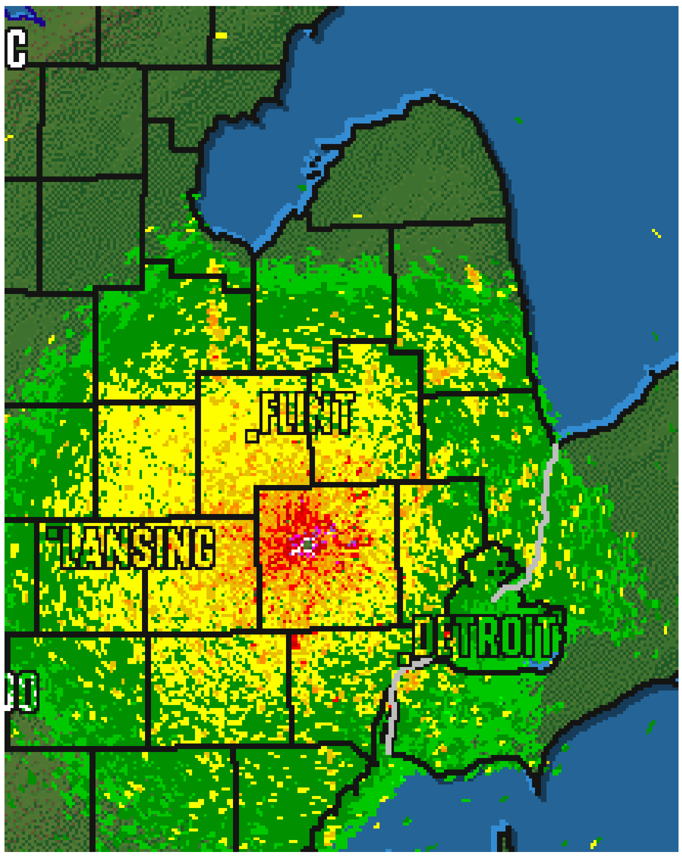
Adventures in Load Leading



By Tom Lacey
&
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Adventures in Load Leading

DTE Energy

INTRODUCTION

Recently the Load Research group at DTE Energy designed a Load Leading Service to supplement the existing Load Profiling offered by Detroit Edison, our electric subsidiary. The purpose of the service is to assist Customer Choice Marketers and Suppliers in matching supply to demand and avoiding expensive penalties for under or over supply. Although some Suppliers do have expertise in matching supply to their projected customer loads, many do not and find the minimal charge (Detroit Edison proposes to charge) easily offsets the penalties assessed for under/over supply.

In brief, Load Leading provides Suppliers/Marketers with an hourly load projection for the next seven days. If a Supplier/Marketer supplies to the hourly projection provided by Detroit Edison (regardless of the projection's accuracy) they are held harmless regarding supply penalties and are charged the marginal price of DTE supplying the shortage or paid market price by DTE for over supply.

This paper will discuss how DTE Energy's Load Research department developed the service and the results achieved.

Why?

Electric choice attracted new suppliers into the market who had little or no experience in forecasting electric load in Detroit Edison's service area. The suppliers needed the ability to forecast load for energy only customers who had no actual hourly history. Through the years, Detroit Edison has maintained active Load Research samples of its energy-metered customers, which allows the Company to confidently predict hourly loads. This means Detroit Edison can use its existing resources and the marketers do not have to independently develop their own load research departments. This service allows the suppliers to more accurately schedule their loads and thus help avoid imbalance penalties. As Table 1 shows this is very important because such penalties can be very onerous.

The value of Load Leading service is clear, consequently, the Michigan Public Service Commission ("MPSC") required Detroit Edison to develop a week ahead forecast for residential and commercial customers that provides an accuracy of +/- 20-percent at 80% confidence for all on-peak hours.

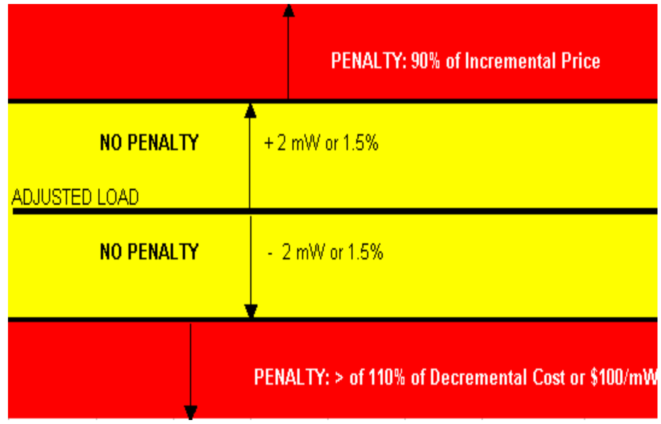


Table 1

'The Model Development Side'

MODEL DEVELOPMENT

Planning

The MPSC required it, but could Load Research do it? No load-forecasting model existed for these rate classes. However, two things were in our favor. First, existing samples for both the residential and commercial classes already existed and were actively maintained. These samples were designed to achieve an accuracy of +/- 10-percent at 90% confidence at the time of the monthly system peak. Second, a day ahead forecasting model had been developed for Interruptible Air Conditioning ("IAC"). A drawback of the IAC forecast model is it only forecasts the summer months between the hours of 1100 and 2400. Clearly, quite a lot of work needed to be done. It was decided to develop separate load forecasts for both residential and commercial customers, using the same framework. For the sake of brevity, this paper will concentrate its discussion on the development of the residential model.

