A Method for Deriving an Empirical Hourly Base Load Shape from Utility Hourly Total Load Records

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ABSTRACT

Electric utility program planning increasingly requires time-of-day based estimates of total load and the savings potential offset from that load. Most utilities have records or statistical estimates of the actual total load for every hour of a year for major customer classes (residential, commercial, industrial). However, these records are for the aggregate load and cannot disaggregate the load into its end-use components. This paper describes a new spreadsheet-based method by which a reasonably precise base load hourly load shape can be derived from hourly total load information. Then with an accurate base load estimate, the heating and cooling end-use load shapes may be drawn from the appropriate seasonal information. This method ultimately leads to the estimation of monthly average and monthly peak day load shapes for major end uses. The application of this more exact method has shown that heating and cooling load shapes will differ significantly from month to month for physical and behavioral reasons. This paper illustrates the method using examples based on actual utility load data.

Introduction

Current interest in hourly load information is driven by utility planning for peak loads, and especially how these peak loads may be affected by ramped up utility efficiency programs, demand response programs and direct load control programs. The demand response and load control programs are essentially discretionary, and the load response from these is estimated by various demand response realization rates. However the purpose of this current work is to estimate the hourly load changes due to efficiency programs. The load effects from efficiency programs are not deliberately invoked as with demand response, but are the passive consequence of various energy efficiency programs. As such, these load effects arise from changes in the distributed utility system load and are evident in differing degrees at all hours.

Site level load monitoring has diminished significantly since the 1990's but the load information developed 10-20 years ago (Pratt 1990) still underlies most of our current load knowledge of site end-use load characteristics. In many cases hourly load information is useful regardless of when it was developed, but the important distinction here is between specific site load measurements and aggregated utility load measurements. There are two prominent distinctions of the aggregated utility load relative to site loads:

1. Significant portions of the peak impacts due to efficiency programs will be due to reductions in the "distributed demand (or load)."[1] These distributed demand reductions

[1] The terms *load* and *demand* will sometimes be used interchangeably here. Strictly speaking, the demand is the power measured at the site meter, and the load is the power measured at the generation or distribution level including transmission and distribution losses.

will not be evident in the site measurements but they will be evident in changes in distributed demand at the utility level.

2. Each utility has unique circumstances. The most important pertain to the saturations of electric space and water heat, and the lesser circumstances pertain to cooking, dryers, secondary electric heating, vacancies, climate and time zones, and etc. This utility specific uniqueness results in differences in the shapes of the heating and cooling loads that are the prime drivers of peak load growth.

Aggregate utility loads are subject to load planning that requires hour by hour load estimates for the full multi year planning window. There is a need to integrate hourly utility load analysis more closely with the load analysis associated with energy efficiency planning. It will not be adequate to characterize efficiency related load impacts by a single summer and winter load impact number. If (when) energy efficiency programs grow to the point that a significant portion of the load growth is met by efficiency, then prudent load planning will require that hourly efficiency load offsets can integrate with in situ utility load measurements and other unique circumstances.

All of these points support the convenience of methods of estimating energy efficiency load impacts that can use, and be consistent with, specific utility load data. The main challenges are that utility load data has aggregated the energy end-use effects, and the data has significant weather-related volatility. The main advantage is that such data is timely and available. The primary purpose of this work has been to develop a methodology for modeling the hourly load offset impacts of energy efficiency programs using available utility specific load data. The fundamental premise of this paper is that a careful analysis of this readily available aggregated load data can unravel the aggregated data into its primary constituent end-use load shapes.

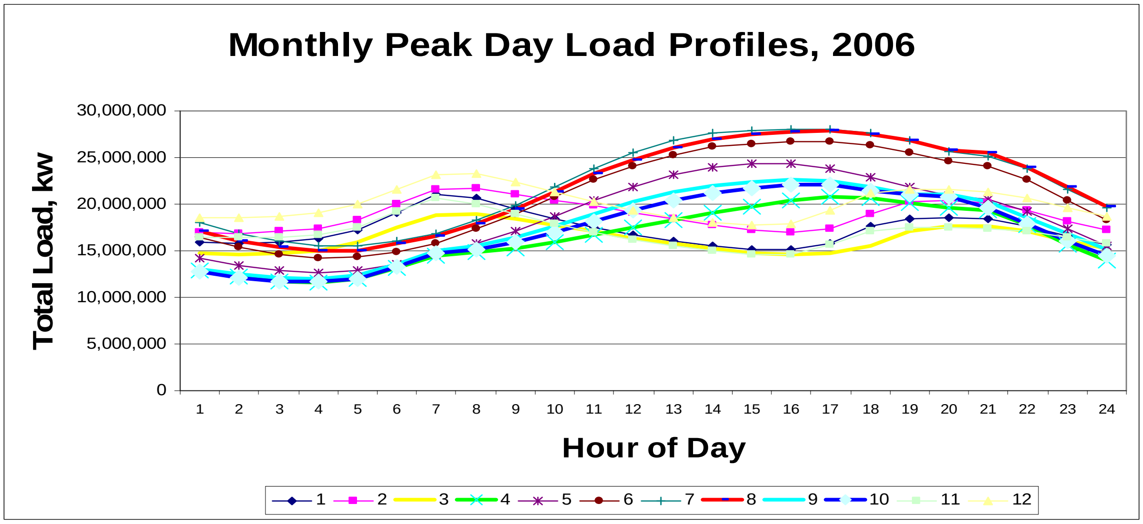
Briefly, this process of decomposing residential or commercial sector energy use starts with a partitioning of the monthly energy use into the basic weather sensitive and baseload end-use components by constructing a monthly temperature vs. energy use curve and fitting a simple model to it. Then the key first step in deriving the end-use load shapes is to find the load shape of the non-heating/cooling base load. With the use of this base load shape the heating and cooling end-use load shapes can be derived.

