City/CUB Exhibit 2.1

Study of the Correlation between Usage and Demand for Non-Space Heat Residential Consumers of ComEd

Executive Summary

1. Analysis of data provided by ComEd demonstrates that distribution cost is not driven by the number of ratepayer accounts and that all of the distribution costs should be allocated on the basis of energy usage.

2. Temporary low usage caused by unoccupied apartments and single family homes does not support the conclusion that no amount load is correlated with usage, but is correlated with the existence of a consumer account. The same is true for low use caused by home vacancy due to vacations.

3. Load factors tend to be better for low use consumers than for high use consumers in the residential class, when correctly measured on a coincident peak or on a class basis.

4. ComEd's load research data contains many errors and biases that maybe increasing costs to residential consumers by a large margin.

5. There have been dramatic changes in the multi-family load factor used in ComEd's cost studies over the years, which have increased cost allocation and prices to the class.

6. The load factor for multi-family consumers is more than 39% inside the City of Chicago while it is about 32% outside of the City. The load factor of single family consumers is also higher inside the City than outside the City, although there are biases in ComEd's measurement of City of Chicago single family loads, which makes the comparisons less rigorous. The difference in load factors implies that outside city consumers should be allocated 23% more distribution cost than City consumers.

Objectives of the Analysis

Flaws in ComEd's Residential Usage Study (ComEd Exhibit 2.33) can be demonstrated by constructing an objective analysis derived from statistical evaluation of usage and load research data. The basic propositions that should be tested in an objective analysis of demand and usage include the following:

1. What is the correlation between maximum energy usage in an hour, day or month relative to the average energy usage over a year (*i.e.* how much of the variation in peak demand can be explained by variation in average use)? This correlation between alternative measures of demand and energy use can be tested by performing statistical analysis of demand and energy for individual consumers or alternatively by examining the correlation for groups of consumers. Because of differences in the relationship between usage and peak across individual consumers, the discussion below demonstrates that it is better to evaluate the correlation by creating consumer group increments according to usage level and then correlating demand and energy for the usage level groups.

2. If there is some randomness in the relationship between usage and demand across individual consumers, should this randomness be attributed to the existence of a ratepayer account? This issue involves whether some of the variation in demand is explained by usage and other variation is explained by the simple presence of a ratepayer account. The question of whether some variation in demand is completely independent of usage can be tested by arranging ratepayers into different usage groups as described above, and then evaluating the level of the intercept in a regression equation. The reason this analytical approach (aggregating consumers into groups and then running a regression equation on the usage groups) addresses the issue of whether any randomness in demand comes from the existence of a customer account is demonstrated through modeling alternative relationships using Monte Carlo simulation.

3. What is the load factor for groups of consumers with different usage levels? If the proposition of ComEd is correct (the proposition that usage is independent of load), then the load factor (average use divided by peak use) of large consumers should be much higher than the load factor for small consumers since the average use would be higher and the peak use would be independent of average use. On the other hand if the load factor is constant across usage or even decreases with usage, then it is highly inequitable to charge higher prices for distribution equipment for consumers with low usage levels. In computing load factor it is important to use the coincident peak or the class peak, and not the peaks of individual consumers.

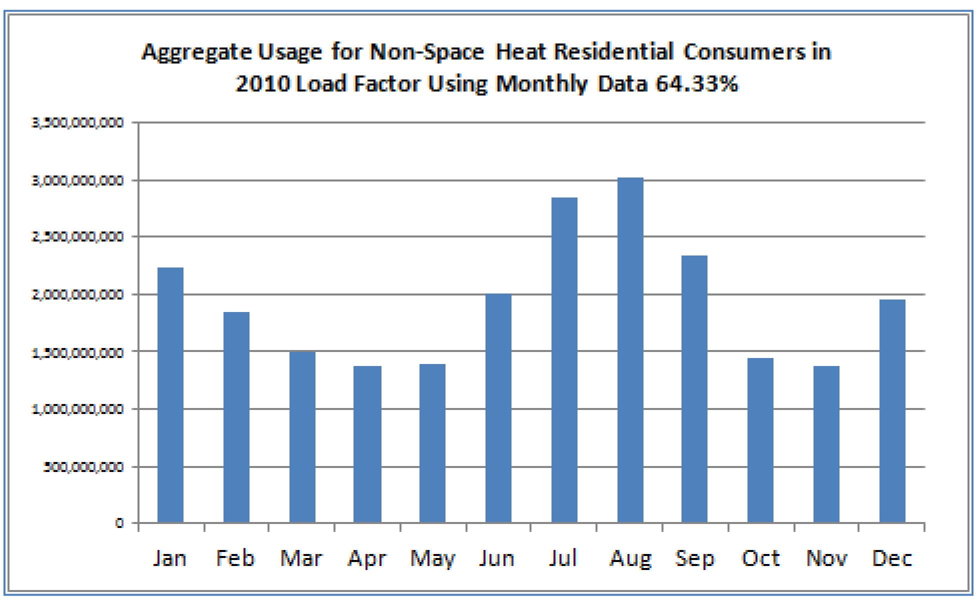
4. Can randomness in the relationship between peak load and usage that arises from home vacancy when moving or from vacations correctly be attributed to a customer account rather than usage?

Part 1: Analysis using Comprehensive 2010 Data for Non-Space Accounts

ComEd has provided monthly usage data for virtually all of the individual ratepayers for the year 2010. This data can be used to test the relationship between usage during the peak month and usage over the course of a year. In analyzing the data, only the non-space heat consumers have been selected, as space heating involves a fundamental difference in the manner in which electricity is used. While the monthly data for non-space heat consumers provides a general indication of peak usage relative to average usage, the monthly usage data cannot be used to evaluate the relationship between energy usage in the peak hour and average energy use over the year. The analysis of average usage relative to peak hourly usage is presented in part 3 below.

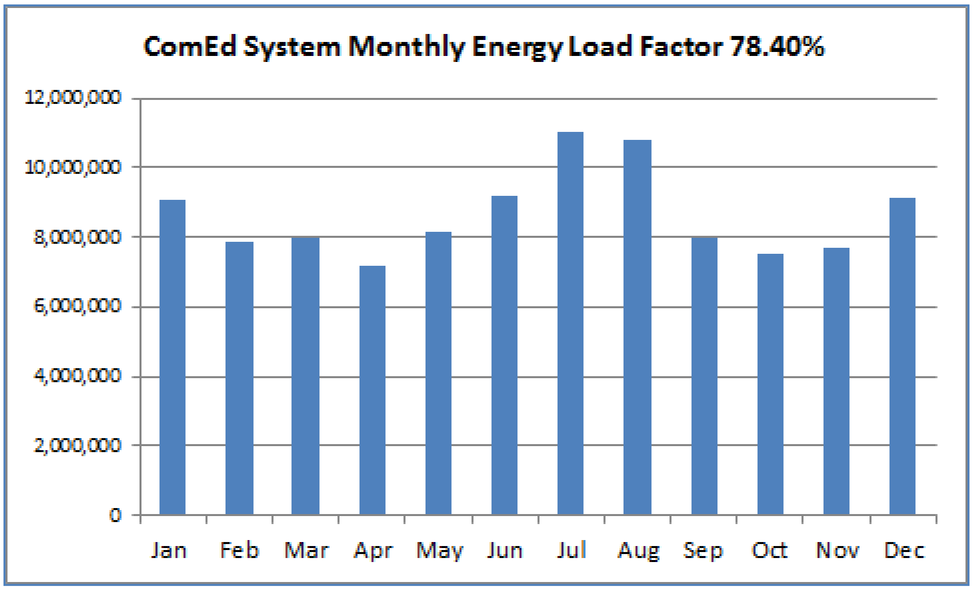
In 2010 the maximum aggregate usage across the non-space heat residential class occurred in the month of August as shown in the graph below. Relative to peak usage in August, average use across the year was 64% of the usage in the highest month. The 64% statistic can be termed a load factor. (Any load factor is defined as some level of average use over an extended period divided by some definition of maximum use during a shorter period.) In the context of the monthly usage data, the load factor can be defined as:

Load Factor from Monthly Usage Data = Average Monthly Use/August Monthly Use



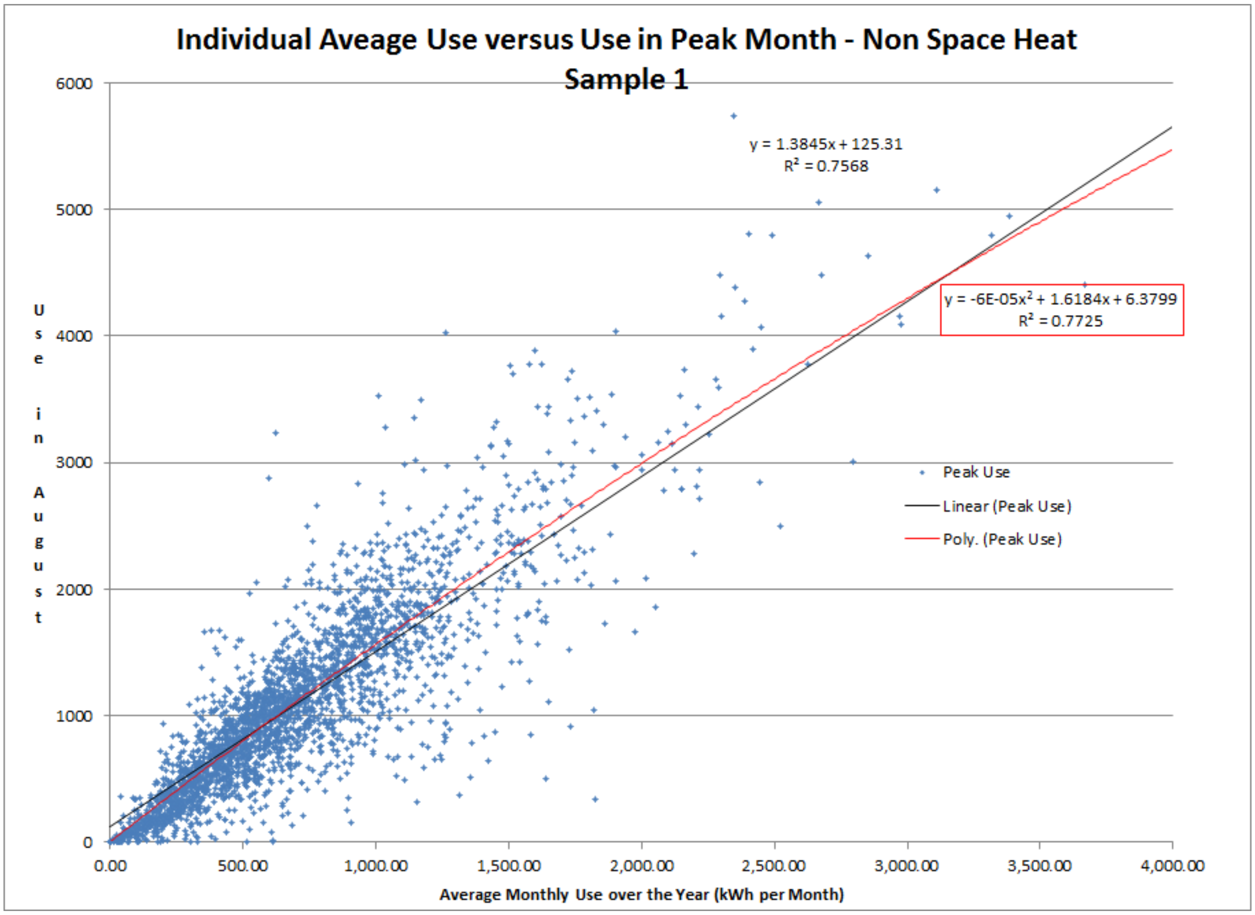
The aggregate residential usage data can be compared to energy usage on the entire ComEd system, including all non-residential as well as residential consumers. For the entire ComEd system in 2010, the load factor was 78.4% and the month with the maximum peak occurred in

July. (Hourly data from the PJM website was used for this analysis.) For the entire system, the peak load occurred on August 12 at 5:00 PM. Given that the peak usage month was August for residential consumers and because the peak hour occurred in August, the peak month for analysis below is defined to be August.



Average Annual Use and August Monthly Use for Individual Ratepayers

The relationship between average customer use over the whole year and use during the month of August provides a general picture of the correlation between usage and demand. To evaluate this relationship I have constructed scatter plots of the average use and the peak use for various samples of consumers using the 2010 usage data. (I was unable to make a graph of every consumer because of the volume of the data and because the graphs with very large density do not show overlapping points.) In presenting the scatter plots, I have included lines that fit the data as well as the R-squared, which measures the percent of variance in the peak load that can be explained by variance in usage.



The scatter plot data demonstrate the following:

1. The correlation coefficient between average use and maximum use is about 87% (the square root of the 77% R-squared). This suggests that about 13% of the standard deviation in peak load for individual ratepayers cannot be explained directly by an equation where each consumer is assumed to have the same relationship between peak and average load.

   The correlation of less than 100% may come about because different ratepayers have different use/peak relationships. For example, consumer A may have an equation where Peak = 1.5 x Average Use while consumer B has a relationship that is characterized by Peak = 2.5 x Average Use. I term this the consumer peak/use relationship in the discussion below. To the extent that consumers have different peak/use relationships, they appear as dots away from the fitted lines in the graph. Further, if an apartment is vacant during the summer months, then the average use may be high but the peak use would be almost nothing. Other factors that explain why the correlation is not 100% include situations such as when a family is away on vacation for much of August. In this case the peak load would seem to be low relative to the average use and the dot would be below the trend line. The important point in the context of the propositions tested is whether the correlation of below 100% implies that some of the peak demand is caused by the simple existence of a customer account. Randomness caused by different peak/use relationships or vacations does imply that the relatively smaller unexplained variation on the graph could be caused by individual consumer accounts.

2. Given statements in the ComEd Residential Usage Study that consumers who have low use may suddenly have high use during peak periods (for example in the part of the report that discusses vacation homes), one would expect many dots to occur where average usage is low but peak usage is high. These dots would appear in the upper left hand quadrant of the graph. The graphs above demonstrate there are not many points in these areas and demonstrate that ComEd's anecdotal stories have virtually no impact whatsoever in the context of the entire sample.

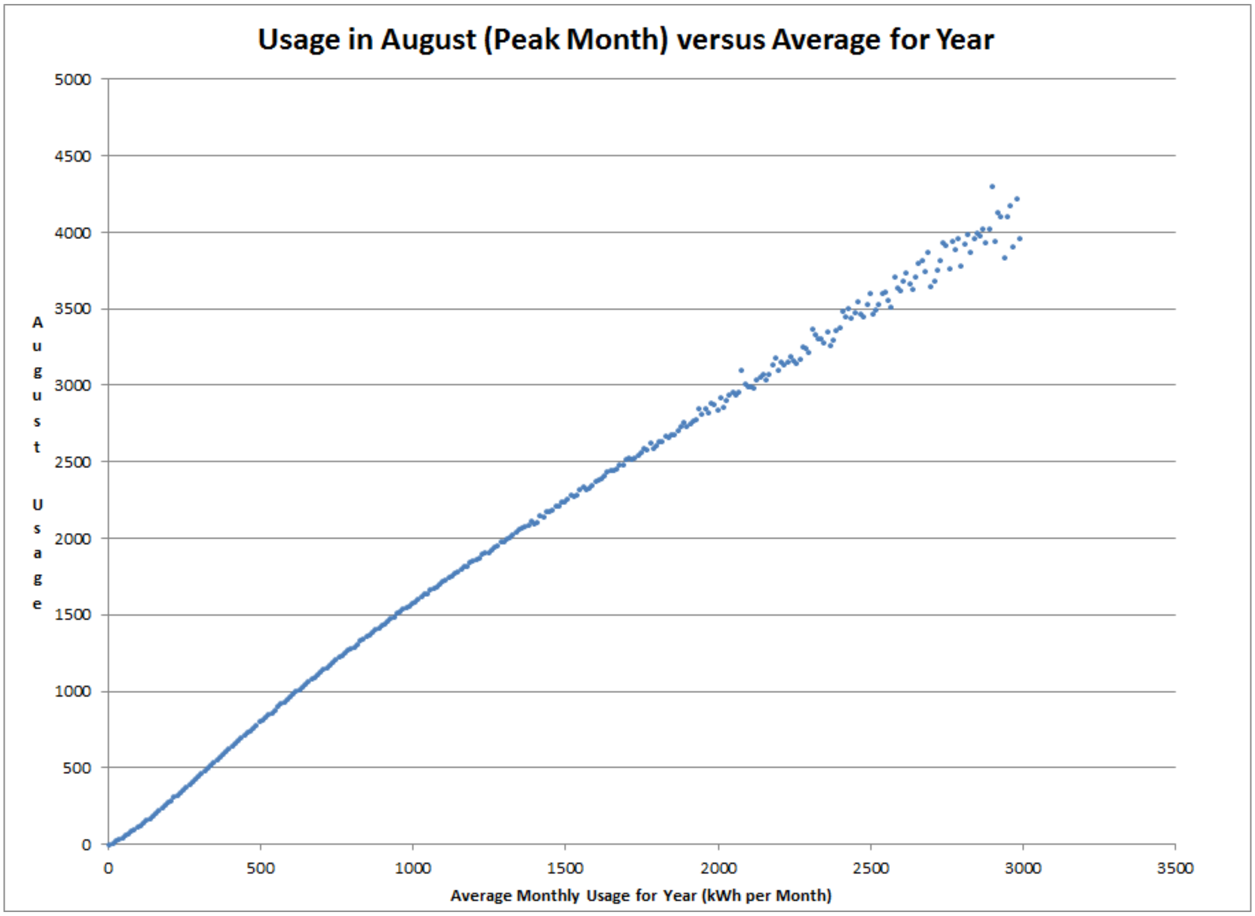
3. If part of the peak load was due to the presence of a customer account and not related to average use, then one would expect that the intercept on the graphs (where the trend line crosses the y axis) to be clearly positive. In the extreme case where peak use is unrelated to average use, the intercept would be the average value of the peak use. To illustrate this point, consider an example where a house is divided from one ratepayer into two ratepayers with the average use cut in half. The graphs above look nothing like what would occur if average usage were entirely unrelated to peak usage. As explained below, because load factors tend to be better for low use consumers, the relationship between peak use and average use is best represented by a polynomial equation. The graphs above show that when a polynomial equation is used, the intercept is approximately zero (it may not be exactly zero because of mathematical specifications of the relationship between peak and average use.) As explained in the simulation analysis below, an intercept of zero implies that none of the variation in peak load can be explained by the simple existence of a customer account.

Average Annual Use and August Monthly Use for Ratepayers Aggregated by Usage Group

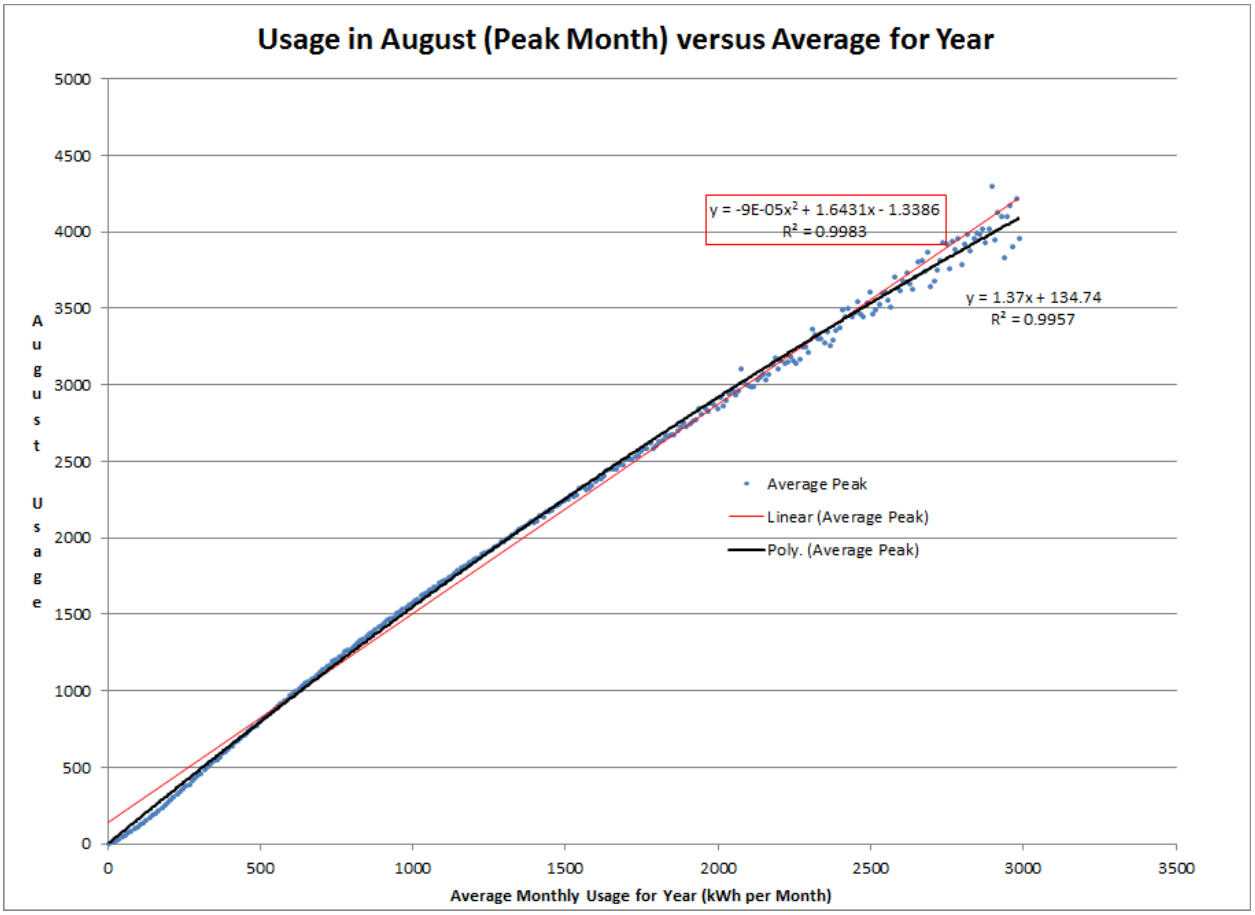
To further test the relationship between average usage and peak month usage, the average usage data for each consumer was categorized into 10 kWh per month increments. For each 10 kWh per month increment the sum of the average annual use and the sum of the August monthly use was computed. After summing the data, the average annual use and average use for the peak month were calculated. For example in the monthly usage increment between

490 and 500 kWh per month there were 27,000 accounts and the average usage was 485 kWh per month while the peak was 782 kWh per month. The process of averaging use by small increments corrects for situations such as the vacant apartment or the vacation scenarios discussed above. For example, if one apartment is vacant in August and another in January and a third in March, then after the data is aggregated, the distortions in individual accounts are eliminated. One can then evaluate whether such vacancies cause low use categories to have a different use/peak relationship relative to high use categories. Similarly if different ratepayers have different peak/usage relationships, but all of the consumers have a positive usage/peak relationship, the differences tend to be averaged out. In that circumstance, the remaining variation in peak use that is not related to average use can be attributed to random variation associated with the simple existence of an account.