Constraints

We operated under the following constraints in planning our approach. The model needed to be:

- Forward looking
- Able to produce a separate forecast for each hour and day of the year
- Plus or minus 20-percent accuracy at 80-percent confidence for all on-peak hours
- Supportable before the MPSC

Given these constraints and as a result of our experience in developing the IAC forecast, it was decided to develop a multiple variable regression equation. This approach was best because it would be easier to obtain MPSC approval for two reasons: first, they had seen it before and second, its opaque step-by-step approach.

Variables

The first step in developing the regression equation was defining the dependent variable (what we are trying to predict) and the independent variables (what will use to explain the variability). The dependent variable would be average customer demand (kW). The independent variables that were considered fell into four broad categories:

(1) Weather related (temperature, humidity, etc.),
(2) Time/calendar related (season, month, day of week, etc.),
(3) Economic indicators (CPI, auto labor hours, etc.) and
(4) Hybrids.

The hybrids were combinations or permutations of the other variables such as the product of maximum temperature and average temperature. (See Table 2 for a selected list of variables tested).

Data Collection

The next step was collecting the values for the above variables for each hour of history to be considered. The dependent variable was determined using a load research software program and interval demand data from our residential sample. This supplied the average use per customer per hour from March 1997 through September 2002.

The values for the independent variables were collected from various Internet websites, though generally such data was not differentiated by hour. For example, cooling degree days is the same for all 24 hours of the same calendar day. Hourly weather information was available internally at Detroit Edison. The independent and dependent variable data were combined into a single database, from which regressions were run using a statistical software program.

Load Leading Model Development Variables

Weather related:
Average temperature
Cooling degree days
Cooling degree days one day ago
Cooling degree days two days ago
Heat Index
Heating degree days
Heating degree days one day ago
Heating degree days two days ago
Hourly temperature
Humidity
Max temperature
Min temperature
Previous Days Average Temp
Previous Days Max Temp
Square of ave temp
Square of hourly temp
Temperature one hour ago
Temperature two hours ago

Time related:
Day of month
Day of week (DOW)
Friday
Holiday
Month
Month week
Prev DOW
Quarter
Season
Weekday/Weekend

Economic:
Auto Labor Hours
Auto shut down
CPI
CSI

Hybrid:
Various

Table 2

Validity of Variables

The independent variables included in our equations were determined through a laborious process of trial and error. In order to be included in the equation, the variables had to, when combined with other variables, pass a series of statistical tests, including the following:

Variable Test

Statistic	Min. Level	Goal
p-value	0.05	0.00
Adj. R-squared	0.80	0.95
Durbin Watson	1.00	2.00

Inclusion of Variables

One key driver for the inclusion of variables in the equation was the segmenting of the equation, meaning how many separate equations are needed for the model. Initially it was decided to develop at least twenty-four separate equations, at least one for each hour. Next, it was tested whether the model should be further segmented into seasons, quarters, or months. (Monthly segments would have meant 288 separate equations 12 months * 24 hours). However, in every case except a single annual model (with 24 separate equations), gaps would occur where our required accuracies could not be achieved. For example, if the model was segmented into four seasons, excellent results were achieved in the summer with tight fits, but the resulting winter equations were well below the minimum accuracy levels that were set. Ultimately, the only method that worked for all 24 hours and all 365 days was a single annual model with 24 separate hourly equations.

Another factor that affected our inclusion of variables was a conscious effort to avoid over fitting (not to include too many variables). In the final model, no single hourly equation has more than six variables. In many cases valid variables could be excluded with a minimal drop in the r-square statistic but with improvement in the simplicity and fit of the model.

Final Model

The final model included the following key features:

- 12 different independent variables spread over 24 hourly equations:
  - -Average temperature squared
  - -Cooling degree days
  - -Day of week
  - -Heating degree days
  - -Holiday
  - -Maximum temperature
  - -Month
  - -Season
  - -Weekend
  - -Yesterday's average temperature
  - -Yesterday's cooling degree days
  - -Yesterday's heating degree days
- Between four and six variables in each hourly equation
- Cooling Degrees Days included in all 24 equations.

Also, the final model has adjusted R-squares for the 24 equations of between 72-percent and 90-percent with an average of 84-percent

Lessons Learned

The process of developing this model taught several lessons regarding the usefulness of certain variables and strategies. For example, using a single annual model is useful because it allows for inclusion of seasonal or monthly variables where needed. The use of weather data from the previous day is very useful in predicting the following day's load especially in the first twelve hours because of the lag affects of temperature. Cooling and heating degree days are especially helpful in explaining variability in demand in an annual model because they highlight extremes respectively in the summer and winter.

