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ESTIMATION OF SITE-SPECIFIC ELECTRICITY CONSUMPTION IN THE ABSENCE OF METER READINGS: AN EMPIRICAL EVALUATION OF PROPOSED METHODS

David L. Ryan and Denise Young

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Executive Summary

The objective of this study is to describe, review and empirically evaluate the relative performance of alternative methodologies that may be used to estimate electricity consumption for individual sites in periods when no actual meter reading is undertaken. The empirical analysis is based on a random sample of approximately 30,000 sites drawn from the customer base of EPCOR Distribution Inc. (EDI) in Edmonton, Alberta. Separate sub-samples were obtained for residential, small commercial, and medium commercial sites, with the data pertaining to metering cycles over the period from January 2001 to mid 2004.

Five estimation methodologies are used to estimate electricity consumption over metering cycles. The estimates from these methodologies are compared to actual consumption, providing a measure of the error that occurs in the estimation process. Various evaluation criteria are applied to these errors in order to summarize the performance of each estimation methodology in aggregate and over different types of sites (residential, small commercial, and medium commercial) and over different time periods. These evaluation criteria include the average estimation error, the root mean square percentage error, as well as other criteria which may better reflect the disenchantment that customers might experience should they be invoiced for overestimates. These potential 'disenchantment' effects are captured via the proportion of overestimates that are large, as well as the proportion of sites that experience frequent large overestimates.

Our findings indicate that no single estimation method is better in all circumstances or according to all criteria. The method currently used by EDI, which is based on information from the immediately preceding metering cycle, performs best for residential sites and also performs well for small commercial sites. It does not perform as well for medium commercial sites, although the sub-sample of observations used in our analysis is much smaller for this type of site. An alternative method that is also based on information from the immediately preceding metering cycle also performs well in our data set, and in some cases does better than or as well as the EDI method. However, particularly for small and medium commercial sites, other estimation methods that utilize electricity consumption history from the same period in the previous year perform better according to some evaluation criteria.

Our analysis also indicates that the relative performance of the various estimation methodologies is somewhat sensitive to the sample that is used in the evaluation. Nevertheless, for residential sites, the two methods that form estimates of consumption based on information from the immediately preceding meter cycle generally perform the best. An examination of performance across different years or months reveals that no single estimation method performs well in all cases. For residential sites, the EDI method performs well regardless of the particular year, but not in all months. The EDI method is frequently outperformed by an alternative method (that is also based on information from the previous meter cycle). Interestingly, both these methods exhibit strong seasonal patterns, tending to overestimate in some months and underestimate in others, although the over- and under-estimation periods differ for different types of sites. This suggests that the performance of these methods may be enhanced by including additional seasonal information.

In terms of the evaluation criteria related to potential customer 'disenchantment', the EDI method has the lowest rate of substantial overestimates for residential sites of all the estimation methods that were considered, although approximately 10% of all estimates exceed actual values by more than 25%, even for the best performing method. In general, for all types of sites, the methods that utilize information from the previous meter cycle tend to yield better estimates according to this criterion than those based on information from the same period in the previous year. In terms of the frequency with which particular sites experience overestimates of their electricity consumption, these same two methods tend to result in smaller proportions of sites that receive overestimates in a large proportion of cases.

An empirical examination of the inclusion of proxies for variations in weather conditions and other seasonal factors in the estimation process indicates that these adjustments do not always improve the ability of the various estimation methods to provide accurate estimates of electricity consumption.

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1. Introduction

Since reading of electricity meters is an expensive and time-consuming undertaking, in most jurisdictions meters are not read for each and every invoice that is issued to a customer. Rather, many of these invoices are based on estimated rather than actual electricity consumption. In the case of *Epcor Distribution Inc.* (EDI), invoices for a substantial portion of the customer base are issued monthly while the meters for these customers are generally read bi-monthly. Hence, for residential and small commercial customers in particular, every second electricity invoice is based on estimated - rather than actual – electricity consumption.

Although electricity consumption for an individual site is not known in the absence of a meter reading, total electricity consumption (or net system load, NSL) for all sites since the last meter reading for any given site is known. This NSL information is used by EDI, along with site-specific information from the previous meter reading at a site, to estimate electricity consumption for individual sites for billing periods with no available meter reading. On average, these estimates should be accurate in that the sum of estimated electricity consumption over these sites during the estimation period can be set to equal actual consumption for this same period.

From the point of view of the electricity supplier there would appear to be no aggregate gain or loss involved in incorrectly estimating electricity consumption for particular individual sites, since any overestimates can be exactly offset by equivalent underestimates for other sites.[1] When electricity prices are constant, there should also be little overall impact on electricity consumers arising from minor inaccuracies due to the estimation of electricity consumption in periods when no actual meter reading is undertaken.

Regardless of the estimate that is made, when the next actual meter reading is taken, actual consumption pertaining to the entire period between meter readings (the metering cycle) is known. Since this period includes the sub-period for which consumption had previously been estimated, billing of the difference between this actual consumption figure and the previously estimated amount means that the electricity consumer has been correctly billed for the amount of their electricity consumption over the entire metering cycle. Thus, over-estimation of consumption in the first sub-period simply involves a temporary loan from the electricity consumer to the electricity supplier, while under-estimation results in a temporary loan in the reverse direction. Provided the sum of estimated electricity consumption over these sites during the estimation period is set equal to actual consumption for this same period, there is no net revenue transfer in either direction. However, (a subset of) consumers may be dissatisfied with the process if they are systematically subject to significantly overestimated bills.

