Load and Electricity Rates Prediction for Building Wide Optimization Applications

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ABSTRACT

A method for predicting building loads, such as hot water load, and utility rates, such as electricity rates, over a horizon into the future is presented. Building loads and utility rates prediction find application in several energy consumption fields, including, but not limited to, optimal control of central energy plants, peak load shaving, peak load shifting, etc.… In this work, the predicted load is characterized by deterministic and stochastic terms. The deterministic term takes into consideration the factors affecting a building load and a utility rate, such as outside air enthalpy. On the other hand, the stochastic term allows for the prediction of future errors using current and past prediction errors. The prediction method developed employs various techniques including clustering analysis, linear regression modeling, auto-regressive modeling, and curve-fitting. The approach taken has been applied to historical cold water, hot water, and electric load and electricity rates data. Simulation results show the feasibility of the method developed.

1. INTRODUCTION

The reduction of energy consumption, use of renewable energy, and preservation of natural resources are becoming increasingly important. Several applications in the energy efficiency field aim at minimizing energy consumption and/or cost. To achieve this, these applications employ optimization techniques that require future prediction of the performance and various loads of a facility, campus, building, or an energy plant, such as hot water, cold water, and/or electric load. The prediction horizon may be as short as few hours to ten days into the future, depending on the application at hand. Wenzel *et al.* (2014) implement a method for optimizing a central plant using model predictive control. That optimization approach makes use of campus load predictions over a horizon for determining the dispatch schedule of the plant. Furthermore, the minimization of utility cost requires an accurate prediction of utility rates, such as electricity rates, over a given horizon. Therefore, a method for predicting building loads and utility rates over a given horizon into the future has been developed.

Building load and utility rates prediction has been addressed in the literature in various types of applications. Seem and Braun (1991) implemented an adaptive method for real-time forecasting of the electrical demand of a building. Seem’s method is based on the cerebellar model articulation controller. Nielsen and Madsen (2006) took a grey-box approach in the development of a model linking the heat consumption to climate and calendar information. Catalina and Iordache (2013) developed a method for the fast prediction of heating energy demand using multiple regression models with the building global heat loss coefficient, the south equivalent surface, and the difference between the indoor set point temperature and the sol-air temperature as predictor variables. Most recently, Platon *et al.* (2015) addressed the hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis. In this paper, the building loads and utility rates prediction method developed makes use of clustering analysis, curve-fitting, linear regression modeling, and auto-regressive modeling.

As indicated in Seem and Braun (1991) and other publications in the literature, building loads and utility rates are influenced by several factors such as weather, day of week, time of day, operation schedules, etc.… It is imperative for any real-time load prediction method to account for as many of these factors, if not all. In this work, the method developed takes into consideration the several factors contributing to building loads and utility rates. The load predicted consists of a deterministic term and a stochastic term. The deterministic term is calculated using linear regression models, whose coefficients are determined offline. These models rely on the typical load value for a given time of day and day-type (days with similar load profiles) and weather forecast. The latter is obtained from the National Oceanic and Atmospheric Administration (NOAA) through their National Digital Forecast Database

(NDFD) service. The stochastic term is determined using an Auto-Regressive (AR) model, whose coefficients are also determined offline. The AR model calculates future prediction errors based on the current prediction error. The stochastic term of the predicted load gives the method developed its adaptive property, and thus increases the accuracy of the prediction by updating the forecast using current measurements of the load. The coefficients of the models used in determining both, the deterministic and stochastic terms, are calculated offline using historical weather, building loads, and utility rates data. The model coefficients are updated in real-time adaptively using most recent training data.

For a given set of training data, the method developed generates a set of regression models for each day-type. Day-types are determined by a day-typing algorithm which specifies days with similar load profiles based on cluster analysis techniques. Outside air enthalpy and a typical load profile constitute the predictors variables in each set of regression models. Each day-type is characterized by a different typical load profile which is generated using an optimal data fitting technique. The AR model coefficients are determined using the residuals obtained from different sets of regression models. Given the determined models, the current load measurement, and weather forecast, the future load values are calculated by selecting the appropriate regression model and summing the deterministic and stochastic terms.

This paper is divided as follows. Section 2 provides a high-level description of the load prediction method. Section 3 introduces the techniques used to generate the pertinent linear regression models and the auto-regressive model offline. Section 4 introduces the approach taken to generate the predicted load online at any given time instant using the models generated offline. Simulation results are presented in Section 5. The paper is then concluded in Section 6.