Another lesson learned, is that cooling degree days and average temperature are near perfect substitutes for each other, therefore, only include one of them. Holidays behave very differently not just from non-holidays but also from each other, consequently, the holiday variable is only useful between 1100 and 1300 hours.

Economic variables are not included in the residential model. This is not surprising, however, they also are not included in the commercial model. This was not expected because in earlier studies, which included data from the years 1997 to 2000, economic variables were useful in explaining variability. However, when data from the years 2001-2002 is added the accuracy disappeared. This is because the unprecedented effects of 9-11 caused distortion in normal economic patterns.

December was the most difficult month to predict. Shopping hours change and the day of the week Christmas falls on makes it very difficult to discern patterns to explain demand levels. Another pitfall to avoid is including variables not known until well after the fact, such as unemployment rates for the current month.

In the final analysis the model is useful in predicting customer loads. It includes data from both good and bad economic times, as well as varied weather conditions.

The single annual model is also simpler to explain, understand and use.

TESTING

With the model created, the next steps were:

(1) Develop a software system to bring in weather and other required information (which will be explained later) and
(2) Test out the model and determine how well it predicts actual load.

It was decided to test several time periods, at least one for each season, however this paper will only discuss the detailed analysis for the month of July 2002.

In the month of July 2002 (see Table 3), the average hourly percentage error by day (the difference between actual demand and predicted demand) is under 9.5-percent. Table 3 also shows us a maximum daily error of 28-percent (July 4th). How does one better understand the 10-percent error and why is the July 4th error so high?

In order to answer these questions it was decided to subdivide our analysis into two areas:

(1) Accuracy of the predictive model and
(2) Accuracy of the weather forecast.

The month of July 2002 in the Detroit area included twelve days with maximum temperatures of 90° F or higher, and an average temperature of 77° F. Both are well above July and annual normals; therefore, this month would be a good test of the model under extreme conditions.

Of the twelve variables included in the residential model, only the seven weather variables need to be forecast, such variables as month or day of week, do not. All seven weather variables can be calculated from the maximum and minimum temperatures. Detroit Edison has a 7-day forecast of these temperatures available internally; how Detroit Edison is able access this forecast will be described in detail later.

Accuracy of The Weather Forecast

What is the best way to test the accuracy of the 7-day weather forecast used? Rather than chart and compare actual daily temperatures to the forecast, it was decided a better test of accuracy is to compare the predicted demands using the model with actual temperatures to the results using the 7-day forecasted temperatures.

Detroit Edison Company
Difference Between Actual Demand and Predicted Demand Using 7-day Forecast

Date	Actual Demand (kW) *	Pred. Demand (kW) Temps per 7-day Forecast *	Absolute Difference	Percentage Difference
1-Jul-02	1.60	1.51	0.09	5.4%
2-Jul-02	1.69	1.55	0.14	8.4%
3-Jul-02	1.67	1.39	0.27	16.4%
4-Jul-02	1.66	1.20	0.46	27.6%
5-Jul-02	0.97	1.05	0.08	7.8%
6-Jul-02	0.91	1.01	0.10	11.4%
7-Jul-02	1.09	1.08	0.00	0.4%
8-Jul-02	1.35	1.26	0.08	6.2%
9-Jul-02	1.24	1.05	0.19	15.7%
10-Jul-02	0.90	0.81	0.09	10.0%
11-Jul-02	0.80	0.88	0.09	10.7%
12-Jul-02	0.82	1.02	0.20	24.2%
13-Jul-02	0.99	1.13	0.13	13.4%
14-Jul-02	1.21	1.14	0.07	5.6%
15-Jul-02	1.42	1.29	0.13	9.3%
16-Jul-02	1.53	1.44	0.10	6.3%
17-Jul-02	1.56	1.45	0.11	7.4%
18-Jul-02	1.38	1.17	0.22	15.6%
19-Jul-02	1.21	1.13	0.08	6.5%
20-Jul-02	1.16	1.24	0.08	6.9%
21-Jul-02	1.23	1.21	0.02	1.6%
22-Jul-02	1.41	1.33	0.08	5.4%
23-Jul-02	1.06	0.98	0.08	7.6%
24-Jul-02	0.83	0.83	0.00	0.5%
25-Jul-02	0.87	1.01	0.14	16.6%
26-Jul-02	1.08	1.13	0.05	4.3%
27-Jul-02	1.24	1.24	0.01	0.6%
28-Jul-02	1.42	1.26	0.16	11.2%
Total	34.26	32.77	3.25	
Daily Average	1.224	1.170	0.116	9.5%

* - Average of the 24 hourly max. demands.

Table 3

For the month of July 2002, the average hourly demand was calculated three different ways:
(1) Actual demand,
(2) Predicted demand using the 7 day forecast and
(3) Predicted demand using actual temperature.