In this report, we describe and evaluate five basic methods of establishing electricity consumption estimates for individual sites in periods when no actual meter reading is

[1] Note, however, that because all of the estimate factors for all sites are based on different periods of time, the sum of estimated consumption might be slightly more or less than actual consumption. Therefore there is normally UFE – unaccounted for energy – left over when the process ends.

undertaken. In addition to the method currently used by EDI, four other methods are evaluated, including those used by (or suggested for use in) other jurisdictions.

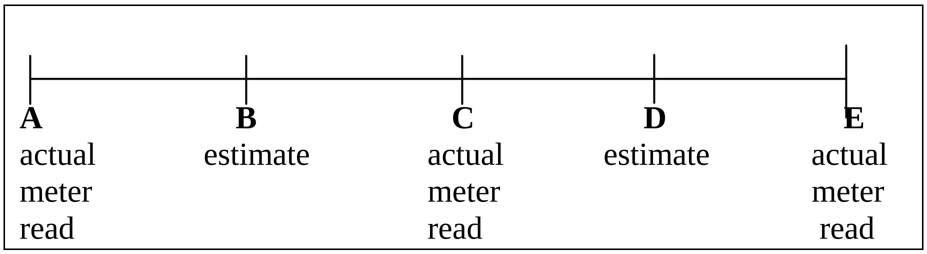
Our evaluation of various estimation strategies is based on data pertaining to a sample of individual residential, small commercial, and medium commercial sites supplied by EDI, predominately in Edmonton, Alberta. The criteria that are selected are designed to compare the abilities of various estimation methods to accurately forecast electricity consumption according to a series of metrics. The measures that we consider are: the average difference between estimated and actual consumption, root mean square percentage error, and the proportion of observations for which large overestimates result from each estimation method. Due to the fact that actual consumption by individual sites is never known in building periods when meters are not read, our evaluation is based on a slight modification of actual practice. We form estimates of consumption pertaining to an entire metering cycle for each proposed method and compare these estimates to the known consumption over that cycle.

The remainder of this report is organized as follows. Section 2 provides a framework for describing the various methods that are used to estimate electricity consumption, and identifies a general approach that can be used to evaluate the different methods. A description of the data and various summary statistics are contained in Section 3, while the various estimation methodologies that are evaluated are described and reviewed in Section 4. Section 5 describes and analyzes the main results that are obtained when the various estimation methodologies are used to estimate consumption in our sample of data. This section also contains a detailed description of the various criteria that are applied in our evaluation of the electricity consumption estimates obtained using the different estimation methodologies. Adjustments that could be made to the estimation methods to account for weather and other seasonal factors are considered briefly in Section 6. Section 7 summarizes and concludes.

2. Background

To provide a framework for describing the various methods that are used to estimate electricity consumption in periods when no meter reading is taken, as well as to identify the issues involved in evaluating alternative methods and the data that are required, it is convenient to consider the following schematic, which pertains to any particular site that receives invoices based on consumption estimates between meter readings.

Figure 1: A Schematic of Metering at a Particular Site



A meter cycle refers to the period between consecutive meter reads such as from A to C, or from C to E. Actual consumption is known for these periods. The issue that is addressed in this report concerns the estimates that are made at points B and D, when no meter reading is obtained. At these points the customer is invoiced for the amount of electricity that has presumably been used since the previous meter read, that is, from A to B, or from C to D, respectively. While it is clearly desirable to estimate this consumption as accurately as possible, particularly in an era when prices may be changing frequently, the extent of any over- or under-estimate that may be made at B or D should have no long-term implications for the customer, since it will be corrected with the invoice that is issued following the next meter reading. For example, if the customer is estimated to have consumed “x” kWh of electricity from A to B, and at the next meter read at C it is found that they consumed “y” kWh in total between A and C, then if they are invoiced for “y-x” kWh consumption between B and C, they will have been charged correctly for their consumption over the complete meter cycle from A to C.

Ideally, in order to evaluate the accuracy of the estimates that are made at points like B and D, estimated consumption for periods such as from A to B would be compared to actual consumption for those periods. Unfortunately, in the absence of meter readings, those actual consumption values can never be known. Therefore, it is necessary to use alternative measures to evaluate the accuracy of the estimates. One approach that has been used, and which will be considered in more detail in Section 4.1 is to express the estimated consumption of a particular site in the estimated period (say from A to B) as a share of total consumption in that period, since total consumption (that is, consumption by all sites) in the estimated period is known. Algebraically, this can be written in terms of the following relationship (where hats (^) over variables indicate estimated measures):

(1) $$\hat{s}_i^{AB} = \hat{C}_i^{AB} \Big/ NSL^{AB}$$

where $\hat{C}_i^{AB}$ is estimated consumption by site *i* over the period from A to B,

NSL^{AB} is Net System Load over the period from A to B, which is actual aggregate consumption across all sites over the period from A to B, and

$\hat{s}_i^{AB}$ is the estimated share of aggregate consumption over the period from A to B that is attributable to site *i*.