The Texture of the Data

Peak day load shapes. In its basic form the load data consists of 8,760 hours of load measurements for a sector or whole utility. An attempt to review this data will show that it is quite variable, with a great deal of scatter about any particular hour. If there is order in this data, it is not immediately evident. The first step toward finding the order in this data consists in finding the peak days for each month. Figure 1 shows total utility monthly peak day load shapes, and these will be used to illustrate the basic forms of the aggregated load shape.

Peak day load profiles are generally of two basic forms: (a) The cooling dominated profile with a maximum load at about 5 PM (17:00), and (b) the heating dominated profile with two load peaks corresponding to heating at about 7 AM and 8 PM. Non-peak day load curves can and do take on a very wide variety of shapes through a varied mixing these two basic forms.

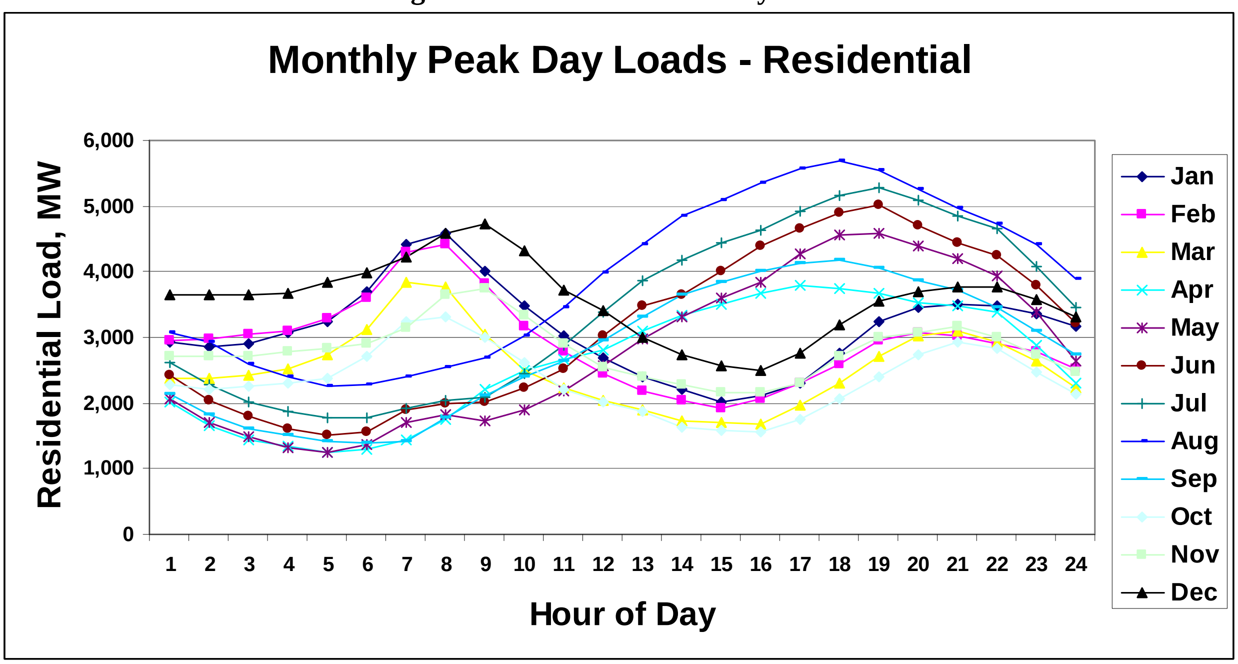
Figure 1. Monthly Peak Day Load Profiles



In the four swing months, March, April, September, and October, both forms of the load profile will be evident, but only one of the forms will turn out to be the peak for the month.

In most utilities, the residential sector is the driver for the peak loads. Figure 2 shows the monthly peak loads for a residential sector at a particular utility that will be used as an example in the subsequent discussion.

Figure 2. Residential Peak Day Loads



It is clear in this figure that the residential peak day loads have a similar general form to those shown in Figure 1, but with greater difference between the highest and lowest loads, thus driving the utility peak loads. The peak loads are always being influenced by heating or cooling events. However, it is also likely that some of the non-peak days of some months are minimally influenced by the heating or cooling activity. The challenge is to find the days or hours which are least influenced by heating/cooling, and the most promising place to look is in the swing months.

Locus of minimum load. The hours with minimal heating/cooling influence are examined by finding the "locus of minimum load" which is illustrated in Figure 3. The locus of minimum load is defined as the minimum load for each hour of the day for the month or period in question.[2] Figure 3 shows that this minimum load has a much lower magnitude than the peak loads for the corresponding months as shown in Figure 2, and it also shows that the locus of minimum load has a somewhat similar shape for all of the six mild weather months.

Figure 3 also suggests that there was no single day in the mild weather months that was not effected by some minor heating or cooling.