These results are summarized by day on Table 4 and graphically presented on Graph A. Please note that the lines for predicted demand on Graph A using the 7-day forecast and actual temperature follow the shape of the actual demand.

Another view of this data is on Table 5. It shows three things: the absolute value of the differences between:

(1) Actual demand and predicted demand using actual temperature data (how well does the model predict using actual temperatures),
(2) Actual demand and predicted demand using the 7 day forecast (how well does the model predict using the 7-day forecast) and
(3) Predicted demand using actual temperature data and predicted demand using actual temperature data (how close are two prediction methods to each other).

Detroit Edison Company
Average Per Customer Per Hour Max Demand For July, 2002

Date	Actual Demand (kW) *	Predicted Demand (kW) * Temps per 7-day Forecast	Predicted Demand (kW) * Actual Temperatures
1-Jul-02	1.60	1.51	1.57
2-Jul-02	1.69	1.55	1.62
3-Jul-02	1.67	1.39	1.63
4-Jul-02	1.66	1.20	1.62
5-Jul-02	0.97	1.05	1.08
6-Jul-02	0.91	1.01	0.98
7-Jul-02	1.09	1.08	1.17
8-Jul-02	1.35	1.26	1.34
9-Jul-02	1.24	1.05	1.18
10-Jul-02	0.90	0.81	0.99
11-Jul-02	0.80	0.88	0.84
12-Jul-02	0.82	1.02	0.87
13-Jul-02	0.99	1.13	1.07
14-Jul-02	1.21	1.14	1.24
15-Jul-02	1.42	1.29	1.39
16-Jul-02	1.53	1.44	1.48
17-Jul-02	1.56	1.45	1.49
18-Jul-02	1.38	1.17	1.34
19-Jul-02	1.21	1.13	1.15
20-Jul-02	1.16	1.24	1.12
21-Jul-02	1.23	1.21	1.16
22-Jul-02	1.41	1.33	1.26
23-Jul-02	1.06	0.98	1.08
24-Jul-02	0.83	0.83	0.86
25-Jul-02	0.87	1.01	0.92
26-Jul-02	1.08	1.13	1.06
27-Jul-02	1.24	1.24	1.16
28-Jul-02	1.42	1.26	1.33

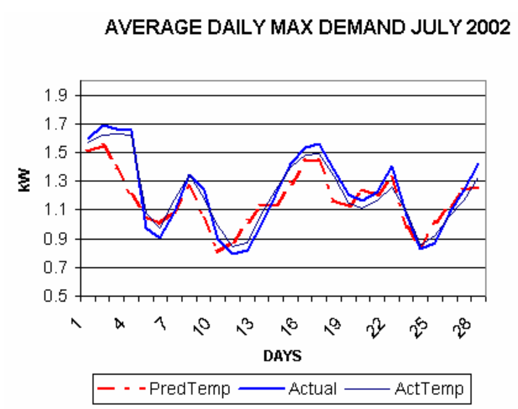
* - Average of the 24 hourly max. demands.

Table 4

Detroit Edison Company
Absolute Difference Between Actual and Predicted
Hourly Max Demands July 2002 (kW)

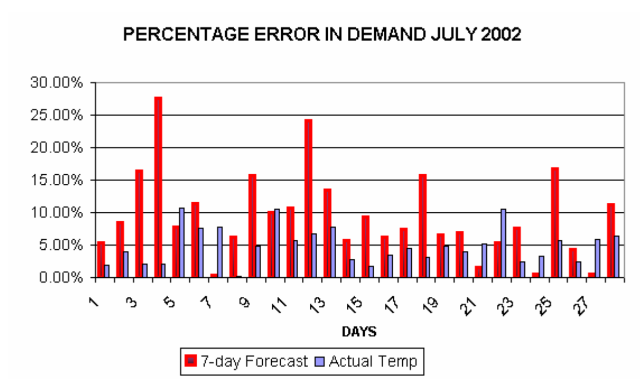
Date	Betw. Actual and Pred. Dem. Using Actual Temperatures	Betw. Actual and Pred. Dem. Temps per 7-day Forecast	Difference Betw.Predicted Demands
1-Jul-02	0.031	0.086	0.055
2-Jul-02	0.067	0.141	0.074
3-Jul-02	0.035	0.272	0.237
4-Jul-02	0.035	0.458	0.423
5-Jul-02	0.104	0.076	0.028
6-Jul-02	0.069	0.103	0.034
7-Jul-02	0.085	0.004	0.089
8-Jul-02	0.003	0.084	0.081
9-Jul-02	0.061	0.194	0.134
10-Jul-02	0.095	0.090	0.185
11-Jul-02	0.046	0.085	0.039
12-Jul-02	0.054	0.198	0.143
13-Jul-02	0.077	0.133	0.056
14-Jul-02	0.033	0.068	0.100
15-Jul-02	0.025	0.132	0.108
16-Jul-02	0.053	0.096	0.043
17-Jul-02	0.070	0.115	0.045
18-Jul-02	0.043	0.216	0.173
19-Jul-02	0.059	0.079	0.020
20-Jul-02	0.046	0.080	0.126
21-Jul-02	0.064	0.020	0.044
22-Jul-02	0.149	0.076	0.073
23-Jul-02	0.026	0.080	0.106
24-Jul-02	0.028	0.004	0.023
25-Jul-02	0.049	0.145	0.095
26-Jul-02	0.026	0.046	0.072
27-Jul-02	0.073	0.007	0.080
28-Jul-02	0.090	0.160	0.069
Total	1.596	3.249	2.757
Daily Average	0.057	0.116	0.098
Percentage of Actual Demand	4.7%	9.5%	8.0%

