A Generalized Knowledge-Based Short-Term Load-Forecasting Technique

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Abstract - A newly-developed algorithm for short-term load forecasting is generalized. The algorithm combines features from knowledge-based and statistical techniques. The technique is based on a generalized model for the weather-load relationship, which makes it site-independent. Weather variables are investigated, and their relative effect on the load is reported. Moreover, it is fairly robust, inherently-updatable and provides a systematic way for operator intervention if necessary. This property makes it especially suitable for application in conjunction with demand side management (DSM) programs. The algorithm uses pairwise comparison to quantify categorical variables, and then utilizes regression to obtain the least-square estimation of the load. The technique has been tested using data from four different sites in Virginia, Massachusetts, Florida and Washington. The average absolute weekday forecast errors range from 1.22% to 2.7% over all four seasons in a year.

Keywords - Load forecasting, inherently updatable, operator-assisted, knowledge-based, site-independent forecasting algorithm, pairwise comparison, priority vector, demand side management.

1.0 Introduction

Many techniques for short-term load forecasting have been reported in the literature. These techniques may roughly be categorized into two groups:

(1) **Statistical Techniques:** among these are the Box-Jenkins method [1], multiple linear regression [2], adaptive models [3], and general exponential smoothing [4].

(2) **Expert-System Based Techniques:** these are rule-based techniques where the rules are derived from human experts. This approach was first developed by Rahman and Bhatnagar [5]. Further illustrations for this method can be found in Rahman [6-7]. Many others have used the same approach, such as Jabbour et al. [8] and Hsu et al. [9].

Many of these techniques are used in the industry, and are in many cases, capable of producing fairly accurate forecasts. The problem with statistical techniques, however, is their computational requirements, as these methods need to be updated with changing conditions. In fact, whole new statistical models need to be developed whenever the load conditions change sufficiently.

On the other hand, expert systems are more responsive to changing conditions. However, it is not always easy to express the available expertise in clear quantitative terms. This often leads to inconsistent rules. For this reason, there is a growing interest in industry to replace the human expertise by something more consistent and reliable.

There is also a great deal of interest in utilizing artificial neural networks (ANN) for short-term load forecasting. A few of the recent papers are cited in the reference [10-14]. Neural networks, however, are not easily updatable to changing conditions over the course of a season. This requires the re-training of neural networks, which can be expensive. Moreover, operators have little or no opportunity to confirm the forecast. Generally, the neural network is a "black box" for the operator that he has to either accept or reject.

In general, accuracy is directly proportional to the complexity of the forecasting algorithm. In the case of neural networks, the need for accurate forecasts requires that a whole different neural network be developed for each different hour of the day, and for each different day of the week. Such complexity increases the risk of a total failure of the forecast. This is true for special cases, such as extreme weather conditions, or a special event on the target day, etc. In such cases, operator intervention becomes necessary. In general, no predetermined set of rules is possible for all cases. It is essential, therefore, that the operator be able to update the forecasting algorithm easily. Hence, in addition to accuracy, robustness, and updatability to changing conditions, it is highly desirable to have a forecasting algorithm with operator-intervention features.

Operators, however, can not easily verify or adjust the forecast unless they understand how it is obtained. They also need to know what past experience has been used to reach that prediction about the future load. If a certain day in history witnessed a special event, the operators can intervene, for example, by dropping that day from the historical database, or by using a correction factor, etc. By properly selecting the input data set rather than just changing the forecast load values, which is exactly what operators currently do, the operator intervention becomes justifiable, and more consistent.

Until now, there has not been one generalized short-term load forecasting technique which applies to geographically diverse sites. Methods cited in the literature are tested basically using data from one site only. Large errors start to appear when these algorithms are tested over data from other sites. It is highly desirable, therefore, to design a general model for the weather-load relationship, and develop a generalized technique for short-term load forecasting which applies to multiple sites in different seasons.

In this paper, a new load forecasting technique is discussed. This technique follows an intuitive approach similar to the way the operators perceive the forecasting problem. It uses the pairwise comparison technique [15] to prioritize categorical variables. The methodology is general and applicable to many sites. Site-specific features are also modeled in this technique, and hence it can be customized for a certain site with minimum effort. It also has the advantage of providing the operator with a whole set of weighting parameters to update if necessary. It allows the screening of the intermediate computations and decisions, and hence operators can intervene at any stage. The technique is robust since it does not depend solely on the exact values of the weather forecast. It is inherently updatable because the forecast does not depend on any preset model for load-temperature relationship. As the loading conditions change, only a few parameters need to be updated, and these updates are fairly straightforward.

Due to the structure of the algorithm, it is straightforward to incorporate DSM impacts into the load forecast. For example, the relevant historical data can easily be filtered to properly account for

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the DSM effects. This is a built-in feature of the algorithm.

The paper is divided into five parts. In part one, the weather-load relationship is explored. Part two discusses the pairwise comparison technique. Part three explains the forecasting algorithm itself. In part four the algorithm is tested using data from four different sites. Part five is the conclusion. Detailed description follows.

2.0 Weather-Load Relationship

The relationship between load and weather is the single-most important parameter in forecasting the short-term load. Understanding this relationship is essential for making a reliable load forecast.

There are two reasons for requiring weather-load relationship for the proposed algorithm.

(1) To design a model for the load *sensitivity* to the weather.

(2) To define the concept of similar days or day segments. This is needed when searching the historical database for records that are similar to the target record as far as the effect on the load is concerned.

The weather-load relationship varies with the season, day of the week, and segment of the day. Many details of this relationship are site-specific, but are not incorporated in the algorithm. Only the site-independent general features are used so that the algorithm can be generalized. There is always room for enhancements. Factors related to weather and consumer habits that impact the load are discussed in the following.