2. High Level Description of the Load Prediction Method

The load prediction method developed generates an hourly load forecast at any time instant over a predetermined horizon into the future. The load forecast generated at time instant n consists of a deterministic term, $\hat{L}_{det}(n)$, and a stochastic term, $\hat{L}_{sto}(n)$, as shown in Equation (1). The deterministic term accounts for the factors affecting the load such as time of day, day of week, weather variables, and operation schedules. Weather variables may include Outside Air Temperature (OAT), Outside Air Humidity (OAH), Outside Air Enthalpy (OAE), Cooling/Heating Degree Days (CDD), and/or Cooling/Heating Energy Days. In this paper, the weather variables used for describing the prediction method are OAT and OAH. Operation schedules may refer to calendar events such as federal holidays, manufacturing schedules of an industrial facility, in-session dates of an Academic institution, etc….The deterministic term is generated using linear regression models, whose coefficients are determined offline. It is dependent on the typical load value for a given time of day and a given day of week. It is also dependent on weather variables such as OAT and OAH. Forecasts of OAH and OAT are available from NOAA through their NDFD service.

The stochastic term acounts for any factors the deterministic term is not able to capture or errors in load measurements. It is generated using an AR model, whose coefficients are initially determined offline and adaptively updated online. At any current time instant and given that current load measurements are available, a current load error or prediction error (residual) is calculated and future prediction error values are iteratively determined using the AR model. The residual forecast constitute the stochastic term of the load forecast. The stochastic term gives the load prediction method its adaptive property. An auto-regressive model, which is shown in more detail in the following section, determines future values of a time-series using its present and past values. Thus, a trend depicted by the past values of the time series, which in this case is the prediction errors or residuals, will affect what the predicted future value is. In the next section, the offline determination of the linear regression models coefficients and the AR model coefficients is presented.

$$load_{forecast}(n) = \hat{L}_{det}(n) + \hat{L}_{sto}(n) \tag{1}$$

3. Offline Determination of Model Coefficients

As mentioned earlier, several factors contribute to the value of a load over a predetermined horizon into the future. These factors are time of day, day of week, weather variables such as OAT and OAH, holidays, and schedules, which are specific to a given facility, building, or campus (for a university, for example, these are in-session and out-of-session schedules). The load prediction method developed captures these factors using historical load and weather data and clustering and modeling methods. The historical data is used offline as training data for determining day-types and the corresponding model coefficients necessary for generating a load forecast online. The offline determination of model coefficients consists of several steps. A high-level flow of the latter is shown in Figure 1.

The training data is first divided into n_{groups} groups based on the given schedules. Then, the data from each group is passed through the day-typing algorithm. The latter determines which days of the week have similar load profiles. Then, the training data of each group is divided into $n_{cluster}$ sub-groups based on the outcome of day-typing. Thus, there will be $n_{group} \times n_{cluster}$ sets of training data, to each of which a set of models and coefficients corresponds. For each set, in order to capture the effect of the time of day, an optimization technique is used to find the optimal typical load profile. The effect of weather variables is captured through linear regression techniques, where a model representing the deterministic term of the load for each set as a function of the weather variables and a typical load profile is determined. In this work, Outside Air Enthalpy (OAE) is used to capture the effect of both OAT and OAH, simultaneously.

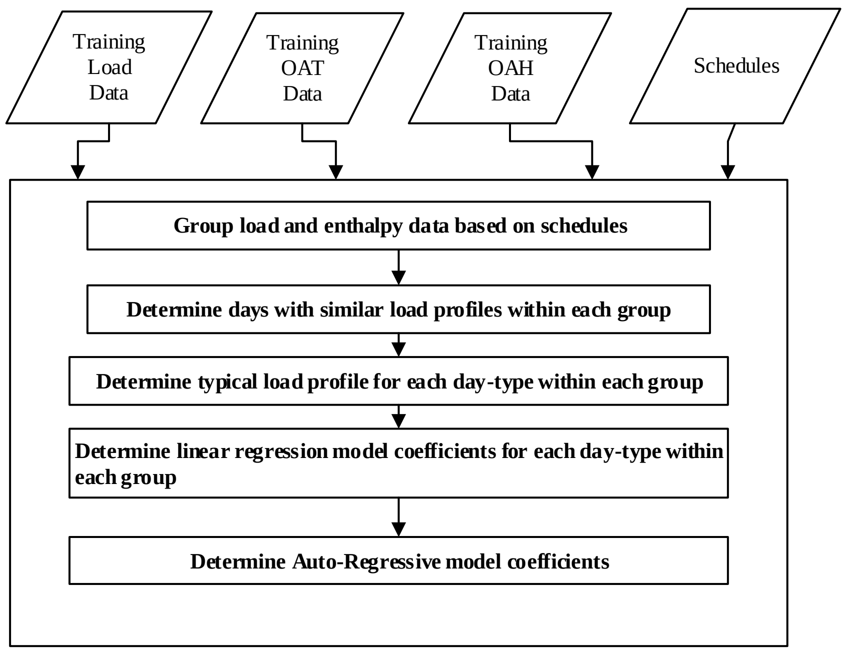

Figure 1: High-level flow of offline determination of model coefficients

After determining all the necessary coefficients pertaining to each set of data, the residuals determined by subtracting the predicted or estimated load from the actual load of all sets are used to train the AR model and determine its coefficients. Thus, for any given problem, there will be $n_{group} \times n_{cluster}$ day-type fits (typical load profiles), $n_{group} \times n_{cluster}$ regression models, and an AR model. These fits and models are, then, used online when generating load forecasts over a predetermined horizon in the future. The next subsections provide in more detail a description of the aforementioned steps of the offline determination of the model coefficients.