Figure 3. Locus of Minimum Load

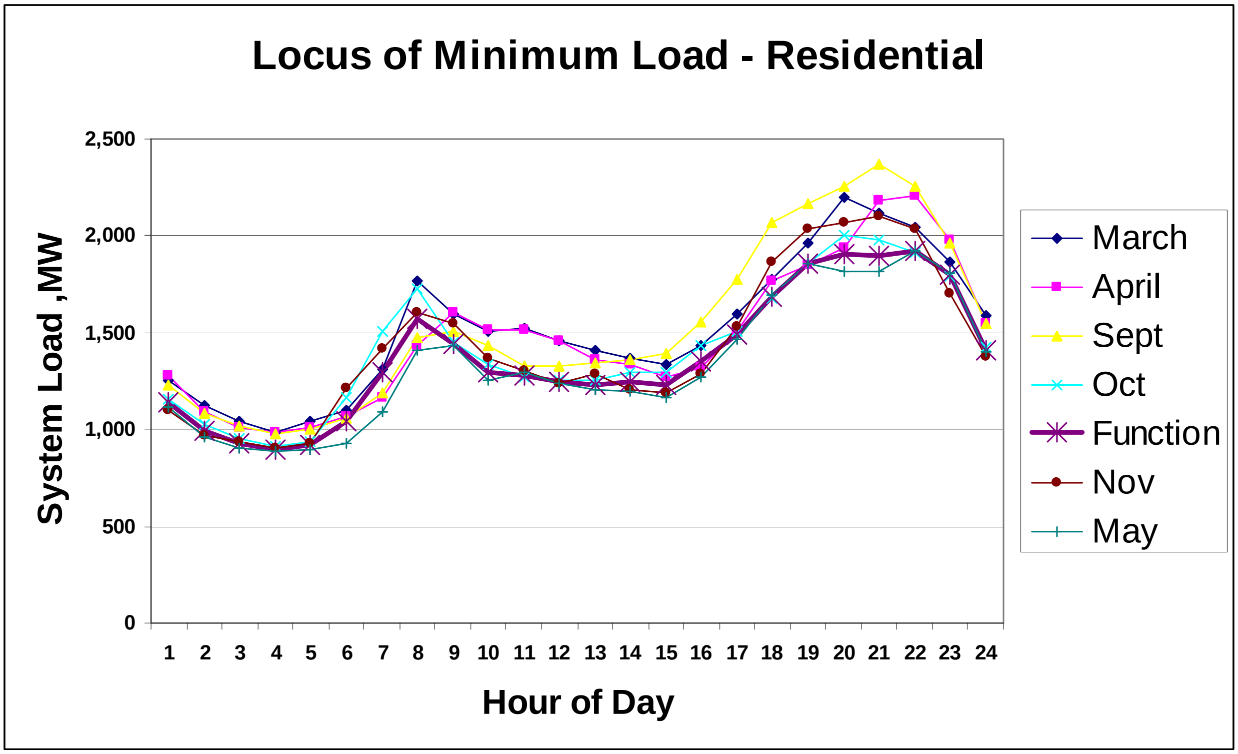
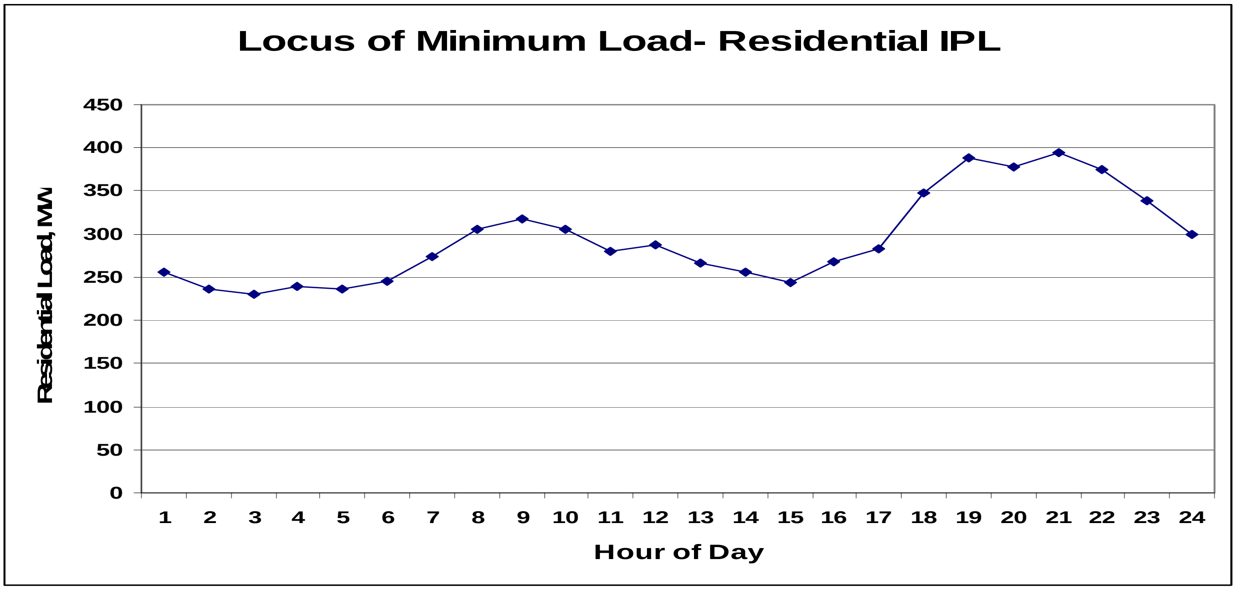


Figure 3 shows a remarkably similar pattern for six months of the year. The other six months had a much higher and more erratic minimum load because these were the strong heating/cooling months, and the minimum load included some of the heating or cooling. Here, the mean of the October and May locus of minimum load shapes is designated as the baseload function, heavy line, and it will be taken here as the envelope of the non-heating/cooling loads.

Figure 4 shows the locus of minimum load for another utility. In this case there was no single month with the lowest load for all hours so the absolute minimum was assembled from the lowest load for each hour for the four swing months (March, April, September, October).

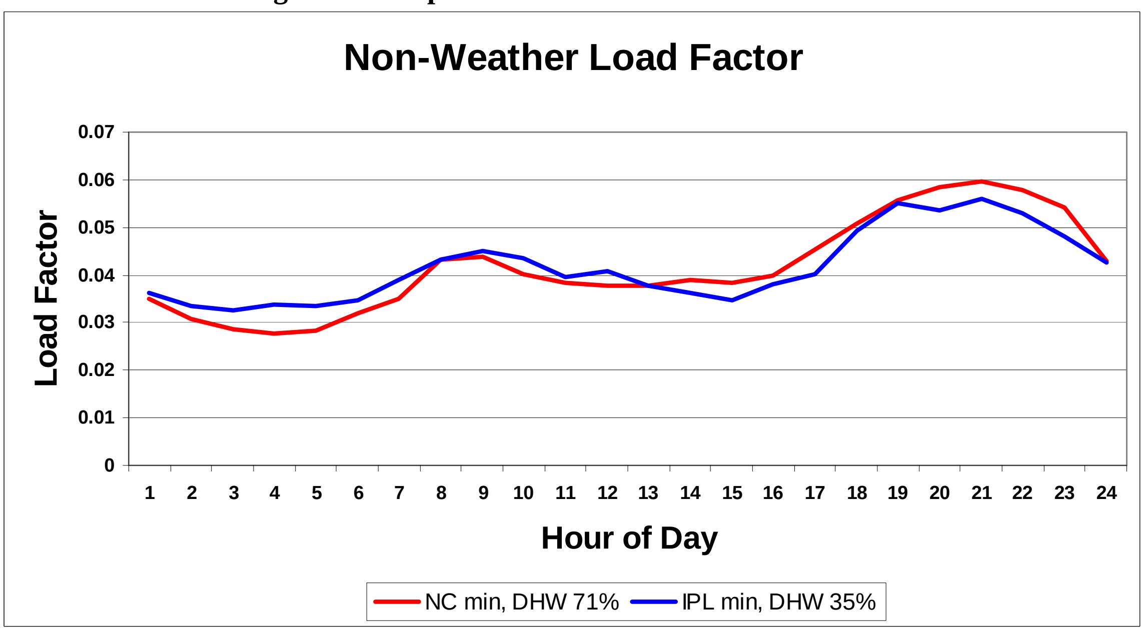
[2] In the commercial and industrial sectors it is important to distinguish weekdays from weekends, but in the residential examples used here, this distinction is not significant