Then, following the next meter reading, when actual consumption by that site over the meter cycle from A to C is known, the actual share of that site in the total consumption over the period from A to C can be calculated. Algebraically, this share can be written as:

(2) $$s_i^{AC} = C_i^{AC} \big/ NSL^{AC}$$

where C_i^{AC} is actual consumption by site *i* over the period from A to C (so that estimated consumption from B to C is given by $\hat{C}_i^{BC} = C_i^{AC} - \hat{C}_i^{AB}$),

NSL^{AC} is Net System Load over the period from A to C, which is actual aggregate consumption across all sites over the period from A to C, and

s_i^{AC} is the actual share of aggregate consumption over the period from A to C that is attributable to site *i*.

The extent to which the estimated share over A to B ($\hat{s}_i^{AB}$) and the actual share over A to C (s_i^{AC}) differ can then be used as a measure of the inaccuracy of the estimate. Thus, for example, if these two shares were equal ($\hat{s}_i^{AB} = s_i^{AC}$), the estimate would be viewed as perfect. However, this measure of the (in)accuracy of the estimate is only useful if the share of total consumption attributable to a particular site is the same in every portion of a meter cycle, which is unlikely to be the case. In other words, even if $\hat{s}_i^{AB} = s_i^{AC}$, the estimate over the period from A to B might not have been accurate – it could be the case that over the estimate period from A to B the site actually consumed less than $\hat{C}_i^{AB}$, so that their actual share for the period A to B was less than $\hat{s}_i^{AB}$, while in the remainder of the meter cycle, from B to C, they consumed more than $\hat{C}_i^{BC}$, so that their share in the latter part of the meter cycle was greater than s_i^{AC}. Therefore, a comparison of these two shares does not provide an objective measure of the accuracy of the estimate in the period from A to B.

An alternative approach to evaluating various methods that might be used to estimate consumption in a period when a meter reading is not taken involves focusing solely on periods that involve actual meter readings. In this way, the estimates that are obtained for a particular period using the different estimation methods can be compared to actual outcomes for that same period. For example, in Figure 1, meter readings are taken at point C and at point E, so that actual consumption is known in the period A to C and in the period C to E. Now, for example, rather than estimating consumption for the period A to B using known information about a particular site prior to point A, as well as known information about aggregate measures, such as NSL, over the period from A to B, the estimates could be made for the entire period from A to C. In this case the estimate would be formed based on known information about a particular site prior to point A, as well as known information about aggregate measures, such as NSL, over the period from A to C. In this way, the estimation that is undertaken over the period from A to C exactly mimics the estimation that would be done from A to B. However, now the estimate that is obtained for the entire meter cycle from A to C can be compared to the known value of actual consumption from A to C, thus providing an objective means of evaluating the accuracy of the estimation method. This is the method that is used in this report to assess the accuracy of various methods for estimating consumption in a period when no meter reading is taken.

3. Data

3.1 Data Structure:

To evaluate different methods for estimating electricity consumption in periods when no meter reading is taken, data were obtained from EDI on a random sample of approximately 30,000 sites. These sites were drawn from EDI's customer base of residential, small commercial, and medium commercial customers, with the data pertaining to metering cycles over the period from January 2001 to mid-2004.

In order to implement the various methods, which are described in detail in the Sections 4.1 and 4.2, the following information was obtained for each site over a meter cycle, such as from A to C in Figure1:

- Start Date (hour, day, month, year)
- End Date (hour, day, month, year)
- Actual Consumption
- NSL (aggregate consumption over all sites)[2]

From this information, the number of days and hours in the meter cycle were calculated, as well as the ratio of consumption by this site to total consumption by all sites over the same period (corresponding to the actual share s_i^{AC} in the previous descriptions). The data that are available for each site do not include the date/time at which consumption was estimated. However, for subsequent analysis, an end date for the estimate period – corresponding to a point such as B or D in Figure 1 – is assigned for each meter cycle for each site as the mid point of the meter cycle period. Although actual consumption is not known in this estimate period, the corresponding NSL is known, and this information was also recorded along with the end date and time for the estimate period.

The information that is described above was obtained for each site for every meter cycle starting at Jan 1, 2001. Initial meter cycles were often incomplete, and were therefore discarded from our sample. The resulting data set therefore contains complete information from a sequence of meter cycles for each site. Since the start date and end dates of a meter cycle differ across sites, and since not all sites consume electricity in every meter cycle, the number of complete meter cycles containing usable information varies across sites.