3.1 Day-Typing

Day-typing is a pattern recognition algorithm aimed at determining days of the week with similar load profiles. Days having similar load profiles are referred to as one day-type. Building electric loads, for example, tend to have two day-types: weekday and weekend. Figure 2 shows an example of the electric load over several weeks for the Stanford University campus in 2011. As can be observed, the load over the weekend significantly differs from that over the week. Even though it is obvious graphically that there are two day-types, it is not usually the case. This is why a pattern recognition algorithm was developed by Seem (2005), which statistically determines days with similar load profiles. Day-typing captures the effect of day of the week on a load forecast, and thus, it is essential for generating load forecasts. A high-level description of the pattern recognition algorithm developed by Seem (2005) is shown in Figure 3. Given a time series of load data, daily features are generated. The two features considered by Seem are the average daily load and the peak daily load over a one hour period. These features are then transformed in order to alleviate the effect of seasonal load changes. After transforming the feature vectors, seven clusters are created, where each cluster corresponds to each day of the week. Univariate and multivariate outlier identification procedures are then applied to each cluster in order to remove any abnormal or unusual feature vectors in each cluster.

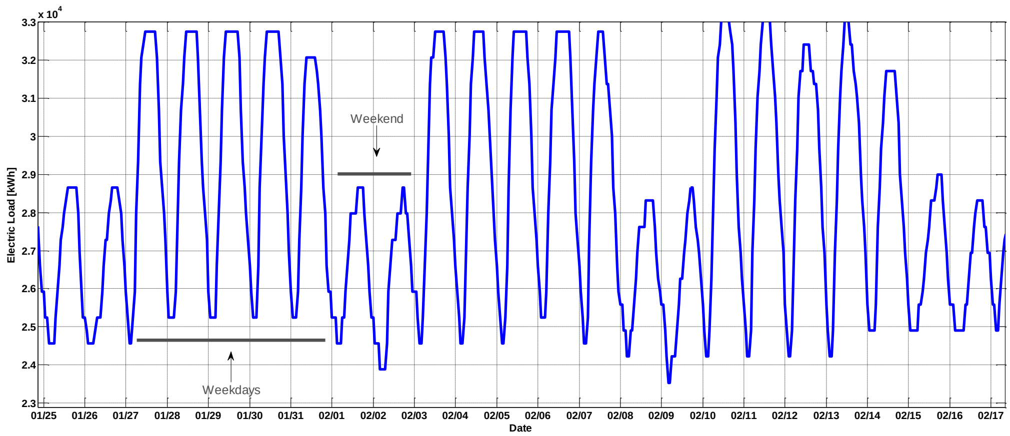

Figure 2: Example of Day-Types

Finally, days of the weeks with similar load profiles are determined using clustering analysis. For more details on the pattern recognition algorithm, refer to Seem (2005).

In this work, the algorithm developed by Seem is used to generate the day-types of a given load. The day-types are used to divide the different groups of training data (historical load and OAE data) into sub-groups, where each sub-group corresponds to a particular day-type. The load data in each sub-group is then passed through a data-fitting method, which finds the optimal load fit for a particular day-type. More details on determining the day-type load fit is presented next.

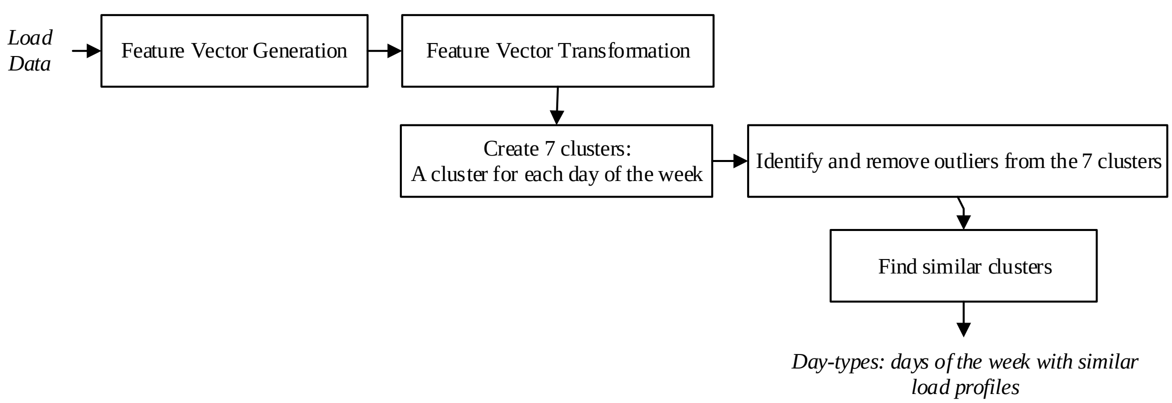

Figure 3: Major steps in pattern recognition algorithm for determining days of the week with similar load profiles. Seem (2005)

