% ($\frac{\hat{Y}-Y}{Y}$). In the testing, the MSE ranges between 0.14 to 0.73, but the CV-RMSEs are all less than 5%. However, the author compared the proposed method with other methods without stating the difference in the number of input variables, and the difference in time resolution. The mere comparison of CV-RMSE thus renders meaningless. Also using CV to indicate CV-RMSE is not good, because it is usually reserved for cross-validataion. The author further brought about the issue of residual does not follow normal distribution, but claimed that it is at least consistent (the errors seems to be independent).

The author summarized the advantage of SVM: 1) It minimizes the upper bound of the generalization error, instead of just training error. This ensures a better generalization guarantee in the unseen data. 2) the objective function is convex, so the local optimal is the global optimal. 3) It could provide a sparse solution, where the learned model can be represented by only a small subset of the input data. The authors selected the RBF kernel in the model as it can model non-linear relation, and is simpler with fewer hyper parameters. 4) It performs well even when the number of training data is small (4 year utility bill).

6.12 Kernel regression for real-time building energy analysis [4]

The authors proposed kernel regression method hourly building energy signature modeling. In terms of predictive power, it outperforms conventional neuron network models, especially for cases where the size of training data is small, and in terms of interpretability, the model coefficients (bandwidths) encodes the importance of the corresponding parameter, which could in turn give insights about the physical condition of target building: the most relevant time scale for temperature reflects the thermal inertia (insulation and thermal mass); the importance of the wind factor corresponds to the height of the building with respect to surrounding buildings. On the other hand, the weights in neuron network models are generally meaningless. Also since the number of parameters are smaller than neuron network, kernel regression is less prone to overfitting (Figure 9). It could also prevent outputing infeasible solutions such as predicting negative energy consumption. It performs especially well in buildings with complex non-linear behaviour.

In order to be applied to a large building portfolio, the authors pointed out that a good model should be more scalable and deployable. Acquiring the physical details and tuning the parameters in the calibrated simulation approach could be difficult for large building portfolio, and simpler models with looser physical basis becomes increasingly popular. In general, these energy models could be useful in building energy system diagnostics, fault

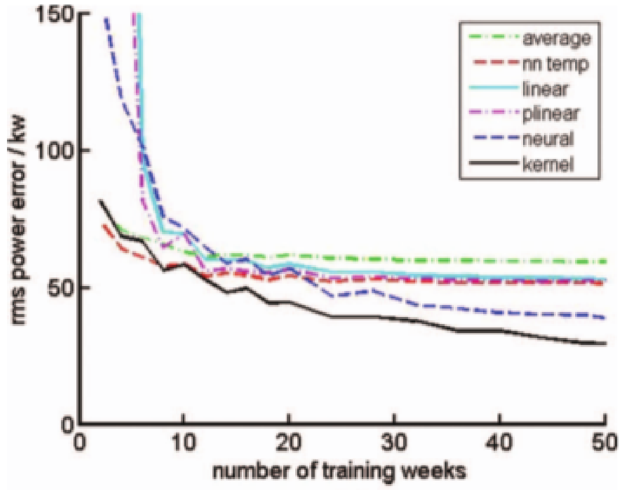

Figure 9: Comparing rms of test set by number of train data

or event detection, smart building control, and building energy retrofit saving calculation. The model presented in this study aims to tackle energy prediction and peak power event detection.

The author summarized a list of models developed since last 90s. For the black box models with no physical basis, a lot of neuron network based algorithms were developed, ranking top during both phases of the ASHRAE ‘Great Energy Predictor Shootout’ competition. The winner methods are: Mackay’s baysian modeling with neuron network [30] in phase I, and the method of Dodier and Henze [8] in phase II. To determine which input variables are more relevant, the former used a Automatic Relevance Determination (ARD) prior, and the latter used the Wald’s test [8]. After the competition, work have been done in frequency domain modeling, online neuron networks, SVM regression, etc.. For the grey-box models with simplified building physical specification, parameters are estimated from the data by maximizing likelihood or minimizing loss. Two example are presented: [3], and [29].

For the proposed method, there are 4 input variables to the model: time, temperature, humidity, and wind velocity. The input variables are transformed to 14 features before fed to the model. The time input is transformed to 8 parameters of four scales with Equation 18

$$[\cos(\frac{2\pi t}{T}), \sin(\frac{2\pi t}{T})] \tag{18}$$

The temperature, humidity, and wind hourly inputs are transformed with exponential weighting functions. Before the transformation, the inputs are normalized with mean and standard deviation. Separate models of weekday, weekend, and holidays are trained.