2.1 Weather Parameters

Many curves were plotted and the following parameters were tested to observe their effect on the load.

1. Time of the year (*season* and/or *wk*).
2. Day of the week (referred to as *wd* or weekday).
3. Hour of the Day (*hr*), a number between 0 and 23.
4. Hourly Temperature (T).
5. The temperature 24 hours before (T_{24}).
6. Past 24 hour average temperature (T_{lag}).
7. Wind speed (*Ws*).
8. Sky cover (*Sc*), which is a number from 0 (clear sky) to 10.
9. Humidity, expressed in either relative humidity (*Rh*), dew point temperature (*dpT*), or the wet bulb temperature (*wbT*).
10. Wind-Chill Index [6] (denoted *WCI*).
11. Temperature-Humidity Index [6] (*THI*).
12. Past averages of the parameters 4-11. Past 24-hour, 7-day, and 7-week averages were tested.

2.2 Humidity, Wind Speed and Sky Cover

Humidity is significant in summer when the temperature is within a certain range dependent on the site. This range is roughly between mid-seventies and mid-nineties (in degrees Fehrenheit). If the temperature is lower, air conditioning load is minimal or non existent, while this load saturates at temperatures above this range.

Similarly, wind speed is significant in winter if the temperature is within another range, which is also site-dependent. This range is roughly any temperature below forty.

The sky cover is not significant in most cases except when it is 10/10 for quite some time. The reason for this is that the sky cover is usually measured over a very large area, and unless it has been 10/10 for some time, estimated to be around 6 hours, there is no way of telling how the overall load would be affected. Rain is very possible in this case. Rain has a severe effect on the load, especially if it happens on a hot day, however, it can not be predicted. A persistent 10/10 sky cover is one way of detecting this.

2.3 Seasonal Effect

It is assumed that there are two seasons: winter and summer. Fall and spring are transitional seasons where the load conditions gradually change from one season to the other. Energy consumption over these two seasons gradually changes, although the temperature level change might not be as gradual. This effect may be accounted for by considering four types of days:

1. **Normal Days:** steady weather, hot in summer or cold in winter. How hot and how cold depends on the site.
2. **Abnormal Days:** a day with an irregular short-term (1-2 days) kind of weather, such as a cool day in summer or a warm day in winter. Again, this is site-dependent.
3. **Extreme Days:** a very hot summer day or a very cold winter day. These periods are generally short-term (1-2 days).
4. **Transitional Days:** a warm spring day (cold fall day) which is interpreted as the beginning of summer (winter). On such a day air conditioners or heaters are turned on in large buildings.

These types of days may constitute classes of days where the similarity between days is restricted to these classes. Transitional days, for example, are generally dissimilar to normal days, even though the temperature profile is the same. This is a situation where operator experience is helpful, for they can determine what type of day the target day is going to be. By selecting similar days from history, apparent similarity between classes is avoided.

2.4 Daily Temperature-Load Curves

To smooth out temperature fluctuations and to account for the temperature-load lag, the following variable is used instead of temperature. It is referred to as the equivalent temperature.

$$T_{eq}(n) = 0.25[T(n-1) + T(n) + T(n+1) + T(n+2)]$$

where n is the hour of the day, and $T(n)$ is the temperature at that hour. This gives a lag of one-and-a-half hour. This should account for the temperature-load lag.

2.5 Accumulated Heat

Heat accumulates inside buildings as the temperature increases. This slows down the load variations. If the temperature is currently decreasing in a winter's day, the residual heat accumulated so far slows down a sharp increase in the load. In a summer's day, the accumulated heat slows down a possible drop in the load if the temperature is decreasing. The temperature range 60°F-70°F seems like a neutral zone where heat accumulation does not have a significant impact on the load.

The following variable T_{acc} is used to model the accumulated heat (if any) in the past 24 hours.

$$T_{acc} = \begin{cases} \frac{1}{24}\sum_{i=0}^{23} f(T(n-i)-70) & Tlag > 70 \\ 0 & 60 \le Tlag \le 70 \\ \frac{1}{24}\sum_{i=0}^{23} T(n-i) & Tlag < 60 \end{cases}$$

where the function f is a hard rectifier, defined for any value x as

$$f(x) = \begin{cases} 0 & x < 0 \\ x & x \ge 0 \end{cases}$$

2.6 Inertia

Late night and early morning hours load is very much determined by the level of the load during the previous evening hours. This is observed in the low load levels on Monday mornings, and in the mornings immediately following holidays. The energy consumption during the previous night is a very good measure of this effect.

2.7 Segment-Dependent Temperature-Load Relationship

Segments are selected based on work habits and temperature. The load is determined by different factors in different segments. Hence these factors are checked when similarity is to be determined:

Night and Inertia: 9:00 PM - 4:00 AM weekdays and weekends. The monotonically decreasing load at this time is determined by (1) equivalent temperature, (2) temperature profile during these hours, and (3) the energy consumed during the previous night. Two segments are used, however, one from 9:00 to 11:00 PM, and the other from midnight through 4:00 AM.

Morning Peak: This reflects the work index. This peak is between 5:00 and 8:00 AM on weekdays, and between 7:00 and 11:00 AM on Saturdays and Sundays. In this segment, load is determined by (1) equivalent temperature and (2) temperature profile from 12:00 midnight.

Daytime Hours: These are divided into two segments on weekdays: one from 9:00 AM to 12:00 noon, and the other from 1:00 PM through 4:00 PM. During these hours the load is determined by (1) temperature and (2) accumulated heat. For weekends, only one segment is used.

Evening Peak: Occurs between 5:00 and 8:00 PM. Load is determined by (1) temperature, (2) temperature profile since noon, and (3) accumulated heat.