3.2 Data Fitting

After dividing the data into groups based on schedules and then into sub-groups based on day-typing results, the result is $n_{group} \times n_{cluster}$ sets of training data, where the days in each set have similar load profiles. The task now is to capture the effect of the time of day factor. Figure 4 shows an example of a sub-group of cold water load training data. The sub-group contains cold water load data of days with similar load profiles. As can be observed, the load profile has a bell curve shape, where the highest consumption takes place in the early to late afternoon. The objective is to find an optimal load data fit for each sub-group corresponding to a particular day-type that will best represent the load profile in that sub-group. This will be called a day-type fit from here on. A day-type fit is dependent on the time of day, therefore there is a need to find a mechanism that allows for calculating the day-type fit at any time of day. In order to achieve an optimal day-type fit for a sub-group and to have the capability of calculating the fit for any time of day, a spline is used to represent the day-type fit, where the spline knots are optimized. A spline is a piecewise-defined function of polynomials. A spline is defined by the knots where these polynomials connect. Predetermining the location of these knots (i.e. the times of day at which these knots are considered), an optimal value of these knots is found using an optimization technique. The location of the knots is fixed and the locations chosen for load prediction are the abscissae of the bold blue circles shown in Figure 4. These locations were chosen as to best capture the general shape of the load profile, especially where there is a change in the curvature. The objective function to be minimized is defined as follows:

$$J = \min_{\mathbf{y}_s}\left(\sum_{i=1}^{m}\left(\mathbf{y}_i - \hat{\mathbf{y}}\right)^T\left(\mathbf{y}_i - \hat{\mathbf{y}}\right)\right) \tag{2}$$

where $\mathbf{y}_s$ is the vector of spline knots, $\mathbf{y}_i$ is the vector of actual load values for the i^{th} full day in a sub-group, m is the total number of full days in a sub-group, and $\hat{\mathbf{y}}$ is the estimated day-type fit of a sub-group.

In this work, the MATLAB 2013b optimization function *fminunc* with the Quasi-Newton optimization algorithm and the function *spline* were used. Figure 4 shows the optimal value $\mathbf{y}_s$ obtained for the example sub-group shown. Thus, a unique day-type fit corresponds to each sub-group. The day-type fit is represented by a set of cubic-splines, which are used to calculate the load value, $L_{fit}(t)$, for a given time of day, t. In the next section, the linear regression models, which make use of the day-type fit discussed in this section, are presented.

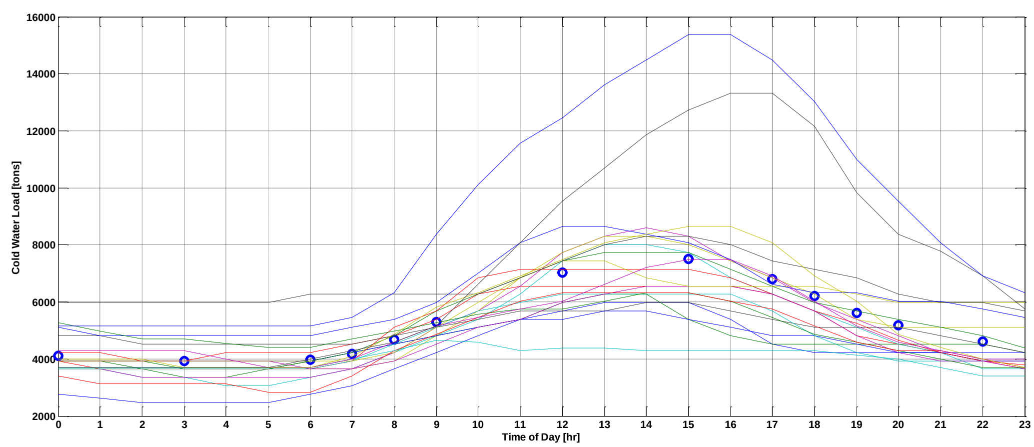

Figure 4: Daily cold water loads of the same day-type

3.3 Linear Regression Models

The remaining factor to be accounted for in calculating the deterministic term $\hat{L}_{det}(t)$ of the load value is the weather. Loads are dependents on OAT and OAH. The effect of OAT and OAH can be accounted for simultaneously by considering OAE. As shown in Figure 5, for example, hot water load is highly correlated to OAE. The same can be said about other loads such as cold water and electric loads. Linear regression modeling (Weisberg, 1985) is implemented to calculate the load value as a function of enthalpy. It is worth noting that instead of using OAE as a predictor variable, degree days such as CDD and HDD may also be used and may improve the performance of load prediction as observed from Figure 5.

