Improved Methods to Load Prediction in Commercial Buildings

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ABSTRACT

Accurate load prediction methods in commercial buildings can provide a benefit to understanding the energy behavior of commercial buildings for improved building energy management. A crucial first step to understanding the potential energy savings and to developing a proper building energy management system in commercial buildings is the development of a proper baseline estimate that can be used as an accurate gage of future real savings in commercial buildings. Without an accurate method, load predictions and calculated energy savings can vary from 5-10% with even larger error on days when unusual occurrences may cause major fluctuations in load behavior. We introduce the use of fuzzy logic to improve the load prediction potential for commercial buildings. The method is then compared to an existing baseline calculation commonly used for predicting commercial building electrical loads. The method proposed involves the development of membership functions using various inputs, including real-time, morning-of, and previous ten-day data. The algorithm uses Modified Learning from Experience (MLFE) to generate membership functions using a training set of chosen inputs. These membership functions are then improved with a Recursive Least Squares (RLS) method that determines a single output power prediction within a given tolerance set by the user, for a given time. Improvements, using this method, are seen in the robustness of the predictions to abnormal circumstances affecting inputs, thus allowing minimization of plant uncertainty, improvement of stability and performance for building control systems used for load shedding, and energy efficiency improvements.

Introduction to Current Methods

The central aim of this paper is to review current methods for predicting hourly power use and to develop an alternative method that provides a level of accuracy comparable or better than current methods. An additional goal is to design a method that is easily implementable in real world automated building management systems during demand response events. For clarity, Demand Response (DR) can be defined as actions taken to reduce electric loads when contingencies, such as emergencies and congestion, occur that threaten supply-demand balance, or market conditions raise supply costs.

A number of methods have been developed in the interest of accurately predicting commercial building electrical loads for issues stemming from the need to gage building energy efficiency or demand response strategy effectiveness. A number of authors have contributed new insights to prediction models for commercial building power consumption. These types of models include seasonal regression, simple average, Fourier series, and artificial neural network models. The use of fuzzy logic has become widespread in many applications in which systems are uncertain, or non-linear, including short-term load forecasting for transmission networks, yet the use of fuzzy logic for the prediction of hourly building electrical load has not yet been examined or published.

Researchers at Lawrence Berkeley National Laboratory have developed seasonal and 10-day regression models as well as simple three or ten day averages with morning correction factors. In their study, seven load prediction methods are developed and tested on 32 commercial buildings. Accuracy and bias are compared for each of the models (Coughlin et al. 2008).

Other models of predicting commercial building load have used Fourier series methods that utilize the periodic behavior found in commercial buildings. These methods utilize seasonal, weather, and hourly parameters such as ambient temperature, humidity and solar radiation to develop a general linear regression modeling procedure at the hourly level. These methods were tested at Zachary Engineering Center and accurate results were produced (Dhar, Reddy & Claridge 1993).

A number of publications have focused on the use of artificial neural network (ANN) models in accurately forecasting load. These models mimic the learning process of the human brain in learning relationships that may exist between input parameters and controlled and uncontrolled variables (Kalogirou 1998). Artificial neural networks function as adaptive systems that change their structure based on external or internal information flowing through the network during the learning phase (Quaiyum et al. 2011). There are many different types of ANN models, but they can be classified into three main categories; feed-forward, feedback, and auto-associative methods.

Feedforward neural networks are arguably the simplest type of ANNs and are used commonly in predicting uncertain outcomes. Information moves only in one direction, from the input nodes through parallel hidden nodes and then on to the output nodes. In feed-forward ANN models, a learning rate, the number of hidden nodes in the ANN, and the number of epochs are specified, and the predicted output of the model is given in equations resembling the following form $P_{out}(i) = \left(Load_{high} - Load_{low}\right)ANN_{out}(i) + Load_{low}$, where ANN_{out} is the output of the ANN model (Ortiz-Arroyo, Skov and Huynh 2005).