3.0 Pairwise Comparison

In the following we discuss how the above-mentioned characteristics and relationships can be used to characterize the load under different conditions. Pairwise comparison is a promising way to make this possible. It is a robust technique for generating the likelihood quantities corresponding to each possible judgement. This allows one to choose the judgement with the maximum likelihood. The theory of the technique was established by Saaty [15]. Rahman and Shrestha [16,17] were the first to develop power system applications for this method. They demonstrated that it is better than traditional statistical methods in situations where accurate models are difficult to design.

In [16], the application of this technique in a load forecasting algorithm was investigated, and a methodology of implementation was discussed. For a certain target hour in the future for which the load is to be forecasted, there is a set of selected similar records from history. This set of records is called the *similar set*, and is selected from history using the characteristics in the previous section. Each record in this set represents weather and load information for some hour back in history. The algorithm typically uses regression over the similar set. Variables like hour of the day (*hr*), weekday (*wd*), and probably sky cover (*Sc*) are categorical by nature, hence are difficult to use as such in regression. That is where pairwise comparison is needed to quantify such categorical variables, one at a time, by replacing them in the regression with their priority measures. A load value is associated with each possible value of a categorical variable. This load value represents how much the load is likely to be when the variable assumes a certain value, while isolating the effect of the other variables. By comparing these load values in a pairwise fashion, a priority vector for each value of the categorical variable is obtained. This vector replaces the old "categorical" values, thus quantifying these variables for regression.

A similar set H is divided according to the values of the categorical variable under quantization. For each existing value hr_j of hr, the group of records in H where $hr = hr_j$ constitute a subset H_j of H. These susets are significant as discussed next.

Definition 1: A similar set H is said to be *balanced with respect to a variable Var* iff for each subset H_j of H; $j = 1, .., m$, the average value of Var over H_j, denoted $Var_{av\,j}$, is equal, to the target value Var_0.

It is rare that a similar set be completely balanced, and practically impossible to have it balanced over all variables. Often, the selected records are in such a way that the average temperature is different than the target temperature value T_0. Since the temperature is the most significant weather variable, it is a reasonable assumption to make that the average load over these records be biased by an amount which corresponds to the bias in the temperature, especially if that bias in temperature is significant. This might be the case for any significant variable. It is also assumed that the bias relationships (e.g. temperature-load) are constant for a season within a small neighborhood of the target vector. The following definitions formulate this idea.

Definition 2: A similar set H is said to be *biased with respect to a variable Var*, iff for some value j; $j = 1, ..., m$, $Var_{av\,j}$ is not equal to Var_0.

Definition 3: The *bias vector* of a biased similar set H with respect to a variable Var is the vector $[b_j(Var)]$; $j = 1, ..., m$, where

$$b_j(Var) = Var_{av\,j} - Var_0$$

The ideal situation is to have $b_j(Var) = 0$ for all j; $j = 1, ..., m$, for all variables Var. This is very rare in real applications. Hence it is attempted to force these bias values to zero, thereby adjusting the load values appropriately. This is done to the significant weather variables only. The mean loads taken over the different subsets H_j; $j = 1, ..., m$, of the balanced similar set are used for the L-values.

The need for this formalization becomes obvious in the next section.

4.0 The Forecasting Algorithm

In this paper, knowledge-based rules are introduced to the pairwise comparison algorithm to allow operator intervention, and to make the algorithm updatable with changing conditions. Moreover, the algorithm is general and applicable to any site. Only minimal site-independent experience is used to generate the rules.

Each day is divided into several time segments as described earlier. These time segments may be slightly different from season to season, and from site to site. The time segments are chosen to reflect both the human factor and the weather factor. The forecast is made on a segment by segment basis.

4.1 The Basic Method

Given a historical database of hourly weather and load information, and the weather forecast for a certain time segment of a future day, it is required to find a good estimate of the load that is going to be encountered at these hours. There are, however, several steps in coming up with the final forecast, as described in the following. The algorithm consists of the following steps:

(1) Knowing some information about the type of day the forecast is being done for, find a set of criteria for selecting similar days and loads from history.

(2) Using this set of criteria, select a limited set of data from the past history. Call this selected set the *similar set.*

(3) Adjust the selected set information to take into account whatever features that may apply; e.g. annual growth, special hours of the week, base load of the day, etc..

(4) Select the categorical variable(s) and balance the similar set. Use the adjustment tables corresponding to the site. The L-values of the similar set are the initial load estimates from the similar set.

(5) If the similar set contains enough points, apply the pairwise comparison technique to the L-values and replace the categorical variables by their priority values. Use statistical regression to get the least-square error estimate of the load for each hour in the segment. This would be the load forecast.

Selection of the similar set is knowledge-based. The same knowledge is used to adjust the selected data to account for load growth, special hours of the week, base load of the day, etc...

The algorithm has both statistical and expert-system features. It is not dependent on any preset model, it relies on the similar set, which is selected from history for every new target hour. This is what makes the algorithm inherently-updatable, since new information gets used as time passes. Further details about the algorithm follows.

4.2 Selection of the Similar Set

Given the weather forecast for the target segment, it is required to select from history a set of records believed to be similar to the target segment. This is an intuitive approach, for only a subset of the historical database is relevant at a time. A complete segment at a time is selected. The similar set, therefore, contains an equal number of records for each hour.

Records are selected from history according to the following:

- All weekdays may be selected for any weekday forecast. Only Saturdays are selected for Saturday forecast, and only Sundays are selected for a Sunday forecast. This is true for all seasons and for all sites. The seasonal day classes should not be mixed.
- Records from no more than a few weeks back in history may be selected. For a previous year, records a few weeks before or after the same date may be selected. How few is few depends on the season and the site.
- For each target segment, only those variables which determine the load in that segment are checked. For a segment to be selected into the similar set, the value of the historical record should be close to the target values. The allowance neighborhood is determined by the temperature range, the season, and the site.
- Humidity and wind speed are checked if the target temperature is within the humidity or wind speed range. Sky cover is checked only if it was 10/10 for at least six hours. Again, the historical values should be "close" to the target values.