For each of the $n_{group} \times n_{cluster}$ sub-groups of training load data, a unique day-type fit exists. The deterministic term of the load value is dependent on both the day-type fit and OAE. In addition, OAE is also correlated to the day-type fit. Therefore, two regression models are necessary for calculating an estimated value of the load. The first regression model has OAE as the response or dependent variable and the day-type fit of a given sub-group as the predictor or independent variable as shown in Equation (3). The objective of this regression is to orthogonalize the predictor variables $\mathbf{OAE}$ and $\hat{\mathbf{L}}fit$. Orthogonalization of predictor variables eliminates the correlation between them.

$$\mathbf{OAE}_k = \beta_0^k + \beta_1^k \hat{\mathbf{L}}fit_k + \mathbf{w} \tag{3}$$

where β_0^k and β_1^k are the model coefficients of the k^{th} sub-group, $\mathbf{OAE}_k$ is the vector of enthalpy observations in the k^{th} sub-group , $\hat{\mathbf{L}}fit_k$ is the vector of day-type fit observations corresponding to those in $\mathbf{OAE}_k$, $\mathbf{w}$ is the model error, and $k = 1 \cdots n_{groups} \times n_{clusters}$. Least Squares Regression is used to estimate the value of the model coefficients. The model coefficient estimates and are used to calculate the estimated enthalpy as shown in Equation (4).

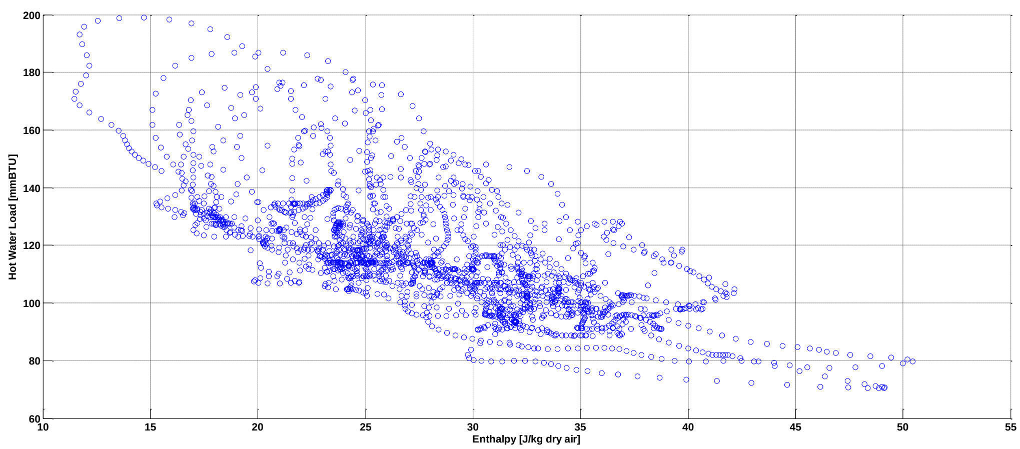

Figure 5: Example of the correlation between load and outside air enthalpy

$$\mathbf{O\hat{A}E}_k = \hat{\beta}_0^k + \hat{\beta}_1^k \hat{\mathbf{L}}fit_k \tag{4}$$

The actual load data $\mathbf{Load}_k$ is then regressed on $\hat{\mathbf{L}}fit_k$ and $\mathbf{OAE}_k - \mathbf{O\hat{A}E}_k$ as follows:

$$\mathbf{Load}_k = \alpha_0^k + \alpha_1^k \hat{\mathbf{L}}fit_k + \alpha_2^k (\mathbf{OAE}_k - \mathbf{O\hat{A}E}_k) + \mathbf{e} \tag{5}$$

where α_0^k , α_1^k , and α_2^k are the model coefficients of the k^{th} sub-group, $\mathbf{OAE}_k - \mathbf{O\hat{A}E}_k$ is the vector of enthalpy residuals, $\mathbf{e}$ is the model error, and $k = 1 \cdots n_{groups} \times n_{clusters}$. Least Squares Regression is used to estimate the value of the model coefficients. The model coefficient estimates $\hat{\alpha}_0^k$, $\hat{\alpha}_1^k$, and $\hat{\alpha}_2^k$ are used to calculate the estimated deterministic term of the load $\hat{\mathbf{L}}_{det_k}$ as shown in Equation (6).

$$\hat{\mathbf{L}}_{det_k} = \hat{\alpha}_0^k + \hat{\alpha}_1^k \hat{\mathbf{L}}fit_k + \hat{\alpha}_2^k (\mathbf{OAE}_k - \mathbf{O\hat{A}E}_k) \tag{6}$$

Each sub-group, then, is characterized by a set of coefficients $\hat{\beta}_0^k$, $\hat{\beta}_1^k$, $\hat{\alpha}_0^k$, $\hat{\alpha}_1^k$, and $\hat{\alpha}_2^k$ and a spline used for calculating the optimal day-type fit corresponding to a sub-group. These coefficients and spline are then used online when generating the load forecast as will be shown later.
As mentioned earlier, the load forecast consists of two terms, a deterministic term and a stochastic term. In the following section, the offline determination of the AR model coefficients, which calculates the stochastic term of the load forecast, is presented.