3.2 Data Requirements for Estimation Methods:

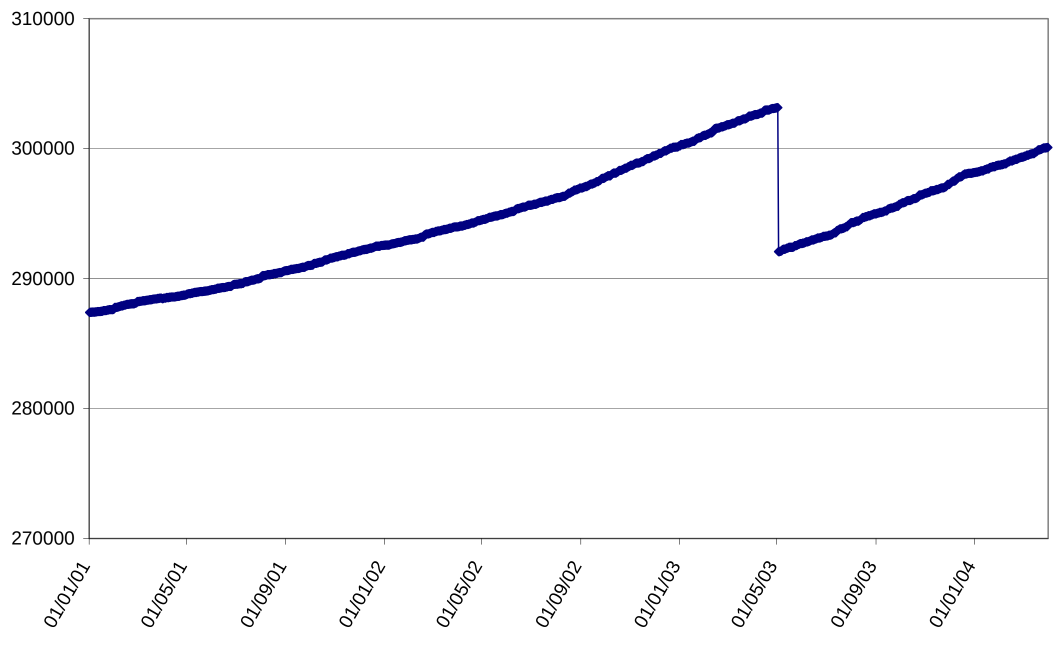
Almost all of the methods that have been proposed or used to estimate electricity consumption in periods when no meter reading is taken make use of some aspect(s) of a site's electricity consumption history. Therefore, for each meter cycle for each site it is necessary to assemble this electricity consumption history. As described in detail in the Section 4, for some estimation

[2] Note that NSL is revised, possibly several times, as additional information becomes available. Since these revisions typically take several months, possibly even longer than one year, the only information that can be used for estimating consumption in periods when meters are not read is the initial estimate of NSL, which is the measure used here.

strategies the consumption history that is required pertains only to the immediately preceding meter cycle, but for others it pertains to the corresponding meter cycle in the preceding year, or the sequence of meter cycles since the corresponding meter cycle in the preceding year. As a result, for many meter cycles the electricity consumption history that would be required for some estimation methods cannot be obtained, in which case these meter cycles cannot be included in the empirical analysis.

In addition to site-specific information, some methods that are used to estimate consumption make use of other particulars, such as weather-related variables, and information on the total number of sites that are included in NSL. Relevant weather variables were obtained for Edmonton, while EDI provided data on the number of sites included in NSL. Unfortunately, part way through the data period (May 2003), a clean-up of sites was performed, with a large number of sites (approximately 3.7%) removed from the database due to such factors as, for example, buildings that had been demolished, etc. However, it is not known if these sites that were omitted in May 2003 were not consuming electricity for the entire sample period, that is, since January 2001. It does appear from Figure 2 that the growth rate in the number of sites is approximately the same after the site clean-up as before, suggesting that these sites could probably also be excluded from the site count prior to May 2003.

Figure 2: Number of Sites, EDI, 2001-2004



3.3 Sample Sizes for Residential, Small Commercial and Medium Commercial Data Sets:

Since the medium commercial sites in the sample tend to be metered on approximately a monthly cycle, while most residential and small commercial sites are metered on an approximate two-month cycle, and since the electricity consumption characteristics of these different types of sites may differ, we treat these different types of sites separately in our analysis. For residential customers, the sample includes information from 26,990 sites, consisting of 493,419 individual observations on meter-reading cycles. Once observations with zero consumption are eliminated, there are 26,973 sites remaining, comprising 489,451 observations, or an average of 18 usable meter cycles per site. On average, these residential meter-reading cycles span 58 days and involve consumption of 990.62 kWh.

The small commercial data set consists of 61,955 meter-reading cycle observations pertaining to 2,696 sites. When observations with no consumption activity are removed, there are 2,681 sites remaining, with a total of 60,233 meter-reading cycle observations, an average of 22.5 usable meter cycles per site. These small commercial meter reading cycles span 46.4 days on average, with an average consumption of 3681.04 kWh.

The medium commercial data set contains data from 300 active sites. There are 9,840 observations, 9,795 of which are from periods with non-zero activity, so that on average there are 32.5 usable meter reading cycles per site. This high number of cycles indicates that for this category of sites the meters are read almost every month at each site. This is reflected in the average meter cycle length of 31.46 days. Average consumption over these 9,795 meter-reading cycles is 21003.26 kWh.

For various reasons, including missing values for other information required for estimation, and the need to construct electricity consumption histories for each meter cycle (which cannot be done for the first set of cycles for each site), fewer observations are actually used in the subsequent empirical analysis.

4. Methodology

Using the three samples of EDI data, we apply five main methods of estimating electricity consumption in periods when no meter reading is taken. Two of these methods utilize historical electricity consumption information from the previous metering period, while the remaining three utilize electricity consumption information from the same general period in the previous year (sometimes in conjunction with additional information from the period for which consumption is being estimated). As discussed previously, we generate estimates corresponding to the five methods for an entire meter cycle rather than just for part of a cycle, as is done in practice. This facilitates a comparison of the estimates that are produced with subsequent actual consumption data, so that the accuracy of the estimates can be assessed. It is possible that estimation over an entire meter cycle, which covers a longer period than is considered in practice may result in less reliable estimates. However, any resulting decrease in reliability should affect all estimation methods considered, so that there is no *a priori* expectation that this longer estimation period will affect the comparisons of accuracy across methods. The same evaluation criteria are applied to all methods: average difference between estimated and actual consumption, mean square percentage error, and the proportion of observations for which there are "large" overestimates. These criteria are described in more detail in Section 5.1.