Selection is based on the weather values at the target point. In many cases, the weather forecast could be too erroneous. The algorithm, however, is vulnerable to such errors. Weather forecast comes in the form of an interval estimate with a degree of confidence. Using preset allowance neighborhoods for temperature that are determined by the range of the target value (and not by the value itself), the selection of the similar set becomes dependent on the range of the target temperature rather than on the exact value.

Problems arise when the day tends to have a special or fluctuating weather. If the weather is steady over many days, enough records could be selected. As the day becomes special, the number of similar records in history becomes small. Hence the allowance neighborhoods of the selection parameters should be set in such a way that (1) reasonably similar records be selected, and (2) the similar set contains a sufficient number of records. In many cases, however, one or both requirements fail, especially at special or extreme days.

Operators can intervene at this point to filter out "special" irrelevant days from the similar set. Special days include extreme weather days, days with a fluctuating weather, or when demand side management was applied, special occasions, etc. Such special cases are very difficult to detect from the tables of historical information. Hence operators are more likely to account for these special cases. This algorithm allows them to do so in a consistent fashion.

4.3 Adjustments to the Similar Set Data

These adjustments are site-dependent and knowledge-based. Experienced operators at a certain site usually know what adjustments should be made to the load values as necessitated by the conditions of the target segment or on the selected record's day. In general, the load value of a certain selected record from history is adjusted by a correction factor. This factor may be due to regular factors or it may be due to a very special reason. Examples of regular corrections are the annual load growth, load offset on Friday night in residential areas, and regular peak weekday. Special reasons may be a special occasion on the selected day, a certain drop in temperature, extreme weather, and so on.

The annual growth rate, and the special hours of the week are the most common cases for adjustment. They should be accounted for in all sites. Other adjustments are less frequent and site-specific.

Growth rates are season and site-dependent. They are normally predicted in the industry using the annual peaks. These values, however, represent the annual peak growth rates, but can not give a clue as to how a unit load has changed from one year to the other. The growth rates for this algorithm are taken by observing the monthly consumed energy over the years and comparing values for the same months. It is assumed that each season has a different growth rate. This makes sense because the growth of heaters for winter may be different from the growth of air conditioners in summer.

It is observed that for some sites, certain times of the week witness a special increase or decrease in demand. These special cases are accounted for by correcting load values, just like the annual load growth. Each time segment of the week is assigned a weighting factor w: w would be 1 for a normal weekday. For peak weekday morning, for example, w would be smaller than 1, but would be larger for a Monday morning when the load is lower than normal. Only weekday load values have such weights, since weekends are handled separately. The weighting factors are obtained by comparing the values of energy consumption at different time segments in the weekdays for the site in consideration. Again, this is a place for operator experience. Each load value in the similar set is multiplied by the weighting factor that corresponds to the time the value is selected from. This scales all values to the level of a normal weekday. Once these load values are processed and a final prediction of the load is obtained, this value is eventually divided by the weighting factor of the target hour.

4.4 Dynamic Adjustments

As discussed in the previous section, the similar set is very rarely balanced over the significant variables. These adjustments are made to balance the similar set with respect to temperature and/or other significant weather variables. The load values are modified by a certain amount which is believed to equalize the bias of the weather variable. For the sites tested thus far, only temperature bias was equalized.

Load is most sensitive to temperature during the peak hours of the day. This sensitivity to temperature increases as the target temperature becomes extreme. The relationship can be modeled by a table of dL/dT values corresponding to each temperature range, each time segment, and to each season [6].

The similar set is balanced by adding the equalizing load amount to all the records where there is some bias in the temperature. This ensures that all load averages are offset by an equal amount. Temperature values should also be corrected so that the individual values $T_{av\ j}$ are equal to the target value. This is done also by subtracting the temperature bias from each record. When the target value is an interval estimate, the best thing to do is to adjust those values using the center of the estimated temperature range.

4.5 Initial Load Estimates

The L-values taken from the balanced similar set may be used as an initial estimate of the target load. This is very useful in cases where regression is impossible or when it is known to fail. Such is the case when the weather is fluctuating, or when the weather is extreme. In such cases, there are too few similar points in history to perform regression, and the initial load estimates are the best that could be done with the available information.

4.6 Pairwise Comparison

This is applied to the L-values. The priority vector is the output of this technique, which replaces the categorical variable values. This has the effect of quantifying these variables into the priority measures. Moreover, the replacement of the "categorical" values by the priority values renders the regression very robust. No matter what the similar set is, the least square error linear estimate does not modify the load much from the L-value given to the hr value that equals the target hour.

Pairwise comparison should be applied for the hour of the day hr. This is because the hour of the day is the most significant categorical variable of all. The other categorical variable, the day of the week, is accounted for using the correction weights. The sky cover may be another categorical variable, where the categories would be (1) rainy or (2) not rainy.

4.7 Regression

Regression is used to fine tune the initial estimates of the load. It is done only if the number of records in the similar set exceeds a certain minimum number. Statistically, this minimum is one plus the number of variables used in regression. Experience shows that no less than seven records per hr value should be used, since hr is the categorical variable that is quantified. There is no upper bound. Regression is made over the adjusted similar set data using a certain subset of the weather variables. This gives a weight factor for each variable, hence the least-square error estimation of the load is determined for each hour in the target segment.