Feedback artificial neural networks (FB ANN), or recurrent neural networks, contain information that travels in both directions. The internal state of the network can exhibit dynamic temporal behavior unlike feedforward neural networks (Graves et al. 2009). Feedback neural networks have been examined for building load prediction by Spanish researchers P. Gonzales and J. Zamarreno. The process they use takes input temperatures (used in a temperature predictor for temperature forecasting), time and past power data. The FB ANN does not allow the possibility of system interruption for stability so it includes non-characteristic or abnormal days in its prediction method. The model includes feedback of the actual output variable for the past input variables and predicts the next value depending on the quality of the "acquired knowledge" of the system. This system was compared to other ANN methods and performed much better than feed-forward, auto-associative, and non-linear Bayesian regression methods (Gonzales & Zamarreno 2005).

Fuzzy methods have been implemented in a number of areas over the past thirty years. A common application of fuzzy methods is in short-term load forecasting for stability of the electrical grid. Short term load forecasting is especially significant for economic load dispatch, load management scheduling, optimum power flow with minimum transmission loss, fuel management, and contingency planning (Sachdeva & Verma 2008; Pandian et al. 2005). Through these studies with short term forecasting, fuzzy methods have been proven capable of being applied to uncertain systems effectively and thus these methods can be extended to determining power consumption in buildings.

Current Methods Chosen for Comparison

As mentioned in the previous section, there are a multitude of methods that exist in the area of load prediction, yet, many of these methods are highly complex or require large amounts of computational software to be completed. One of the main goals of the method to be developed is easy implementation, meaning it is low cost and requires minimal computation time, which allows us to meet the goal of effective reference-tracking feedback control. The method selected for comparison requires similar computation times and costs. We compared our method to LBNL's BLP3 method due to the fact that it has performed well and requires little computation and no dependence on special software for implementation.

LBNL's BLP3 Method

LBNL's BLP3 Method is a method that selects the three highest temperature days of the previous ten and calculates the simple average power at each hour. It then includes a correction factor that takes into account variations from the average morning behavior that is present the morning of the prediction date. The correction factor uses the power of the morning of prediction and morning power averages for three days used in the following form:

$$C = \frac{P_{11AM} + P_{10AM}}{P_{avg,11\ AM} + P_{avg,10\ AM}}$$

The model is a simple modification of the standard model used in the state of California that takes a three day average (Coughlin et al. 2008).

MLFE/RLS Method

The proposed MLFE/RLS Method uses inputs for a given day and produces a single output value for a baseline prediction at each time step, using what is known as fuzzy set theory. Fuzzy set theory is based on the fact that uncertainty is always present in complex, real life systems, including building energy systems. Uncertainty has been viewed over the centuries as incompleteness, imprecision, and complexity. This uncertainty exists as an integral feature of all abstractions, models, and solutions and thus may require a solution that accepts the uncertainty present in the system (Ross 2004).

Uncertainty can be manifested in many forms: it can be fuzzy (unclear, imprecise, approximate), it can be vague (not specific, amorphous), it can be ambiguous (too many choices, contradictory), it can be in the form of ignorance (dissonant, not knowing something), or it can be due to natural variability (conflicting, random, chaotic, unpredictable).

Since its introduction by Lotfi Zadeh in 1965, fuzzy set theory has brought about a shift from the logic of probability theory, which is based on classical binary (two-valued) logic to continuous-valued logic. Fuzzy logic involves a mapping between elements of two or more domains. Just as an algebraic function maps an input variable to an output variable, a fuzzy system is capable of mapping an input group to an output value or group (Mendel 1995).