Kernel regression or kernel smoothing method makes prediction with a “weighted average of nearby data items, with the weights being controlled by a kernel function” [4] (Gaussian kernel with diagonal covariance in this study Equation 19).

$$k(\mathbf{x}, \mathbf{x_i}) = \mathcal{N}(\mathbf{x} - \mathbf{x_i}; 0, diag(\sigma^2)) \tag{19}$$

(it might mean this form $k(x, x_i) = \exp(-\frac{\|\mathbf{x}-\mathbf{x_i}-0\|^2}{2\sigma^T\sigma})))$

In the training stage, the objective or the L2 loss function (mean squared error) is minimized with respect to σ (the vector of bandwidths) using cross-validation. An approximation approach is adopted to increase the computation efficiency by keeping only the nearest k data points in the summation).

$$loss = \frac{1}{|S|}\sum_{i=1}^{|S|}(y_i - \hat{y}_i)^2 \tag{20}$$

The method is tested with two data sets: the ASHRAE Predictor Shootout dataset, and another data set of 4 buildings with 1.5 year of hourly electricity and environment inputs. It is compared with a few other baseline models: Temporal average, Temperature neighbours, Multivariate linear, Piecewise linear, and Neural network. For multivariate linear and piecewise linear models, a separate model is learned for each hour of the day, and for weekdays, and weekends.

With the 1.5 year data set, every 1st and 2nd week of the 1.5 year data (52 weeks total) is selected as the training set, and every 3rd week of the 1.5 year data (26 weeks total) is held out as the test data set. The performance of different methods are evaluated with CV(RMSE). training data.

	Algorithm					
Building	Average	Temp nn	Linear	p. linear	Neural net	Kernel
A	16.99	11.86	12.20	12.41	10.68	**10.49**
B	22.46	19.47	20.05	19.87	14.76	**10.86**
C	9.98	8.49	8.54	8.61	7.75	**7.14**
D	12.00	**10.33**	10.34	10.49	10.75	10.67

Figure 10: Test result

With the ASHRAE data set, the method is compared with other top ranking methods in the competition. It is comparable to other neuron network approaches, but is worse than the top method. The authors propose future works could include 1) using L1 loss function to enforce a sparse solution, 2) include automatic parameter selection (PCA maybe?), and 3) testing on larger building portfolio.

This paper provides a clear guidance of the model design and testing procedure. It also contains useful information about implementation tricks, which could help in further model implementation design.

6.13 Contextually Supervised Source Separation with Application to Energy Disaggregation [46]

The paper presented a solution to single-channel source separation problem (decompose an observed signal to several un-observed component signals) under the motivation of "energy disaggregation of hourly smart meter data". The method is tested on a large scale: thousands of homes. The data for supervised setting is difficult to get, and the un-supervised setting is ill-defined and has arbitrarily many solutions. Thus the authors proposed a hybrid approach of contextual supervised setting. The "contextual features" are features that influences the un-observed signals, environment variables in the application of building energy disaggregation. They proved that under the condition that the contextual features for different hidden signal components are roughly linearly independent, then the method achieves high accuracy with high probability.

The input to the method include: 15-min or hourly power meter data, collected from PG&E by the utility from Northern California homes. The context feature is temperature, retrieved from Weather Underground with census block level addresses. Radial-bases functions (RBFs) are used on the non-linear relationship between temperature and energy. The energy are disaggregated into four categories: base (time-of-day dependent), cooling, heating, and other (featureless). l_1 loss function is used for all components, but for heating and cooling energy, a smoothing matrix (S_n) is used to model the "lag effect".