The set of variables used in regression should at least contain the hour of the day *hr* and the temperature *T*. Relative humidity *Rh* (or equivalent) and/or wind speed *Ws* may also be used, but experience shows that the temperature-humidity index *THI* and/or wind-chill index *WCI* perform better in regression. Experiments also show that *THI* is significant only if the target temperature is in a certain range which depends on the site, but is generally above 75°F and below 95°F. A similar site-dependent range of temperatures also exists for the significance of the *WCI*, normally below 40°F. The day of the week *wd* should be used in regression as well.

Linear or nonlinear regression may be used. The linearity is justifiable only if the range of regression is limited. Although the load is known to be a nonlinear function of all the significant variables, a linear model may be assumed if the samples are all within a small neighborhood around the target point. It might be necessary, however, to use nonlinear models. This would be done by replacing one variable or more by a certain point function. Regression may be done over these point functions. This might be useful to account for certain known nonlinearities, especially at extreme temperature points.

5.0 Results and Discussion

Hourly load and weather data from four different utilities were available. The utilities serve the states of (1) Massachusetts, (2) Washington, (3) Virginia and (4) Florida (Orlando area). The load forecasting algorithm discussed above was tested for each site over a period of one month per season. The forecast was done with a 24-hour lead time. Similar records up to three years back in history were selected. Actual weather values were used as an input. Holidays were removed from the database.

The criterion used in this test is the absolute relative error defined for a certain hour *n* as follows

$$\text{Relative Error }(n) = \frac{\text{Forecast Load }(n) - \text{Actual Load }(n)}{\text{Peak Load for the Day}}$$

The parameters necessary for applying the algorithm were generated off-line using the available data only. Growth rates were taken on a season-by-season basis. Similarly, adjustment tables, daily time segment assignments, and the temperature selection intervals were all generated without any specific knowledge about these sites. Weekday segment correction weights were not used at this point. These parameters were the same for all sites, except for the adjustment tables and growth rates.

Table 1 Average Absolute Errors for January Weekdays

hour	Massachusetts		Washington		Virginia		Florida	
	% err	SD	% err	SD	% err	SD	% err	SD
0	1.57	1.03	1.88	1.03	2.10	1.03	2.17	1.01
1	1.41	1.03	1.61	1.02	2.29	1.04	1.81	1.02
2	1.61	1.02	1.45	1.03	2.69	1.08	1.59	1.01
3	1.71	1.02	1.42	1.06	2.47	1.03	1.74	1.02
4	1.83	1.03	1.40	1.02	2.06	1.01	1.66	1.06
5	1.65	1.02	2.13	1.05	1.98	1.02	3.21	1.21
6	1.83	1.01	1.80	1.07	2.12	1.07	3.33	1.25
7	1.75	1.02	2.18	1.01	2.31	1.03	3.23	1.24
8	1.51	1.04	2.18	1.05	2.28	1.06	2.82	1.12
9	1.62	1.07	1.44	1.01	2.29	1.03	2.75	1.17
10	1.65	1.09	1.40	1.07	2.24	1.03	2.67	1.01
11	2.06	1.13	1.78	1.09	2.52	1.04	2.50	1.09
12	1.95	1.09	2.14	1.03	2.80	1.06	2.79	1.13
13	1.92	1.09	1.89	1.07	2.80	1.06	2.32	1.10
14	2.18	1.10	2.26	1.03	2.92	1.05	2.41	1.04
15	2.53	1.09	2.58	1.12	2.13	1.02	2.81	1.03
16	2.50	1.07	3.19	1.39	1.77	1.02	3.02	1.07
17	1.72	1.06	2.60	1.37	1.83	1.15	2.69	1.19
18	2.25	1.20	1.97	1.37	1.77	1.03	3.15	1.26
19	2.79	1.22	2.15	1.19	1.99	1.10	3.24	1.19
20	1.99	1.20	2.41	1.35	2.81	1.24	2.90	1.18
21	1.83	1.07	1.81	1.29	2.05	1.11	2.43	1.07
22	1.77	1.04	1.50	1.22	2.01	1.04	1.67	1.04
23	1.60	1.03	1.47	1.20	1.83	1.08	1.76	1.07
avg	**1.88**	**1.07**	**1.94**	**1.13**	**2.25**	**1.06**	**2.53**	**1.11**

Monthly averages of absolute relative percentage errors of the weekday forecast, and the standard deviations of these errors over a one-month period, for the particular hours for different sites are presented in Tables 1 through 4. Each of these tables shows the error statistics over one month period for each of the 24 hours. The numbers at the bottom are the averages for the day. Standard deviations are also averaged for clarity. These daily averages range from 1.22% (Washington, summer) to 2.70% (Florida, spring). Standard deviations are all slightly higher than 1%. These results compare very favorably with most forecasting algorithms cited in this paper. For example, the mean absolute percentage error (MAPE) in [1] is 3.73%. The monthly MAPE ranges in [5] from 2.43% to 3.30%, and in [8] from 1.8% to 3.3%. The annual MAPE in [9] was