Like many systems that contain large amounts of uncertainty, commercial buildings may also utilize fuzzy logic to accurately predict behavior of a system. Fuzzy logic has the ability to predict system behavior that does not require complete accuracy but a relatively high degree of accuracy, usually set by the user with the advantage of significantly shorter calculation times. It is also very useful in predicting, within a reasonable tolerance, the behavior of systems with highly nonlinear characteristics. Systems using fuzzy logic also have a high potential to understand complex systems, devoid of analytic formulations, or systems in which the causes and effects are not generally understood but can be observed.

Theory & Calculations

The new method requires a set of training data to generate membership functions that require a set of inputs that have been "fuzzified", and returns a single delta output, which in our case is the real power, in kilowatts, for the entire building. Data for non-holiday weekdays over the past 6 months were gathered and used to train the algorithm. The algorithm can then be run for each individual time step, which in the preliminary testing phase is every half hour, but can eventually be implemented for every 5 or 15 minute interval, an appropriate interval for many of the processes related to HVAC which have settling times of the same order of magnitude.

The given set of inputs used for the training the MLFE algorithm includes previous day average power data for the building, morning-of power data for the building, and current real-time weather data. The inputs and outputs used for the MLFE/RLS prediction method are the following:

- **Previous days power data:**
  X_1: 3 hottest days of previous 10 days average power data for each time step (**PL**(d,h))
- **Morning-of data:**
  X_2: Actual load at 10 AM day-of, **AL**(d,10)
  X_3: Actual load at 11 AM day-of, **AL**(d,11)

- **Real-time weather data:**
  X_4: Relative humidity at each time step , **RH**(d,h)
  X_5: Outside air temperature at each time step, **OAT**(d,h)

- **Output:**
  Y: Power at each time step, **AL**(d,h)

The data above is first normalized using the maximum values for each category present in the entire data set[1]. Once the parameters have been normalized, Gaussian membership functions have been used for input output functions; although a series of different membership functions could have been used. The output membership function is a delta function, or impulse function having no width, that occurs at a value b_i with full membership. The idea of membership can conceptually be understood as the degree at which some individual parameter belongs to a given classification. The individual parameter can be assigned a numerical value, $m \in [0,1]$ based on how closely it represents the given class for which the value is assigned. In building

[1] Normalization must be performed to eliminate improper weightings for the generation of membership rules due to the large difference in scale between parameters.

membership functions, rules are developed for our system of multiple inputs and a single output in the following manner:

IF X_1 and X_2 and X_3 and X_4 and X_5 THEN Y

Gaussian Membership functions take the form of Equation (1).

$$\mu = exp\left[-\frac{1}{2}\left(\frac{x_i - c_i}{\sigma_i}\right)^2\right] \qquad (1)$$

x_i : ith input variable
c_i : ith center of the membership function (where membership achieves maximum value)
σ_i : spread of ith membership function (constant)

Figure 1. Typical Gaussian Membership Function

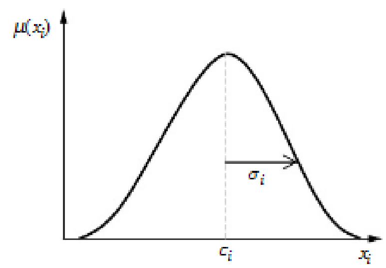


Figure 2. Delta Membership Function

First, a Modified Learning from Experience (MLFE) algorithm must be used to generate a rule-base, since we have no knowledge of the characteristic behavior of the building from the data sets available. The rule-base consists of the number of rules and the rule parameters.

The process is initiated by setting the number of rules, R= 1, and for b_1 , $c_1^1, c_2^1, c_3^1, c_4^1, c_5^1$ we use the first day training data-tuple $(X_1, X_2, X_3, X_4, X_5)$. X_1 is set to be c_1^1 , X_2 is set to be c_2^1 and so on, and b_1 is set to y^1. In the method, it is important to note that b_i is the point in the output space at which the output membership function for the ith rule is a delta function, and c_j^i is the point in the jth input universe of discourse where the membership function for the ith rule achieves a maximum. The relative width, σ_j^i, of the jth input membership function for the ith rule is always greater than zero.[2] The spread will be varied based on hourly data to find the optimal spread for the test days.