Figure 4. Locus of Minimum Load – IPL



Loads represented in Figures 3 and 4 are for utilities differing in size by almost an order of magnitude, and for the purposes of comparison, these load shapes have been normalized into hourly load factors in Figure 5.

Figure 5. Comparison of Non-weather Load Factors



The hourly load factor is defined here as the fraction of the total daily energy used in each particular hour. It is apparent in Figure 5 that these hourly load factor curves are remarkably similar for distinctly different utilities, but physically they represent different situations. The principal difference lies in the different electric water heating saturations of the two utilities. The utility with the 71% DHW saturation shows a greater range in its profile because of the greater fraction of DHW. The purpose of this comparison is to illustrate the similarity of these curves for utilities differing significantly in size and latitude. The difference in these curves due to differing DHW saturations is valid, and both curves can be successfully used in the subsequent apportionment of end-use energy, and in the derivation of hourly end-use load factors. In essence, the load factor is as much a measure of behavior as it is of energy use.

Key assumptions. The key assumption underlying the concept of the locus of minimum load is that the minimum load for a particular hour is not a fluke. It assumes ***the behavior of a large number of utility customers (of the order of a million) is repeatable and statistically bounded***. It is physically probable that a load much larger than the minimum can result from a weather event, but it is statistically improbable for the behavior of a large number of people to result in a much lower load.

Another fundamental assumption underlying this work must also be examined. ***This minimum daily load shape is assumed to be approximately the same throughout the year***.[3] This assumption is partially validated by the similarity of the minimum load curves for the six mild weather months in Figure 3. These assumptions could be validated by a large number of long-term monitored sites, but this has not been done, and we remain beholden to these fundamental assumptions.

Parsing the End-Use Load Shapes

The minimum loads represented in Figures 3 and 4 are a unique abstraction from the annual hourly load information for a sector, residential, commercial etc. The reality of this unique abstraction is bolstered by the observation that the basic shape of this minimum load is similar from utility to utility and across geographic differences.

Ultimately, this unique locus of minimum load will play two key roles: 1) it will define the fraction of the utility's energy that is non heating and cooling, and 2) it will be used as an hourly true up reference for the sum of the non-heating/cooling end-use loads. Both of these key roles will be discussed and illustrated below.

The derivation of end-use load shapes has two primary stages: first the energy must be separated into its primary end uses for each month. Then the primary end uses must be distributed among the 24 hours of the day. For this discussion these two stages will be referred to as the *energy model* and the *demand model*.

The energy model. The energy model drives the demand model. The energy model is intended to separate the energy for each month or day into its primary end uses. For each end-use and each month, the energy model estimates average daily energy use, kWh/day. The demand model will then use the daily energy use and distribute it among the 24 hours of the day. The largest and most important fundamental end uses are heating, cooling and baseload. In practical utility analysis, the baseload is subdivided further into DHW, lighting, internal loads (cooking plugs, etc.), and external loads. These six end uses are the ones that will be considered here.

[3] Two of the non-heating/cooling loads, lighting and DHW, have a slight seasonal variation. The lighting variation is due to changes in day length, and the DWH variation is due to seasonal changes in the inlet water temperature. The end-use models can readily account for these seasonal variations. The essential point is that the empirically derived locus of minimum load is a reasonable daily average for the year

A significant portion of the energy use (especially residential) is very temperature dependent. All energy models sufficient to this modeling task will use temperature in some form, either as heating/cooling degree days or as average daily temperature by month. Detailed discussion of the energy model used here is beyond the scope of this paper, but the requirements of such a model will be discussed and the modeling results illustrated.

In principle, a variety of models can be used, including PRISM (Hirst 1989), EZ Sim (Robison & Reichmuth 2001), custom engineering analysis and End-Use Estimation Models used by EIA for interpreting Residential Energy Consumption Survey (RECS) data (EIA 1995). All these models create temperature-based functions which are fitted to monthly energy consumption data, and all of these approaches use a regression technique, with the best fit used as a criterion of truth.

In practice, however, the data is noisy enough (or non-linear enough) to permit a range of apparent good fits, rendering the models somewhat indeterminate as regards a definitive partition between heat/cool energy and baseload energy. The most accurate results will be achieved when the regression fit is also constrained to match some empirical measurement. The locus of minimum load is just such an empirical measurement.[4] In this application, the minimum load defines the average daily (and yearly) non-heat/cool energy, and can be used to divide the heat/cool energy from the rest of the energy. When this fraction of heat/cool vs. other energy has been properly identified, the regression fit for end uses can be trusted.