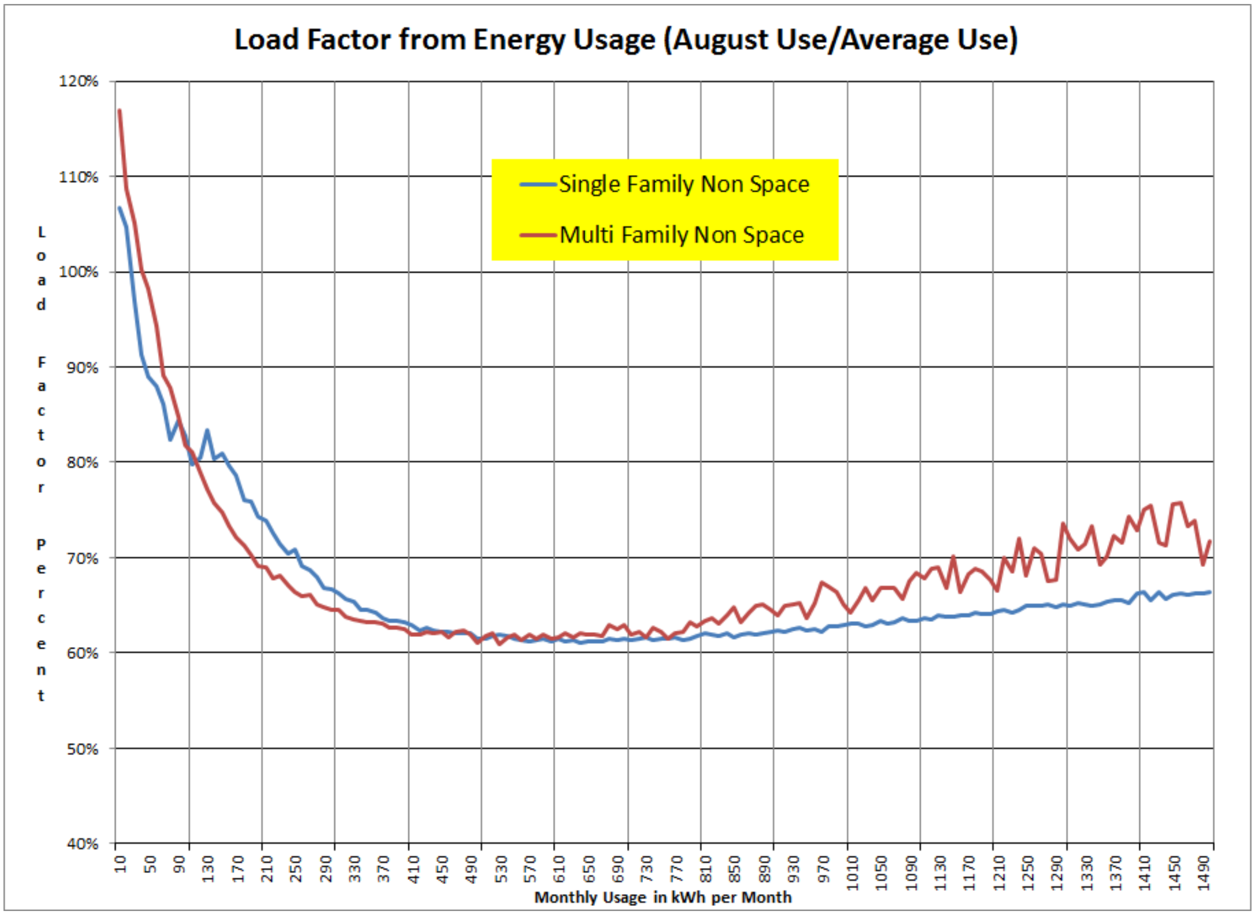
The first chart below shows a scatter plot of the average annual usage and the peak usage for the various 10 kWh usage increments. Note that after aggregating individual consumers into small usage groups virtually all of the randomness goes away. This implies that different consumers have somewhat different usage/peak relationships, but that over multiple consumers these differences average out. More importantly, the fact that the graph crosses the y-axis at zero demonstrates that there is no variation in peak demand that can be explained by the simple presence of a customer account. Reasons for the differences in scatter plots for individual customer accounts relative to the scatter plots with aggregated accounts are explained in the simulation analysis below.



When fitting a line to the data above, it is apparent that the relationship between average usage and usage during the peak period does not follow a simple straight line. For the low usage increments (below 500 kWh per month) there is relatively less peak usage than for the higher usage increments. For extremely high use increments (above 2,500 kWh per month) this relationship of the peak to the usage declines. The graph below shows that when a polynomial equation is fitted to the data the correlation as measured by r-squared is 99.83%. The high correlation, combined with the fact that the line crosses they-axis at zero, demonstrates that there is effectively no peak use that can be explained by the existence of a ratepayer account.



The fact that the relationship between peak monthly use and average use does not follow a straight line can be translated into different load factors. The graph below shows that load factors are higher for low use categories until the monthly usage reaches 500kWh per month. Then, after falling and hitting a plateau, for usage levels of more than 900 kWh per month the load factor begins to increase. The pattern of load factor can be explained by low use consumers being very careful with electricity and using limited electricity for air conditioning. On the other hand the somewhat improved load factor for very high use consumers can be explained by very high use of appliances other than air conditioners over the course of the year. To the extent that load factors are higher for low use consumers, this graph directly contradicts the practice of setting the price of distribution through fixed customer charges. Because the customer charges impose higher prices on low use consumers, ComEd's pricing policy could only be justified if the load factor would increase as usage level increases. It does not.



Part 2: Monte Carlo Simulation that Demonstrates Why Use of Consumer Groupings is Appropriate in the Analysis

A central question in the above analysis is the statistical issue of whether load and usage analysis should be evaluated by the scatter plots for individual consumers or, alternatively, whether it is better to draw conclusions from the analysis where usage groups are tabulated. This and other questions can be answered through constructing a simulation model of consumer behavior. The simulation model of consumer behavior is particularly useful in this context because one can directly test the ComEd hypothesis that peak demand is not related to usage. Further one can test the more reasonable question as to whether some of the variation in peak demand is related to the mere existence of a ratepayer account and some is related to usage.

The simulation model of consumer behavior creates an equation that incorporates random variation due to alternative factors such as the presence of a ratepayer account or different demand/usage relationships. Then it presents the statistical results – scatter plots and regression equations that result from equations that represent the various possible drivers of load such as ratepayer accounts or usage. If the simulated results are completely different from the actual analysis shown above, then one can reject the hypothesis that the underlying equation that modeled the data is correct. On the other hand if the modeled data generates analogous individual and grouped graphs, as shown in the above analysis, this confirms the underlying structure of the assumed model in the simulation.

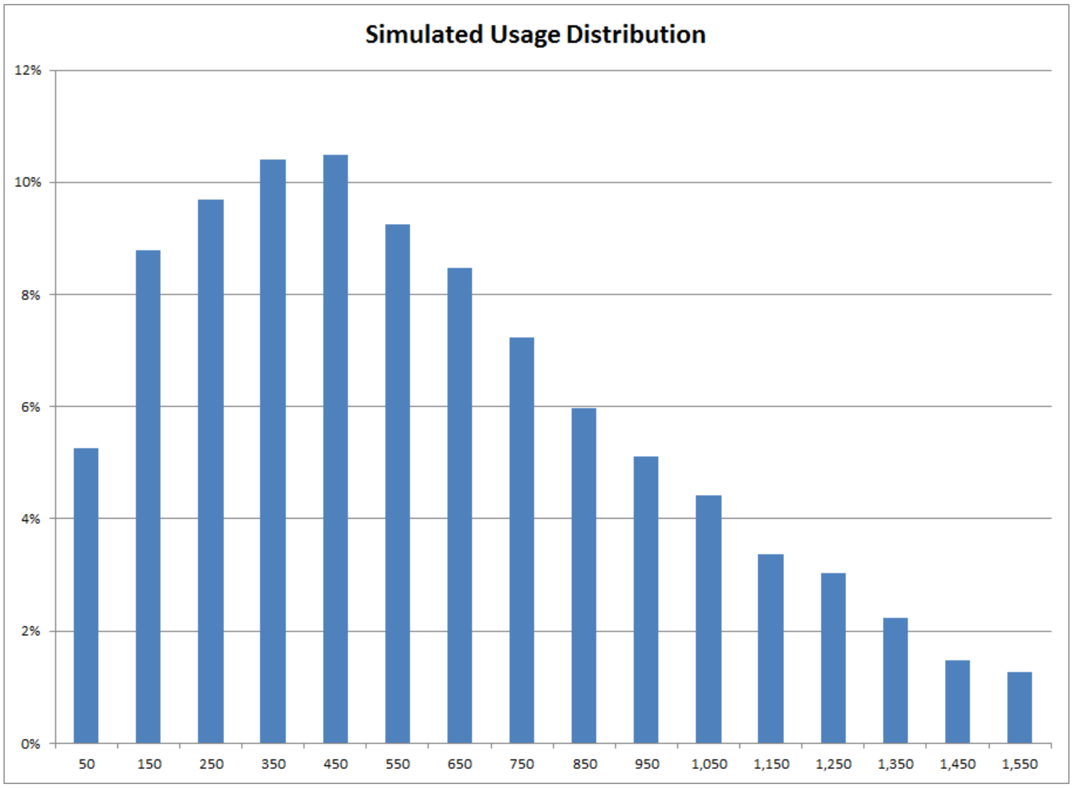
The simulation process can be described by the following three step process:

Step 1: Construct an equation of electricity demand that allows for random variation that can be created from deviations in demand/usage relationships, presence of ratepayer accounts, vacancies during on and off peak periods, and so forth.

Step 2: Simulate randomness in the demand resulting from the equation through performing multiple random draws and filtering the random draws through a normal distribution or a Wiebull distribution.

Step 3: Perform statistical analysis on the simulated outcomes in the same manner as the analysis above and evaluate whether the output (scatter plots) are consistent with the actual data.

For each consumer behavior model, average usage is simulated using a Wiebull distribution. The Wiebull distribution yields a probability distribution that can be skewed to the right. This probability distribution can be used together with random draws to simulate thousands of different values for consumer use. An example of usage distribution resulting from this process is shown in the graph below.



In using simulation, alternative models of consumer behavior were tested. The series of models assumed variously that (1) usage is independent of demand (ComEd's hypothesis); (2) some of the variation in demand comes from ratepayer by ratepayer demand/usage variation, but some demand variation is independent of usage and implicitly driven by the simple presence of a consumer account (a more reasonable version of ComEd's hypothesis); (3) demand is driven only by usage and includes random variation across individual consumers in the demand/usage relationship; and (4) variation in demand comes from both demand/usage variation as well as variation caused by consumers not using demand at the peak and consumers not using demand during off peak period periods. The last case is intended to represent vacation homes and vacancies in the occupancy of apartment buildings.

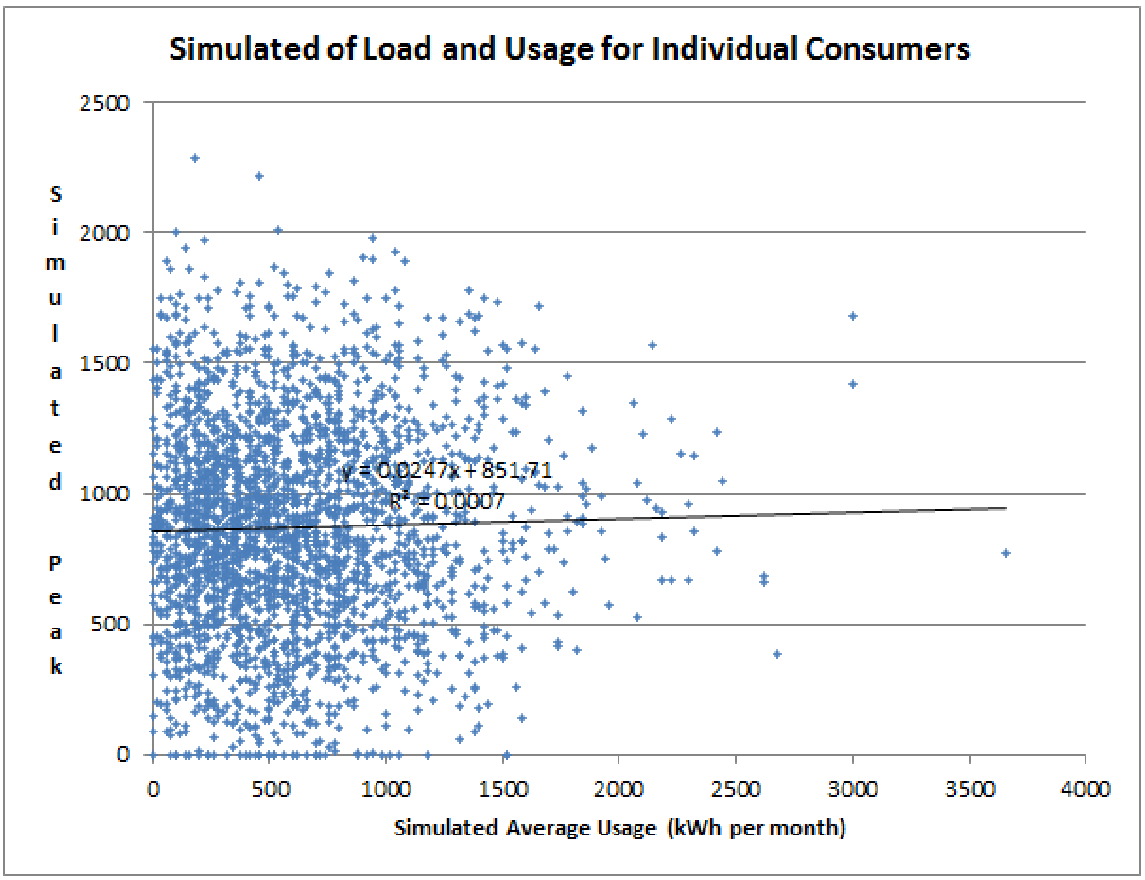
Case 1: No Relationship between Demand and Usage

To create a model where there is no relationship between demand and usage the following equation structure can be used:

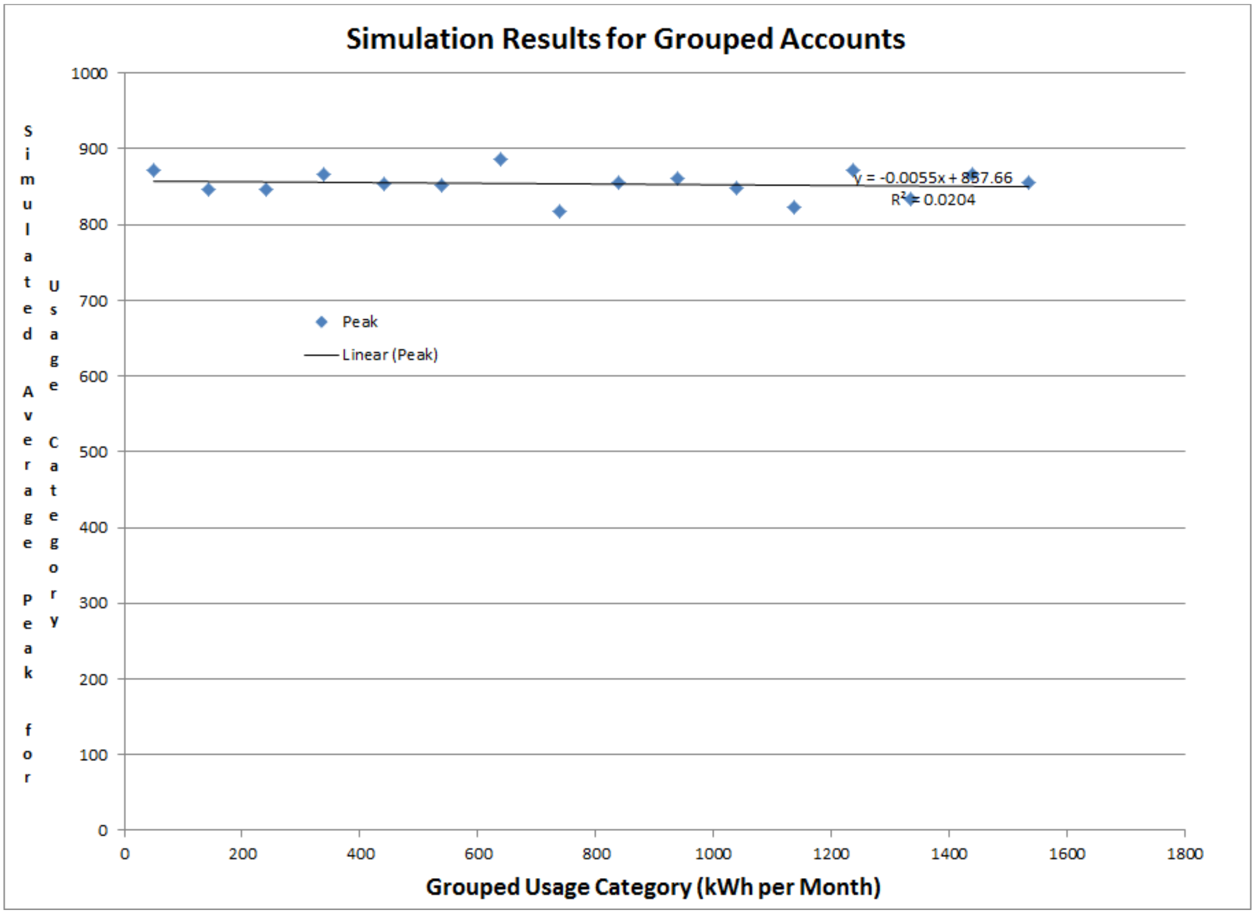
Demand = Constant Demand x Random Factor + Usage x 0

Constant demand is assumed to be 850 kWh per month with a standard deviation of 400 kWh per month.

In this case the usage has no influence on the demand because the usage coefficient is zero, but there is variation in demand that is just random. The random variation is modeled with a normal distribution that yields a demand level that can be above or below the assumed constant of 850 kWh per month. Usage over the course of the year has nothing at all to do with the level of the peak demand as in ComEd's repeated vacation home anecdotes. The results of this case in terms of individual scatter plots (shown below) look nothing at all like the actual data that was presented in the previous part of the report. For the individual accounts, there is no correlation and nothing close to the notion of a zero intercept. Instead, the intercept is simply the average level of demand.



For the scatter plot of grouped usage, there is no positive correlation and the intercept is again the level of the average demand. The grouping of accounts does remove the random variation associated with different demands for individual consumers. As with the scatter plot for individual consumers, the graph looks nothing at all like the scatter plot generated from actual data. The simulation demonstrates that any supposition that average usage is not related to peak usage can be clearly rejected using results from the analysis of the 2010 database. The simulation confirms that a suggestion that usage is not related to demand is simply absurd.