[2] It is important to note that the spreads can never be set to zero. This would result in a division by zero error in the calculation and produce infeasible results as will be seen in the equations later in the paper.

For this example, we would like the fuzzy system to approximate the output accurately; thus we find that we can set the tolerance, ε_f to 0.04. We also introduce a weighting factor, ω, which is used to calculate the spreads for the membership functions, as given later in Equation (3). The weighting factor is used to determine the amount of overlap between the membership function of the new rule and that of its nearest neighbor. For our analysis, we vary the weighting factor to find an optimal spread that will generate an appropriate rule-base.

The output generated from the training data set is then compared to the real power data from the training sets to see how well the fuzzy system maps the information. The required stopping condition for the algorithm is shown below. The difference must be smaller than the user set tolerance (specified earlier) in order for no additional rules to be added.

$$\left|f\left(x^i\middle|\theta\right) - y^i\right| < \varepsilon_f \quad (2)$$

If the tolerance is exceeded, a rule is added to the rule-base to represent (x^2, y^2) by modifying the current parameters, θ. The rule, R is set to 2, and $b_2 = y^2$, and $c_j^2 = x_j^2$. This process of adding additional rules using the next training data set repeats until Equation (2) is satisfied.

If an additional rule is needed, the centers for the new rule are set to the next training data inputs,x_j^i, and the relative widths are determined based on achieving an appropriate overlap between membership functions. This overlap is set by a user defined weighting factor (ω).

$$\sigma_j^i = \frac{1}{\omega}\left|c_j^{i'} - c_j^{min}\right| \quad (3)$$

Where:

$c_j^{i'}$: the current input training data set, x_j^i

c_j^{min}: the nearest membership function centers to new membership function centers $c_j^{i'}$

ω: the user defined Gaussian membership function width weighting factor

After the rule-base has been generated with MLFE, Recursive Least Squares (RLS) methods can be used to calculate $\hat{\theta}(k)$ at each time step k from the past estimate $\hat{\theta}(k-1)$ and the latest data pair that is received, x^k & y^k. Recall that b_i is the point in the output space at which the output membership function for the ith rule is a delta function, and c_j^i is the point in the jth input universe of discourse where the membership function for the ith rule achieves a maximum. The relative width, σ_j^i , of the jth input membership function for the ith rule is always greater than zero.

Now we calculate the regression vector, ξ based on the training data using Eq. (4)

$$\xi_i(x) = \frac{\mu_i(x)\ \prod_{j=1}^{n} exp\left[-\frac{1}{2}\left(\frac{x_j - c_j^i}{\sigma_j^i}\right)^2\right]}{\sum_{i=1}^{R}\prod_{j=1}^{n} exp\left[-\frac{1}{2}\left(\frac{x_j - c_j^i}{\sigma_j^i}\right)^2\right]} \qquad (4)$$

Recall that in the least squares algorithm, the training data x_i are mapped into $\xi(x_i)$, which is then used to develop an output $f(x_i)$ for the model. A covariance matrix is used to determine the least squares estimate vector of the training set, $\hat{\theta}$, which is calculated using the regression vector and a previous covariant using Equation (6). To do this, an initial covariance matrix, P_0 must first be calculated using a parameter, α and the identity matrix, I. P_0 is used to update the covariance matrix, P, in the next time step. A recursive relation is established to calculate values of the P matrix for each time step using Equation (5). The value of the parameter α should be greater than 0. Here a value of 100 is arbitrarily used for α . I is an R x R identity matrix.