The problem is formalized as an optimization:

$$\begin{aligned} \underset{Y,\theta}{\text{minimize}} \quad & \sum_{i=1}^{k} l_i(y_i, X_i\theta_i) + g_i(y_i) + h_i(\theta_i) \\ \text{subject to} \quad & \sum_{i=1}^{k} y_i = \bar{y} \end{aligned}$$

X_i is the bases specific to each hidden signal component. Y is the matrix whose columns are the decomposed signals $Y = [y_1, \ldots, y_k]$, $l_{(}\cdot, \cdot)$ is the loss function measures the difference between the predicted value and the true signal. g_i is a regularization term for y_i, and h_i is a regularization term for θ_i. In energy disaggregation application, the h_i could be dropped since $T \gg n_i$. If all three terms in the objective function are convex, then the problem became a convex optimization. In the setting of energy disaggregation, l_i is in the form of to account for the "lag" effect of temperature on heating / cooling energy consumption (T is the width of the sliding window). "air conditioning is correlated with high temperature but does not respond to outside temperature changes instantaneously; thermal mass and the varying occupancy in buildings often results in air conditioning usage that correlates with high temperature over some window"

$$l_i(y_i, X_i\theta_i) = \left\|(y_i - X_i\theta_i)(I \otimes 1^T)\right\| \tag{21}$$

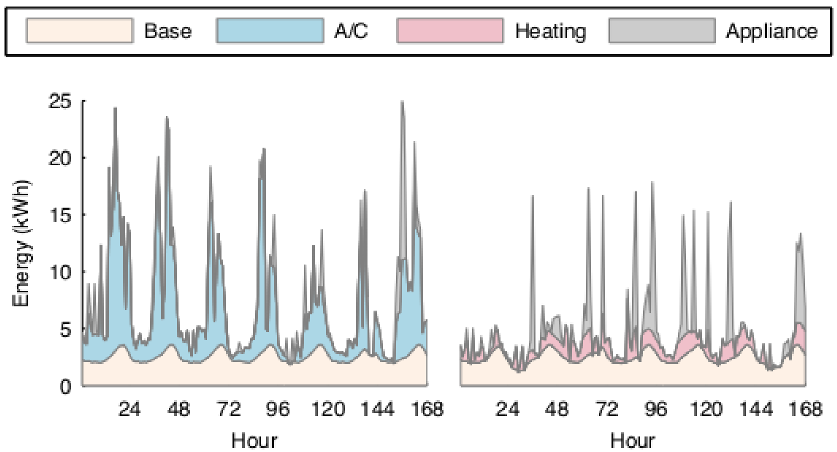

Figure 11: Disaggregation of energy use for a home in CA

Category	Features	l_i	g_i
Cooling	Hour of day	$\|y_1 - X_i\theta_1\|_1$	$\|Dy_i\|_2^2$
Cooling	RBFs over temperature $> 70^oF$	$S_2\,\|S_2(y_2 - X_2\theta_2\|_1$	$0.1 \times \|Dy_2\|_1$
Heating	RBFs over temperature $< 50^oF$	$S_2\,\|S_2(y_3 - X_3\theta_3\|_1$	$0.1 \times \|Dy_3\|_1$
Other	None	$\|y_4\|_1$	$0.5 \times \|Dy_3\|_1$

Table 7: model specification for the test data

The RBF is an approximation of the function approximation of the temperature [12].

The method is validated on a data set of 84 homes with at least 1 year hourly (rolled up from one-minute interval raw data) electric usage in Texas. The proposed method has outperformed the mean prediction heuristic (Mean) and a state-of-the art unsupervised method, sparse coding (NNSC), in this test set.

The method is then applied on a large-scale 4000+ home setting and estimated 15.6% of energy consumption is used in air conditioning and 7.7% to heating in the disaggregation result. It is reasonably close to survey result from EIA 2009 (10.4% for air conditioning and 5.4% for space heating)

The biggest difference of this method 1) it has performance guarantee through proof 2) it is tested against a large data set and benchmarked with other methods.

Category	Mean	NNSC	Contextual (proposed method)
Base	0.2534	0.2793	0.1849
A/C	0.2849	0.2894	0.1919
Appliances	0.2262	0.2701	0.1900
Average	0.2584	0.2701	0.1889

Table 8: Comparison of performance on Pecan Street dataset, measured in mean absolute error (MAE)

6.14 Deep learning for estimating building energy consumption [34]

The authors proposed two deep-learning based energy models: Conditional Restricted Boltzmann Machine (CRBM) and Factored Conditional Restricted Boltzmann Machine (FCRBM). The authors provided briefly mentioned the some existing approaches of hybrid (grey-box) energy models: semi-parametric regression models, exponential smoothing, seasonal time series models.

The proposed CRBM model and FCRBM model are explained in three aspects: the energy function, probablistic inference, and the updating rule. The input to the models are the energy time-series. Environment factors are not included.