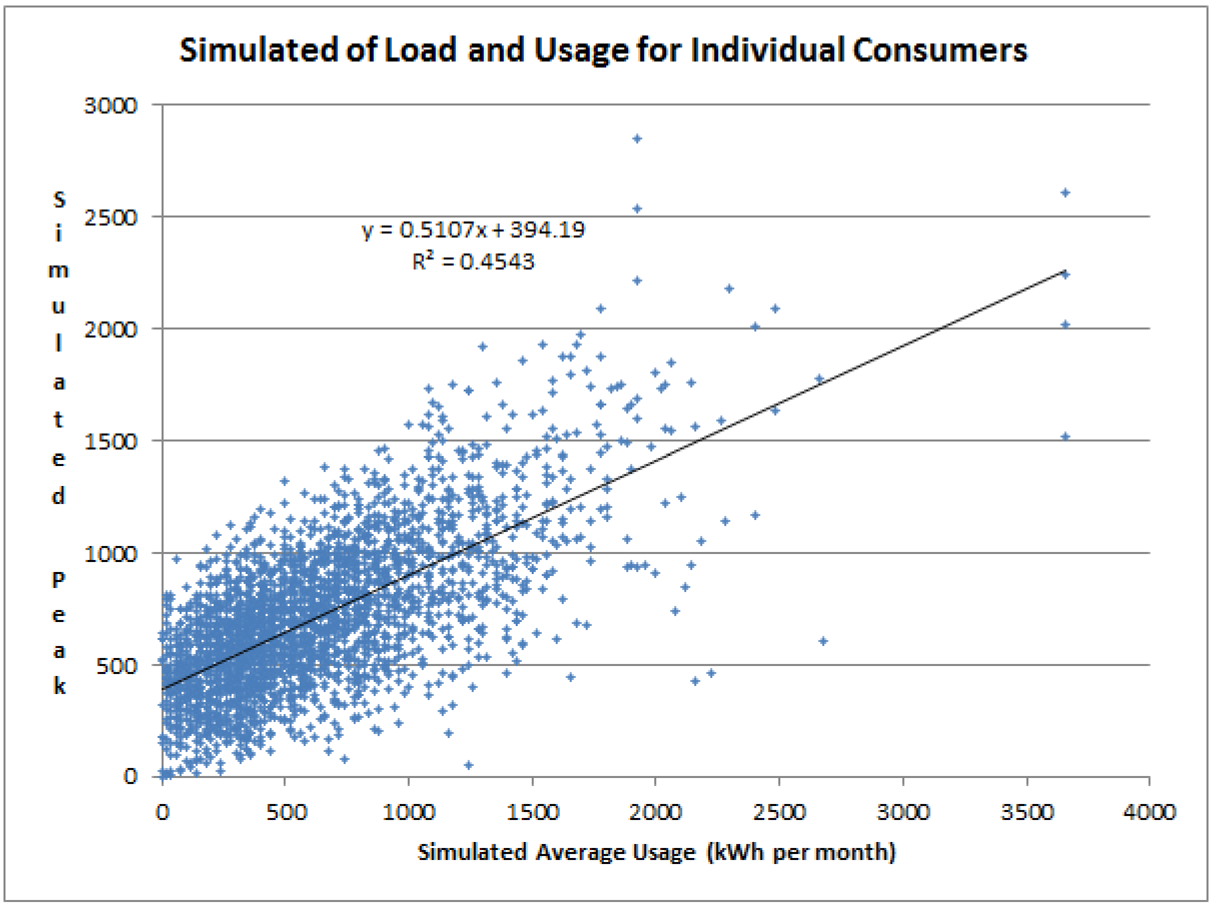


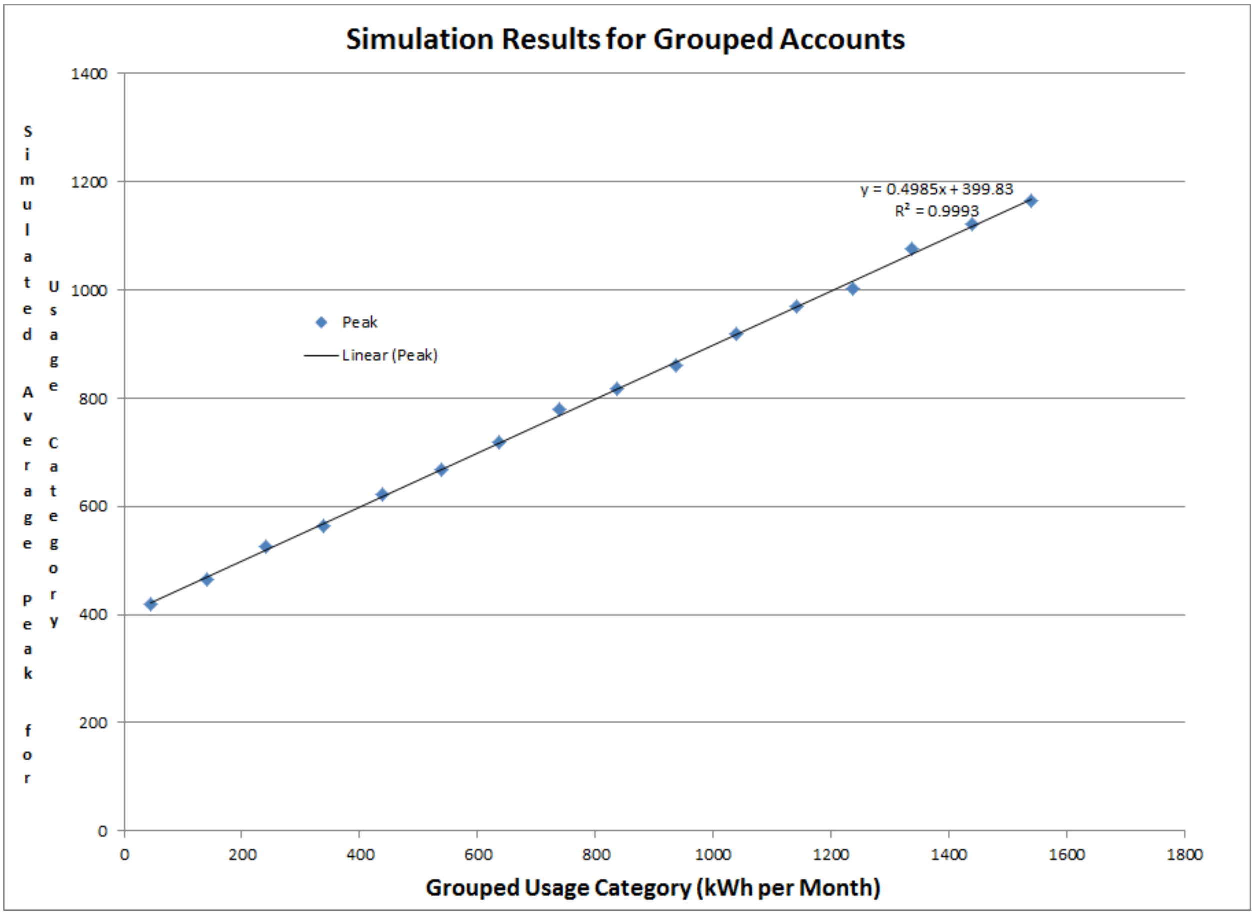
Case 2: Demand Variation from Both Ratepayer Accounts and Usage

In the second case some of the demand is a function of energy usage over the year and some is fixed and independent of usage as above. Both the fixed level and the relationship with demand are random variables, meaning that each consumer can have a different equation. In the second case the relationship with demand can be written as:

Demand = Constant Demand x Random Factor + Usage x (Usage Coefficient x Random Factor)

In this equation the constant demand is assumed to be 400 and the usage coefficient is assumed to be .5. Both the usage and the demand have random variation, meaning that some consumers may have a coefficient of .3 and others of .7. The variation is driven by the assumed standard deviation of .2 in the usage coefficient and the standard deviation of 200 kWh per month around the constant. The graph below shows that the individual scatter plot looks more like the actual data except that the correlation is only 45%, the intercept is not close to the value of zero, and the r-squared of 45% is less than the r-squared of about 77% for actual sample.



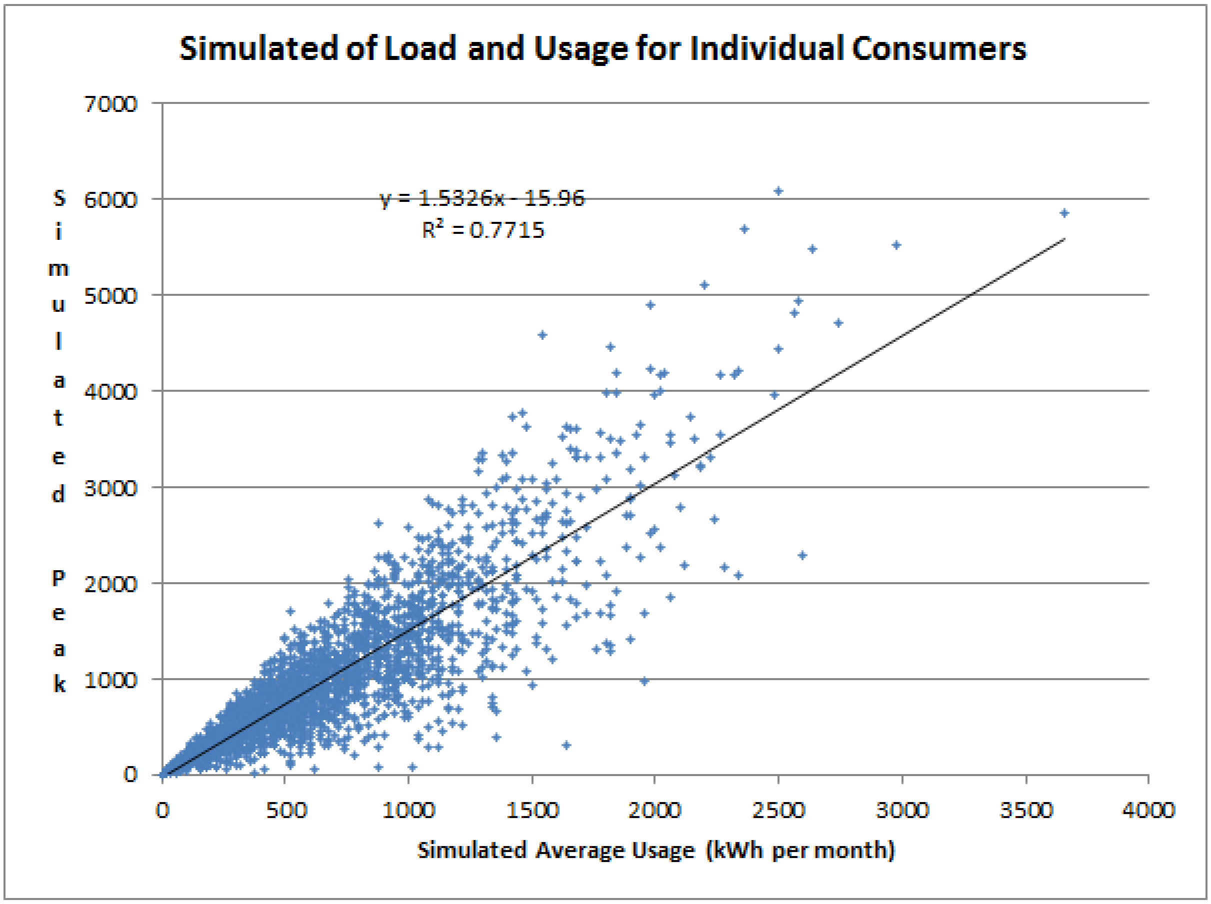


Case 3: Demand Variation from only Usage

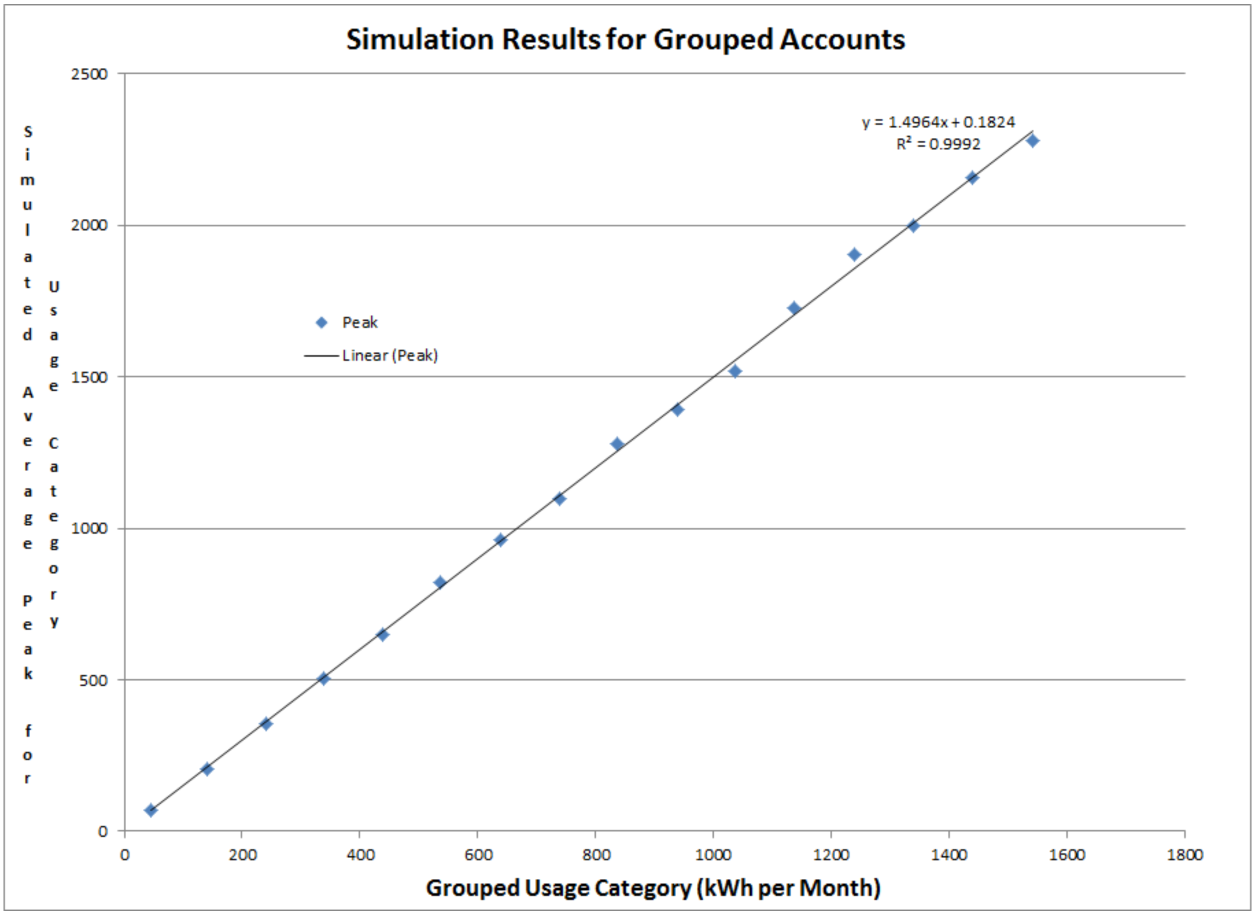
In the third case there is no constant term and the only variation in individual consumer demand is derived from: (1) the usage level and (2) random variation in the demand/use relationship across individual consumers. The equation for case three is:

Demand = Usage x (Usage Coefficient x Random Factor)

When randomness only comes from differences in the peak/use relationship, the simulated consumer behavior closely resembles the actual scatter plots presented in part 1. The first graph below shows that for individual simulated consumers there is a lot of variation around the fitted line. This graph shows that even though all demand variation is driven by usage, the R-squared is well below 100% because of randomness in the demand/use relationship across individuals. In this graph, the intercept term is very close to the origin, because when the usage level is zero, so is the demand.



For the simulation model where demand is not driven by random behavior unrelated to usage, the scatter plots with grouped usage and demand also resemble the actual data. The graph below shows that after the data are grouped, the intercept term is close to zero and the R-squared is close to 100%, as was the case for the case for the actual data. The simulation of this case, with no variation derived from consumer accounts, confirms that none of the demand comes from the existence of a ratepayer account and ComEd's theory that distribution costs should be priced on the basis of the number of accounts is not valid.



Case 4: Demand Variation from Usage, Vacancies and Demand Spikes

The final model of consumer behavior includes randomness in the peak/usage relationship across consumers as well as some of the anecdotes recited in the ComEd study. Other factors included in the model represent vacation homes and vacancies in apartments and other residences. Vacation homes are modeled by including a random dummy variable in .5% of the simulations where the average usage during the year is reduced by 90% but the peak demand remains the same. Vacancies are modeled by reducing the peak demand and holding usage at the same level. This is assumed to occur in 3% of the cases and cause an 80% reduction in demand. The consumer behavior can be represented by the following model:

Demand = Usage x (Usage Coefficient x Random Factor)

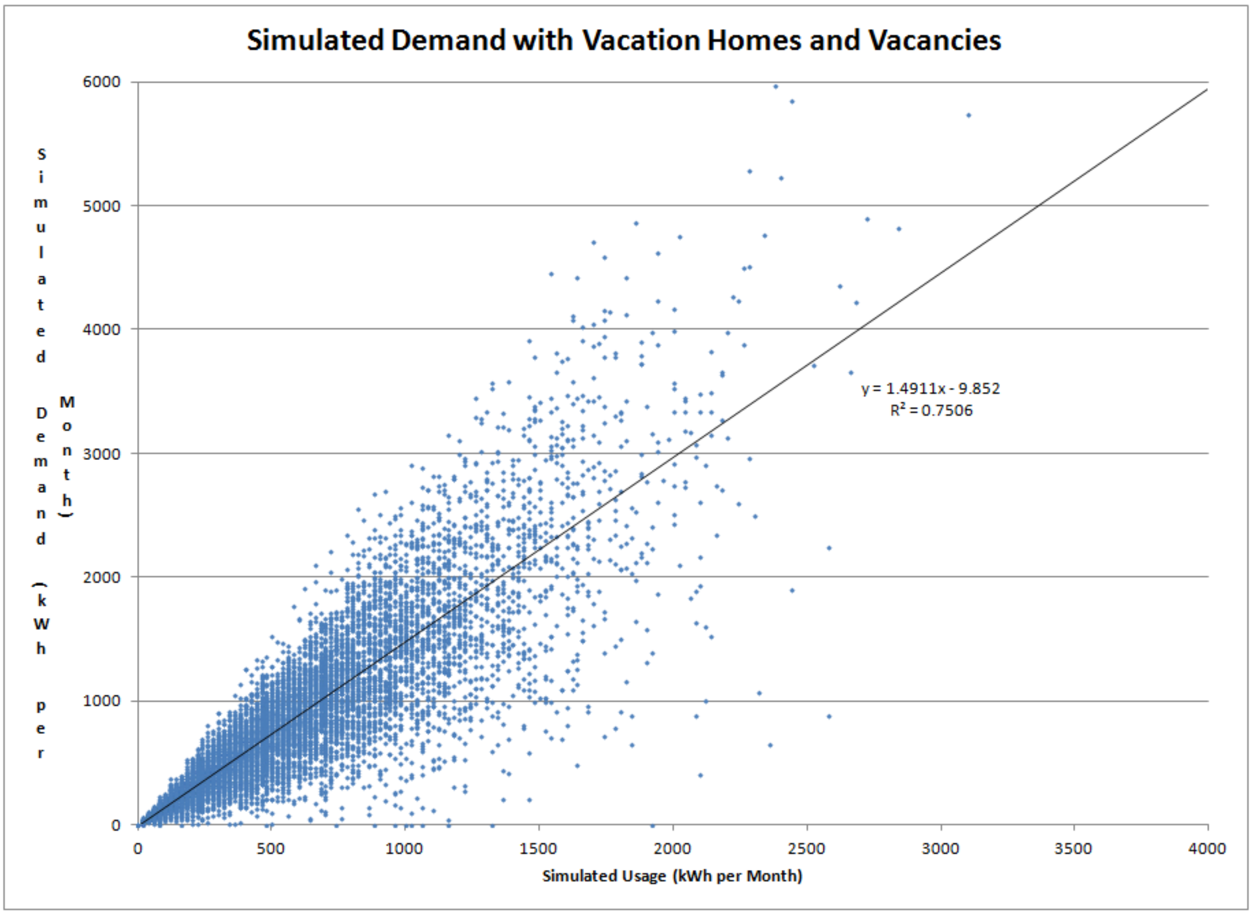
Where:

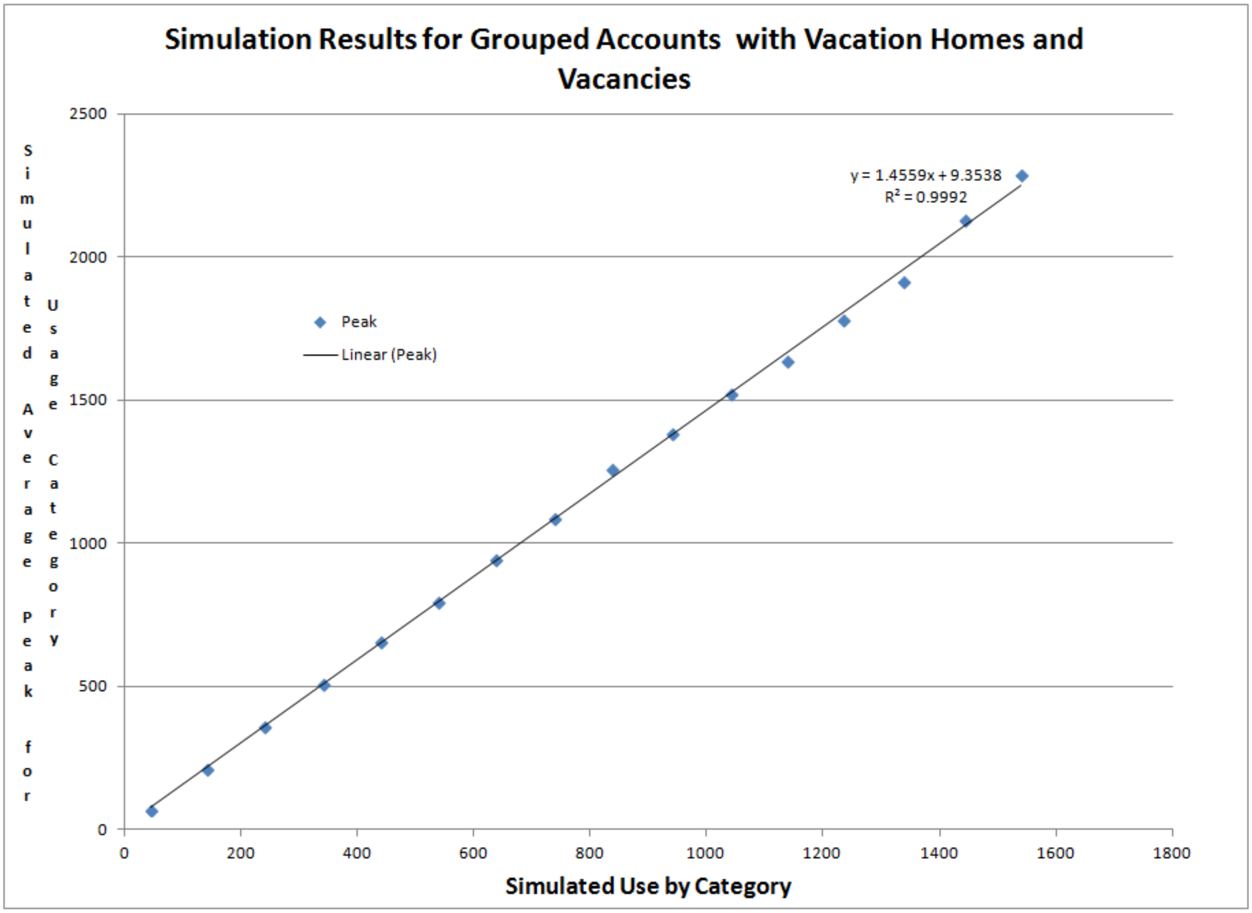
Usage = Base Usage - .9 Usage x Random Variable for Vacation

And:

Demand = Base Demand - .7 x Random Variable for Vacancies

Results of this case are similar to the third case and to the actual data. There is somewhat more variation in the scatter plots of individual consumers, but this variation is eliminated once the consumer groups are aggregated. Importantly, the inclusion of vacation homes and vacancies does not create an intercept term that is different from zero. This implies that vacation homes and vacancies do not create an argument for assuming that a portion of demand is associated with the existence of a consumer account.





Part 3: Load Research Data to Evaluate Peak Demand in Single Hours Relative to Average Use over the Year

In the final part of the analysis, detailed load research data for 2012 is used rather than the billing data for 2010. As with the billing data used in part 1, the analysis is only made for non-space heat consumers. Advantages of using the load research data is that it can evaluate single peak hours of demand rather than the average monthly demand used in the first section. In addition, the load research data can be used to measure load factors for various regions because the data includes zip codes. Disadvantages of using the load research data are that it includes far fewer consumers and there are problems with both the quality of the data and the representativeness of the sample.

In addition to using the load research data for evaluating ComEd's Residential Usage Study, review of the data can be used for other objectives. First, since the load research data is used as a driver in allocating loads across customer classes, problems with the data can have much larger implications than simply evaluating the use/load relationship. Second, as the load research data includes zip codes, the data can be used to evaluate the efficiency of use inside the City of Chicago and outside the City of Chicago.