$$P(0) = \alpha I$$

$$P(k) = \frac{1}{\lambda}\left\{I - P(k-1)\xi(x^k)\left[\lambda I + \left(\xi(x^k)\right)^T P(k-1)\xi(x^k)\right]^{-1}\left(\xi(x^k)\right)^T\right\}P(k-1) \quad (5)$$

$$\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)\xi(x^k)\left[y^k - \left(\xi(x^k)\right)^T \hat{\theta}(k-1)\right] \quad (6)$$

$$f(x|\theta) = \hat{\theta}^T \xi(x) \quad (7)$$

Testing of Methods

Commercial Building Test Bed

Sutardja Dai Hall on the University of California, Berkeley campus acts as the test bed for the two methods. The building provides a dynamic commercial environment and houses a nano-fabrication laboratory. The seven floors of office space and classrooms account for nearly 1 MW of power at peak load. The building runs for one portion of the year on a centrifugal HVAC chiller and the other portion of the year on an absorption chiller that runs on steam. The predictions were carried out on dates in which the absorption chiller was running in the building. A severe short-cycling problem with the centrifugal chiller was discovered and fixed during the months of data acquisition meaning that data was contaminated due to a major change in physical plant behavior. The building provides extensive submetering and the data is accessed through an open-source sMap database developed by researchers at the University of California, Berkeley (Dawson-Haggerty 2011).

Test Method

For LBNL's BLP3 method, five test days were tested in the months of January and February 2012. The method drew data from three of the highest temperature days of the prior ten days. The MLFE/RLS Method required a training set consisting of 11 days ranging from November 2011 until February 2012. The inputs for each of these days were processed and ran through the model. Then, the rule-base was tested for the same five test days. The performance of these methods was tested for accuracy by calculating a simple percentage error for each individual time step for each day. Then the RMS error was calculated over each day, n, in the following form:

$$RMS_{error} = \sqrt{\sum_{i=1}^{n} \frac{\left(P_{pred} - P_{actual}\right)^2}{n}}$$

Results

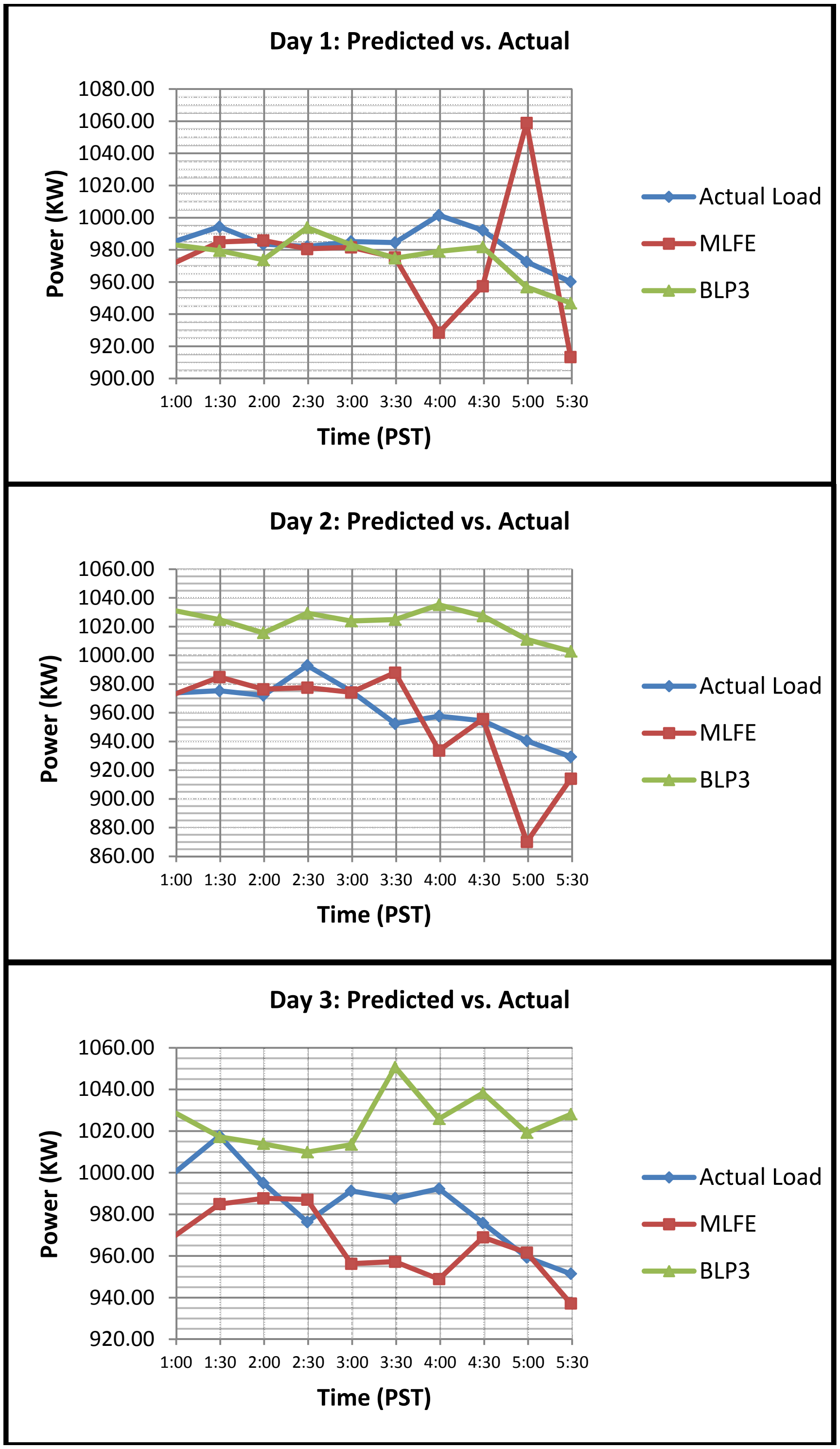
The comparison between the performances of the two methods is summarized in Table 1.