If the model is to be used for estimating the effects of a utility program, it should include the physical parameters that will be influenced by the program and the saturations of various heating/cooling and other appliances. A model of utility program applications must also account for measure interactions, the most significant being the interaction between internal gains and heating and cooling, and the interaction between the thermal efficiency of heat/cool sources and changes in the thermal loads resulting from shell modifications such as insulation, sealing etc. The model used here has been devised for whole utility modeling applications and includes about 20 physical parameters, including the saturations of DHW, space heat, cooking and dryers.[5]

The typical types of regression results, monthly energy use vs. temperature, used in this model are graphically shown in Figure 6. The regression process fits a model to the average site monthly energy use derived from a random sample of about 1,200 sites drawn from a population of about a half a million customers for a particular test year. Figure 6 illustrates the regression fit for only one sub-sector of a whole utility. Typically, a utility will be modeled as 10-20 sub-sectors, separately modeling older and newer residential stock and a variety of significant commercial and industrial sub-sectors. Total utility energy use for a particular month or temperature will be the sum of the sub-sector models.

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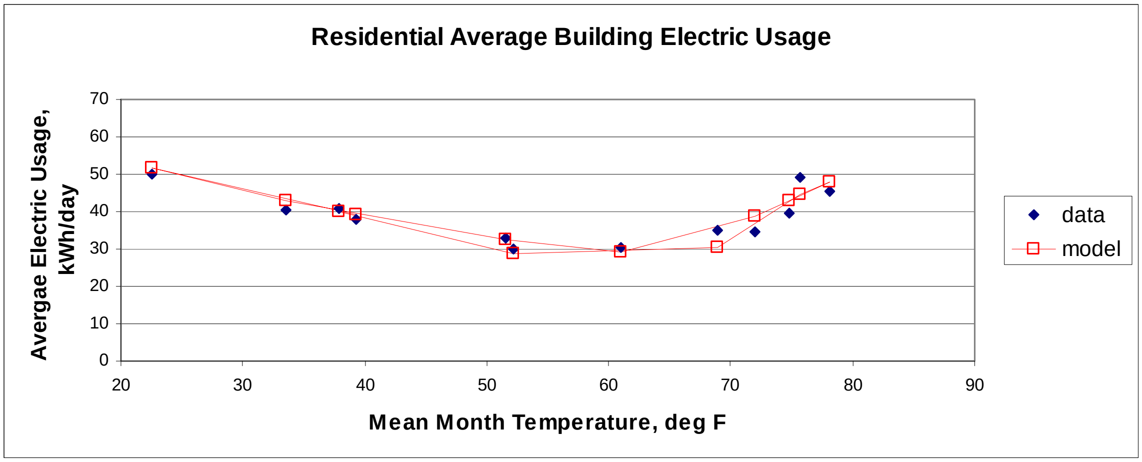
[4] The locus of minimum load is increased by 10% in this application as a hedge against the possibility that the minimum load derived from a particular month usually September/October is too low to serve as the annual average.
[5] This is not a commercially available model, but rather a designation of an engineering process that has been applied to several electric and gas utilities in a custom approach determined by availability of energy and demographic data

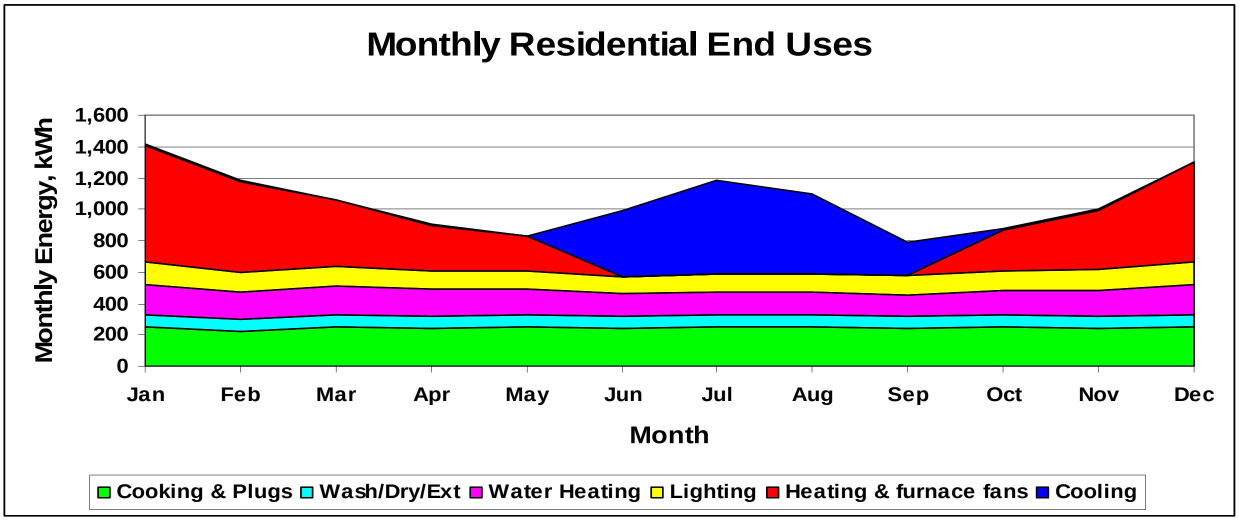
Figure 6. Energy Use vs. Temperature Model



It is apparent in Figure 6 that there is fairly precise and dominant temperature dependence to residential energy use. An orderly pattern of energy use vs. temperature is also evident in most commercial and industrial sub-sectors. This reasonably precise temperature dependence permits the model to be used to normalize the model results from the particular temperatures of the test year to the long term average temperatures of a "normal year." The temperature dependence also permits the model to be used to estimate the peak day energy use corresponding to the temperature extremes that drive the utility peaks.

For simplicity, Figure 6 only shows the total energy as a function of temperature. In the model, this total energy is the sum of the individual end uses as functions of temperature. Figure 7 shows these modeled end uses for an average residence for the normal year.

Figure 7. Normal Year End Uses for an Average Residence



Note in Figure 7 that the end uses are for an average residence. At this utility the average residence has a 30% saturation of electric space heat. A particular electrically heated residence would show much larger space heating energy.[6]

[6] In program planning, the saturations in the model can be adjusted to represent various candidate program participants such as all electric homes.