Problems with Load Research Data

The load research data compiles hourly loads for a relatively small sample of consumers. As normal residential meters cannot tabulate hourly loads, the meters from the selected sample are used to compute the peak load for the entire residential class. If errors are made in the sample, then the results of the entire cost of service study are suspect.

In reviewing the load research data a few problems became apparent:

1. The data contained many missing values where there were no recordings for weeks at a time.
2. Many of the meter readings appeared to be simply repeated rather than constituting the expected time pattern of loads.
3. The sample of consumers was skewed in favor of high use ratepayers. As the high use ratepayers have worse load factors, this bias increases cost allocation to the residential class. The graph below that compares the distribution of load research data to actual accounts by usage increment demonstrates that the categories of 50 – 300 kWh are dramatically represented. These consumers tend to have the highest load factors.
4. The sample of consumers was skewed against consumers in the City of Chicago. As the City has a better load factor than other regions, this also creates a bias that increases cost allocation to the overall residential class.
5. The multi-family sample appears to use multiple accounts from a single building meaning that the sample is not really random.

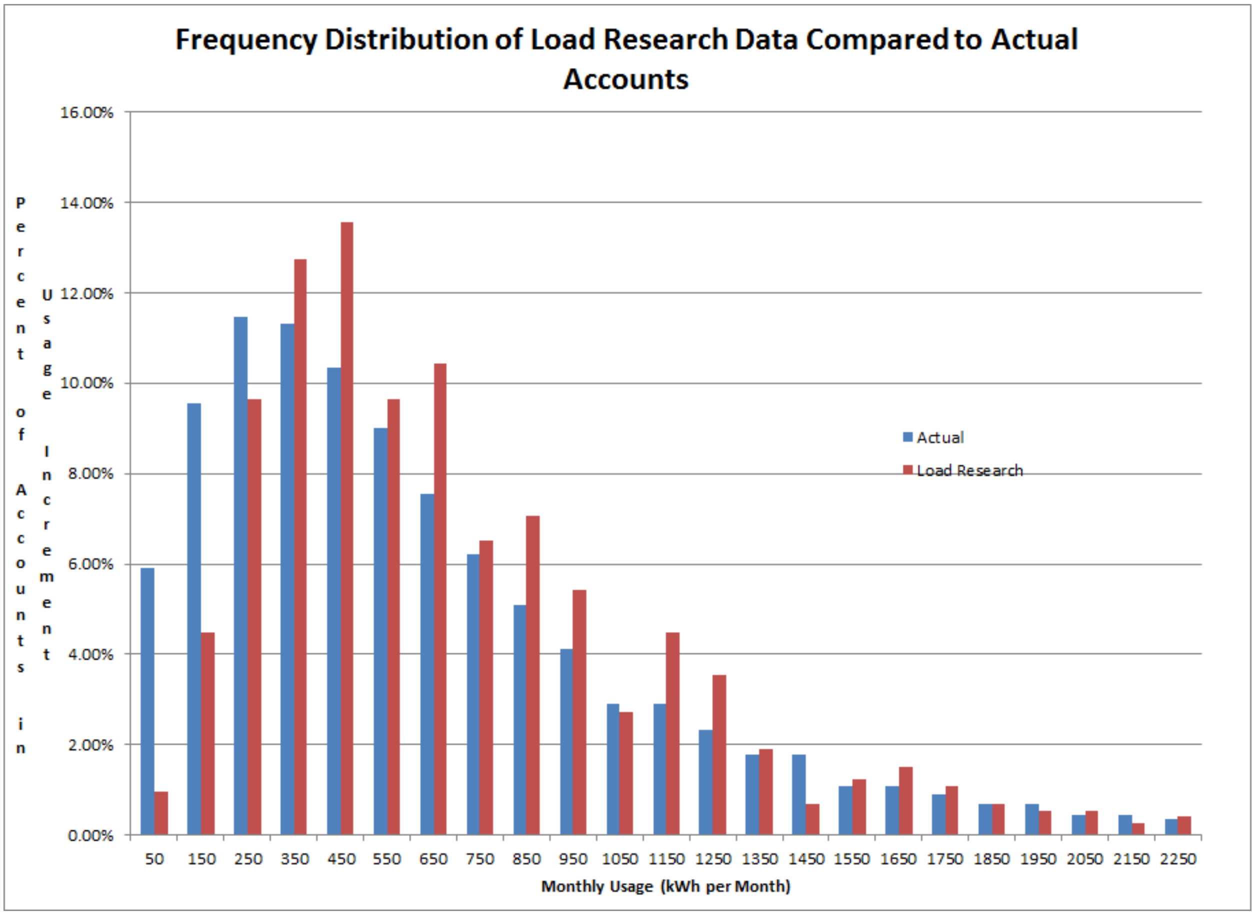
A few of the problems with ComEd's load research data are described below. (Because ComEd maintains that these anonymous data are confidential, I have removed from this report excerpted lines of data that show the actual problems with the data.) One type of problem is missing data. One example comprises ratepayer usage data that includes blank data cells for eleven consecutive days. Another problem type is the apparent repetition of data points. In one instance, several columns of usage data are exactly the same for a period of eighteen days.

The next figure shows how the City of Chicago is under-represented in the data. For example, there were only 26 non-space heat single family consumers sampled in the City, relative to the total customers sampled of 385. This means that the in terms of single family consumers, the

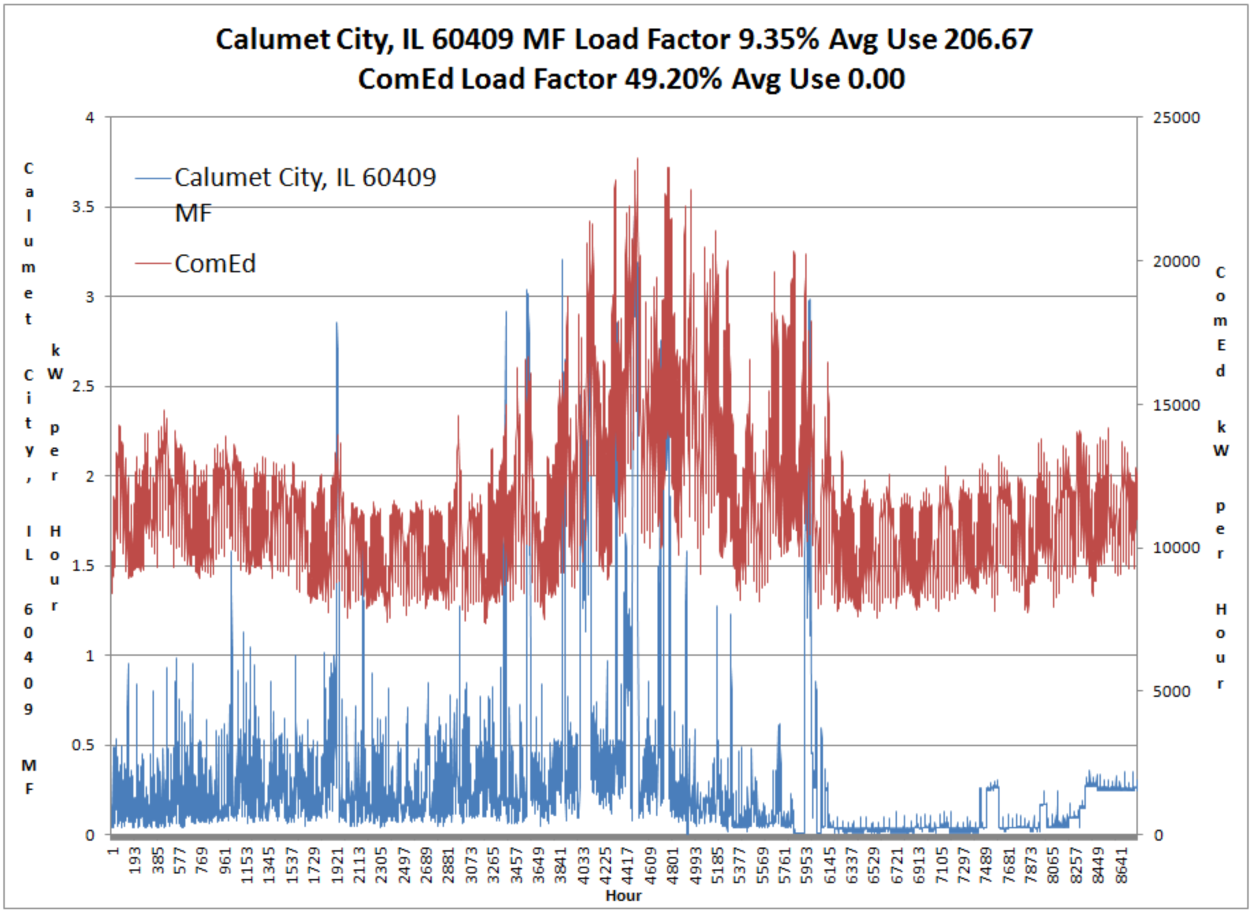
City represented only 6.75% of the sample, while the actual population percentage is 18.89%. The table below shows that there is a similar under-representation for multi-family consumers, although it is less dramatic.

	Single Family Chicago	Single Family Outside Chicago	Single Family Total	Multi-Family Chicago	Multi-Family Outside Chicago	Multi-Family Total
Annual Bills	421,813.58	1,810,878.75	2,232,692.33	610,137.58	432,374.58	1,042,512.17
Load Research	26.00	359.00	385.00	175.00	186.00	361.00
Percent of Actual	18.89%	81.11%		58.53%	41.47%	
Percent of Load Research	6.75%	93.25%		48.48%	51.52%	

The general under-representation of low use consumers in the load research study is illustrated on the graph below. The area under both of the distributions sums to one. The load research sample has far fewer consumers in the low use categories and over-representation in the 350-950 categories. This distortion could have quite a large effect on the allocation of costs to the residential class.

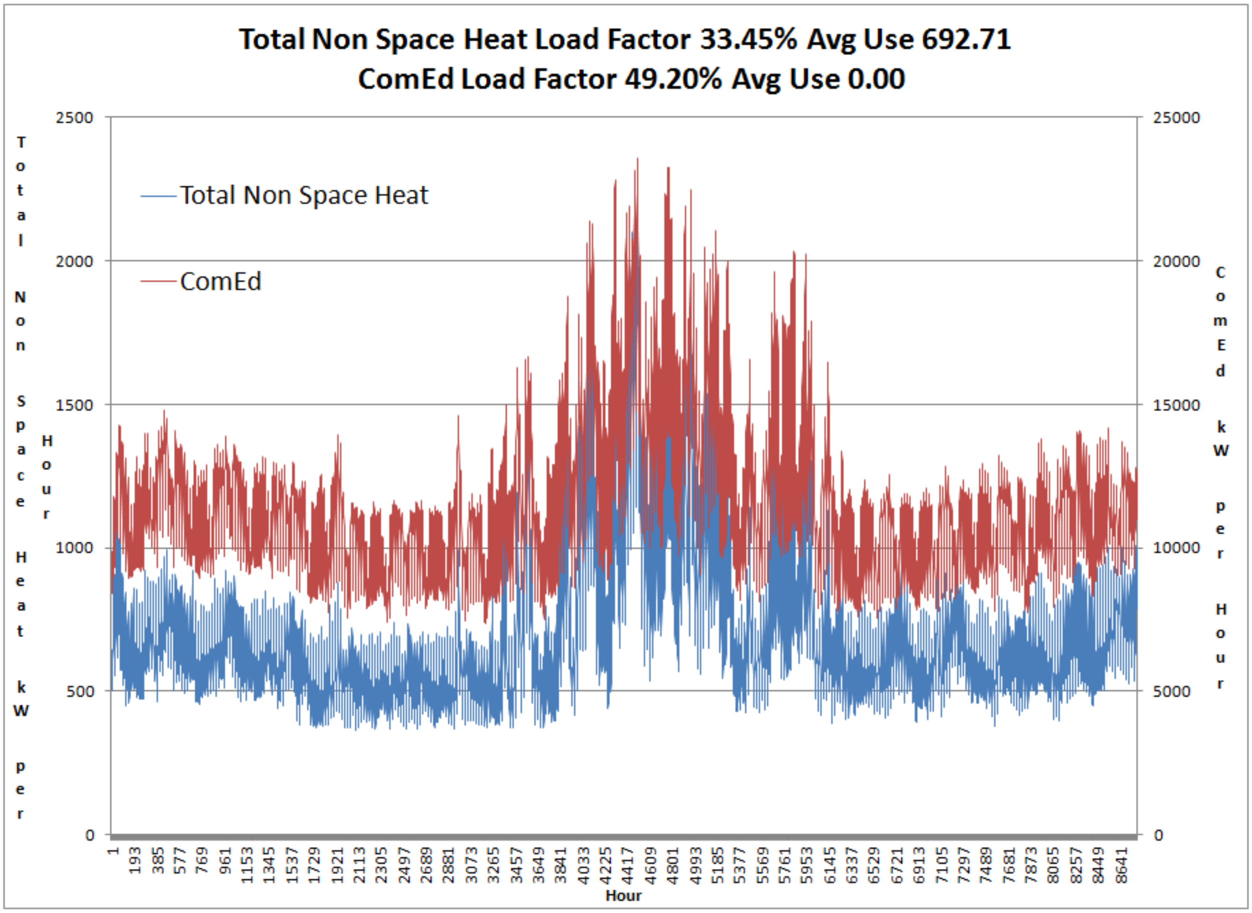


In reviewing the data we have created a graph that can display the hourly data for a selected consumer. The graph below compares aggregate hourly loads to one of the sample consumers from Calumet City. (There are 26 samples from Calumet City that appear to be part of the same apartment block.) In the graph below, there may have been a problem with the meter or alternatively the apartment may have been vacant.



Review of Aggregate Load Research Data

The graphs below review various different aggregations of the load research data. The first graph presents the aggregate loads for the entire ComEd system (for all classes) compared to the aggregate loads in the load research sample. In 2012 the ComEd peak occurred on July 6 at 5:00 PM. The load factor presented on the top of the graph is the average load over the year divided by the July 6th load. The residential load factor is only 33% compared to the overall load factor of 49% (the overall load factor for the system in ComEd's cost study is 46%).



To illustrate the importance of the load factor in cost allocation, the table below shows how much costs to the residential class are increased by virtue of having a lower load factor than for the overall system. If single family consumers had a load factor of 46% instead of 29% (the data in ComEd's ECOSS is different from the load research), then their costs would be reduced by 35%.

	Single Family 2013 Case	Multi-Family 2013 Case	Total System 2013 Case
Energy	20,471,628,554	4,425,830,554	88,042,754,289
Peak	7,804,759	1,646,277	21,687,840
Average Energy per Hour	2,336,944	505,232	10,050,543
Load Factor	29.94%	30.69%	46.34%
1/Load Factor	3.34	3.26	2.16
Peak to Energy with System Load Factor	2.16	2.16	2.16
Peak with System Load Factor	5,042,839	1,090,228	21,687,840
Percent Decrease in Cost from System Load Factor	35.4%	33.8%	100.0%

The second graph of this section shows the loads of the single family and multi-family non-space heat consumers. In ComEd's 1994 rate case, the multi-family load factor was dramatically different from the load factor used in the current case, as shown in the excerpt below, where the multi-family load factor was 54% and the single family load factor was only 31%.

demonstrates that multifamily customers have significantly higher load factors than single family customers. The different characteristics (between multi family customers and single family customers) are shown in Table 3 below.[13]

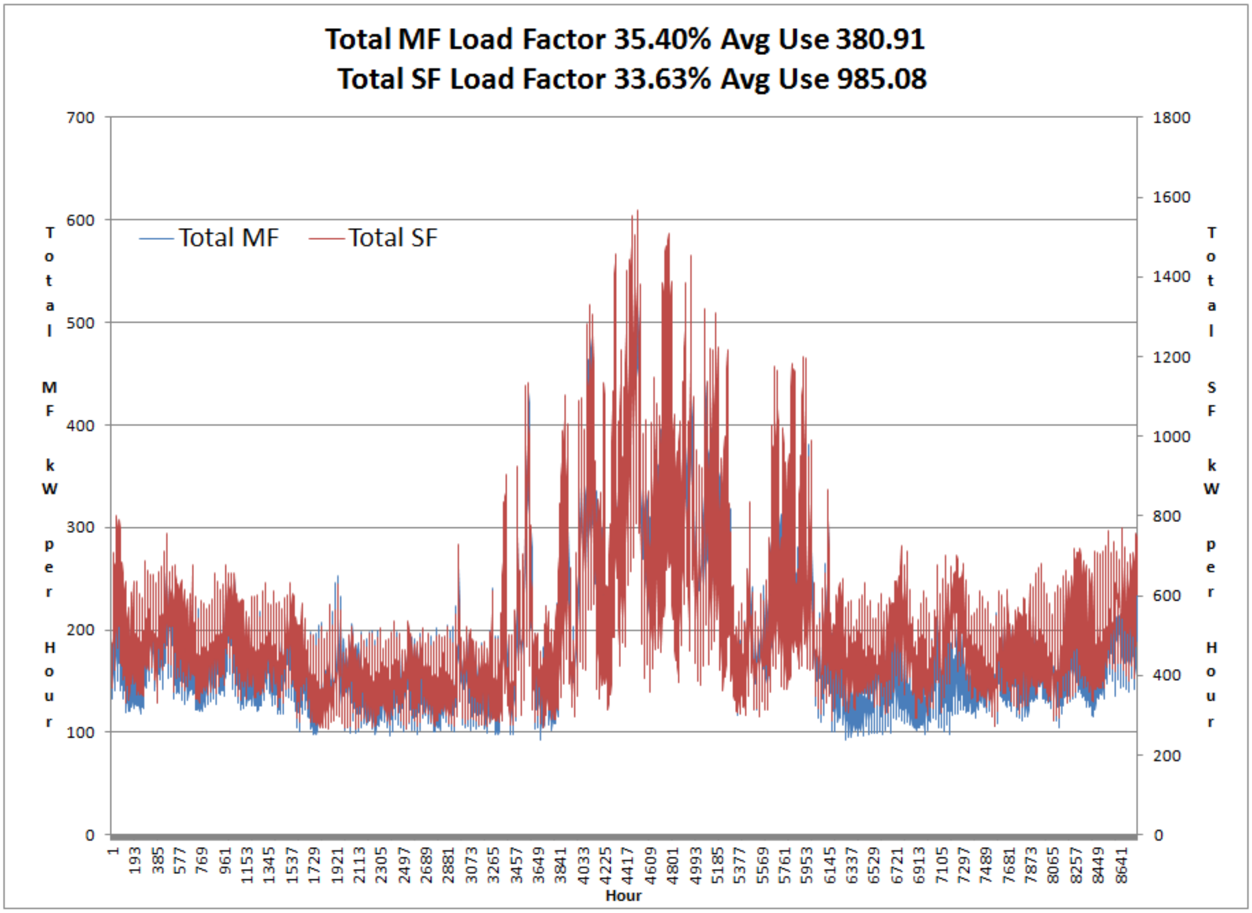
TABLE 3
LOAD FACTORS OF SINGLE AND MULTI-FAMILY
NON-SPACE HEAT CUSTOMERS

	Average Energy Used (MW)	Coincident Peak (MW)	Load Factor	Average Usage Per Month
Single-Family	1,638	5,268	31%	640 kWh
Multi-Family	352	656	54%	271 kWh

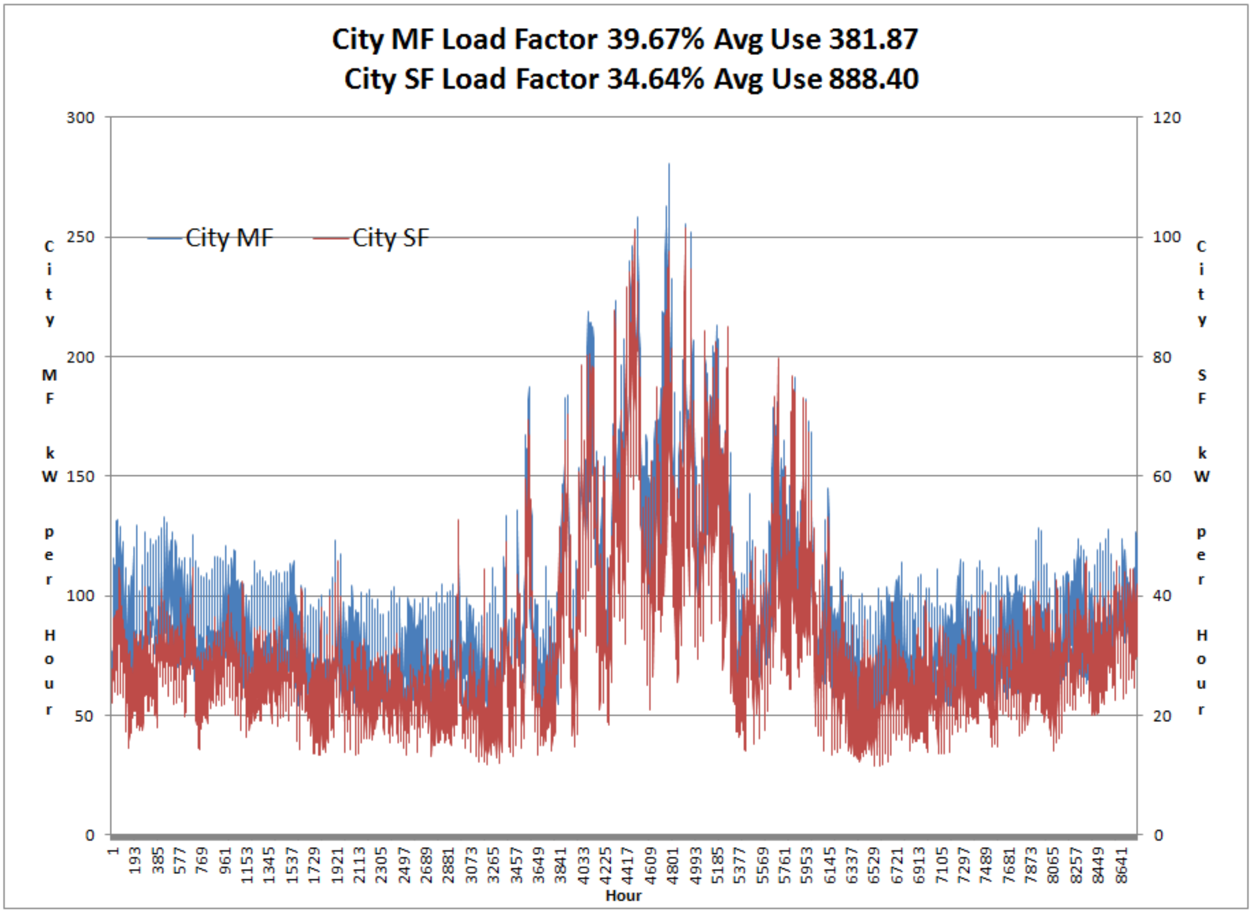
Q23. Explain your approach of using Edison's billing frequency distributions to compute cost-of-service by usage level within the residential class?