For all estimation methods, estimates are only formed for meter cycles that involve current consumption activity.

4.1 Methods based on information from the immediately preceding metering period

Estimation methods that make use of electricity consumption history for a site in the immediately preceding metering period might be expected to provide accurate estimates of consumption in the current period in the sense that the immediately preceding period contains the most recent information that is available about electricity consumption at that site (both in terms of actual consumption and consumption relative to aggregate electricity consumption over all sites). The two methods considered here differ in terms of the information that is used from the previous period, and in the way this information is updated for the current period.

4.1.1 Method A

One approach to estimating electricity consumption for a particular site in the current period utilizes information on consumption of electricity at that site in the immediately preceding metering period, as well as aggregate consumption (across all sites) in the current and immediately preceding periods. In the previous metering period, the difference between two consecutive meter readings, generally about 60 days apart, yields actual consumption for a particular site during that period. Total consumption by all cumulatively metered sites – Net System Load (NSL) – during that same period is also known. Using this information, the ratio of consumption by this one site to NSL can be calculated, thereby yielding the proportion of NSL attributable to this particular site during that previous period (the site's usage factor). Algebraically:

(3) $$s_{i,t-1} = C_{i,t-1} \big/ NSL_{t-1}$$

where $s_{i,t-1}$ is the usage factor for site i in period t-1 (the immediately preceding metering period),

$C_{i,t-1}$ is actual consumption by site *i* in period t-1,

NSL_{t-1} is Net System Load in period t-1, which is actual aggregate consumption over all sites in the immediately preceding period.

Since NSL is also known for the period from the last actual meter read to the date when the estimate is to be made, multiplication of this site's usage factor for the earlier period with the actual NSL for the current billing period yields an estimate of consumption at this site for the period since the last meter reading occurred. Algebraically,

(4) $$EstimateA_{i,t} = s_{i,t-1}\, NSL_t = \left(C_{i,t-1} \big/ NSL_{t-1} \right) NSL_t$$

where $EstimateA_{i,t}$ is the estimated electricity consumption by site i in period t, which is the current period – defined as the time since the last meter reading was taken,

$s_{i,t-1}$ is the usage factor for site i in period t-1 (the immediately preceding period), as defined in equation (3),

NSL_t is Net System Load in the period since the last meter read, which is actual aggregate consumption over all sites since the last meter reading at site i.

This is the method currently employed by EDI. The main advantage of this method is that it takes into account changes in total consumption between the previous period and the current period – if total consumption increases, then the sites are collectively consuming more electricity in the current period than in the previous period, and this will be reflected in increased estimates for each site. Conversely, if total consumption is lower in the current period than in the previous period, this will be reflected in lower estimates for each site. However, if total consumption changed because there are more or fewer sites included, or simply because certain (but not all) sites changed their consumption, this method will tend to overestimate electricity consumption in the current period for many sites and underestimate for many others. Furthermore, in this context, this problem of over- and under-estimation will occur whether aggregate consumption is increasing or decreasing.

4.1.2 Method B

An alternative approach is to base the estimate of electricity consumption in the current period – that is, since the last meter reading – on the known levels of consumption per day at the same site in a previous period. This is known as an Average Daily Use (ADU) estimation method.[3] In addition to ENMAX, ADU methods are used by Fortis in Alberta and by utilities in other

[3] This estimation strategy is outlined in the ENMAX document "Reasonability of Estimation Approaches for Settlement and Billing", dated August 31, 2004.

countries such as Western Massachusetts Electric (WME) and Detroit Edison (DTE Energy) in the U.S. and The Australian Gas Light Company (AGL) in Australia.[4]

Under this approach, consumption for the billing period can be estimated based on the immediately preceding period's average daily consumption at the site as:

$$(5) \qquad EstimateB_{i,t} = \left(C_{i,t-1} \big/ Days_{i,t-1} \right) Days_{i,t}$$

where $EstimateB_{i,t}$ is the estimated electricity consumption by site i in period t, which is the current period – defined as the time since the last meter reading was taken,

$C_{i,t-1}$ is actual consumption by site *i* in period t-1,

$Days_{i,t-1}$ is the number of days between meter reads for site *i* in the previous meter cycle,

$Days_{i,t}$ is the number of days for site i in the current meter cycle (since the last meter read for this site).

The main difference between *Method A* and *Method B* is that with *Method A* it is assumed that a site's share of electricity consumption in the previous period will also apply in the current period, while with *Method B*, it is assumed that the site's daily consumption is the same in the current period as in the previous period. The main advantage of *Method B* is that it focuses on site-specific information. Its main disadvantage is that even if aggregate consumption over all sites changes – for example, due to changes in seasons, etc. – this will not be reflected in the electricity estimates that are formed for any site. Thus, this method would be expected to tend to overestimate electricity consumption for each site when aggregate consumption decreases, and underestimate it when aggregate consumption increases, unless these changes in aggregate consumption were solely due to a decrease or an increase in the number of sites, respectively.

4.2 Methods based on information from the same general period in the previous year

The general methods considered above can also be implemented using data from the same period in the previous year, instead of in the immediately preceding metering period. This modification means that the estimates may be able to capture seasonal influences that are similar in size and timing from year to year. The generalizations to the previous methods are quite straightforward, as shown below.