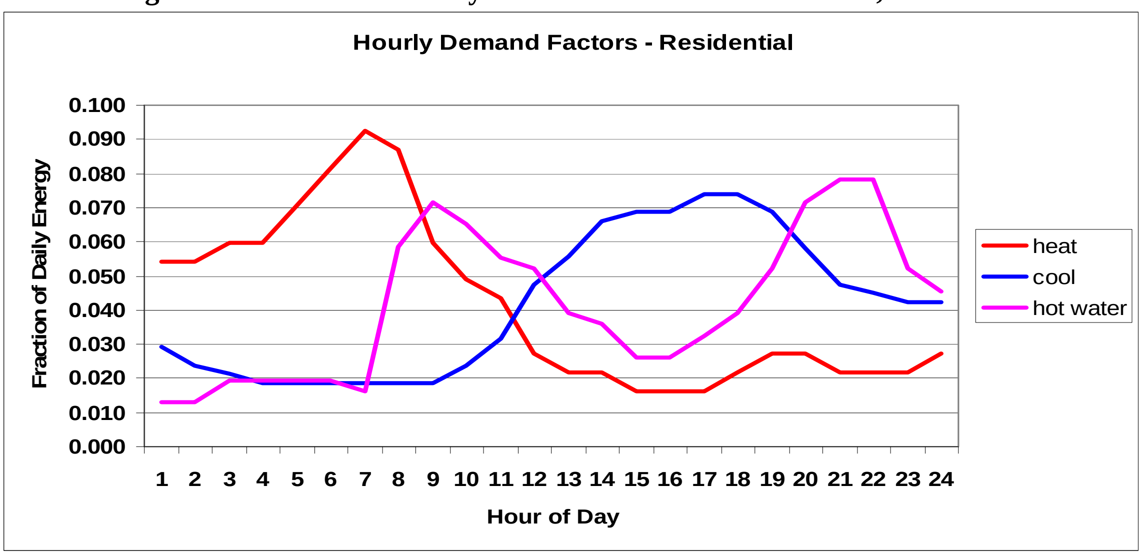
Note also in Figure 7 the overlapping heating and cooling in May and September. This is typical in swing months where there may be heating and cooling during different parts of the day or on different days. There is also the phenomenon of contradictory heating and cooling typically caused by thermostat set points that are too close. These more subtle heating /cooling events can be faithfully captured by a model of this sort if the locus of minimum load can be used as a fitting constraint to establish accurately the fraction of energy that is non-heat/cool.

The average daily energy for each of the six end uses for each month is the final output of the energy model, and the input to the demand model.

The demand model. The objective of the demand model is to estimate the average distributed hourly demand for a large number of customers. The concept of distributed demand assumes that thousands of the same devices (stove, water heater, computer, etc.) will be turning on and off according to use at random times within the hour of interest. The contribution of any one of these devices is the *full load power*duty cycle* for the hour. For example, if a 1400 watt toaster is on for one-tenth of the hour, the distributed demand is 1400 watts times 0.1 hours, or 140 watts. In essence, the distributed demand is the energy used in the hour.

The distribution from daily energy use to hourly energy use is done by means of "demand distribution functions". The demand distribution function consists of twenty-four hourly demand factors that specify the fraction of the total daily end-use energy that occurs in each hour. The 24 hour sum of these demand factors is 1. Figure 8 illustrates typical hourly demand factors.[7]

Figure 8. Residential Hourly Demand Factors for Heat Cool, Hot Water



Notice in Figure 8 that the cooling demand factor is greatest at about 4-6 PM when the cooling energy for each hour reaches about .075*daily average cooling energy. Similarly, the hourly demand factor for heating appears to be maximum at 7 AM when the hourly demand

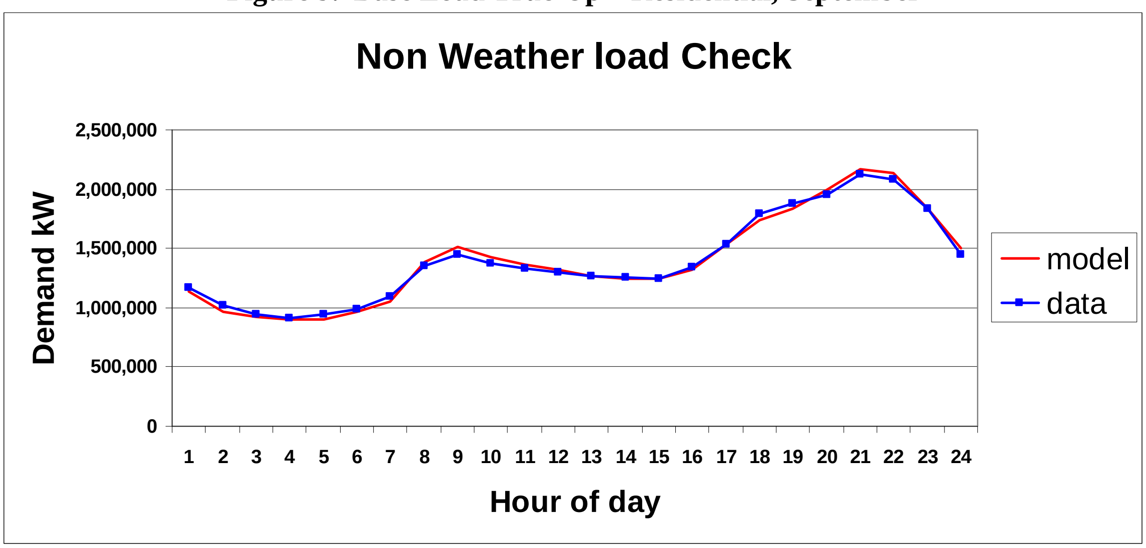
[7] For simplicity, this figure shows only a single heating and cooling demand factor. In practice, unique heating and cooling demand factors are derived for each month because the timing of heating or cooling can vary significantly from month to month. For example early season cooling in June will be centered more during the hot afternoon, while late season cooling in August may drag on well into the evening.

factor is .092 and the hourly heating energy is .092*daily average heating energy. Hot water demand is known to be bi-modal occurring in the morning and late evening.