Table 5



Graph A

In addition, if actual rather than forecasted temperature is used, (see Graph B) the highest error percentage on any single day falls from 28 to 11-percent. The July 4th error we were so concerned about, declines (per Table 5) by 92-percent (0.423 kW/0.458 kW). The reason for this decline is the actual maximum temperature was 94 ° F, but the forecasted high was only 86°F. This caused the model to incorrectly predict the demand. Once the forecast error is eliminated, the prediction is substantially more accurate.



Graph B

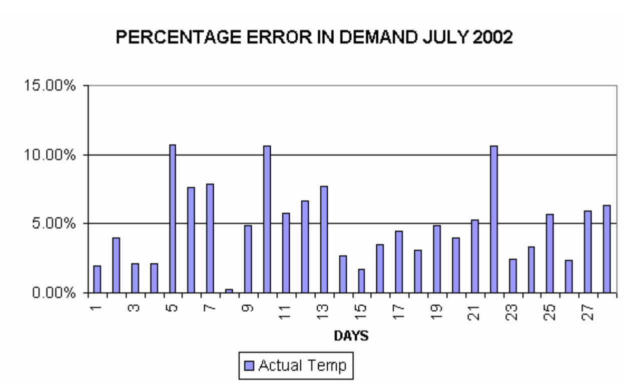
Table 5 shows that the average hourly difference between actual and predicted daily load when using the 7-day forecast was 0.116 kW. However, the average hourly difference between the actual load and the predicted load when using actual temperatures only averaged .057 kW.

This means the forecast increased the error by a factor 2.04 (.116/. 057). In percentage terms, the prediction using the forecast differed from actual demand by an average of just under 10-percent. However, if one eliminates the inaccuracy caused by the forecast, the average error falls below 5-percent.

Overall, this tells us the inaccuracy of a weather forecast is a source of error that one would like be able to minimize, but which is a seemingly uncontrollable hazard of forecasting. One obvious solution is to re-work the model by using fewer weather/temperature dependent variables or find a better forecast. Half of our overall error is explained by the weather forecast, the remaining 5-percent must be within the predictive model itself.

Accuracy of The Predictive Model

The next step is to test the predictive ability of the regression model. Once again we will focus on the month of July 2002. The error caused by the 7-day forecast is eliminated by only using actual temperature data in the model. Graph C reflects the absolute daily difference between actual and predicted demand using actual temperatures. The maximum error is 11-percent with an average of 5-percent. In order to help understand this error, the analysis is divided into two categories: time and temperature factors.



Graph C

Time Factors

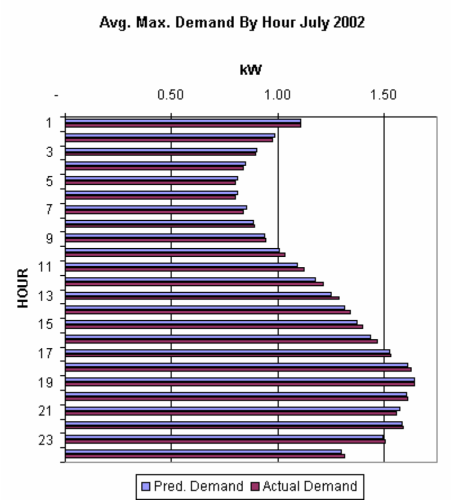
The time-related factors: hours, days and weeks will be considered first. The actual and predicted average demands were determined for each hour, day of the week, and week in July 2002. These amounts are captured on the following graphs: Graph D (by hour) Graph E (by day of the week) and Graph F (week). A quick review of the graphs shows that in each case the actual and predictive amounts increase or decrease in the same direction. For example, on Graph E (Day of the Week), Tuesday has the highest average hourly load for both predicted and actual, while Saturday has the lowest. Similar trends occur on all three graphs. Therefore, time-related factors support the accuracy of the predictive model.