4.2.1 Method C

Some utilities, such as DTE Energy, use ADU strategies based on average daily consumption patterns corresponding to (approximately) the same time period in the previous year.[5] Thus, this

[4] See the Appendix for a selection of websites that describe billing/estimation practices for a cross-section of electric utilities.

[5] See the description of the electricity consumption estimation process used by DTE Energy on the Detroit Edison and MichCon website at http://my.dteenergy.com/myAccount/meterRead.do.

method is a direct generalization of *Method B* in the previous section. In this case, the estimate is calculated as:

$$(6) \qquad EstimateC_{i,t} = \left(C_{i,t-6} \middle/ Days_{i,t-6} \right) Days_{i,t}$$

where $EstimateC_{i,t}$ is the estimated electricity consumption by site i in period t, which is the current period – defined as the time since the last meter reading was taken,

$C_{i,t-6}$ is actual consumption by site *i* in period t-6, that is, six meter cycles previously,

$Days_{i,t-6}$ is the number of days between meter reads for site *i* in period t-6, that is, six meter cycles previously,

$Days_{i,t}$ is the number of days for site i in the current meter cycle (since the last meter read for this site).

Since, for residential and small commercial sites, a metering cycle is approximately 60 days, or two months, consumption measures from six meter cycles previously will approximately reflect consumption in the same period in the previous year. For medium commercial sites where there are generally 12 readings per year, $C_{i,t-6}$ and $Days_{i,t-6}$ would be replaced in equation (6) by $C_{i,t-12}$ and $Days_{i,t-12}$, respectively, so that the estimation method would again reflect consumption from a similar period approximately one year earlier.

One difficulty with implementing this method, and which applies also to any method that utilizes information pertaining to consumption in a similar period in the previous year, is that for various reasons meter readings are not always made on a regular schedule. For example, an unusual reading or some particular event may result in a residential meter being read every month for a period of several months before regular bi-monthly meter readings are resumed. Consequently, electricity consumption and other information from six periods ago (or 12 periods ago for medium commercial sites) may not represent consumption from approximately the same period in the previous year for all sites. To guard against this possibility, and therefore the possibility that estimates obtained in our analysis would not accurately reflect the quality of estimates that would normally be obtained using this method, certain restrictions were placed on data points when using this method. Specifically, data points were excluded from the sample unless the following criteria were met:

- the number of days elapsed since the beginning of the meter-reading interval 6 periods ago (or 12 periods ago for medium commercial sites) must be between 330 and 400 days, so that $C_{i,t-6}$ and $Days_{i,t-6}$ correspond to approximately the same 'season' in the previous year;
- the length of the meter-reading interval for the comparison period must differ by no more than 15 days from the estimation interval for the current period.

4.2.2 Method D

Although, to our knowledge, not currently used by any utilities, *Method A* can also be adapted to incorporate information from the same period in the previous year. That is, the 'usage factor' applied to current aggregate consumption can be calculated as the share of total consumption attributable to a site from the same time period in the previous year rather than in the previous period. Thus, with this approach the estimate would be obtained using the following formula:

$$EstimateD_{i,t} = s_{i,t-6}\, NSL_t = \left(C_{i,t-6} \big/ NSL_{t-6} \right) NSL_t \tag{7}$$

where $EstimateD_{i,t}$ is the estimated electricity consumption by site i in period t, which is the current period – defined as the time since the last meter reading was taken,

$s_{i,t-6}$ is the usage factor for site i in period t-6, that is, six meter cycles previously, as defined by the term in parentheses in equation (7),

$C_{i,t-6}$ is actual consumption by site *i* in period t-6, that is, six meter cycles previously,

NSL_{t-6} is Net System Load in period t-6, which is actual aggregate consumption over all sites in period t-6, that is, six meter cycles previously (based on meter cycles for site *i*),

NSL_t is Net System Load in the period since the last meter read, which is actual aggregate consumption over all sites since the last meter reading at site i.

The data points that are employed in the empirical analysis to obtain consumption estimates using *Method D* are limited to those that satisfy the same restrictions as described previously for *Method C*.

4.2.3 Method E

A variation of *Methods C and D* has been suggested in a recent report by Baraniecki and Koehn (2002).[6] With this approach, the estimate of electricity consumption for a particular site in the next billing period is obtained by determining the percentage of that site's annual consumption that occurred in (approximately) the same period in the previous year, and then applying that percentage to that site's projected annual consumption for the current year. This approach involves a number of steps that can be described as follows:

<u>Step 1</u>: Calculate weights that reflect the percentage of annual consumption by a particular site (site *i*) for comparison periods in the previous year:

$$W1_{i,t-1} = \left(C_{i,t-7} \big/ (C_{i,t-2} + C_{i,t-3} + C_{i,t-4} + C_{i,t-5} + C_{i,t-6} + C_{i,t-7}) \right) \tag{8}$$

$$W2_{i,t-1} = \left(C_{i,t-6} \big/ (C_{i,t-2} + C_{i,t-3} + C_{i,t-4} + C_{i,t-5} + C_{i,t-6} + C_{i,t-7}) \right) \tag{9}$$

[6] J.M. Baraniecki and S. Koehn "Proposed Billing Estimation Method Using Consumption Profiles", Working Paper, EPCOR Energy Services Inc, November 2002.

where $C_{i,t-k}$ is actual consumption by site *i* in period t-*k*, that is, *k* meter cycles previously, where *k* = 2, 3, 4, 5,6, or 7.