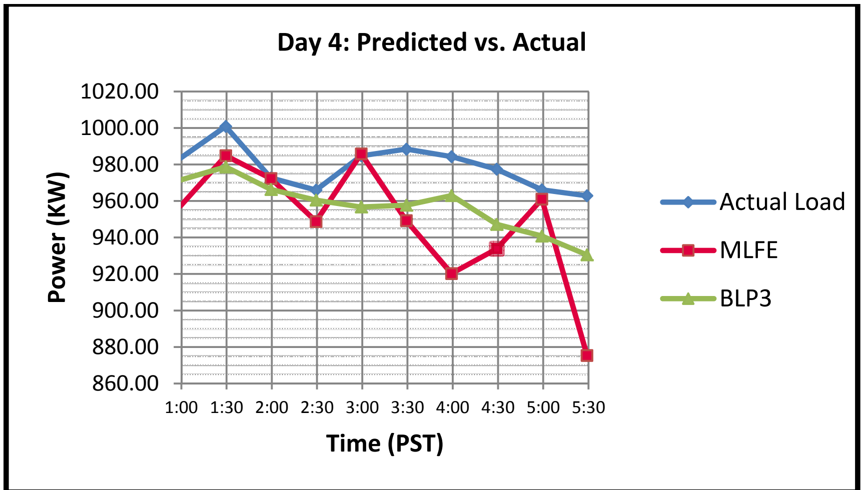
Table 1. Error comparisons for 5 test days for each afternoon time step measured as percentage deviation from the actual measured power (measured in kilowatts)