The models are tested against ANN, SVM, and Recurrent Networks on the "Individual household electric power consumption" data set with 4 years of one-minute electric data (including about 1% missing data) with three sub-meters and one whole house meter. The first three years is selected as the training set, and the last year's data is the test set.

The models are evaluated with root mean squared error (RMSE), correlation coefficient (R), and p value of the hypothesis test against "predicted and real data are unrelated".

Some pre-processing are conducted before the training and testing: the missing data is filled with the average of data at the same date-time of the other years.

As the deep learning is one of the current hot and state-of-the art technique, and it made to the front page of New York Time [15], it is worth reviewing its application in the field of building energy. Although the work in this paper is in the context of smart-grid and demand side control, the predictive model will still be helpful in the identification of the energy retrofit opportunities, and saving calculation. The deep neuron nets needs to be further digested if it was to be implemented, as the model seems to be a bit complicated. There are some limitations to the study: the model is evaluated on one building.

6.15 A decision tree method for building energy demand modeling [47]

The authors developed a decision tree based method to predict energy consumption (??). The advantage of the method is its result is more interpretable with a tree structure. It is demonstrated by estimating the "energy performance index" (or EUI?) of 67 residential buildings in 6 districts of Japan. The accuracy is 93% for the training data, and 92% for the test data. It could also rank the EUI influential factors automatically. The authors mentioned methods of building energy demand modeling: traditional regression, ANN, simulation, and pointed out the drawback of regression method and ANN are they are not easily interpretable. Also they are only applicable to existing buildings. Simulation methods have less predictive power for occupied buildings and also too complicated [47].

The author briefly described the structure of decision tree (what do the nodes and edges represent), and the procedure for learning a decision tree. A more thorough description could be found in Tom Mitchell's book.

The author also mentioned some commonly methods for learning a decision tree: ID3, CART, and C4.5 (used in this study). The tool WEKA is used in the implementation.

In the demonstration example, the target to be predicted is categorical: High EUI, or Low EUI. The cutoff is the average of the max and min EUI of the data set. The input data include energy consumption of electricity, natural gas, and kerosene (5 min interval), 15min indoor environment, building characteristics, and the number of occupant. The numerical temperature is converted to categorical with low temperature being 8.8C to 13.1 C, and high temperature being 14.3C to 17.4C. The building characteristics include house type (detached or apartment), construction (wooden vs non-wooden), floor are, heat loss coefficient, and equivalent leakage area.

The learned model is shown in the following.

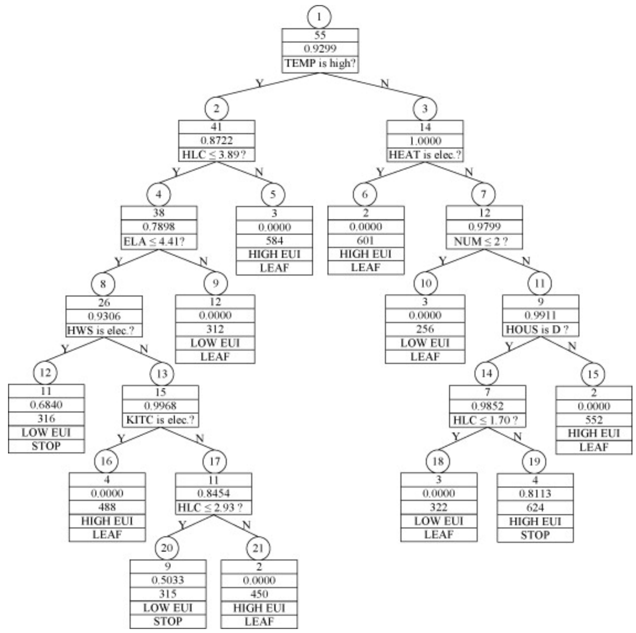

Figure 12: The learned decision tree model [47]

Two points are not clear:

- What is the reference EUI: the model is a classifier, how could it output a numeric value, if it can, why predicting a category instead of the actual consumption?
- How is the confidence level computed?