These end-use demand factors should not be confused with load curves. For all end uses, the hourly demand factor is much less than 1 and it is only used to distribute a daily end-use energy by hours. The hourly end-use load curve results when the hourly end-use demand factor has been multiplied by the associated daily end-use energy. The aggregate hourly load curve is then the sum of the various hourly end-use load curves for each hour. In a full utility demand model there is a set of hourly demand factors for each of the six end uses for each of the primary sectors, residential, commercial, and industrial.

Truing the demand model. The first step in the demand true-up is to adjust the non-weather end-uses, lighting, internal loads, external loads, and hot water. The adjustment consists of modifying the hourly demand factors for these end-uses until the load shape representing the modeled sum of the non –weather end uses is congruent to the empirical non heating/cooling base load shape, the locus of minimum load illustrated in Figures 3 and 4. Note that there is a different locus of minimum load for each principal sector as derived from the hourly load data for that sector. A true up process is done for each sector, residential, commercial and industrial. Once the hourly demand factors are so adjusted they are then used to represent the non-weather load throughout the year and especially in the heating and cooling seasons. Figure 9 shows that a close comparison between the non-weather demand estimated by the model and the empirically derived locus of minimum load for the residential sector can be achieved by altering the demand factors as necessary toward a best fit.

Figure 9. Base Load True-Up – Residential, September



In practice it would be quite daunting to adjust all the load factors for the four non-weather end-uses. Therefore, the external loads which are much smaller than the others use a deemed load factor curve, and the DHW end use also uses a deemed load factor curve derived from other research (Warwick 1993). The internal loads (lighting, refrigeration, cooking and plug loads) is the dominant non weather load and these end uses all use the same end-use load curve.[8] It is the adjustment of the load factors for this internal loads end use that leads to the close fit seen in Figure 9. It is possible to specify the known load behavior of particular end uses of interest such as refrigeration or cooking, as was done for DHW, but at least one significant end use must be left free to be adjusted to match the empirical data.

The next step in the true-up is for cooling. In this case the model, using the already trued up non weather loads, is compared, hour by hour, to the peak day load for each of the cooling months, and the hourly load factors for each of the cooling months are adjusted for best fit between the model and observed peak day loads. It is important to note here that the energy model works in terms of average monthly temperature and energy. Thus the average daily energy in a particular month will be much less than the daily energy during a peak day. Therefore, to support a cooling or heating load factor true up, the energy model is driven to hypothetical peak conditions by increasing (or decreasing) the temperature from the monthly average until the daily energy shown by the model equals the daily energy associated with the peak day. It is important to note that the cooling (and heating) load factors are trued up against the monthly peak day load shape. So the derived load factors will reflect a peak day behavior and load shape which may be different from a typical day load shape. It has been found necessary to derive a different load factor curve for each cooling month because the actual dynamics of the cooling vary from month to month. For example cooling in May never carries over into the small hours of the morning as does cooling in August. However, since the model has been adjusted separately to fit each month, the fit between the model and the true-up data can be expected to appear very good.

Figure 10. Cooling True-Up Residential August

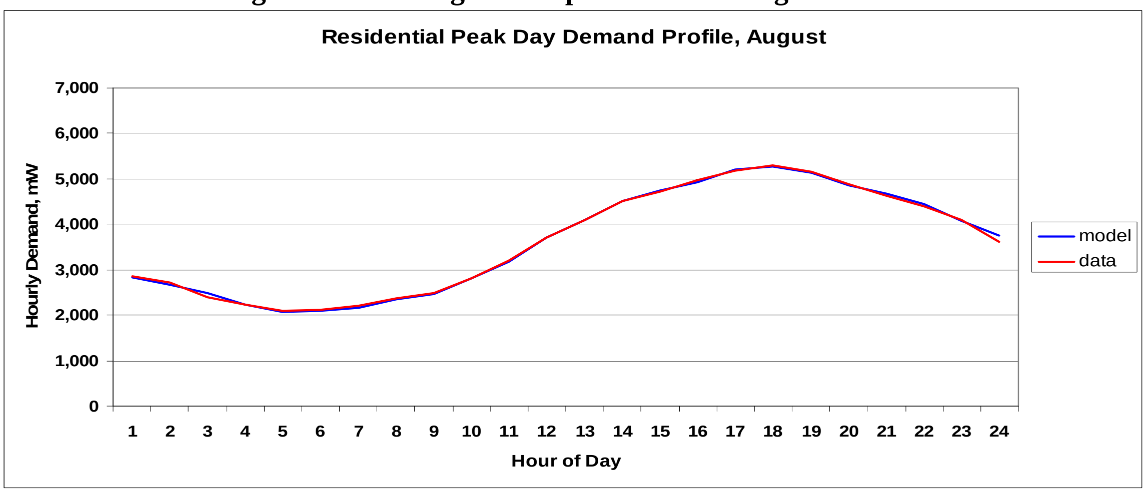


Figure10 shows a close comparison between the demand estimated by the model and the empirical peak day demand after this cooling true-up step for August, and there is a similar close fit for the other cooling months.

The final demand true-up step is for heating. In this case the model is compared to the load study for the heating months and a separate heating load factor curve is derived for each month from the best fit between the model and load study.

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[8] The empirical load information does not support a distinction between internal loads such as refrigeration, lighting etc. these end uses are parsed according to EIA end use ratios, and they are all assigned the same load curve shape.