Table 2 Average Absolute Errors for April Weekdays

hour	Massachusetts		Washington		Virginia		Florida	
	% err	SD	% err	SD	% err	SD	% err	SD
0	1.05	1.02	1.83	1.01	1.95	1.05	2.17	1.01
1	1.09	1.00	2.11	1.03	1.68	1.02	2.02	1.01
2	1.21	1.02	2.18	1.04	2.08	1.03	2.07	1.02
3	1.44	1.04	2.21	1.02	2.18	1.03	2.16	1.03
4	1.67	1.03	3.05	1.01	2.14	1.08	2.42	1.01
5	1.90	1.01	3.36	1.03	2.04	1.05	2.98	1.07
6	2.56	1.04	2.84	1.07	2.62	1.08	2.84	1.04
7	3.26	1.18	2.53	1.11	3.64	1.35	2.15	1.01
8	2.24	1.03	2.29	1.19	2.07	1.08	2.85	1.08
9	2.58	1.07	2.02	1.11	2.45	1.10	2.27	1.03
10	2.14	1.07	1.93	1.02	2.08	1.01	2.84	1.04
11	2.27	1.09	1.61	1.01	1.96	1.03	3.31	1.13
12	1.92	1.08	1.19	1.02	2.16	1.02	2.52	1.15
13	1.87	1.06	1.41	1.04	2.21	1.01	2.97	1.06
14	1.96	1.08	1.06	1.03	1.96	1.00	2.70	1.06
15	2.26	1.09	0.86	1.01	2.33	1.11	2.90	1.04
16	2.72	1.15	2.02	1.31	2.49	1.06	2.76	1.05
17	2.80	1.02	2.39	1.74	3.21	1.03	2.76	1.01
18	3.56	1.04	2.74	1.20	3.31	1.05	2.99	1.21
19	2.86	1.01	2.56	1.72	2.98	1.03	4.65	1.07
20	2.03	1.03	2.48	1.03	2.64	1.09	3.21	1.08
21	1.80	1.05	1.92	1.05	1.73	1.03	2.75	1.08
22	1.56	1.09	2.18	1.02	1.71	1.02	1.99	1.12
23	1.44	1.16	1.82	1.04	1.51	1.04	2.58	1.06
avg	**2.09**	**1.06**	**2.11**	**1.12**	**2.30**	**1.06**	**2.70**	**1.06**

Table 3 Average Absolute Errors for July Weekdays

hour	Massachusetts		Washington		Virginia		Florida	
	% err	SD	% err	SD	% err	SD	% err	SD
0	1.62	1.06	1.21	1.12	1.70	1.01	1.27	1.02
1	1.52	1.05	1.02	1.06	1.45	1.00	1.24	1.01
2	1.34	1.02	0.93	1.03	1.19	1.02	1.09	1.01
3	1.27	1.03	0.89	1.01	1.17	1.02	1.21	1.02
4	1.20	1.03	0.83	1.01	0.98	1.02	1.25	1.02
5	1.70	1.07	2.47	1.01	1.06	1.02	2.16	1.03
6	1.76	1.09	1.78	1.02	0.80	1.02	1.36	1.01
7	2.12	1.05	1.61	1.01	1.40	1.05	1.80	1.01
8	1.76	1.09	1.70	1.02	1.65	1.09	2.28	1.03
9	2.17	1.12	1.20	1.03	1.91	1.01	1.64	1.01
10	2.67	1.31	1.03	1.02	2.09	1.07	1.88	1.02
11	2.47	1.42	1.10	1.02	2.19	1.01	1.77	1.01
12	2.49	1.31	1.19	1.02	2.28	1.06	2.40	1.02
13	3.11	1.24	0.71	1.01	2.21	1.04	2.73	1.04
14	2.94	1.18	1.08	1.01	2.63	1.04	3.01	1.12
15	2.72	1.30	0.80	1.00	2.16	1.11	2.78	1.09
16	2.82	1.39	1.19	1.03	2.17	1.08	3.25	1.12
17	2.87	1.23	1.25	1.01	2.19	1.14	3.92	1.04
18	2.84	1.12	1.38	1.05	1.84	1.12	3.78	1.15
19	2.80	1.05	1.56	1.07	2.27	1.20	3.18	1.04
20	3.11	1.06	1.61	1.02	1.76	1.04	3.08	1.02
21	2.43	1.06	1.21	1.02	1.92	1.10	2.64	1.04
22	2.16	1.05	0.92	1.02	1.92	1.05	1.74	1.05
23	1.80	1.04	0.72	1.01	1.78	1.06	1.36	1.01
avg	**2.24**	**1.14**	**1.22**	**1.03**	**1.78**	**1.06**	**2.20**	**1.04**

Table 4 Average Absolute Errors for October Weekdays

	Massachusetts		Washington		Virginia		Florida	
hour	% err	SD	% err	SD	% err	SD	% err	SD
0	2.05	1.12	1.88	1.08	1.25	1.03	1.86	1.12
1	1.70	1.04	1.36	1.00	1.30	1.03	2.00	1.09
2	1.73	1.03	0.98	1.10	1.17	1.01	1.95	1.04
3	1.39	1.01	1.49	1.12	1.26	1.03	1.76	1.04
4	1.85	1.02	3.82	1.14	1.45	1.05	1.62	1.03
5	3.10	1.04	3.88	1.83	1.63	1.06	1.92	1.01
6	2.52	1.07	2.36	1.50	1.74	1.05	1.56	1.02
7	3.10	1.04	2.34	1.20	1.88	1.01	1.83	1.04
8	3.66	1.02	2.66	1.30	1.60	1.03	1.80	1.04
9	3.68	1.07	1.70	1.00	1.62	1.05	2.10	1.06
10	2.80	1.08	1.60	1.03	1.60	1.02	2.25	1.02
11	2.70	1.08	1.46	1.03	1.93	1.02	2.29	1.04
12	3.11	1.18	1.30	1.04	1.93	1.01	2.35	1.09
13	2.78	1.04	1.50	1.03	2.45	1.03	2.80	1.07
14	2.84	1.08	1.44	1.01	2.43	1.04	3.60	1.02
15	3.06	1.09	2.06	1.01	2.29	1.04	3.73	1.08
16	3.52	1.23	2.79	1.01	2.60	1.02	3.47	1.10
17	3.45	1.06	2.90	1.03	2.89	1.18	3.59	1.21
18	2.25	1.10	3.08	1.20	2.69	1.26	3.60	1.11
19	2.49	1.07	2.98	1.52	2.80	1.09	3.10	1.02
20	2.91	1.13	2.73	1.06	2.63	1.04	2.81	1.07
21	2.47	1.03	2.51	1.10	1.84	1.06	2.49	1.06
22	2.31	1.03	2.63	1.07	1.73	1.03	2.12	1.10
23	2.12	1.01	2.27	1.08	1.71	1.02	1.59	1.10
avg	**2.65**	**1.07**	**2.24**	**1.15**	**1.93**	**1.05**	**2.42**	**1.06**