$W1_{i,t-1}$ is a weight ($0 < W1_{i,t-1} < 1$) that indicates the proportion of the previous year's electricity consumption by site i that was consumed in the same period in the previous year as the immediately preceding metering period, that is, in period t-7, which is seven meter cycles previously.

$W2_{i,t-1}$ is a weight ($0 < W2_{i,t-1} < 1$) that indicates the proportion of the previous year's electricity consumption by site i that was consumed in the same period in the previous year, that is, in period t-6, which is six meter cycles previously.

To understand these weights it is useful to consider a specific example. Suppose that estimated consumption is required for January-February 2004. Consumption in the immediately preceding metering period, November-December 2003 is used later in the calculation but not in the weights W1 and W2. Rather, the two weights, W1 and W2 are based on consumption in the year that precedes this previous metering period, that is, the year commencing in November 2002 and ending in October 2003. The weight W1 captures the proportion of annual electricity consumption that occurred in November and December of that year, that is, the period one year ago that corresponds to the most recently completed metering cycle. Similarly, weight W2 indicates the proportion of annual electricity consumption that occurred in January and February of 2003, which is the period that matches the time interval for which an estimate of consumption is now required in the current year.

The weights W1 and W2 are used in the calculation as follows. First, W1 is used in conjunction with consumption in the immediately preceding meter period (November-December 2003) to project annual consumption for the period commencing in November 2003 and ending in October 2004. Next, the weight W2 is applied to this projected annual consumption to provide an estimate of consumption for January-February 2004. However, before these weights can be applied, various adjustments are made to account for differences in the number of days in the corresponding metering periods in different years. Specifically, this requires the following steps:

<u>*Step 2*</u>: Using the per-day rate of consumption in the just-completed metering period, determine an adjusted consumption amount that would have occurred if this metering period had been of the same length as the corresponding metering period in the previous year.

(10) $$Cadj_{i,t-1} = \left(C_{i,t-1} / Days_{i,t-1} \right) Days_{i,t-7}$$

where $Cadj_{i,t-1}$ is actual consumption by site *i* in the preceding metering cycle adjusted for the number of days in the corresponding metering period one year ago.

<u>*Step 3*</u>: Using the weight W1, and adjusted consumption, project annual consumption for the year commencing at the start of the immediately preceding metering period.

(11) $$PROJANN_{i,t} = \left(Cadj_{i,t-1} / W1_{i,t-1} \right)$$

where $PROJANN_{i,t}$ is projected annual consumption for site *i* commencing at the start of the preceding metering period.

Step 4: Use this projected annual consumption in conjunction with the weight W2 to determine estimated consumption in the next metering cycle, recognizing however that this projection will be for a period having the same length as the corresponding metering cycle in the previous year (that is, a period of length $Days_{t-6}$).

$$PROJ_{i,t} = W2_{i,t-1}\ PROJANN_{i,t} \tag{12}$$

where $PROJ_{i,t}$ is projected consumption for site *i* for the current metering cycle prior to adjusting for any difference between the length of the current metering cycle and of the corresponding metering cycle one year ago.

Step 5: Convert this amount to a daily consumption rate:

$$PROJDAY_{i,t} = PROJ_{i,t} \big/ Days_{i,t-6} \tag{13}$$

where $PROJDAY_{i,t}$ is the projected daily rate for electricity consumption for site *i* for the current metering cycle.

Step 6: Use this daily consumption rate along with the length of the next metering cycle to estimate total consumption for this period:

$$EstimateE_{i,t} = PROJDAY_{i,t}\ Days_{i,t} \tag{14}$$

where $EstimateE_{i,t}$ is the estimated electricity consumption by site i in period t, which is the current period – defined as the time since the last meter reading was taken.

In order for data points to be included in the sample used to form consumption estimates via *Method E*, the same restrictions are applied as with *Method C* and *Method D*. Also, since the number of metering periods per year for medium commercial sites is different to those observed with residential and small commercial sites, it is necessary to make appropriate adjustments in the periods used in the various steps of *Method E* in this case.

5. Results

5.1 Evaluation of Electricity Consumption Estimates

Each of the estimation methods described in Section 4 is used to form estimates of electricity consumption in a subsequent period (when actual consumption is known). Since actual consumption is known, the estimates that are obtained via the five estimation methods can be compared to actual outcomes for the period in order to assess their accuracy. In this report we consider four measures of accuracy. These are:

5.1.1 Average Estimation Error (AEE)

This evaluation measure is obtained by averaging the difference between estimates and actual values across all data points. Algebraically, this measure is calculated as:

(15) $$AEE_j = \frac{1}{N}\left(\sum_{i=1}^{NS}\sum_{t=1}^{T_i}(Estimate_{i,t}^{j} - Actual_{i,t})\right)$$

where AEE_j is the Average Estimation Error for estimation method j, where j indexes the various methods described in the previous section,

$Estimate_{i,t}^{j}$ is estimated consumption for site i in meter cycle period t obtained using method j,

$Actual_{i,t}$ is actual consumption for site i in meter cycle *t*,

T_i is the number of meter cycles for which estimates are made for site *i* (which may be different for different sites),

NS is the number of sites for which estimates are made,

N is the total number of data points used in the evaluation, where $N = \sum_{i=1}^{NS}\sum_{t=1}^{T_i} 1$.