Weather Factors

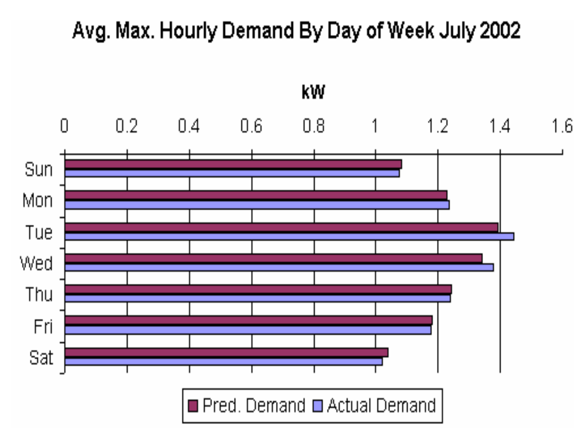
The next step is to analyze the effect of actual weather on the accuracy of the model. In order to test this for the month of July the following four factors were collected:

(1) Maximum temperature,
(2) Average temperature,
(3) Actual demand and
(4) Predicted demand.

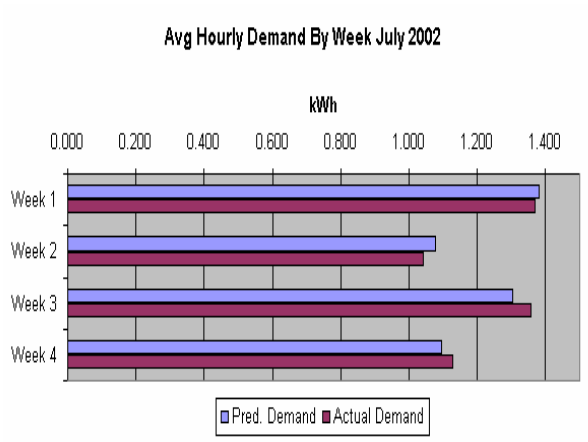
This information is summarized on Graph G. Once again, a quick review of the graph shows that the actual and predictive demands move up or down in tandem. One can also see the expected correlation between higher temperatures and higher demands. Therefore, it can be concluded that the weather related factors also add to the predictive qualities of the model.



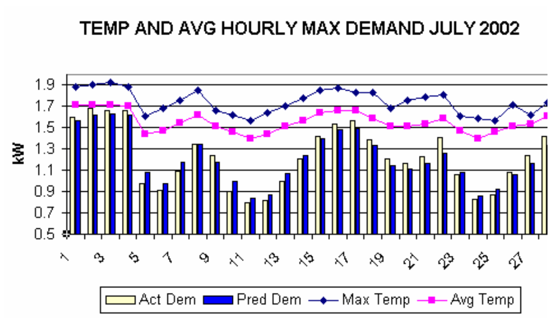
Graph D



Graph E



Graph F



Graph G

Results

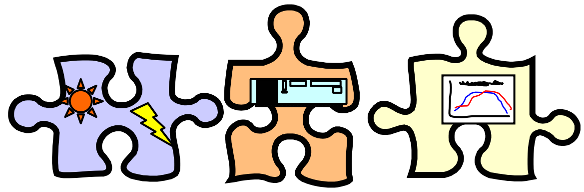
Overall the tests support the value of the model. Further refinements and testing are clearly necessary. The overall 10-percent error appears to be caused 50-percent from inaccuracies in the weather forecast and 50-percent from inaccuracies in the model. With additional data, hopefully we can reduce the 10-percent model error, but we are easily within the Commission required 20% maximum error requirement.

'The Technical Side'

TECHNICAL ELEMENTS OF LOAD LEADING

The Technical Side looks at some of our development experiences involved with taking a model, integrating it with corporate inputs, and delivering this information through our corporate intranet.

Load Leading Components

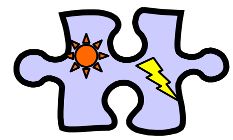


Three main components make up the technical pieces of the Load Leading Model:

- Weather information
- Load Research's client server environment
- Load leading model spreadsheets.

Below, we'll take a closer look at each one of these components and their part of the whole.

Weather Information



Our searches for weather information lead us to our company's meteorologist who had compiled together a weather information data mart. This data mart has real-time feeds from the National Weather Service and other weather information sources. This information is packaged and formatted into text files containing both current and historical weather information.

```
...............................................................
TEMPERATURE (F)
 YESTERDAY
  MAXIMUM          86   1240 PM 104     1936  83       3        93
  MINIMUM          68   1159 PM  45     1984  63       5        65
  AVERAGE          77                         73       4        79

PRECIPITATION (IN)
  YESTERDAY         0.03          2.80 1957   0.11  -0.08      0.00
  MONTH TO DATE     1.31                      0.88   0.43      0.00
  SINCE JUN 1       3.82                      4.43  -0.61      1.07
  SINCE JAN 1      13.13                     16.84  -3.71     16.70
```

Current Daily data (for current daily low)

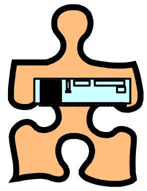
```
KDTW  MRF MOS GUIDANCE      7/10/2003  000 UTC
FHR 24|  36 48|  60 72|  84 96|108 120|132 144|156 168|180 192
THU 10| FRI 11| SAT 12| SUN 13| MON 14| TUE 15| WED 16| THR 17
X/N 77| 63  78| 60  77| 61  81| 63  83| 66  84| 65  80| 62  80
TMP 71| 66  71| 63  72| 64  76| 67  78| 69  78| 68  75| 65  75
```

X/N = 7 Day Forecast starts with today's forecasted high pared with tomorrow's Forecasted low, tomorrow's forecasted high with 2 days forward forecasted Low, 2 days forward forecasted high with 3 days forward forecasted low and so on.