3.4 Auto-Regressive Models

An auto-regressive model is a model representing a time series and has the following form (Haykin, 2002):

$$r(n)+a_1 r(n-1)+\cdots+a_2 r(n-p)=v(n) \tag{7}$$

where $r(n)$ is the value of the time series at instant n , $a_1,a_2,\ldots,a_p$ are the AR parameters, and $v(n)$ is white noise.
An AR model is basically a regression model of the current value of a time series on its past values. An AR model can be used to predict the value of a time series over a horizon of length h into the future iteratively as follows:

$$\hat{r}(n+j)=-\sum_{i=1}^{p}\hat{a}_i r(n+j-i) \qquad \forall j=1,\ldots,h \tag{8}$$

where $\hat{a}_i$ are estimates of the AR parameters a_i which are determined offline using training data. For more information on AR models refer to Chapter 1 in Haykin (2002).

For the purpose of load prediction, an AR model is used to calculate the stochastic term of the load forecast over a horizon into the future. The time series r , in this case, is the load prediction error or residuals obtained from all the sub-groups and sorted in chronological order. The unsorted AR model training residual data is shown in Equation (9). $r_{unsorted}$ is sorted in chronological order before it is used as training data for estimating the AR parameters. Since an AR model is characterized by its order p and its parameters, an appropriate model order needs to be chosen along with determining estimates of its parameters. In order to determine the order of the model, Akaike's Information Criterion (AIC) may be used along the MATLAB function *arx*, which requires having the System Identification Toolbox. The order of the AR model determines how many past values of the time series are needed. Note that for the Stanford project, the AR model is of order 1 and a least-square estimate of the AR parameter is used. The latter was solution to the fact that the *arx* function cannot be compiled when generating an exe or a kernel.

$$r_{unsorted}=\begin{bmatrix}\mathbf{Load}_1-\hat{\mathbf{L}}_{det_1}\\ \vdots\\ \mathbf{Load}_{n_{groups}\times n_{clusters}}-\hat{\mathbf{L}}_{det_{n_{groups}\times n_{clusters}}}\end{bmatrix} \tag{9}$$

Thus, for a given problem, the offline determination of model coefficients generates, using load training data, OAT and OAH training data, and schedules, a set of day-types, splines, estimates of linear model regression coefficients, and estimates of AR model parameters. These are then used online when generating load forecasts. The next section explains how a load forecast is generated online using the different models developed offline.

4. Online Load Prediction

Online load prediction requires a current load measurement, the current and forecast OAT and OAH, the current date and time, the length of the horizon in hours, the model coefficients, splines, and day-types generated offline, a schedule, and a vector of residuals . The vector of residuals is a persistent vector as it is also an output of the online load predictor. The size of the residual vector is dependent on the order of the AR model generated offline and contains the past residual values necessary for calculating the stochastic term of the load forecast.

For a given problem, day-types, day-type fits (splines), estimates of regressive model coefficients, and estimates of AR model parameters are generated offline. These are then used online to generate a load forecast over a predetermined horizon. Figure 6 shows a flow of the major steps in generating a load forecast online at a given instant in time. Given the current and forecast OAT and OAH obtained from NOAA, the current and forecast enthalpy vector $\mathbf{OAE}_{forecast} = \left[OAE(1) \quad \dots \quad OAE(h) \right]$ is calculated, where h is the length of the horizon in hours. Each data point is always associated with its corresponding date and time stamp. The day-types and schedules are used to determine which spline and coefficients (These will be referred to from here on as models) are to be used for each data point. Then, the day-type fit value for each data point is calculated using the corresponding splines. This is followed by the calculation of the OAE estimates, $\mathbf{O\hat{A}E}_{forecast} = \left[O\hat{A}E(1) \quad \dots \quad O\hat{A}E(h) \right]$ as shown in Equation (10).

