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Evaluation of DR-Advisor on the ASHRAE Great Energy Predictor Shootout Challenge

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Abstract
This paper describes the evaluation of DR-Advisor algorithms on "The Great Energy Predictor Shootout - The First Building Data Analysis and Prediction Competition" held in 1993-94 by ASHRAE.

Disciplines
Computer Engineering | Electrical and Computer Engineering

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1. About the Competition

This paper describes the methods and results in making predictions for test problem A given by "The Great Energy Predictor Shootout - The First Building Data Analysis and Prediction Competition" held in 1993-94 by ASHRAE.

Two distinct data sets were provided for prediction (training and testing). Contestants were given these two sets of independent variables with the corresponding values of dependent variables, e.g., energy usage. The accuracy of predictions of the dependent variables from values of independent variables from the test data set was the criteria for judging this competition.

The following criteria was used by the organizers for assessing the respective accuracies of the entries when analyzing the testing set:

$$\texttt{CoefficientofVariation}, \texttt{CV}$$

$$CV = \frac{\sqrt{\left\{\sum_{t=1}^{n}(\hat{y}_t - y)^2\right\}/n}}{\bar{y}}$$

The idea was to look for simpler models that may not have such a strong physical basis, yet that perform well at prediction. The competition attracted 150 entrants, who attempted to predict the unseen power loads from weather and solar radiation data using a variety of approaches. The winner of the competition was an entry from David Mackay [1]. Mackays algorithm was based on Bayesian modeling using neural networks, with an "Automatic Relevance Determination" (ARD) prior to help select the relevant variables from the large number of possible inputs. Although this algorithm won the competition by some margin, a large fraction of the other highly ranked algorithms were also based on some form of neural network.

2. Data Description

The training data was a time record of hourly chilled water, hot water and whole building electricity usage for a four-month period in an institutional build-

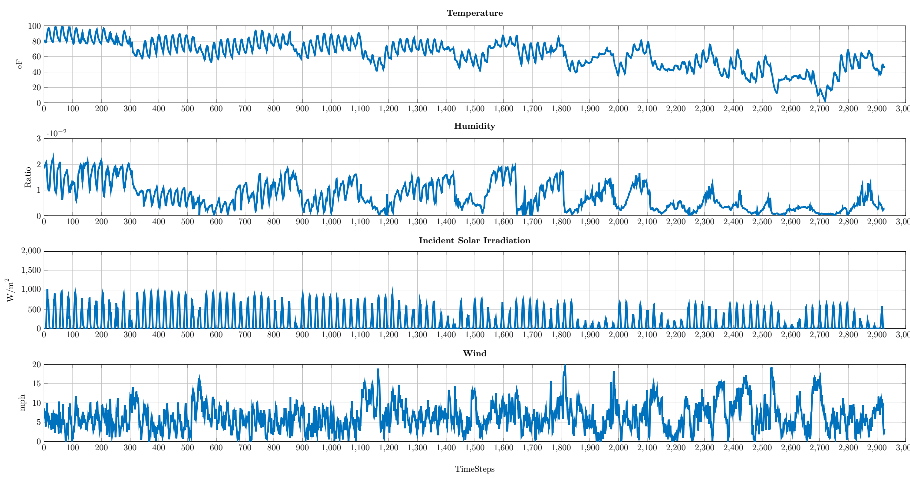

Figure 1: Plot fo the training data for the ASHRAE Great Energy Predictor Shootout Challenge.

ing. Weather data and a time stamp were also included. The hourly values of usage of these three energy forms was to be predicted for the two following months. The testing set consisted of the two months following the four-month training period. The training data had approximately 3000 samples taken hourly during Sep - Dec 1989. The following information was provided for each time step:

1. Outside temperature (°F)
2. Wind speed (mph)
3. Humidity ratio (water/dry air)
4. Solar flux (W/m^2)
5. Hour of Day
6. Whole building electricity, WBE (kWh/hr)
7. Whole building chilled water, CHW (millions of Btu/hr)
8. Whole building hot water, HW (millions of Btu/hr)

The corresponding date is also provided. The training data features or the independent variables are shown in Figure 1. One of the dependent or response variable (WBE) is plotted in Figure 2.

In addition to the variables which are provided, the date for each sample point allows us to define *proxy* or *context* variables of our own. We define three such proxy variables:

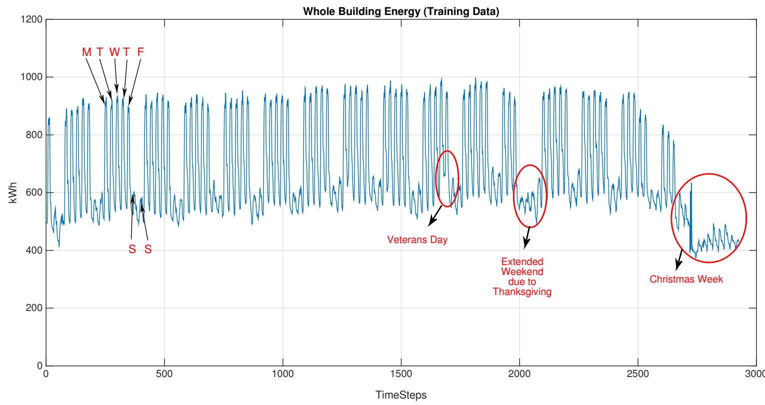

Figure 2: Plot of the whole building electricity (WBE) training data. It can be seen that special days and weekends can be easily identified in the data.

1. Day of Week: This is a number which takes values from 1 to 7 based on what day of the week it is. The intuition behind introducing this variable is that any repeated building use patters fro a specific day will be captured by this variable.