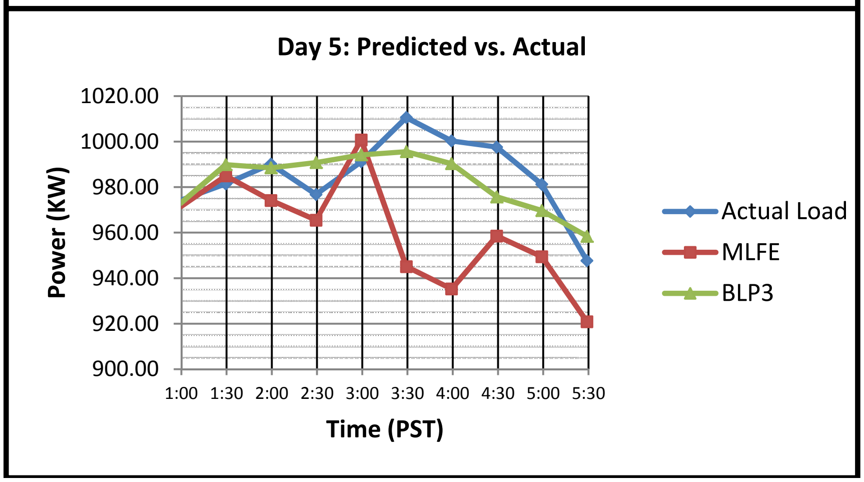
Day 1	Actual	MLFE	BLP3	MLFE%	BLP3 %	Day 3	Actual	MLFE	BLP3	MLFE%	BLP3%
1:00	985.30	972.17	983.00	-1.33	-0.24	1:00	1000.33	969.88	1028.70	-3.04	2.52
1:30	994.30	984.89	979.50	-0.95	-1.49	1:30	1017.70	984.93	1017.20	-3.22	-0.05
2:00	983.48	985.84	973.80	0.24	-0.99	2:00	995.05	987.71	1013.90	-0.74	1.89
2:30	982.01	980.58	993.90	-0.15	1.21	2:30	976.30	987.09	1009.90	1.11	3.44
3:00	985.17	981.60	983.10	-0.36	-0.21	3:00	991.28	956.27	1013.50	-3.53	2.24
3:30	984.50	975.29	974.80	-0.94	-0.99	3:30	987.70	957.23	1050.70	-3.09	6.38
4:00	1001.50	928.56	979.10	-7.28	-2.24	4:00	992.30	948.89	1025.90	-4.38	3.39
4:30	992.20	957.43	981.80	-3.50	-1.05	4:30	975.81	968.99	1038.30	-0.70	6.42
5:00	972.52	1058.91	956.80	8.88	-1.61	5:00	959.33	961.62	1019.20	0.24	6.24
5:30	960.18	913.35	946.90	-4.88	-1.38	5:30	951.45	937.21	1028.10	-1.50	8.05
	RMS	40.68	12.61				RMS	25.43	46.09		
Day 2	Actual	MLFE	BLP3	MLFE%	BLP3%	Day 4	Actual	MLFE	BLP3	MLFE%	BLP3%
1:00	973.80	973.18	1031.00	-0.06	5.88	1:00	983.40	957.32	971.50	-2.65	-1.21
1:30	975.30	984.90	1024.90	0.98	5.08	1:30	1000.80	984.86	978.70	-1.59	-2.21
2:00	972.10	976.40	1015.70	0.44	4.48	2:00	972.61	972.34	966.30	-0.03	-0.65
2:30	992.90	977.52	1029.40	-1.55	3.68	2:30	965.96	948.79	960.50	-1.78	-0.56
3:00	975.00	974.19	1023.90	-0.08	5.02	3:00	984.77	985.87	956.70	0.11	-2.85
3:30	952.40	987.96	1024.90	3.73	7.61	3:30	988.40	949.25	957.70	-3.96	-3.11
4:00	957.70	933.81	1035.20	-2.50	8.10	4:00	984.30	920.22	963.00	-6.51	-2.16
4:30	954.36	955.69	1027.40	0.14	7.65	4:30	977.42	933.80	947.20	-4.46	-3.09
5:00	940.46	870.07	1011.10	-7.49	7.51	5:00	966.16	961.01	940.80	-0.53	-2.62
5:30	929.31	914.11	1002.80	-1.64	7.90	5:30	962.86	875.37	930.50	-9.09	-3.36
	RMS	27.15	61.92				RMS	40.56	23.42		
Day 5	Actual	MLFE	BLP3	MLFE%	BLP3%						
1:00	974.20	971.33	972.90	-0.30	-0.13						
1:30	981.40	984.96	989.90	0.36	0.87						
2:00	990.10	974.17	988.50	-1.61	-0.16						
2:30	976.78	965.49	990.80	-1.16	1.43						
3:00	991.16	1000.75	994.20	0.97	0.31						
3:30	1010.60	945.07	995.60	-6.48	-1.48						
4:00	1000.30	935.28	990.30	-6.50	-1.00						
4:30	997.59	958.52	975.70	-3.92	-2.20						
5:00	981.22	949.41	969.70	-3.24	-1.17						
5:30	947.67	920.84	958.40	-2.83	1.13						
	RMS	35.03	11.55								