Seven day weather information Text file

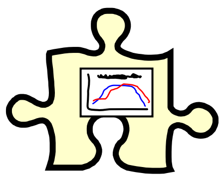
Accessing the weather information data mart files using conventional static linkages through the network proved to be another problem. This method requires special security arrangements, high maintenance and is prone to failure with every system and/or network change. Clearly a new method was needed.

Load Research Client Server Environment



Linking the weather reports into the Load leading models involve utilizing some of the resources found within the Load Research client server and our corporate environments. Our server, wide area network, scheduling utility and application language gave us the means to both link everything together and automate the daily update task. The application language TK/TCL, ended up being a key tool with its nimble data handling and time calculation capabilities. A new feature we discovered during this process was a resident HTTP (Hypertext Transport Protocol) feature. This allowed direct access to the weather reports using its URL (Universal Resource Location) / web address. Our home grown scheduling utility (called LR_Scheduler) was used to schedule execution of the data update task automatically.

Load Leading Model Spreadsheets



The spreadsheets where the model resides needed to be retrofitted with macros to load and format incoming data. Utilization of the resident macro recorder as well as cloning from existing macros helped achieve a smooth retrofit. Having data inputs precisely identified prior to development was also essential. Also, considering how the spreadsheets will display when accessed over the web by evaluating the webpage's format to determine if it is user friendly will help assure subscriber acceptance upon implementation.

Leveraging Corporate Data and Load Research Resources

During this development effort, it became obvious that benefits from previous investments in our infrastructure made while converting to the client server environment were coming to fruition. The ease of connection between corporate resources and the model's spreadsheet would not have been possible within a mainframe environment because of the inability to communicate over a wide area network.

Using URLs to Access Data Through The Corporate Intranet

As mentioned before, use of conventional static network linkages are not a viable option with this application because of high maintenance and rate of failure. URLs or web addresses proved to be a better approach for our dynamic reality.

URLs are more dynamic by their nature and do not require special security setups unless specially set by the owner. In order to access data via URL, it is necessary that your language/application have the means to communicate using HTTP. This protocol is what is used to communicate on the World Wide Web. Items on the web are identified with a URL, which can be thought of as a house address with driving directions.

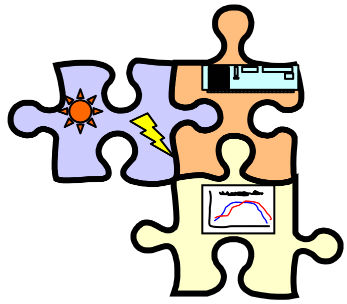
Evaluating Target Data Formats

Computers thrive in an orderly world; therefore a delineated format is best for ease of processing. In short, a delineated file is where each line has the same number of fields, in the same order, separated by a common character (delineator). In our case, we found most of our data on the web to be in report format. Report formatting are text files where the data has been arranged for visual effect/presentation with little regularity to depend on. Here cues may be the number of lines past a heading or the value of the first word in a line. This proved to be the case for us as our programs counted lines on one weather file and looked for keywords on another. I would expect future problems to occur as reporting format changes or even the case changes on a key word. Imaging formats are non-text files that are either encrypted or are actually graphic images. These files are in their final state and cannot be either read or further processed.