Table 6 Average Absolute Errors for April Weekends

	Massachusetts		Washington		Virginia		Florida	
hour	% err	SD	% err	SD	% err	SD	% err	SD
0	1.56	1.16	2.47	1.03	2.38	1.02	1.59	1.05
1	1.30	1.20	2.09	1.02	2.67	1.02	2.47	1.09
2	1.42	1.15	2.05	1.04	2.96	1.03	2.04	1.05
3	1.22	1.16	2.07	1.05	2.79	1.01	2.22	1.11
4	1.46	1.10	1.84	1.08	3.21	1.02	1.97	1.05
5	1.80	1.16	3.11	1.08	3.18	1.04	1.84	1.09
6	2.46	1.14	3.87	1.07	2.96	1.06	2.39	1.10
7	2.06	1.01	2.56	1.10	3.80	1.02	3.65	1.05
8	3.42	1.13	2.60	1.05	3.13	1.01	3.90	1.16
9	2.85	1.09	2.62	1.02	2.13	1.00	3.08	1.13
10	2.46	1.13	2.38	1.05	2.14	1.00	3.25	1.13
11	2.08	1.05	3.15	1.09	3.64	1.01	3.25	1.22
12	1.51	1.09	3.18	1.10	3.69	1.02	3.05	1.34
13	2.13	1.08	2.81	1.11	4.32	1.03	3.79	1.27
14	1.66	1.06	1.47	1.05	3.30	1.00	2.99	1.14
15	1.53	1.03	1.54	1.07	3.27	1.03	3.15	1.15
16	1.76	1.02	2.06	1.06	3.17	1.05	3.85	1.10
17	2.58	1.07	1.95	1.07	2.91	1.04	4.15	1.12
18	4.16	1.18	1.82	1.05	3.56	1.00	4.24	1.14
19	2.26	1.14	3.01	1.05	3.84	1.03	5.74	1.49
20	2.13	1.15	3.61	1.00	2.52	1.05	5.40	1.25
21	1.88	1.04	2.20	1.07	1.39	1.01	4.83	1.44
22	1.67	1.10	2.01	1.06	2.13	1.00	4.05	1.35
23	1.66	1.12	1.83	1.05	2.18	1.01	3.79	1.33
avg	**2.04**	**1.11**	**2.43**	**1.06**	**2.97**	**1.02**	**3.36**	**1.18**

Table 5 Average Absolute Errors for January Weekends

	Massachusetts		Washington		Virginia		Florida	
hour	% err	SD	% err	SD	% err	SD	% err	SD
0	1.20	1.00	2.00	1.02	3.50	1.23	1.35	1.01
1	1.23	1.00	1.67	1.03	3.78	1.35	1.51	1.00
2	1.23	1.00	1.31	1.02	3.43	1.31	2.11	1.00
3	1.21	1.00	1.18	1.00	3.35	1.92	2.29	1.01
4	1.31	1.00	0.92	1.02	3.20	1.94	2.33	1.01
5	1.29	1.00	0.68	1.01	3.40	1.98	2.32	1.01
6	1.48	1.00	0.96	1.00	3.01	1.84	3.63	1.00
7	1.42	1.00	1.92	1.03	2.23	1.95	5.20	1.04
8	0.86	1.00	2.58	1.04	2.02	1.03	3.87	1.04
9	0.82	1.00	2.19	1.02	2.65	1.09	3.23	1.01
10	1.23	1.00	1.79	1.02	2.88	1.35	3.23	1.01
11	1.49	1.00	2.93	1.03	2.66	1.30	4.83	1.00
12	2.09	1.00	3.12	1.07	1.80	1.00	6.96	1.05
13	2.67	1.00	3.62	1.04	2.34	1.05	7.08	1.06
14	2.38	1.01	3.50	1.09	2.44	1.04	2.84	1.00
15	2.04	1.01	4.16	1.07	2.42	1.03	2.67	1.00
16	1.84	1.01	4.53	1.07	2.76	1.02	2.87	1.01
17	1.33	1.00	4.10	1.07	2.75	1.11	3.26	1.00
18	0.83	1.00	1.14	1.02	1.56	1.01	3.50	1.01
19	0.90	1.00	1.90	1.03	2.28	1.10	2.31	1.00
20	1.35	1.00	2.12	1.06	1.60	1.01	3.08	1.00
21	1.34	1.00	0.97	1.01	2.46	1.21	2.18	1.01
22	1.59	1.00	1.40	1.00	2.26	1.14	2.35	1.00
23	1.57	1.00	1.45	1.01	2.32	1.19	2.12	1.00
avg	**1.45**	**1.00**	**2.17**	**1.03**	**2.63**	**1.30**	**3.21**	**1.01**