In the current load research, the load factor has dramatically changed. Now the load factor for the two sub-classes is similar. This could be due to the following:

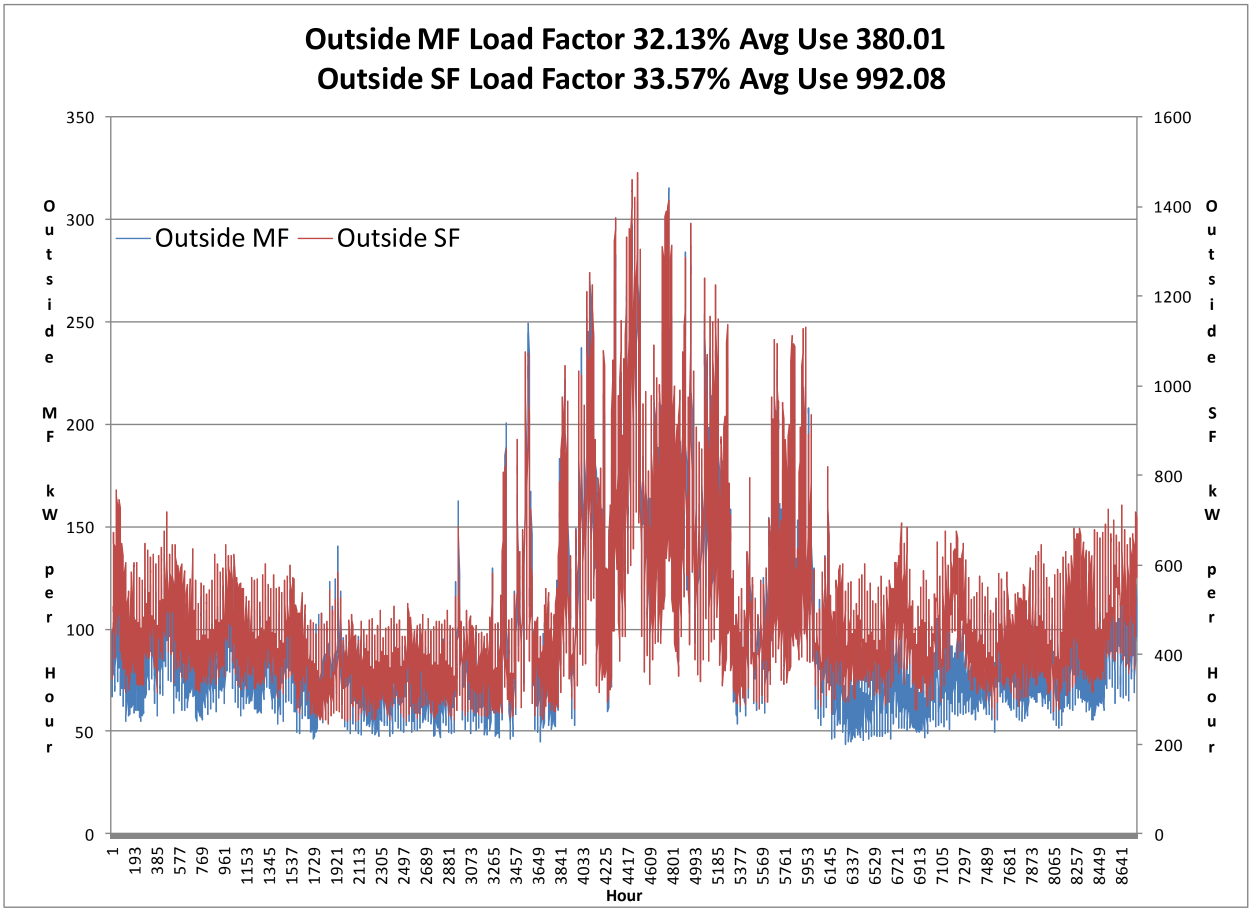
1. Increased use of air conditioners by multi-family consumers
2. Changes in the definition of multi-family and single family classes over the years in which non-detached homes are classified as multi-family units
3. Increases in inefficient condominiums in the suburbs that are added to the class
4. Biases in the load research



The next chart compares the multi-family and single family loads in the City of Chicago using the aggregated load research. Note that the load factor is higher for both the single family and multi-family classes in the City relative to the aggregate single and multi family load factors for whole system. Further, the average use in the load research sample is higher than the overall average use in the City.



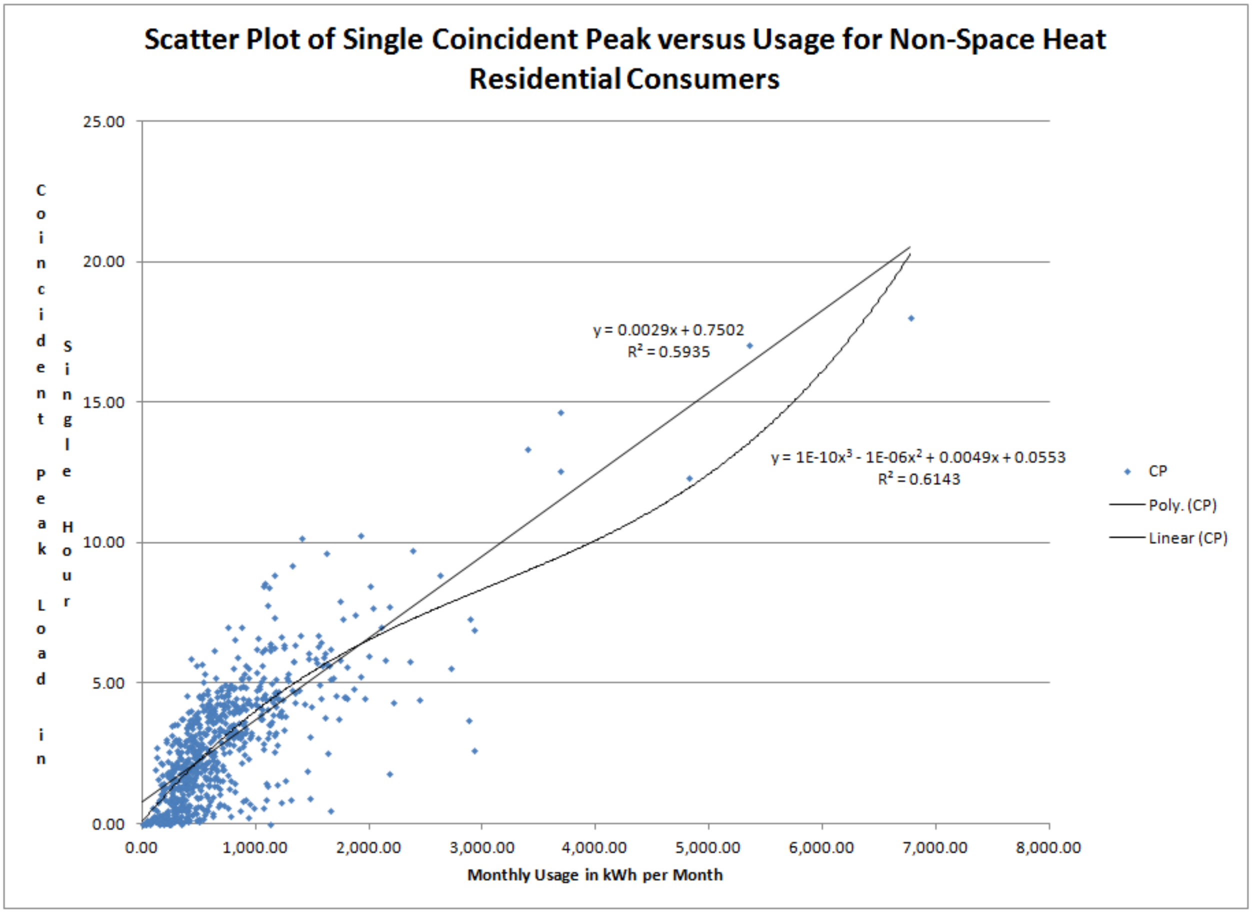
The outside city load factor for multi-family was only 32% as shown on the graph below. As with the City usage, the outside City usage is higher for the sample than the actual population average. To demonstrate the cost of service effects of the 39% load factor relative to the 32% load factor for multi-family consumers inside and outside the City one can first compute the reciprocal of the load factor. This statistic measures the peak load responsibility per kWh used. For City consumers, the number is 2.52. For outside city multi-family consumers the number is 3.11. The difference between 3.11 and 2.52 implies that the cost of service outside the City should be 23% higher than the cost of service inside the City because of the differences in the efficiency of energy usage.



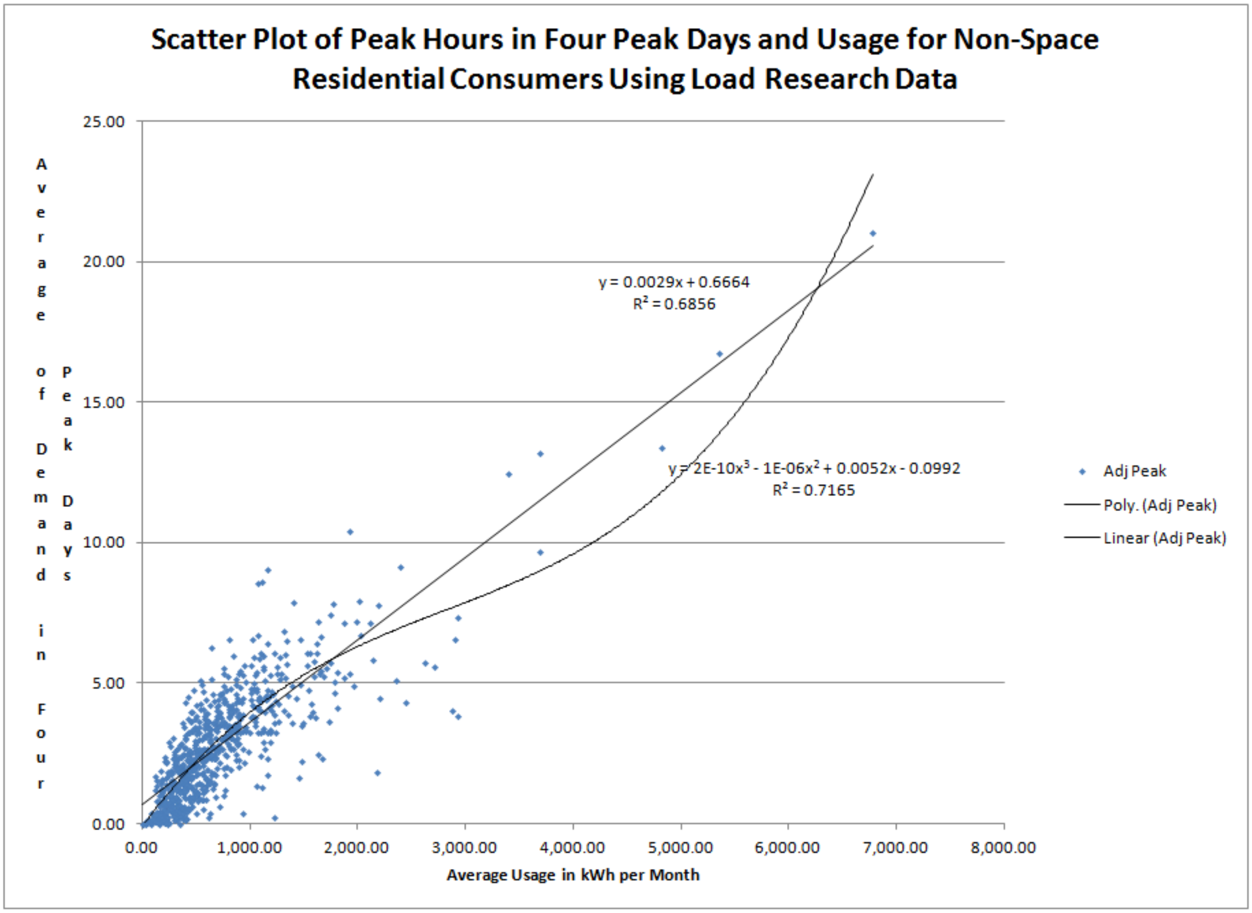
Use of Load Research to Evaluate Peak and Use Correlation

The final section uses data from the load research to further evaluate the issue of the demand usage relationship. The same type of scatter plots and statistical analysis is presented in terms of individual consumer by consumer scatter plots and scatter plots for usage groupings.

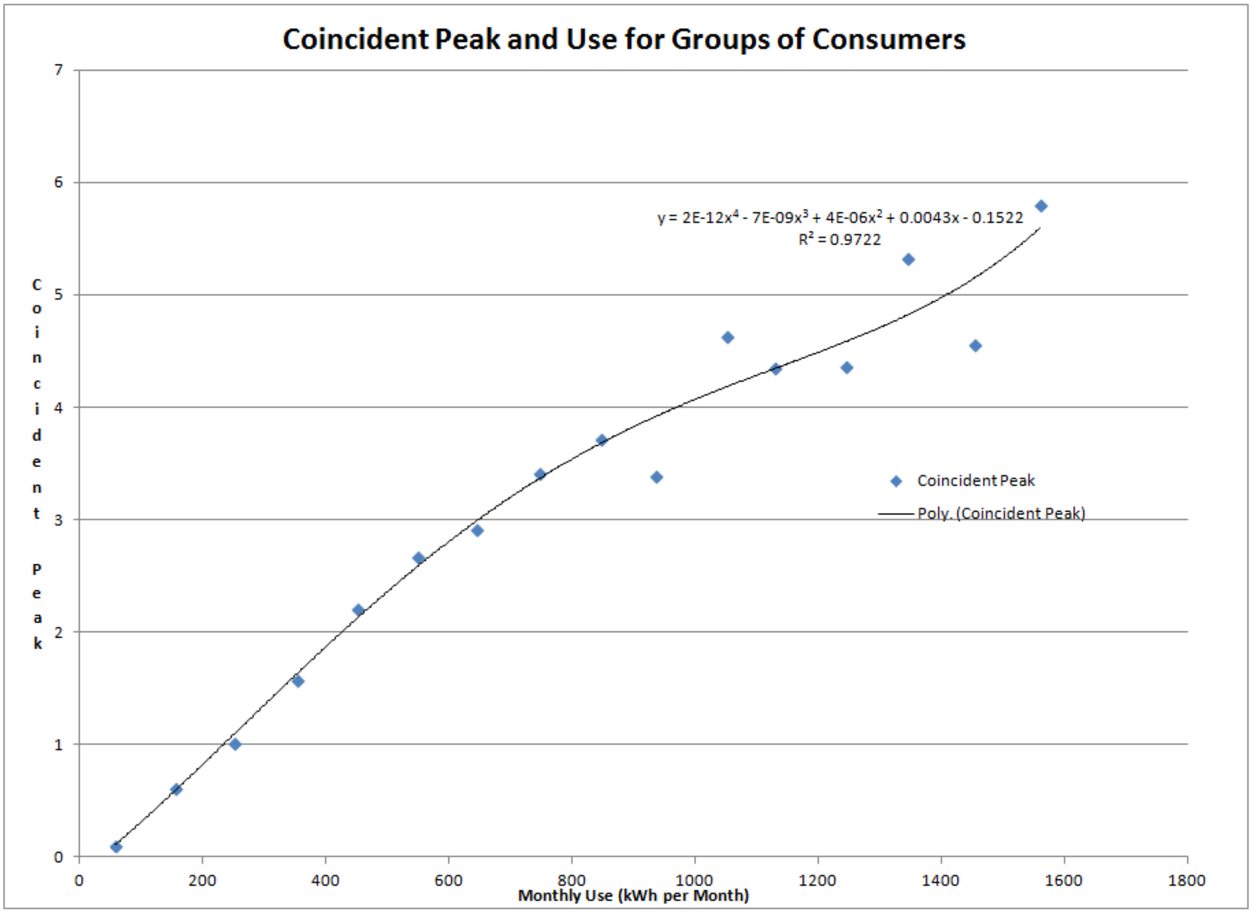
The graph below plots the energy use at the time of the system peak and the average monthly usage over the year for each of the consumers in the sample. The R-squared is lower than the R-squared for the usage data, as there is a lot of variation in a single hour of peak demand due to randomness that may occur on the particular day of the peak.



Given the vagaries in hourly loads, a second analysis has been developed where the average of the peak load in the four highest peak days of the system is used rather than the single peak. This analysis removes some of the variation and results in a higher R-squared.



When grouping consumers into usage classes (this time by 100 kWh increments because of the fewer data points) the relationship between usage and peak becomes clear. The R-squared is very high and the fitted line crosses the y-axis at a level below zero. This implies that no variation in peak demand can be attributed to being a ratepayer.



Sudden Changes in Usage and Demand from Consumer Vacancies and the Load Research Data

One of the principal conclusions in ComEd's Exhibit 2.33 was that houses or apartments in close proximity could have large variations in use. Given the variation in use, the implication is that any address can suddenly become a large or a small user and distribution facilities must be built for a contingency that a small user can become a large user. ComEd explained its finding as follows:

> [I]n comparing the lowest to the highest percentile customers that were located in the City of Chicago, there were numerous instances in which the address for a customer in Percentile 1 was in the same hundred block and street as the address for a customer in Percentile 100. For some multi-family accounts there were Percentile 1 customers literally either across the hall or next door to Percentile 100 customers. Overall, within the City of Chicago, for the SFNH Class, of the 1,463 customers that are in Percentile 100, 244 of them (16.7%) are located in the same hundred block and street as customers that are in Percentile

1. For the MFNH Class, of the 5,181 customers that are in Percentile 100, over 1,000 are located in the same hundred block and street as customers that are in Percentile 1.

This section demonstrates that:

- ComEd's finding is simply the result of vacancies in homes or billing errors --when a large home is vacant because people are moving it would be expected to find large users near low users (where usage is defined per month as in the ComEd study). This is demonstrated by graphs from the load research data.

- ComEd's finding also could be driven by vacations where large homes have low usage when nobody is living in the home for a period. This is again demonstrated by the load research data.

- ComEd's suggestion that regions can have large swings in usage and that usage cannot be predicted by the type of housing in a region is wrong. Data comparing the City of Chicago to the outside city regions demonstrate a stable relationship over time.

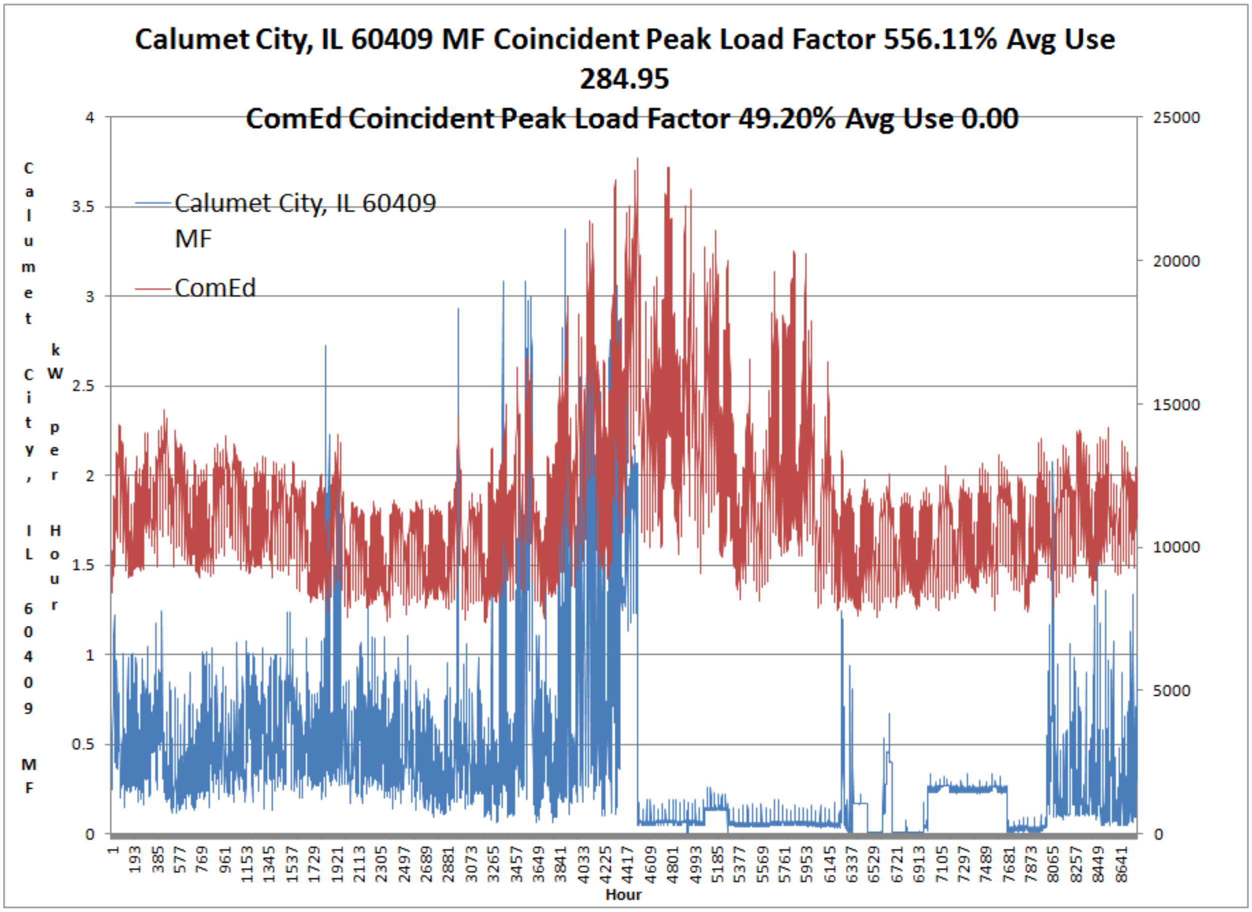
- ComEd's implication that it must build all facilities on the basis of the highest possible load of a single ratepayer account does not conform to the data. If a small studio apartment has some months of low usage because of vacancy, it does not follow that this small apartment with a period of low usage has the same distribution requirements as a large mansion in a wealthy suburb where there also may be vacancies because of people moving and/or people taking vacations. The load research data demonstrates this obvious point by showing that apartments in the same area have very similar use after accounting for vacancies. Similarly, single family homes in wealthy suburbs also have consistent usage over extended periods even though there are occasional periods of low use.