The results of the two predictions are plotted against actual measured load in Figure 3. In the figure, MLFE predicts the load better than BLP3 during early afternoon hours for all test days. During late afternoon hours, it is not clear which method predicts load more accurately.

Figure 3. Plots of BLP3 vs. MLFE/RLS Predicted Load to Actual Load







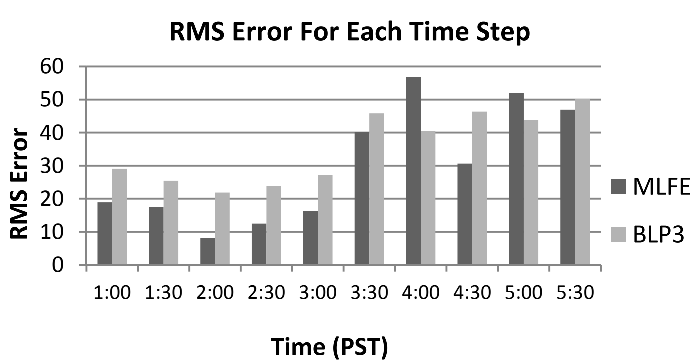
In the previous table, RMS error for each day was observed. Table 2 demonstrates the RMS error at each time step.

Table 2. RMS Error for Each Hour

Method	1:00 PM	1:30 PM	2:00 PM	2:30 PM	3:00 PM	3:30 PM	4:00 PM	4:30 PM	5:00 PM	5:30 PM
BLP3	29.07	25.45	21.87	23.79	27.15	45.79	40.47	46.35	43.81	50.23
MLFE	18.91	17.44	8.15	12.47	16.32	40.26	56.76	30.61	51.89	46.91

Figure 4 shows the RMS errors for each method at each time step.

Figure 4. Plots of RMS Errors of BLP3 vs. MLFE



Conclusions

After testing two different electrical load prediction methods we can see that Modified Learning From Experience (MLFE) with a recursive least squares improvement provides a reasonably accurate model for load prediction. It is comparable to the method set forth by Lawrence Berkeley National Laboratory in predicting the load in a building on the University of California, Berkeley campus. Prediction of the energy behavior in a commercial building was improved in various aspects as seen in the data presented. Early afternoon predictions saw a significant improvement in RMS error for all ten time steps except for 4:00 PM and 5:00 PM, during which the BLP3 method did better. Comparing the RMS error for each day showed BLP3 doing better in three of the five days. However, this can be attributed to the large difference in error at the 4:00PM hour, which was significant enough to dominate the RMS error calculation. Possible future directions may include insight from improvements in measuring building occupancy that may increase the abilities of the MLFE/RLS method in predicting building load behavior. Building occupancy is one of the largest driving factors for building energy consumption due to the high amounts of cooling or heating load that is added to the building environment. With new innovations in gauging building occupancy, we postulate that the prediction capability of the MLFE method will also be improved.

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