Table 7 Average Absolute Errors for July Weekends

	Massachusetts		Washington		Virginia		Florida	
hour	% err	SD	% err	SD	% err	SD	% err	SD
0	3.50	1.06	1.23	1.01	2.56	1.04	1.57	1.10
1	3.48	1.07	1.19	1.04	2.24	1.04	1.45	1.01
2	3.88	1.11	1.02	1.06	2.02	1.04	1.26	1.00
3	3.90	1.08	0.83	1.03	2.22	1.03	1.23	1.00
4	4.36	1.04	0.62	1.03	2.30	1.03	1.37	1.01
5	4.47	1.07	0.81	1.08	2.60	1.03	1.02	1.05
6	4.37	1.09	1.05	1.02	2.55	1.04	1.18	1.04
7	2.00	1.02	1.18	1.02	1.27	1.07	1.24	1.00
8	2.17	1.03	1.24	1.05	2.01	1.05	1.34	1.01
9	2.08	1.03	1.47	1.03	2.37	1.08	1.64	1.06
10	2.65	1.05	1.55	1.05	2.74	1.10	2.12	1.00
11	2.71	1.05	1.39	1.03	3.46	1.12	2.16	1.12
12	2.94	1.01	1.35	1.03	3.28	1.11	2.04	1.21
13	3.03	1.03	1.38	1.04	2.58	1.08	2.16	1.21
14	3.38	1.03	1.38	1.01	2.54	1.08	2.60	1.02
15	2.81	1.05	1.75	1.00	2.25	1.01	3.67	1.53
16	2.92	1.05	1.66	1.01	2.50	1.01	3.22	1.43
17	2.66	1.05	1.40	1.03	1.69	1.00	2.76	1.19
18	2.88	1.03	1.44	1.04	2.21	1.00	3.74	1.20
19	2.92	1.08	1.33	1.03	3.50	1.01	2.96	1.05
20	2.60	1.05	1.49	1.12	2.39	1.01	2.58	1.23
21	2.88	1.04	0.88	1.01	2.91	1.00	2.09	1.02
22	2.67	1.05	1.07	1.01	2.80	1.01	2.12	1.14
23	2.22	1.04	0.61	1.00	2.77	1.00	2.20	1.13
avg	**3.06**	**1.05**	**1.22**	**1.03**	**2.49**	**1.04**	**2.07**	**1.11**

2.52%. The range for the monthly MAPE in [12] was 1.67%-2.18%, and in [14] was 1.49%-1.89%.

Errors are generally higher in fall and spring because of the weather transitions. Results are better in winter and summer. Florida, however, witnesses a very fluctuating weather in winter that makes it similar to a spring or fall season in another site. It should be mentioned here that these results were obtained using the same rules for all sites.

Weekend results are shown in Tables 5 through 8. Daily average errors were higher for weekends. These averages range between 1.22% (Washington, summer) and 3.36% (Florida, spring). The standard deviations were slightly higher than 1%. Overall, the errors were higher than 5% in around 15% of weekend points tested. This is expected, since on weekends the weather load relationship is difficult to keep track of. In fact, every Saturday or Sunday is a special case where the load depends not only on the weather, but also on the special occasions on that day. This is especially true in fall and spring, where the load-weather relationship fluctuates from day to day. This means that it is generally difficult to have a one method that performs well for the weekends without incorporating site specific features. Nevertheless, the generalized methodology applies.

Table 8 Average Absolute Errors for October Weekends

	Massachusetts		Washington		Virginia		Florida	
hour	% err	SD	% err	SD	% err	SD	% err	SD
0	2.83	1.02	2.00	1.15	1.14	1.00	3.26	1.00
1	2.94	1.02	1.40	1.03	6.93	1.36	3.61	1.00
2	2.99	1.02	1.31	1.01	1.48	1.00	3.18	1.00
3	2.77	1.02	1.50	1.00	1.61	1.00	3.11	1.00
4	2.91	1.01	2.08	1.07	2.19	1.00	2.57	1.00
5	2.94	1.01	2.23	1.22	2.03	1.00	2.61	1.00
6	2.45	1.01	3.17	1.37	1.78	1.02	2.40	1.00
7	2.84	1.05	3.31	1.28	2.85	1.00	2.03	1.00
8	3.26	1.02	2.89	1.19	2.23	1.01	1.38	1.00
9	3.55	1.02	2.23	1.19	1.58	1.01	2.39	1.00
10	3.82	1.01	1.94	1.22	1.99	1.02	2.27	1.02
11	3.55	1.00	2.62	1.29	2.88	1.02	2.65	1.01
12	3.79	1.01	2.47	1.28	2.84	1.03	2.63	1.00
13	3.71	1.02	2.77	1.24	3.30	1.05	3.33	1.01
14	3.11	1.05	1.95	1.03	3.99	1.05	3.37	1.02
15	2.99	1.03	1.91	1.06	4.63	1.08	3.31	1.02
16	4.18	1.06	2.75	1.13	5.29	1.09	2.95	1.03
17	5.28	1.08	2.41	1.06	6.33	1.06	2.61	1.04
18	4.25	1.04	1.76	1.04	4.97	1.04	4.29	1.01
19	4.11	1.01	1.92	1.03	2.67	1.02	2.34	1.03
20	2.85	1.02	1.73	1.03	3.09	1.02	2.85	1.03
21	3.62	1.00	2.74	1.04	2.54	1.02	3.03	1.03
22	3.66	1.00	2.67	1.11	1.72	1.01	2.43	1.03
23	3.20	1.01	2.54	1.09	1.49	1.01	2.66	1.01
avg	**3.40**	**1.02**	**2.26**	**1.13**	**2.98**	**1.04**	**2.80**	**1.01**

6.0 Conclusion

The weather-load relationship is explored. Site-independent rules are developed. A newly-developed generalized technique for short-term load forecasting is tested using data from four diverse sites. Only site independent rules for weather and load relationships were used. The forecast errors are observed as 24-hour ahead forecast is made for one month per season for each of the four sites. The average absolute errors for weekday forecast range from 1.22% to 2.7% depending on the season. Thus we are able to show that a knowledge-based technique which uses pairwise comparison produces a fairly good load forecast over a 24-hour lead time for many diverse sites. Furthermore, the technique is fairly robust, inherently-updatable, and allows operator intervention if necessary. It does not require more than three years of past data.

The technique is site-independent. However, it is easily customized by adding the site-dependent characteristics. Such characteristics are formulated in the form of selection and adjustment rules. Once added, these rules are expected to improve the performance of the algorithm for a specific site.

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9.0 Biography

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