Figure 11. Heating True-Up – All Customers, January

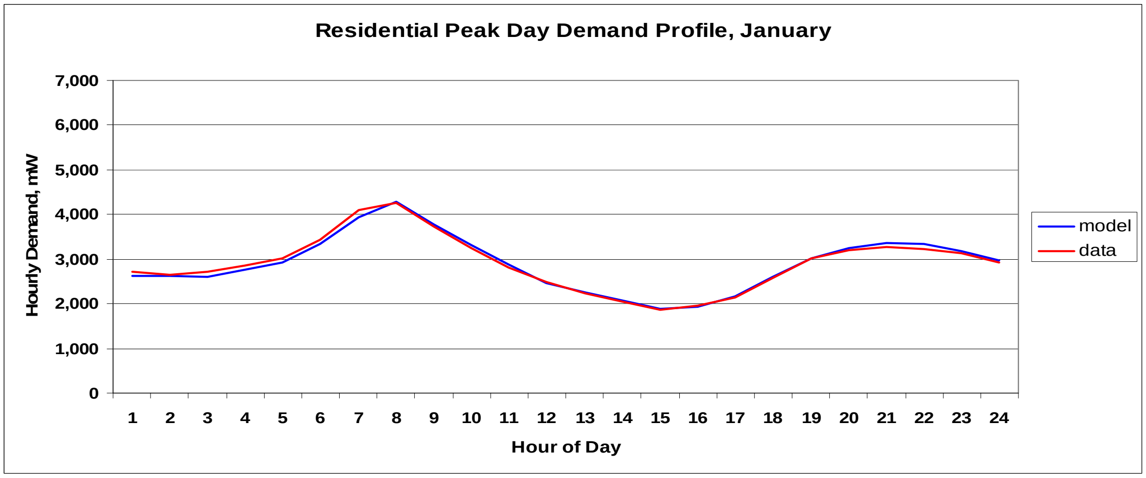
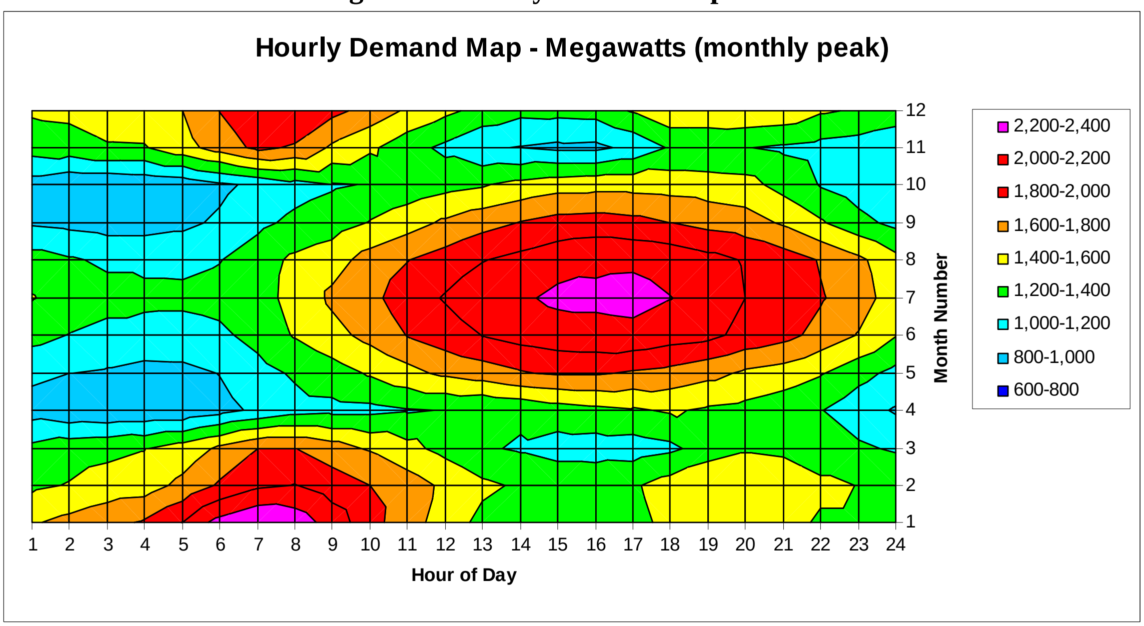


Figure 11 shows a close comparison between the demand estimated by the model and demand from the load study after this heating true-up step. Through these steps, the most significant hourly demand factors (for monthly heating and cooling) are derived. The demand model can estimate the average daily demand versus hour for each month that proceeds from normal monthly temperatures. Or the demand model can estimate peak monthly demand which proceeds from peak temperatures.

Figure 12 shows an annual map of utility hourly loads. This shows the monthly peak day loads. It accurately shows the peak situation but it greatly exaggerates the annual energy.

Figure 12. Hourly Demand Map



A similar figure for average monthly loads is also used where an accurate perspective on annual energy is necessary.

Brief application example. The principal application for this modeling process is to support a coherent estimate the 8760 load impact for a utility energy efficiency program or group of programs. This level of detail is increasingly required in cost effectiveness analysis (Integral Analytics 2006). But beyond the analytical objective lies another important application which is to inform the perspective regarding the value of various efficiency measures.

Consider the case of upgrading a heat pump from the current SEER 13 specification to SEER17. By nature SEER is only an energy rating making no reference to demand impact, and a balanced view of this measure will need to consider the value of demand or load savings.

This model of the annual energy savings from such an upgrade shows energy savings of the order of 7% of the annual energy, and possibly only marginally cost effective on the basis of energy savings. But the demand savings are disproportionately much larger, of the order of 11% off summer peak, and 18% off winter peak. Some confidence in these relatively large demand savings at this utility is afforded by the fact that the demand model was derived for this particular utility. In retrospect, it is reasonable to find the savings for the peak driving heating/cooling efficiency measures concentrating at the peak times. It is noteworthy to find that reasonably significant peak savings can proceed from much less significant energy savings.

The same modeling also illustrates how utility peak loads can grow unexpectedly large in the shadow of only moderately poor equipment efficiency.

Conclusions

A relatively simple model can be devised to estimate hourly load for a utility, and to estimate changes in this load due to individual measures or packages of utility programs.

The principal attribute of such a model is that it has been trued up to the actual energy use and load observed at that particular utility, thereby empirically recognizing and including important physical distinctions (such as high resistance heat usage).

The principal application for this modeling process is to support a coherent estimate the 8760 load impact for a utility energy efficiency program or group of programs. But an even more important application is to inform the perspective regarding the value of various efficiency measures.

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