2. IsWeekend: This is a boolean variable which takes the value `TRUE` for Saturdays and Sundays and `FALSE` otherwise.

3. IsHoliday: Sometimes the building might follow a modified schedule on a weekday due to a holiday or a special day. By referring to the 1989 calender or the training data duration, we are able to identify days in the training and testing data which are special days or holidays.

The motivation of introducing the proxy variables can be understood from Figure 2. One can note how weekday consumption patters appear similar, except on certain holidays where the power consumption is irregular or seems to follow a weekend schedule (e.g., Thanksgiving). Likewise, the building has an irregular power consumption profile during the entire Christmas week, probably because of a vacation schedule.

3. Results

We run the random forests method on the training data to learn three different models, one each for predicting the whole building energy WBE, chilled water consumption, CHW and hot water consumption HW. The test data consists of 1282 samples of weather information and date from the first two months of 1990. Our objective is to predict the WBE, CHW and HW for these two months.

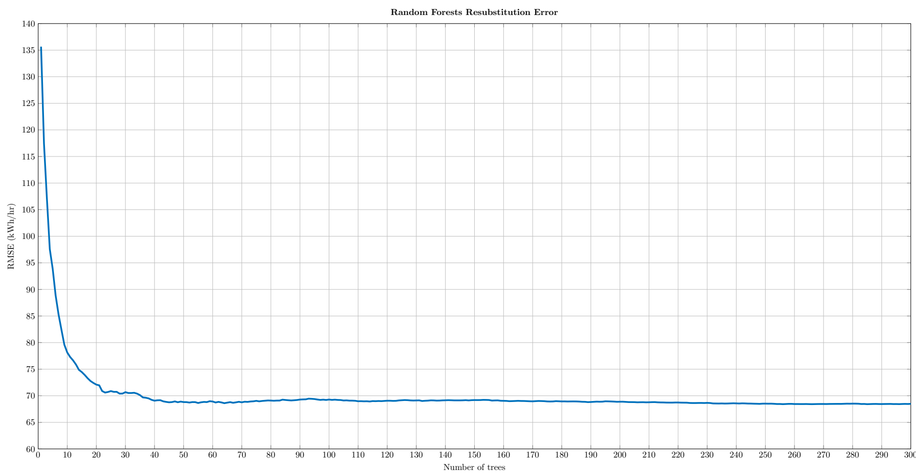

Figure 3: Resubstitution error is shown for the number of trees in the random forest method.

Table 1: Shootout Competition Results

ASHRAE Team ID	WBE CV	CHW CV	HW CV	Average CV
9	10.36	13.02	15.24	12.87
Random Forests	**11.72**	**14.88**	**28.13**	**18.24**
6	11.78	12.97	30.63	18.46
3	12.79	12.78	30.98	18.85
2	11.89	13.69	31.65	19.08
7	13.81	13.63	30.57	19.34

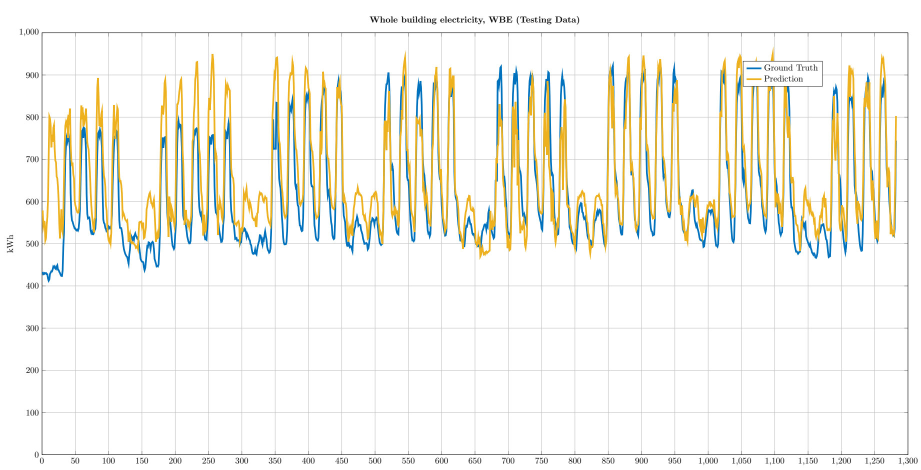

Figure 4: Comparison between predicted and ground truth values for WBE for the testing data.

The comparison between the predicted WBE values and the ground truth are shown in Figure 4. The coefficient of variation is 11.72%. The re-substitution error (on the training data) is plotted for a different number of trees used by the random forest in Figure 3. In the actual competition, the winners were selected based on the accuracy of all predictions as measured by the coefficient of variation statistic CV. The smaller the value of CV, the better the prediction accuracy. ASHRAE released the results of the competition for the top 19 entries which they received. In Table 1, we list the performance of the top 5 winners of the competition and compare our results with them.

It can be seen from table 1, that the random forest method ranks 2^{nd} in terms of WBE CV and the overall average CV. The other algorithms in the table are (9) Mackays Bayesian Non-Linear Modeling, (6) Ohlssons Feedforward Multi-layer Perceptron, (2) Feustons Neural Network with Pre and Post Processing. Algorithm (9) (Mackay) generates the best results overall, beating many other neural network implementations in the competition, which suggests that it is some particular feature of this implementation, e.g., input preprocessing, network architecture, or training approach, that is important.

However, the results we obtain clearly demonstrate that random forests can generate predictive performance that is comparable with the ASHRAE Shootout winners.

References

[1] David JC MacKay et al. Bayesian nonlinear modeling for the prediction competition. *ASHRAE transactions*, 100(2):1053–1062, 1994.