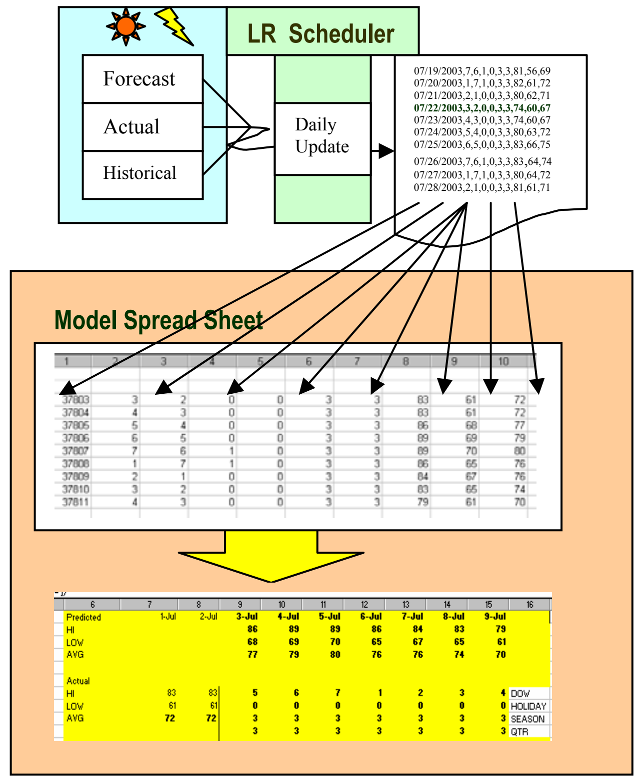
Observation of File Update Windows

Often, update processes are triggered/executed by a systems scheduler. A scheduler is the program that schedules and executes programs at specific times. Long running, resource intensive jobs can be set to run during overnight hours as not to disturb the work flow during peak daytime hours. Within this structure, a job runs on what is referred to as a schedule. By learning what schedule a file is updated, you learn where your windows of access are. We were not so lucky, as the files in the weather information data mart were updated by the irregular real-time feeds from the National Weather Service and other weather information sources.
This required us to observe the file update behavior over a couple of weeks, which gave us a range of update execution times. In our case, we used the late end of the time range as our access window. Once the window of each file was known, the common time denominator could be established. We finally hit on some luck as each of our files' access windows actually lined up. Had they not, scheduling multiple jobs would have been necessary.

Resulting Architecture



Our model has been running for six months now with very little trouble. In fact, the only error so far was when one of the weather reports was unavailable for a couple of days, triggering an un-trapped (un-messaged or not reported) error condition. Other coding refinements and better error trapping will be incorporated in future releases.



Gathering Daily Weather Reports

Every morning after the weather information data mart is updated, our Load Leading daily update task is executed through our LR_Scheduler. This task accesses one report to get the 7-day forecast, another for current day actual readings and another for historical information. Once these reports are accessed, the desired information is parsed out and extracted.

Reformatting Collected Data

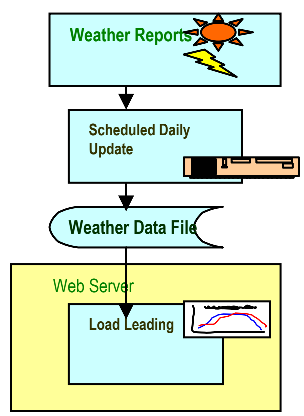
With the information extracted, the process of formatting involves the integration of forecasted, actual and historical weather information into one comma delineated spreadsheet-ready file. Part of each record is meta data. Meta data is simply information about each records'content. Examples of meta data would be:

- Whether a particular day is a holiday
- The day of week
- The season it falls under
- Which quarter a day falls within
- The previous day of week

Each point above has a code and is part of each date record, in addition to the maximum, minimum and average temperatures for that day. The order of each record is important as well. The three records are actual data starting from two days back to the current day. The next seven records are forecasted values. Once written and closed, this file is ready for the reporting spreadsheet. The format itself will save a lot of processing on the spreadsheet side. This is important because the more processing that occurs on the spreadsheet, the more sluggish the refresh behavior.

Reporting Model Results

Upon entering the spreadsheet, a macro is triggered that reads in the file created by the Load Leading daily update task. This mechanism was cloned and slightly modified from a logging macro within another application and inserted into the load leading model spreadsheets. The data from the file is read into a hidden sheet. Each rate class model references this hidden sheet for the values needed to fuel its model.



Once the Load Leading Service is made available, the affected models' spreadsheet graphics will be displayed on a website accessible by the subscribers. Very few changes are required for these spreadsheets to be web ready. First, a URL needs to be created for the file created by the Load Leading data-gathering task. Next, the reference to this file within the start up macro needs to be updated to use that URL.

LEVERAGING THE EXPERIENCE FROM DEVELOPING LOAD LEADING

As much of the Load Leading software was cloned from other applications, future applications will utilize everything from concept to code from this application. Also, the experience and additional access to corporate resources gained from this development effort will cause us to revisit our other applications and re-evaluate our work plans. Weather normalizing previously developed and future models will top our to-do list.

Opening the Automated Data Door

Learning how to access information through the web was the most significant capability gained from the technical side of this project. This opens the door to other data inputs ranging from Net System Output to accessing data from our translation group. The ability to directly access data eliminates manual steps allowing processes to be automated. Depending on how the data is stored, it can either be loaded into an integrated database or simply referenced within a query. Either way, more information is now available to be utilized across the entire range of Load Research applications.

Adapting Application for an Automated Daily Class Analysis

The Load Leading model itself can be expanded to include all of our rate classes creating a rate analysis application website. One could take this a step further and include an interactive 'what if' simulation. Here one could plug in parameters such as weather factors, inclusion or exclusion of customers, or volumes on specific times in order to analyze impact on load. The point here is that many possibilities exist in just the area of class analysis. Further possibilities obviously exist in the other areas of Load Research.

New Capability Makes Load Research Analysis More Available to Those Who Need It

With the ability to deliver information on the web, we are able to provide analysis to our clients when and where they need it. We are also able to provide a more in-depth analysis as a result of having more information directly available. Load Research will become an even more strategic asset to our organization.

FUTURE DISCUSSION

Now you have a feel for our Load Leading experience, and some of the benefits gained. This publication only touched on the high points of this experience, as there is so much more to tell. We welcome both further discussions on this matter or any comments you may have. Forward your comments to the authors at:

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