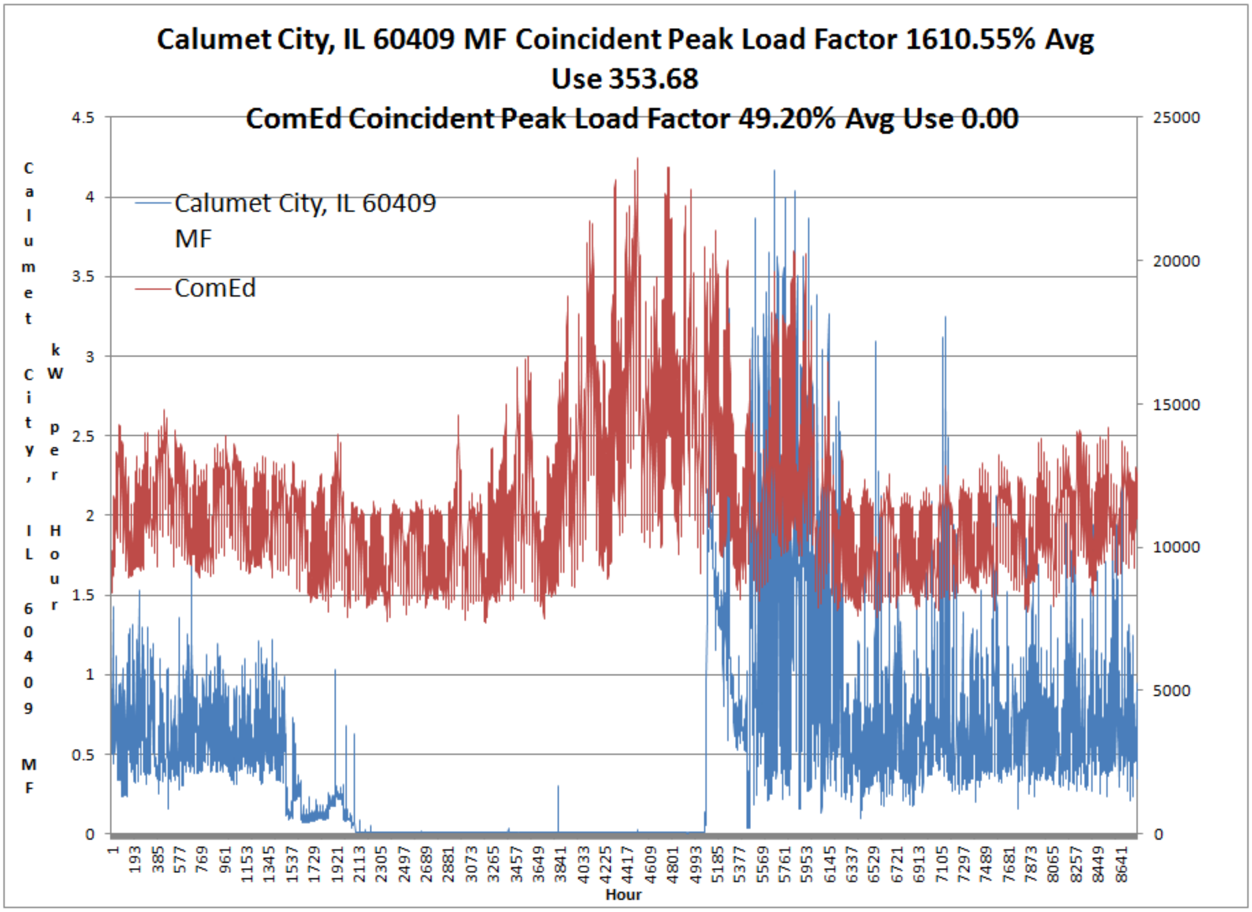
Load Research Data Demonstrates that ComEd's Finding is the Result of Vacancy Due to Moving or Vacations

The graphs below illustrate the issue of low use from moves or vacations. The graphs illustrate cases where low use occurs for temporary periods. These cases could be classified as the one percent low usage percentile in ComEd's study. The various cases demonstrate that the low use is temporary and the typical use returns after the low use period. When the usage returns to the normal level, it is stable at the level that is defined by the housing type.

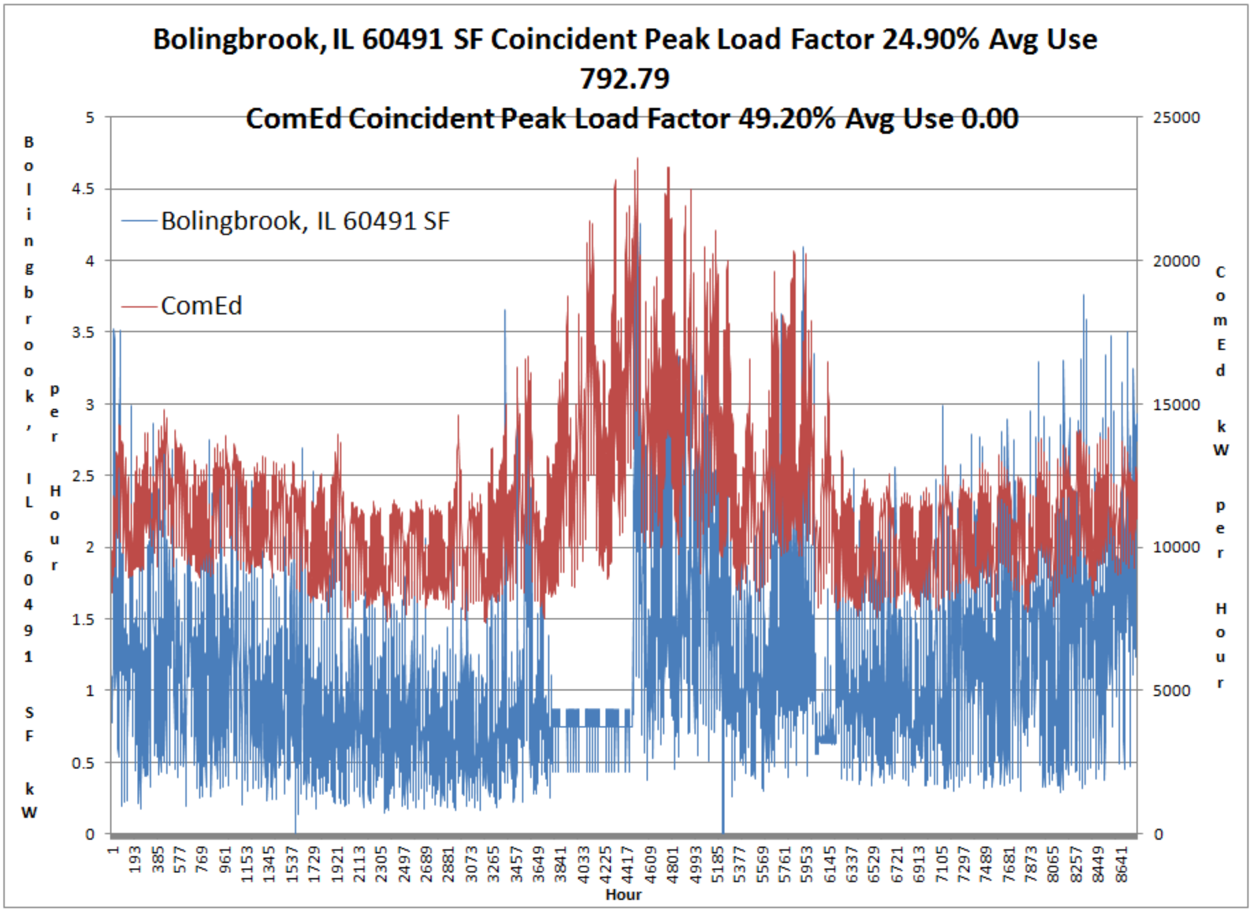
The first two graphs show usage for consumers in an apartment in Calumet City. The decline in usage shown in the graphs is probably the result of people moving out of the apartment. Note that the different consumers have similar average usage and that usage returns to the average after the vacancy.

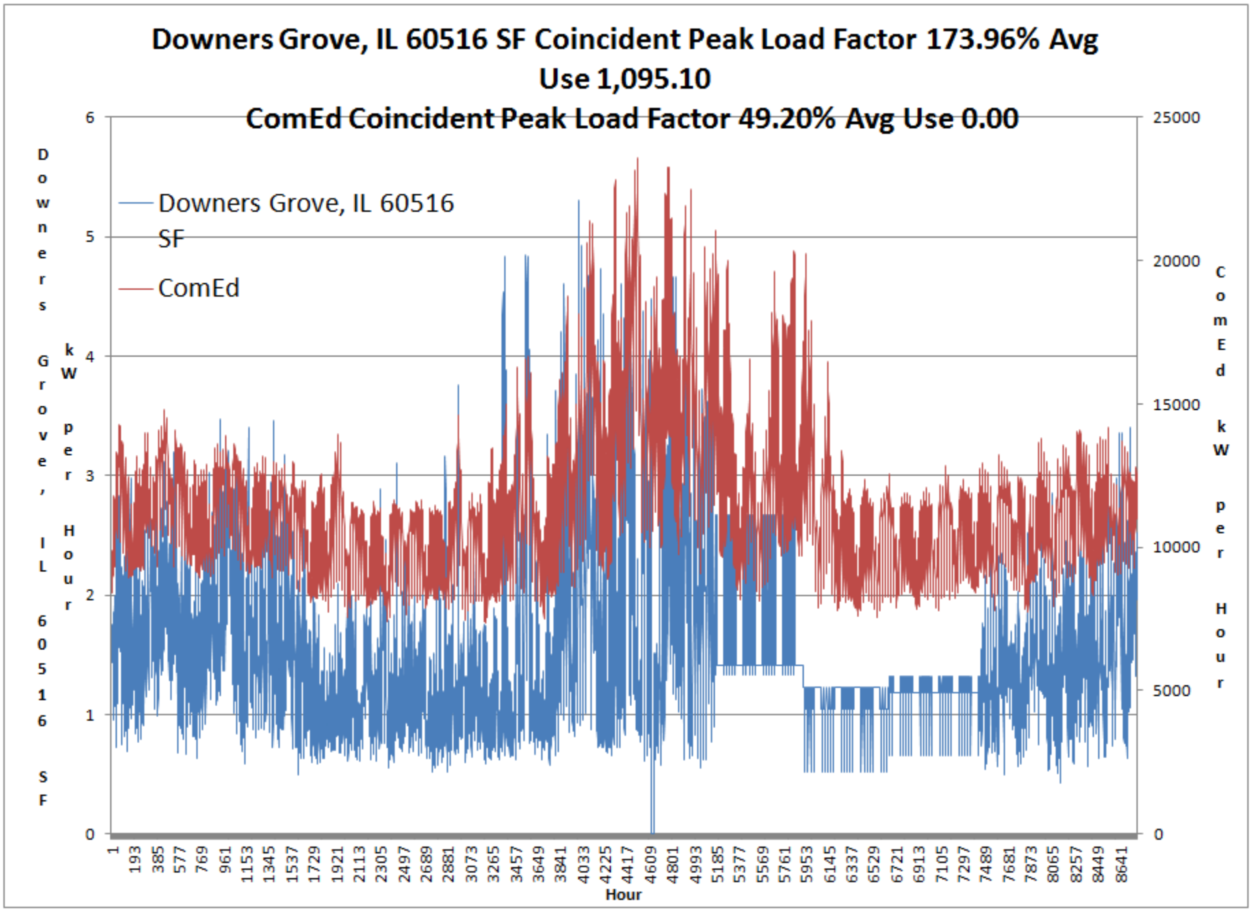
The implication of this analysis is that the amount of distribution equipment required for different dwellings is not significantly influenced because of low use during periods of people moving.





The two graphs below show load research data for single family homes where usage suddenly falls and could result in the addresses falling into the 1 percentile category. The falls in demand below could be due to errors in the collection of load research data; people taking vacations, or people moving. The key point is that after the load falls it returns and the temporary falls in demand do not have any influence on the required distribution equipment driven by demand.


Bolingbrook, IL 60491 SF Coincident Peak Load Factor 24.90% Avg Use 792.79
ComEd Coincident Peak Load Factor 49.20% Avg Use 0.00
Bolingbrook, IL 60491 SF
ComEd
Bolingbrook, IL 60491 SF kW per Hour
ComEd kW per Hour
Hour



Different Regions do not Exhibit Large Swings in Use as ComEd Suggests

The fact that there are some high users in Chicago as ComEd reports is not surprising. But the relationship between usage and region from year to year is very stable. The tables below show the average, median and different percentiles of usage inside and outside the City for different years. These tables show that the usage data is stable across time. This refutes ComEd's position that a home in the same hundred block can suddenly switch from low usage to high usage.

In inspecting the data below, one can observe the single family average and median usage inside and outside the City. The median usage in the different regions varies by 150 kWh per month (non-space heat). The City median is consistently 450 kWh per month and the outside city is consistently 600 kWh per month. Similar consistencies exist in the average use and in the low use and the high use categories.

2006

Usage in kWh per Month

	Average Chicago	25% Chicago	Median City	75% City	Average Outside	25% Outside	Median Outside	75% Outside
Single Family	661.64	275.50	450.50	750.50	840.03	375.50	600.50	900.50
Multi-Family	364.40	100.50	250.50	425.50	375.21	150.50	250.50	425.50
Single Family Space Heat	1,637.69	488.00	1,038.00	2,000.50	869.63	275.50	513.00	988.00
Multi Family Space Heat	1,870.31	750.50	1,250.50	2,250.50	878.00	325.50	600.50	1,038.00

0

2010

Usage in kWh per Month

	Average Chicago	25% Chicago	Median City	75% City	Average Outside	25% Outside	Median Outside	75% Outside
Single Family	682.01	225.50	450.50	750.50	862.29	375.50	600.50	900.50
Multi-Family	373.58	100.50	200.50	425.50	388.18	150.50	250.50	425.50
Single Family Space Heat	1,495.29	400.50	850.50	1,750.50	826.43	225.50	450.50	850.50
Multi Family Space Heat	1,759.01	650.50	1,038.00	2,125.50	850.29	300.50	563.00	988.00

2011

Usage in kWh per Month

	Average Chicago	25% Chicago	Median City	75% City	Average Outside	25% Outside	Median Outside	75% Outside
Single Family	666.84	275.50	450.50	750.50	840.89	375.50	600.50	900.50
Multi-Family	366.95	100.50	200.50	425.50	377.66	150.50	250.50	425.50
Single Family Space Heat	1,518.41	425.50	900.50	1,750.50	841.35	225.50	488.00	900.50
Multi Family Space Heat	1,785.53	650.50	1,163.00	2,125.50	866.22	325.50	600.50	1,038.00

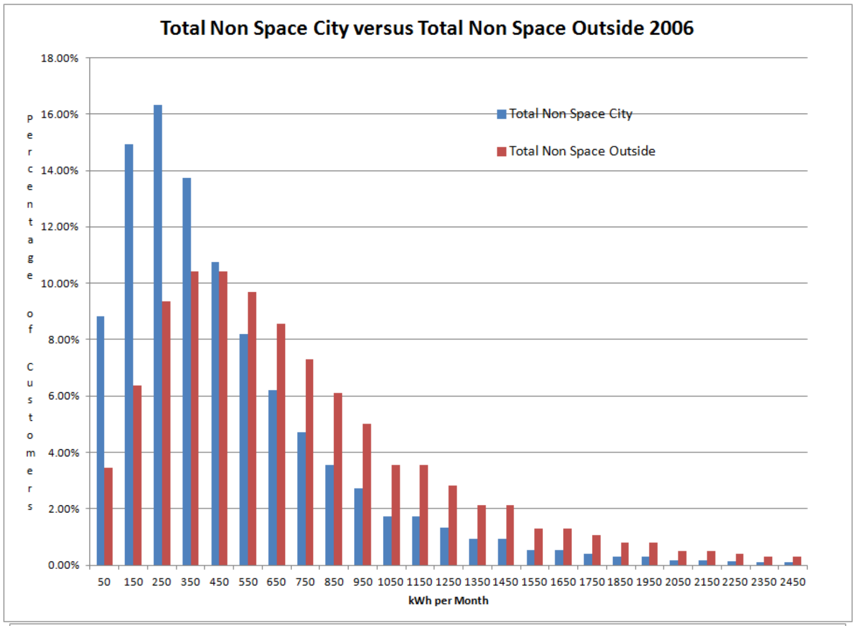
2012

Usage in kWh per Month

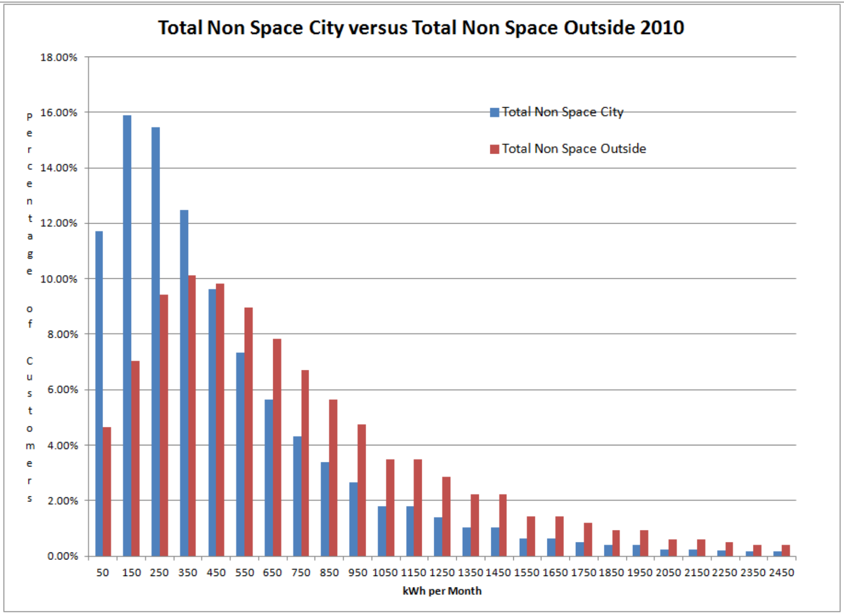
	Average Chicago	25% Chicago	Median City	75% City	Average Outside	25% Outside	Median Outside	75% Outside
Single Family	670.33	275.50	450.50	750.50	839.66	375.50	600.50	900.50
Multi-Family	369.83	100.50	225.50	425.50	381.82	150.50	250.50	425.50
Single Family Space Heat	1,367.96	425.50	850.50	1,625.50	729.11	225.50	425.50	800.50
Multi Family Space Heat	1,589.50	650.50	1,038.00	1,875.50	769.73	325.50	513.00	900.50

The graphs shown below illustrate the distribution of usage inside and outside the City of Chicago for various groups of non-space consumers for the years 2006, 2010, 2011 and 2012. As with the summary data in the tables above, the distribution graphs demonstrate consistent usage across time. This consistency is counter to the ComEd implication that usage patterns can suddenly change and that high users can suddenly become low users.

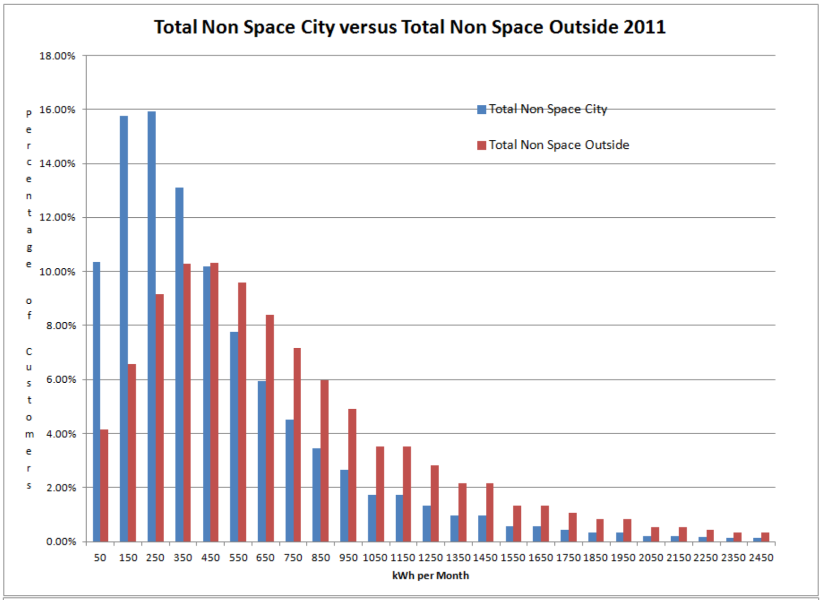
The first four graphs show the total non-space use including both single-family and multi-family dwellings. These graphs show that City use has not changed relative to City use over the past seven years and is very stable.