The author claimed that a rank of importance of the influential factors can be extracted from the model: the root node is the most important factor, the closer a node is to the root, the more important the factor is. However, I have doubts about this, the selection of the spliting factor at each level, as the author mentioned, is based on the “information gain”. If the “information gain” indicates the rank of importance needs further research. Nevertheless, the authors reached some interesting interpretations of the learned decision tree model: temperature (indoor) is the most important factor; the tree is not symetric, meaning different factors are found important in the high and low temperature group; in the high-temperature (indoor) group, high heat loss coefficient and equivalent leakage are corresponds to high EUI, etc.

There’s a comparison between the influence of water heater fuel type on EUI with HLC and ELA controled Figure 13. The author argued that generally, the red points are higher than the blue points. However there’s a bit confusion here, as what do the line segments represents.

Table 9: Rank of factors

Potential factors	High temperature districts Significant factors	Rank	Low temperature districts Significant factors	Rank
House type			✓	3
Number of occupants			✓	2
Floor area				
Heat loss coefficient	✓	1	✓	4
Equivalent leakage area	✓	2		
Construction type				
Space heating mode			✓	1
Hot water supply mode	✓	3		
Kitchen energy mode	✓	4		

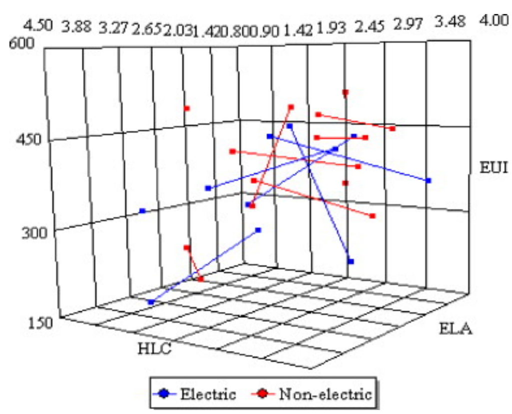

Figure 13: The comparison between electric and non-electric water heater on EUI [47]

Another comparison of the fuel type of space heating also showed high EUI tends to associate with electric heating.

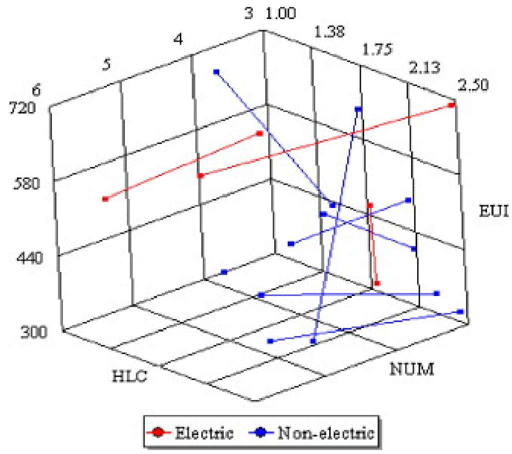

Figure 14: The comparison between electric and non-electric space heating (HEAT) on EUI [47]

6.16 Evaluation of the Predictive Accuracy of Five Whole Building Baseline Models [16]

This paper compared the predictive performance of five whole building energy baseline methods: Pulse Adaptive Model (PAM), multi-parameter change-point, mean-week, day-time-temperature, and LBNL models, and showed that the PAM, day-time-temperature, and the LBNL perform better then the other two models. The evaluation metrics include: median absolute percent error, correlation (??), root mean squared error, and relative bias.

6.17 Something about RNN

6.18 Machine Learning [33]

6.18.1 Neuron network

6.18.2 Decision tree

6.19 Bishop book

6.19.1 Regression

6.19.2 SVM

6.20 Boosting

The paper explains boosting with an example of distinguishing spam from non-spam emails. The method rises from the observation that it is easier to create a "weak learner" (base learning algorithm) that finds some rough rules then to find a single accurate procedure. By repeatedly calling the "weak learners" on subsets of data, a lot of rough rules are generated. After T iterations, the boosting combines the weak rules with a weighted majority vote. The subsets are chosen so that the weak learner focuses on "hard" examples.

6.21 Saving Electrical Energy in Commercial Buildings [6]

The thesis develops a method to predict operating parameters with hourly electric meter data. The operating parameters are a set of operating modes, each containing a peak and a base with average start and end times, and a regression model [6]. These operating parameters can be used for energy consumption prediction, saving calculation, portfolio benchmarking, etc. The method is tested on 10 buildings with 21 years of energy data, against the method ??.

6.22 Forecasting Energy Demand in Large Commercial Buildings Using Support Vector Machine Regression

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