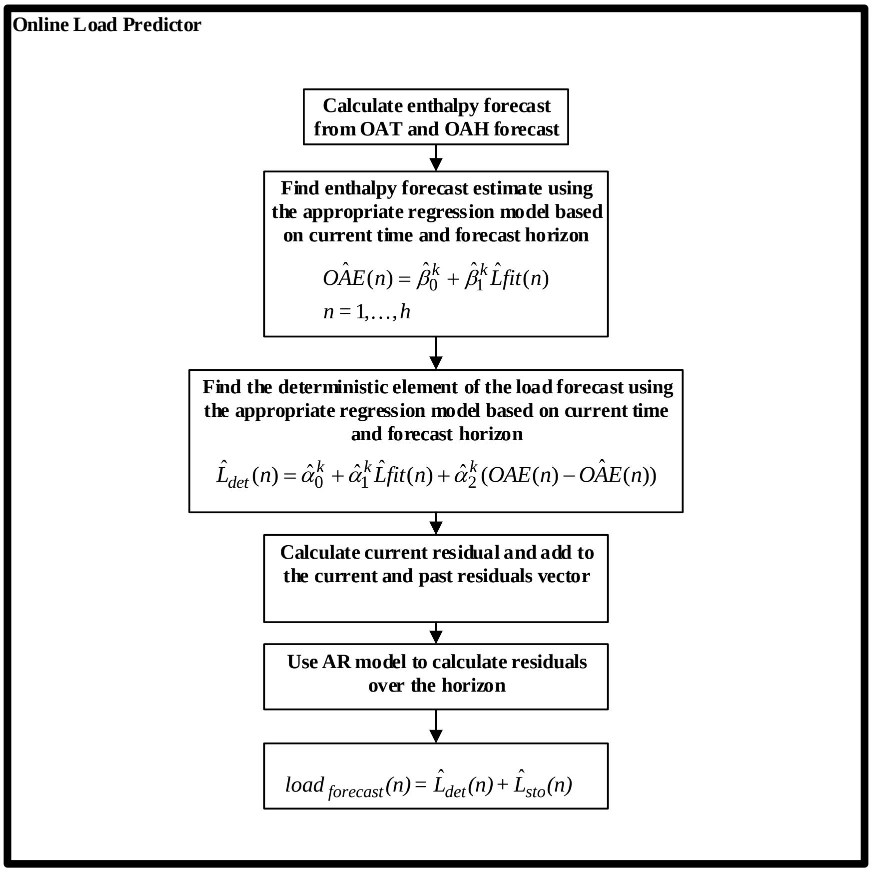

Figure 6: Major steps in online load prediction

$$O\hat{A}E(n) = \hat{\beta}_0^k + \hat{\beta}_1^k \hat{L}fit(n) \qquad n = 1,\dots,h \tag{10}$$

Then, the deterministic term of the load forecast $\hat{\mathbf{L}}_{det} = \left[\hat{L}_{det}(1) \quad \dots \quad \hat{L}_{det}(h) \right]$ is calculated as shown in Equation (11).

$$\hat{L}_{det}(n) = \hat{\alpha}_0^k + \hat{\alpha}_1^k \hat{L}fit(n) + \hat{\alpha}_2^k (OAE(n) - O\hat{A}E(n)) \qquad n = 1,\dots,h \tag{11}$$

The current residual is then calculated using the current load measurement as shown in Equation (12) and the stochastic term vector is generated using the AR model shown in Equation (8). Finally, the load forecast is the sum of the deterministic and stochastic terms.

$$r(1) = currenLoad - \hat{L}_{det}(1) \tag{12}$$

5. SIMULATIONS

In this section, simulations of the load prediction method are shown. Figures 7, 8, 9, and 10 show the forecasts for the hot water load, cold water load, electric load, and electricity rates respectively. The models generated offline uses training data corresponding to the month of March. The simulations shown are at the end of day April 1st and the forecast horizon length is 240 hrs. The simulations show that the load prediction method is able to generate load forecasts that are close to the actual loads.

CONCLUSION

A load prediction method capable of generating accurate load forecasts is presented. The method developed is applicable to cold water load, hot water load, electric load, and electricity rates. It takes into consideration several factors affecting a load. These factors consist of schedules, time of day, day of week, and weather variables. The method generates a load forecasts consisting of deterministic and stochastic terms. It makes use of day-typing, regression modeling, and auto-regressive modeling techniques. The method developed is characterized by an adaptive property due to the stochastic term in the generated load forecast. Further improvements to the method is the use of cooling degree days and/or heating degree days instead of outside air enthalpy.