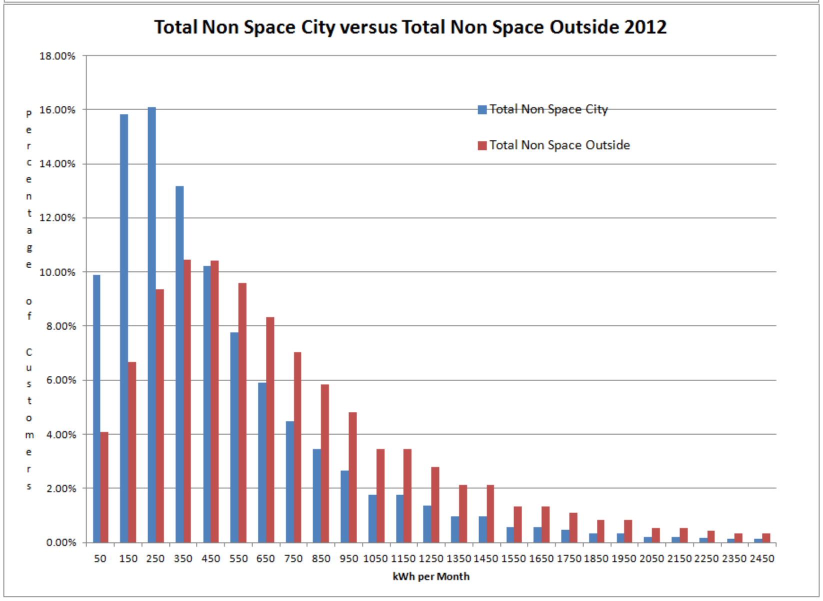


Total Non Space City versus Total Non Space Outside 2006
percentage of Customers
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Total Non Space City
Total Non Space Outside
50 150 250 350 450 550 650 750 850 950 1050 1150 1250 1350 1450 1550 1650 1750 1850 1950 2050 2150 2250 2350 2450
kWh per Month

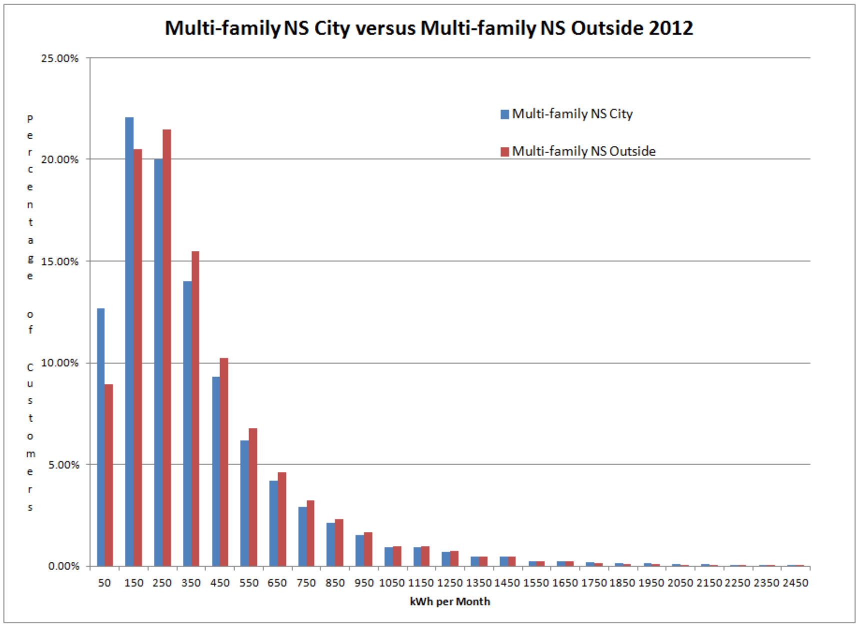


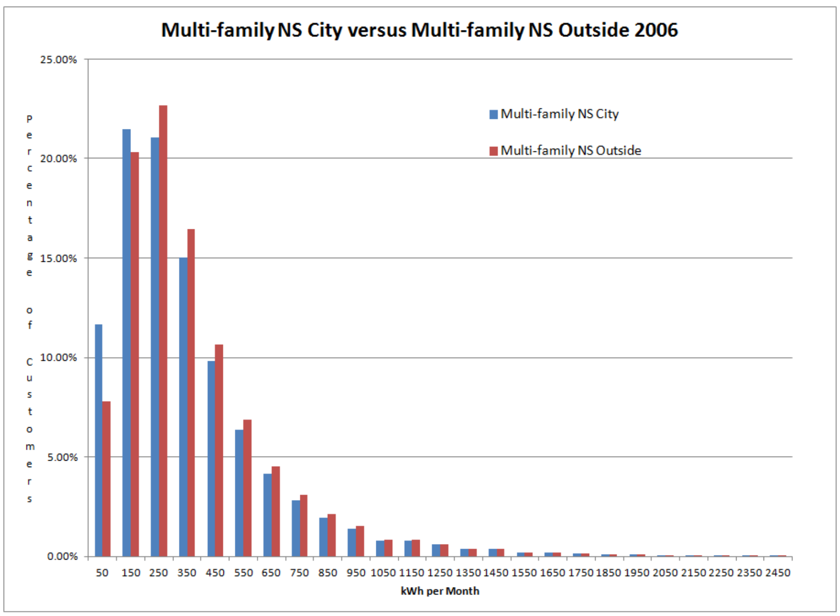
Total Non Space City versus Total Non Space Outside 2010
percentage of Customers
18.00%
16.00%
14.00%
12.00%
10.00%
8.00%
6.00%
4.00%
2.00%
0.00%
Total Non Space City
Total Non Space Outside
50 150 250 350 450 550 650 750 850 950 1050 1150 1250 1350 1450 1550 1650 1750 1850 1950 2050 2150 2250 2350 2450
kWh per Month



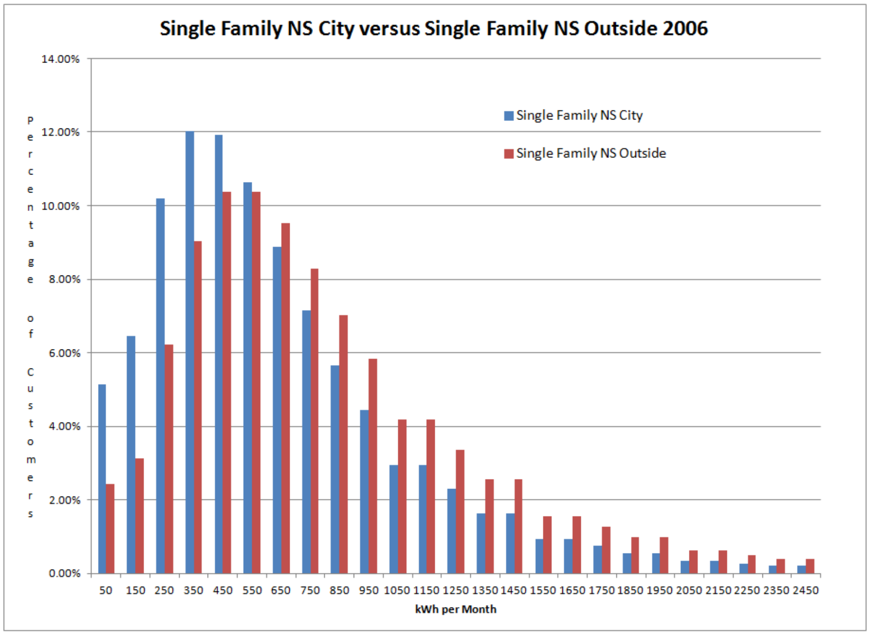


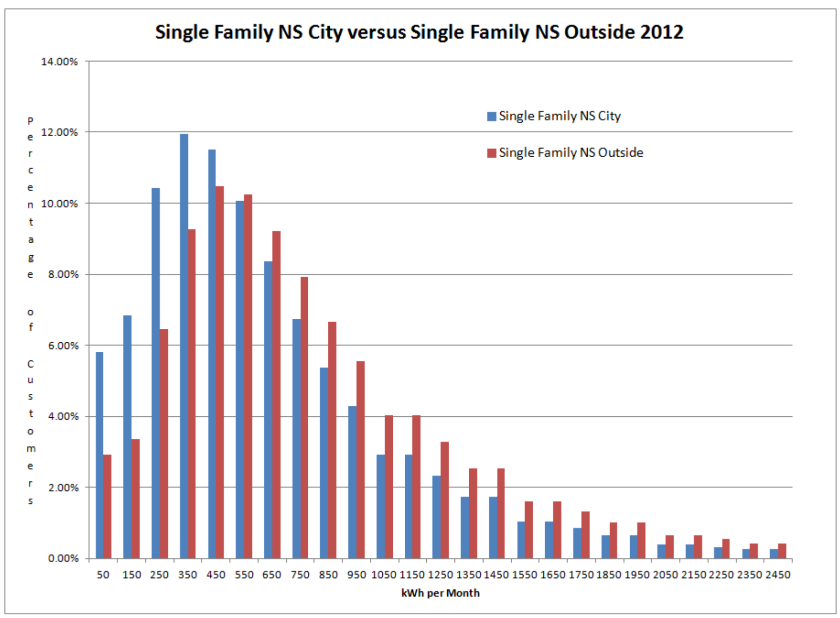
The next two graphs show the same data for multi-family dwellings. These graphs demonstrate that usage inside the City and outside the City is fairly similar for people who live in apartments. As with the aggregate data, the multi-family distribution is stable across time. The graphs show that the variation in usage is lower for multi-family consumers than for single family dwellings, with usage concentrated in the 150 kWh per month to 350 kWh per month range.





The final two graphs show the same data for single-family non-space heat dwellings. These graphs demonstrate that usage inside the City is consistently less than outside City usage and that the variation is larger than for the multi-family group.





Load Factor from Load Research Data

This section further elaborates on computation of load factors from the load research data. The first part of the section discusses alternative techniques for computing load factors and explains that computing load factor from the individual peak demands of consumers is irrelevant from the perspective of cost of service analysis. Data in this section demonstrate that the dates of peak load for individual consumers is not consistent with the peak load and that diversity must be included in the load factor computations for a class.

Definition of Coincident Peak

Coincident peak demand is the demand of a consumer at the time the system reaches its peak load for the entire year. In the case of ComEd, this generally occurs on a hot summer weekday in the mid or late afternoon. For ratepayers who have time recoding meters, the coincident peak is easy to measure – one simply plops out the level of energy use at the time of the system peak. For residential and small business ratepayers who do not have meters that record hourly loads, ComEd must measure the coincident peaks using load research.

Coincident peak is less than (or equal to) the sum of the maximum individual peak demands of all consumers on a system because some ratepayers (such as space heating customers, ski lodges, schools, churches and lighting customers) do not reach their maximum peak demand at the time of the system peak. One can compute the coincident factor for a customer-class as the coincident divided by the sum of individual peak demands of the class (this is not the within class diversity discussed below).

Coincidence Factor = Coincident Peak Demand/Sum of Individual Peak Demand

Since the coincident peak must be less than or equal to the sum of individual demands, the coincident peak factor must always be less than or equal to 1.0. The diversity factor, which measures the difference between the coincident demand and the sum of individual demands, can be defined as one divided by the coincidence factor.

Definition of Individual Maximum Demand or Billing Demand

Individual maximum demand or billing demand is simply the sum of the maximum demand for all customers in a rate class regardless of when the demand occurs. For individual maximum demand, there is no diversity. The sum of the maximum billing demand will always be greater than or equal to the coincident demand. This is because if the maximum individual demand for every single consumer occurs during the system peak hour, then maximum individual demand will be the same as coincident peak.

From the perspective of cost causation of primary distribution facilities, measurement of system-wide individual maximum demand does not have any significance. This is because primary costs are driven by maximum actual regional loads experienced on the equipment. One can tabulate higher loads than coincident peak and claim that these loads provide some kind of margin of safety for construction of primary facilities. However the higher loads are irrelevant because they are never faced by the primary distribution equipment.

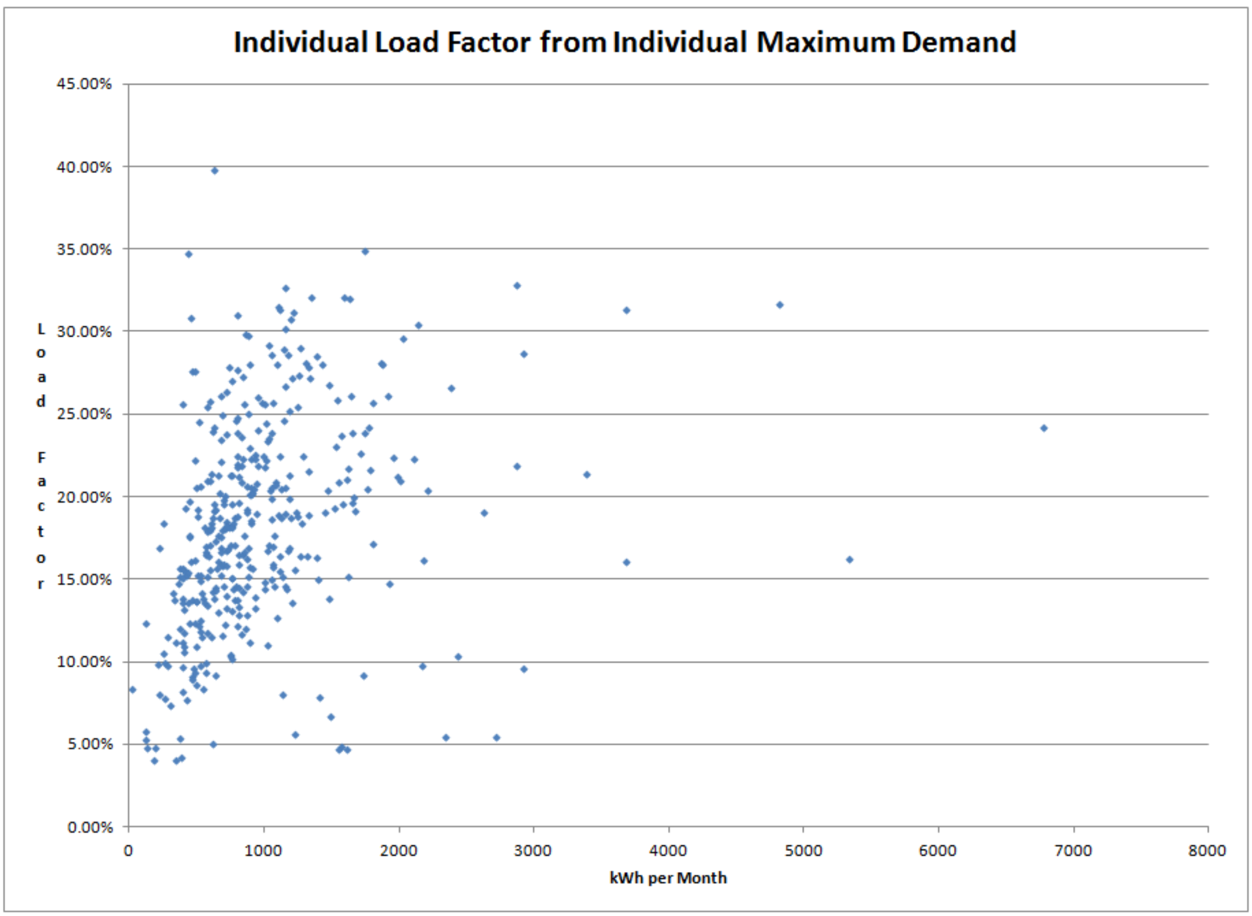
Definition of Non Coincident Peak

Non coincident peak (as defined by ComEd) computes the maximum system-wide load of a customer class, coincident with the class itself, but ignoring the aggregate loads placed on distribution equipment by other customer classes. Because of diversity among customers in a class, the non-coincident peak load for a class is always less than or equal to maximum individual demand.

There are a host of problems with use of non-coincident peak to allocate distribution costs. First, non-coincident peak has nothing to do with regional peak demands and is measured on a system-wide basis just as is the case for coincident peak. Second and more importantly, the within-class diversity that is so beneficial to certain classes in measuring NCP has nothing whatsoever to do with cost causation.

Maximum Demands in ComEd's Load Research Data

In its rebuttal testimony ComEd presented load factors from individual peak demands. As explained above, this load factor is irrelevant in the context of a cost of service study. For the single family non-space heat class, the graph below demonstrates the relationship between load factor measured on the inappropriate basis of individual peaks and usage.



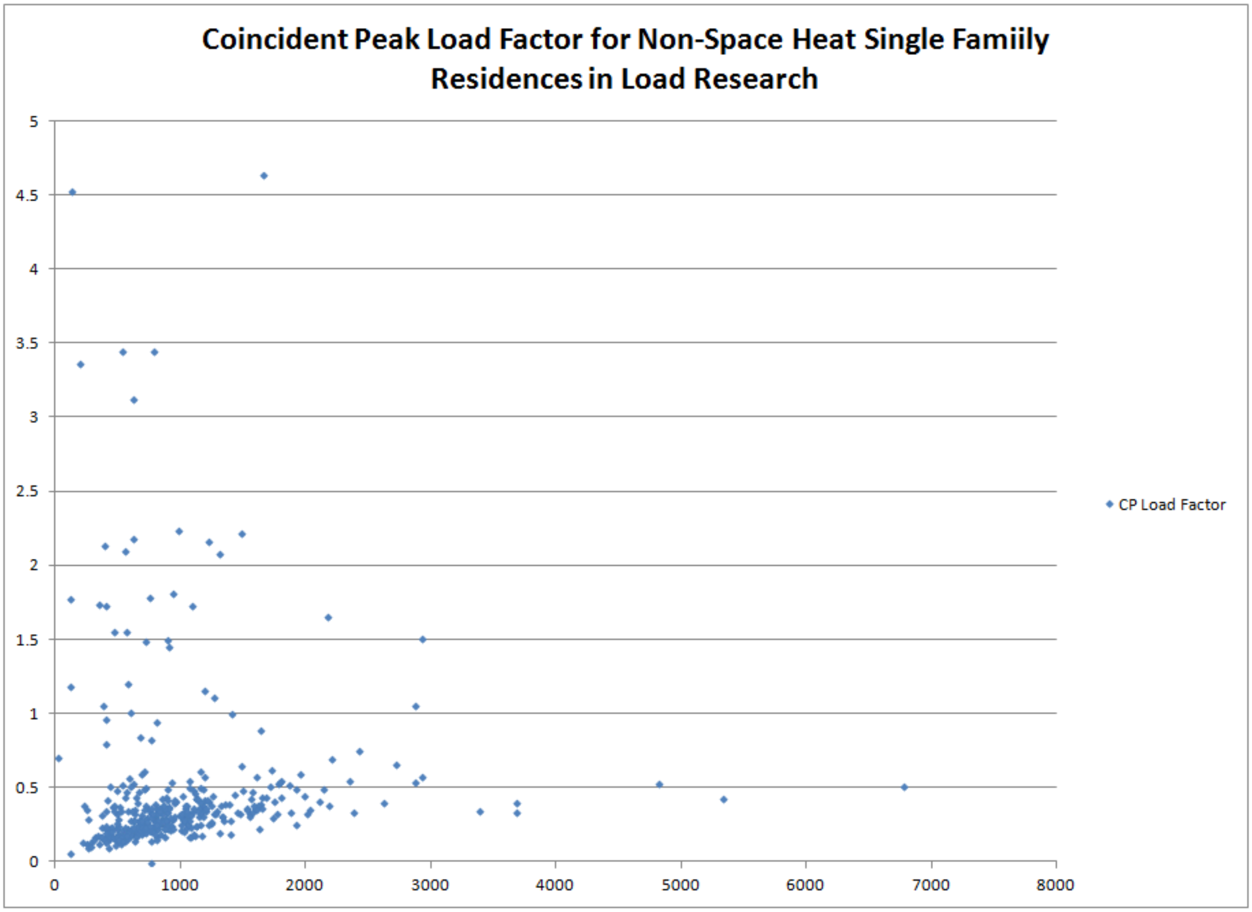
The load research data provided by ComEd shows the dates of maximum load for the individual (anonymous) consumers in the load research sample. The data showing the date and the time of their peaks demonstrates that the individual peaks frequently occurred at different times than the coincident peak of July 6. (Because ComEd maintains that these anonymous data are confidential, I have removed from this report excerpted lines of data that illustrate this variance.) My conclusion that these various individual peaks are not meaningful for coincident peak allocations is supported by data excerpted from various locations in the data set that show the different dates of individual (anonymous) consumers' peaks. The pattern holds for City and non-City, as well as multi-family and single family, consumers.

The table below presents the total maximum demands for alternative months from the non-space residential consumers. The table shows that only 40% of the maximum demand occurred in the coincident peak month of July. The number of consumers that experience a maximum peak on the day of the coincident peak is much less.

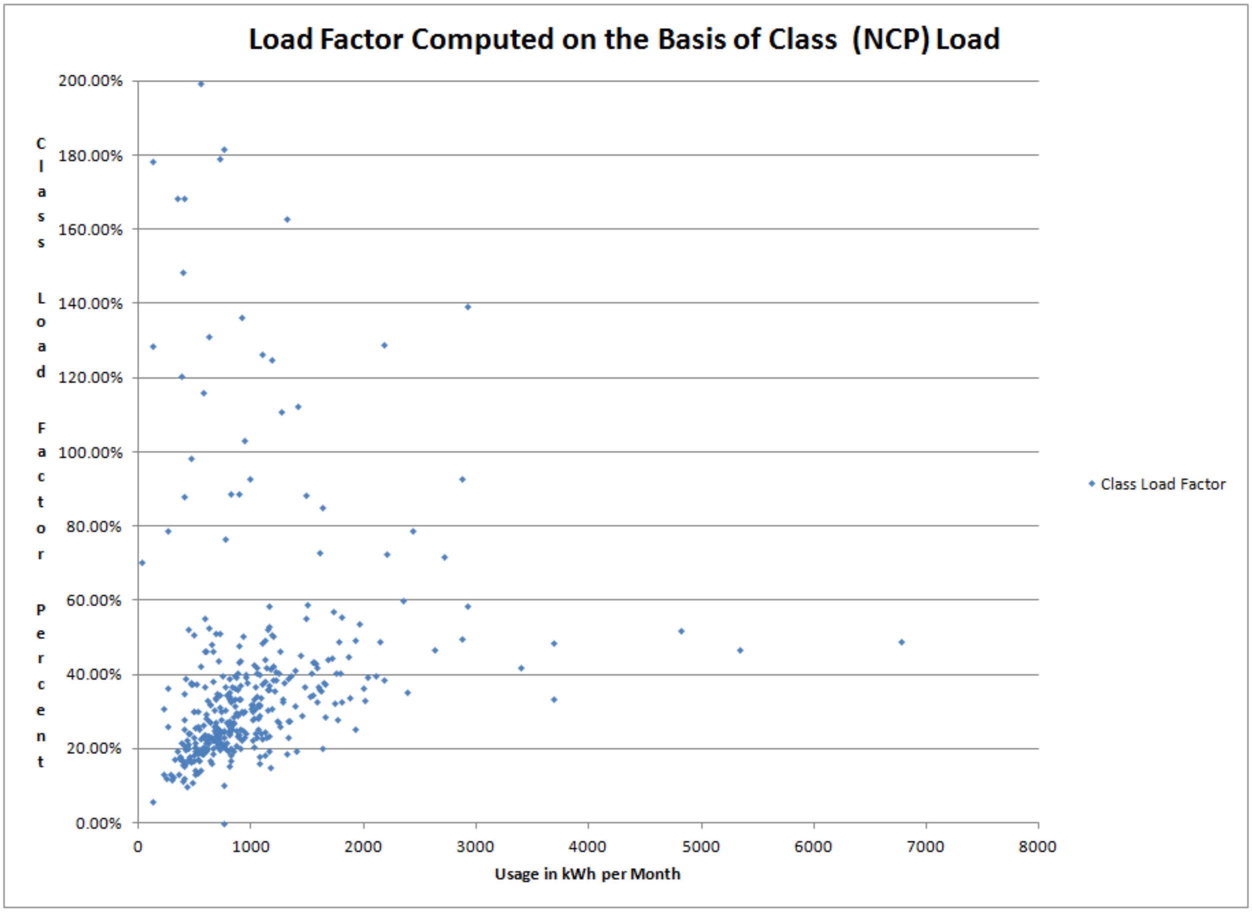
	Month	Count	Percent
1	Jan	37	4.96%
2	Feb	22	2.95%
3	Mar	17	2.28%
4	Apr	10	1.34%
5	May	57	7.64%
6	Jun	96	12.87%
7	Jul	305	40.88%
8	Aug	75	10.05%
9	Sep	45	6.03%
10	Oct	27	3.62%
11	Nov	20	2.68%
12	Dec	35	4.69%