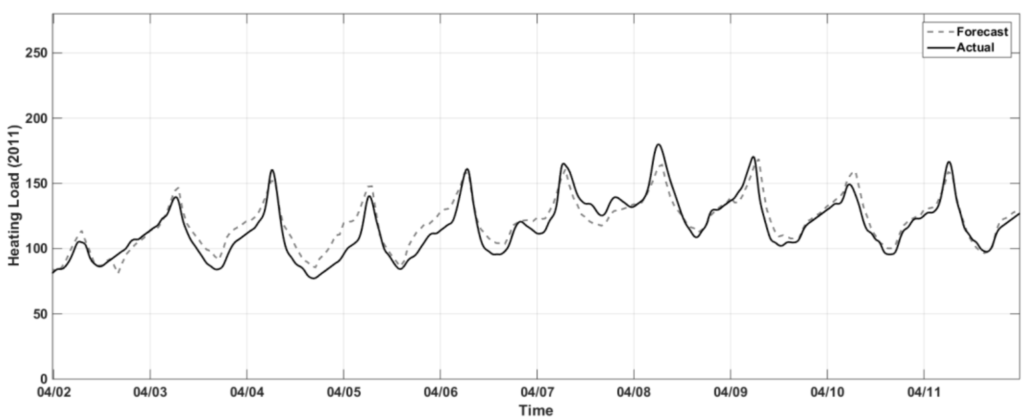

Figure 7: Example of a 10 day-forecast of hot water load

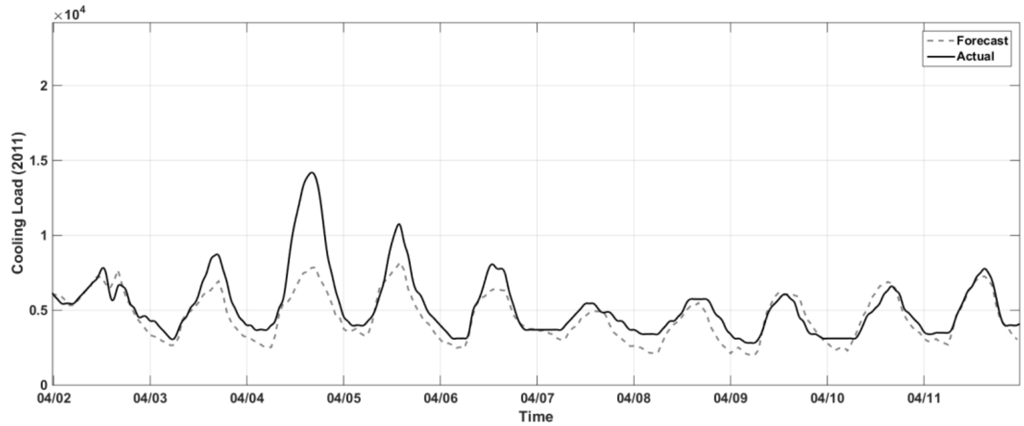

Figure 8: Example of a 10 day-forecast of cold water load

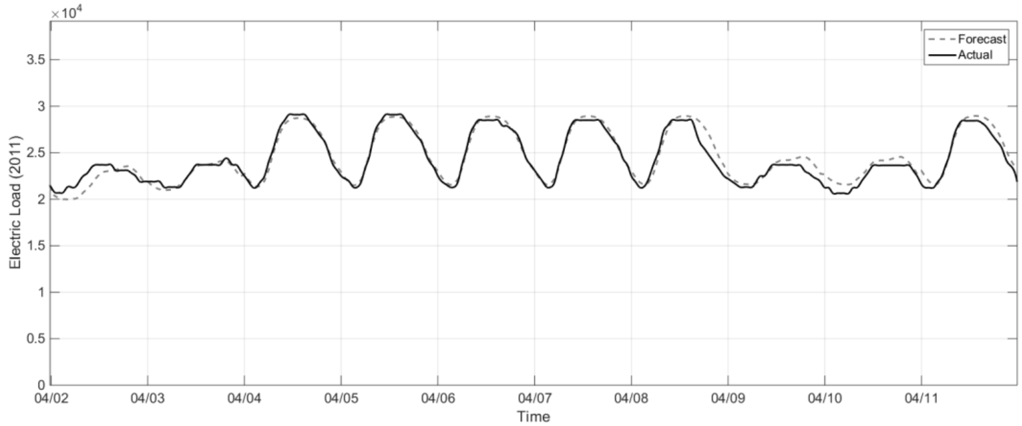

Figure 9: Example of a 10 day-forecast of electrical load

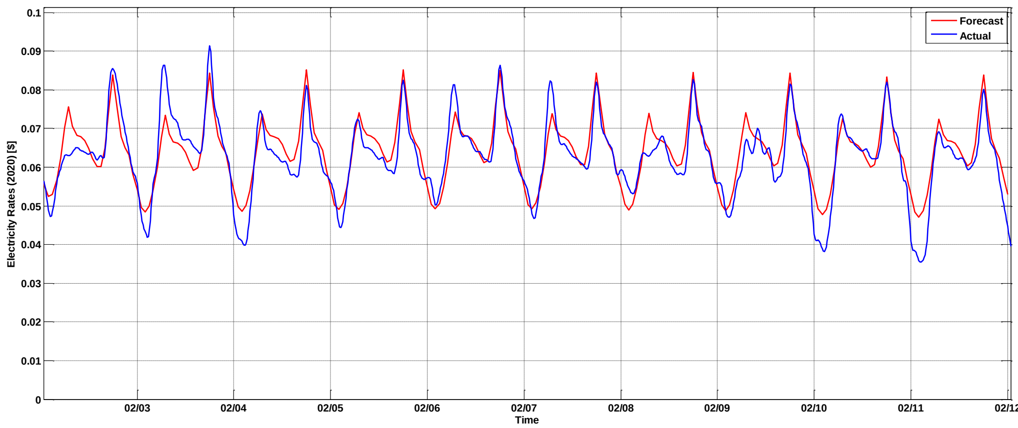

Figure 10: Example of a 10-day forecast of electricity rates

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