Coincident Peak and NCP Load Factors

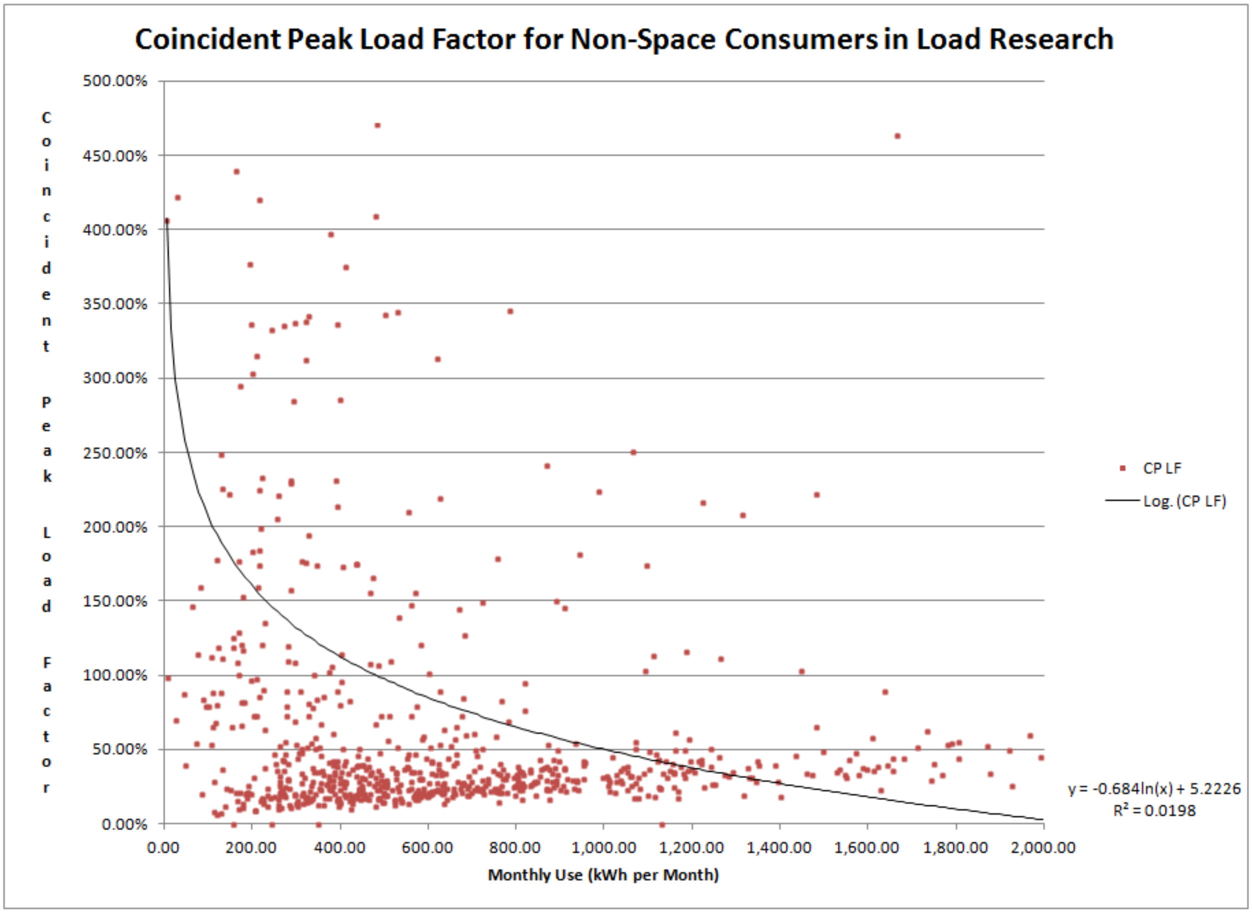
The graph below shows load factor for the same consumers, but measured on the basis of the coincident peak. Comparing the two graphs demonstrates that the load factors computed on the different bases are not comparable. (The load factor computed on the basis of coincident peak can be greater than one if use at the peak is below average use for the year.) It also shows that while there may be some increasing relationship between usage and load factor computed on the basis of individual peak demands, no such conclusion can be made when the more appropriate coincident peak factor is used. Note that if there is no relationship between load factor and usage (*i.e.,* one cannot reject the hypothesis that the relationship is a straight line), then this would confirm the proposition that use and demand are correlated as well as the notion that the presence of a ratepayer account does not have any influence on demand. The load factor is the average use divided by the peak use, and if it is constant, then the peak use increases in the same proportion as the average use. If the load factor were flat, then as usage goes up so does demand.



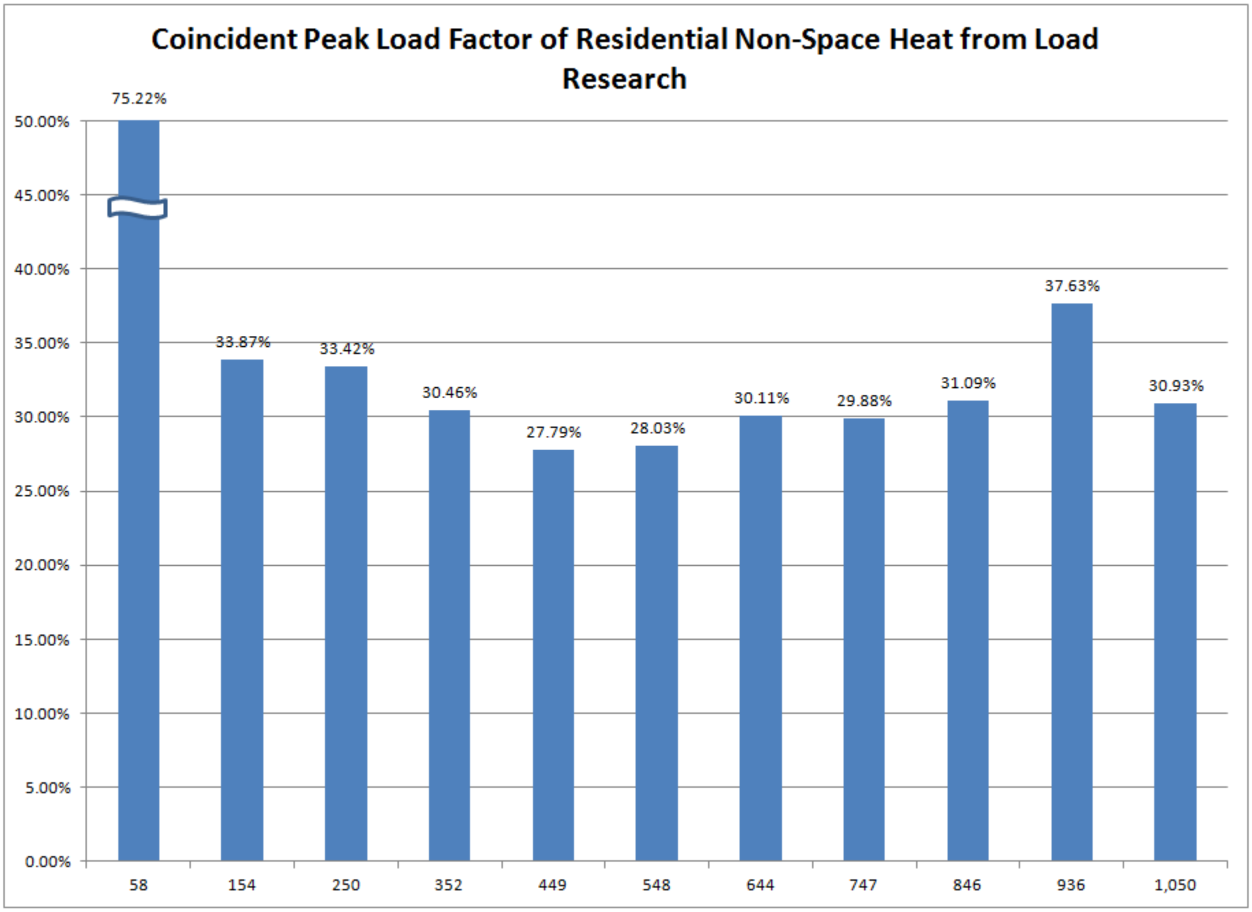
The next graph below is a scatter plot of class peak factors relative to usage for the single family non-space heat class. This is the load factor relevant for assessing the NCP as defined above. In the ECOSS, the NCP is used for allocating secondary wires. For the non-space single family consumers, the class peak occurred one hour after the coincident peak for the system, using the load research sample (at 6PM on July 6th rather than the system peak of 5:00 PM). Because the coincident peak and the class peak are so close, the graph below demonstrates that the relationship is about the same.



The graph below is a scatter plot of coincident peak load factors relative to usage for the entire non-space class heat (*i.e.*, including multi-family non-space heat consumers). While the relationship is weak, when one fits a line to the graph, the relationship is negative, suggesting higher load factors for low use consumers.

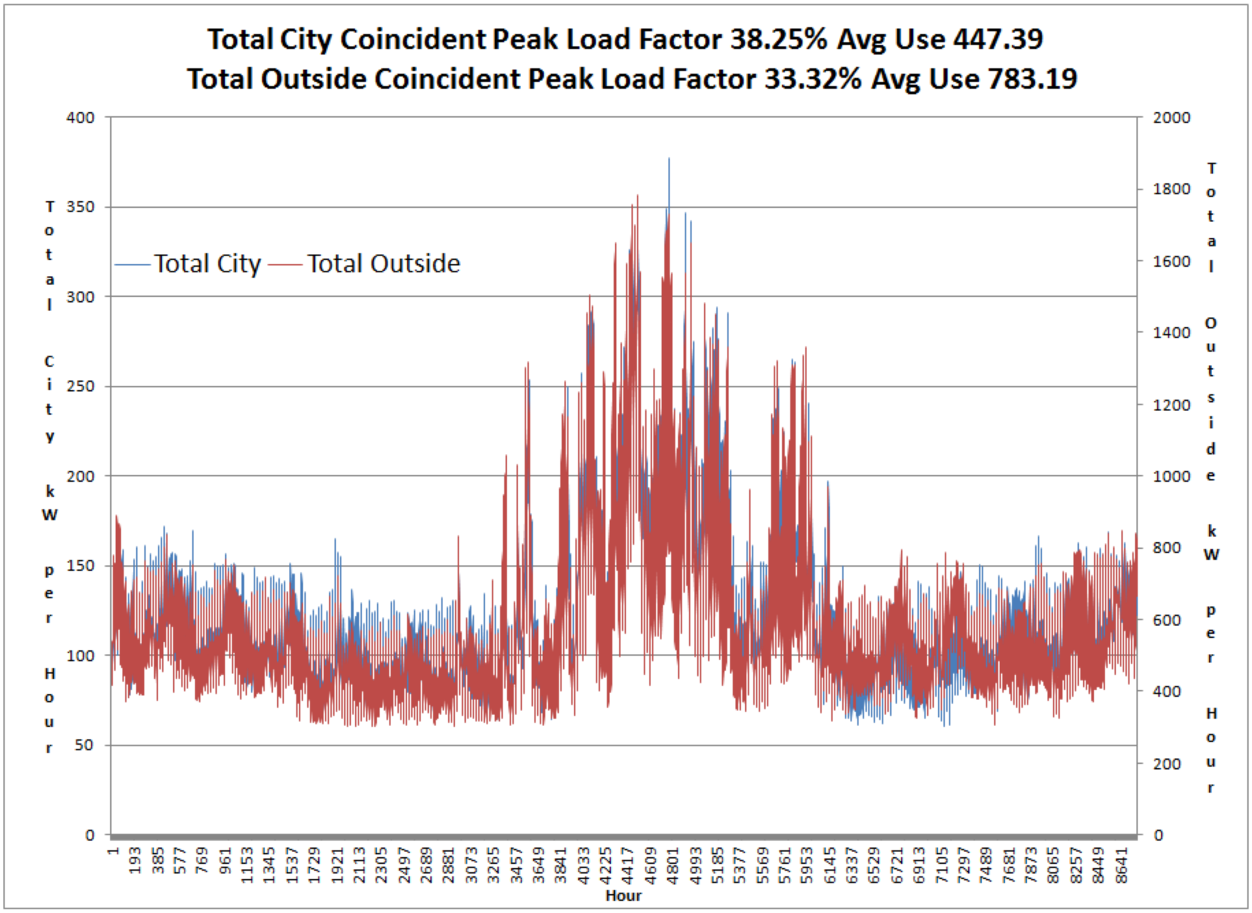


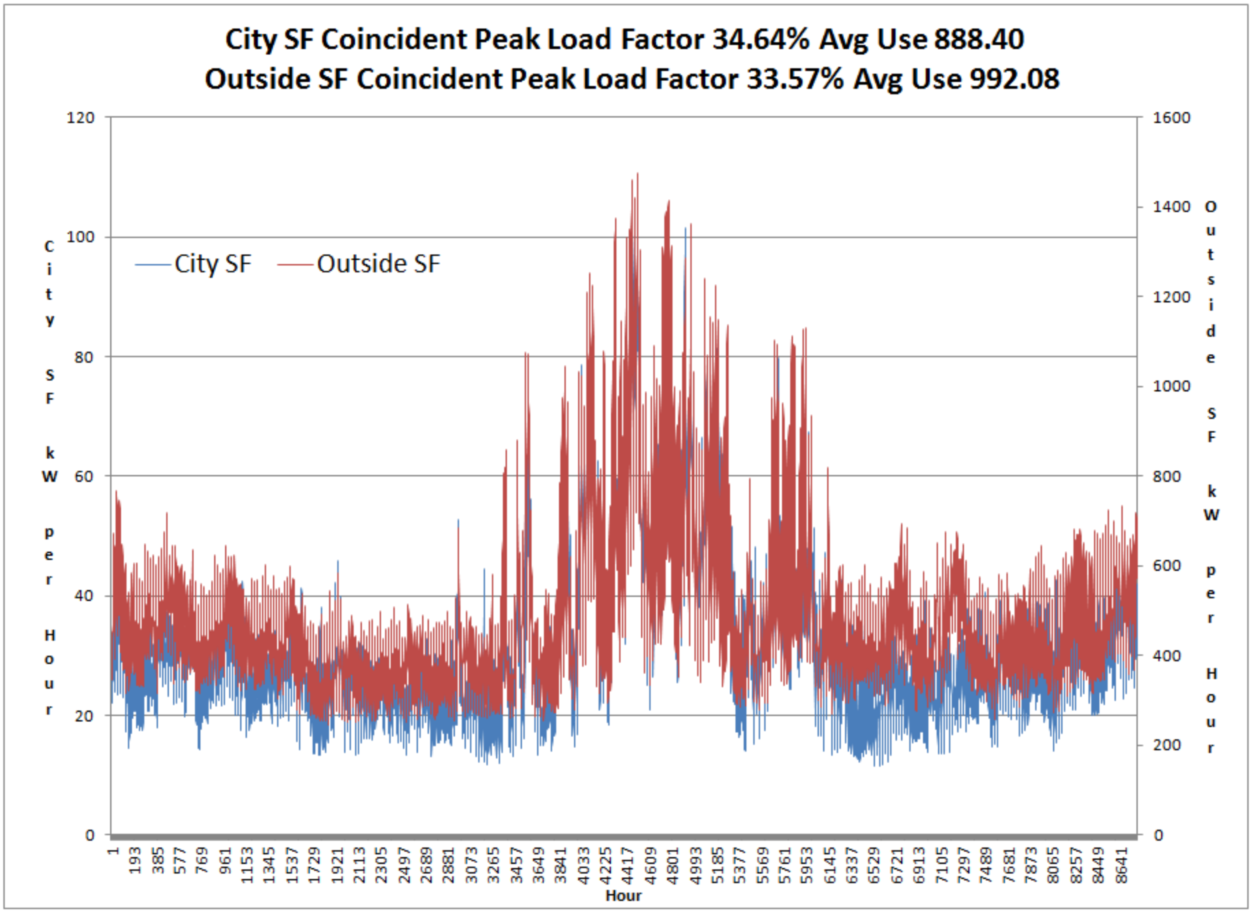
The chart below shows the coincident peak load factor for consumer groups in the load research data. The consumers are grouped into increments of 100 kWh of average use per year. After the data is grouped, the load factor of the lowest usage increment is much higher than the load factor for the higher use increments. After the very high load factor for the lowest increment, the load factor decreases until usage of 450 kWh per month occurs. For usage increments above 650 kWh the load factor increases by minor amounts. Data in the graph is influenced by the relatively small sample.

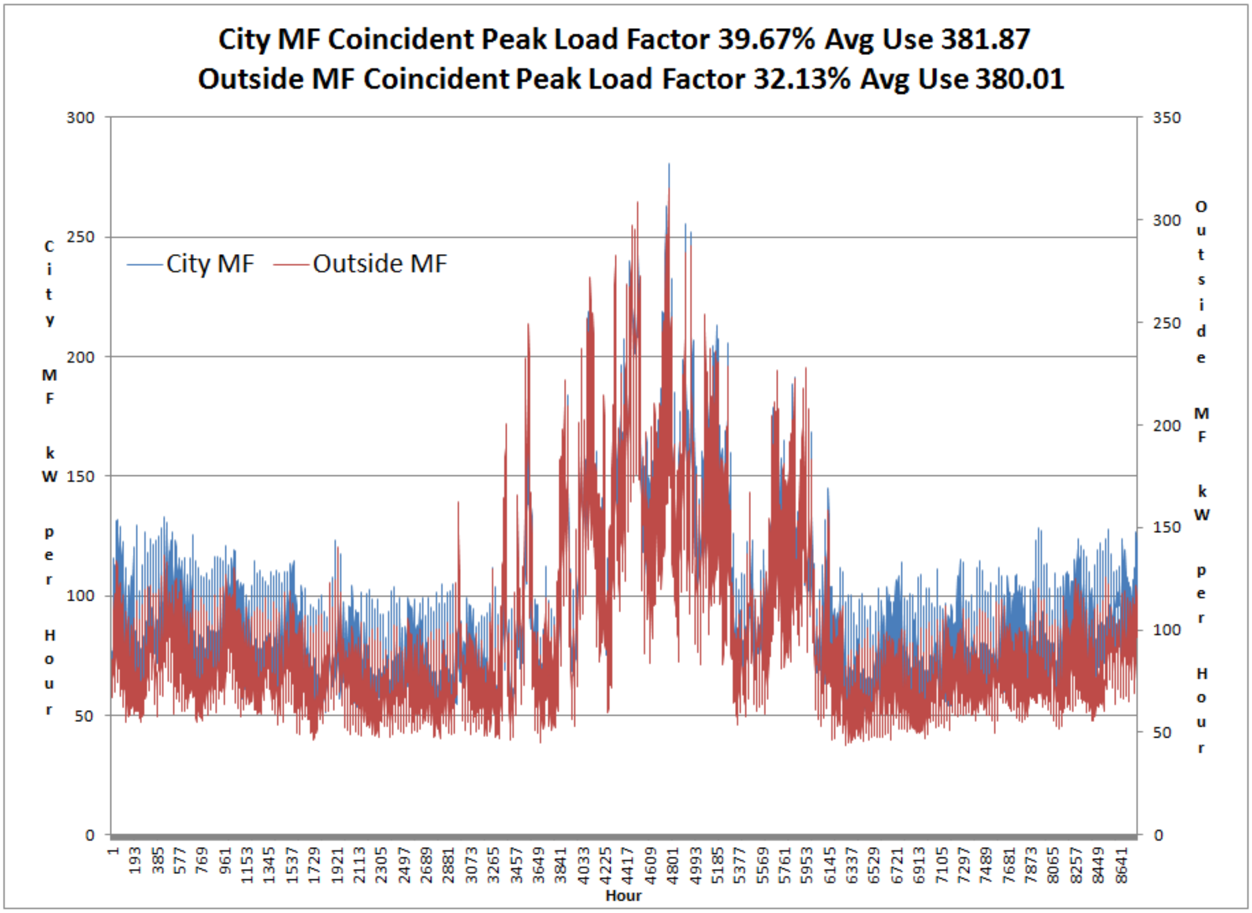


City and Outside City Load Factors

The final set of graphs show the details of the City and outside City load factors in the load research data. Recall that City consumers are under-represented in the load research sample for single family non-space heat consumers. For multi-family consumers, the better load factor is not simply explained by usage, as the usage level is similar inside and outside of the City. If the single family load research was more representative, the load factor for the entire residential class may be reduced.


Total City Coincident Peak Load Factor 38.25% Avg Use 447.39
Total Outside Coincident Peak Load Factor 33.32% Avg Use 783.19
Total City
Total Outside
Total City kW per Hour
Total Outside kW per Hour
Hour
0
50
100
150
200
250
300
350
400
0
200
400
600
800
1000
1200
1400
1600
1800
2000
1
193
385
577
769
961
1153
1345
1537
1729
1921
2113
2305
2497
2689
2881
3073
3265
3457
3649
3841
4033
4225
4417
4609
4801
4993
5185
5377
5569
5761
5953
6145
6337
6529
6721
6913
7105
7297
7489
7681
7873
8065
8257
8449
8641


City SF Coincident Peak Load Factor 34.64% Avg Use 888.40
Outside SF Coincident Peak Load Factor 33.57% Avg Use 992.08
City SF
Outside SF
City SF kW per Hour
Outside SF kW per Hour
Hour
0
20
40
60
80
100
120
0
200
400
600
800
1000
1200
1400
1600
1
193
385
577
769
961
1153
1345
1537
1729
1921
2113
2305
2497
2689
2881
3073
3265
3457
3649
3841
4033
4225
4417
4609
4801
4993
5185
5377
5569
5761
5953
6145
6337
6529
6721
6913
7105
7297
7489
7681
7873
8065
8257
8449
8641



City MF Coincident Peak Load Factor 39.67% Avg Use 381.87
Outside MF Coincident Peak Load Factor 32.13% Avg Use 380.01
City MF
Outside MF
City MF kW per Hour
Outside MF kW per Hour
Hour
300
250
200
150
100
50
0
350
300
250
200
150
100
50
0
1
193
385
577
769
961
1153
1345
1537
1729
1921
2113
2305
2497
2689
2881
3073
3265
3457
3649
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