An advantage of this evaluation measure is that it is straightforward to calculate and has intuitive appeal in that it can be interpreted simply as an average error. A larger absolute value of AEE with a particular method would indicate that the method in question has larger errors on average, and is therefore less desirable. However, AEE can be small even though there are very large errors for particular sites in certain meter periods provided that overestimates (*Estimate* > *Actual*) in some cases are offset by underestimates (*Actual* > *Estimate*) in others.

5.1.2 Root Mean Square Percentage Error (RMSPE)

This evaluation criterion accounts for most of the deficiencies of the AEE criterion by considering the size of the error relative to the value that was being forecast. RMSPE incorporates the idea that larger errors are more problematical if they occur relative to small values of actual consumption. Furthermore, RMSPE squares this percentage error so that positive and negative errors cannot offset each other. Unlike AEE, RMSPE can only be zero if every forecast for every site and every meter cycle is perfect. This criterion is defined algebraically as follows:

$$(16) \qquad RMSPE_j = \sqrt{\frac{1}{N}\sum_{i=1}^{NS}\sum_{t=1}^{T_i}\left(\frac{Estimate_{i,t}^{j} - Actual_{i,t}}{Actual_{i,t}}\right)^2}$$

where $RMSPE_j$ is the Root Mean Square Percentage Error for estimation method j, where j indexes the various methods described in the previous section.

Smaller values of RMSPE indicate a more accurate estimation method.

5.1.3 Other Measures

In addition to standard statistical evaluation methods, such as AEE and RMSPE, another approach to gauging the effectiveness of particular estimation methods is to assess the extent or frequency of the over- and under-estimates that are made when applying particular estimation methods. No single estimation method can perfectly estimate consumption for every consumer in every period. Presumably consumers know this, and accept that, in the absence of monthly meter readings (for which they would likely bear the associated costs), the estimates that are used in periods when no meter reading is taken are likely to either exceed or underestimate their actual consumption in that period. As noted earlier, since any such discrepancies will be rectified when the next meter reading is taken, these discrepancies simply involve a temporary loan either to or from the electricity supplier.

However, electricity consumers are likely to have asymmetric tolerances for over- and under-estimation of their electricity consumption. In particular, it might be expected that consumers are less concerned with underestimates than with overestimates, since the former simply requires them to pay more next period and less in the current period, and most – although not all – consumers likely prefer paying later rather than sooner.[7] In addition, consumers would probably prefer smaller over-estimates – and possibly even under-estimates – than larger ones. This might be an especially important factor for electricity providers to consider in an environment where customers have options in terms of the choice of provider for their electricity needs.

5.1.3.1 Proportion of Large Consumption Overestimates

To assess the extent to which consumer goodwill toward their electricity supplier may be affected, an alternative measure that can be used to evaluate the various electricity consumption estimation methods is to calculate the proportion of estimates that are "large" in the sense that they exceed actual consumption by a specified percentage. Algebraically, this measure can be expressed as follows:

[7] Obviously this is not the case for all consumers, since some may choose a balanced billing option whereby they overpay in periods with lower consumption in order to underpay (often later) in periods with higher consumption.

(17) $$PROPLARGE(x)_j = \frac{1}{N}\left(\sum_{i=1}^{NS}\sum_{t=1}^{T_i} LARGE(x)_{i,t}^{j}\right)$$

where

(18) $$LARGE(x)_{i,t}^{j} = \begin{cases} 1 \quad if \quad \left(\dfrac{Estimate_{i,t}^{j} - Actual_{i,t}}{Actual_{i,t}}\right) > 1 + (x/100) \\ \\ 0 \quad otherwise \\ \end{cases}$$

where $PROPLARGE(x)_j$ is the proportion of observations for which actual consumption exceeds estimated consumption by more than *x* percent using estimation method *j*, where j indexes the various methods described in the previous section,

$LARGE(x)_{i,t}^{j}$ is equal to 1 if using method *j* estimated consumption exceeds actual consumption for site *i* in meter cycle period *t* by more than *x* percent, and is equal to zero otherwise,

x is the percentage by which the estimated consumption for site i in meter cycle period t obtained using method j must exceed actual consumption for that same site for the estimation error to be considered to be large.

In the empirical analysis we consider values for *x* of 5%, 10% and 25%.

5.1.3.2 Proportion of Sites with Frequently Large Overestimates

A related measure is concerned not so much with the size of positive estimation errors (where estimated consumption exceeds actual consumption), but with the frequency with which these positive estimation errors recur for the same consumers. Such a measure could be motivated by the “ill will” that is likely to result if an estimation method tends to overestimate electricity consumption systematically for a large percentage of customers rather than if the overestimates are spread ‘randomly’ across customers.

A measure that can be used to reflect the frequency with which electricity consumption is consistently overestimated at certain sites is the proportion of sites for which more than a specified percentage of their estimates exceed their actual consumption by more than a particular percentage. An example of such a measure would be the proportion of sites for which at least 50% of the estimates exceed actual consumption by at least 10%. Algebraically, such a measure is defined as follows:

(19) $$PROPOVER(x,y)_j = \frac{1}{NS}\left(\sum_{i=1}^{NS} INDOVER(x,y)_i^j\right)$$

where

(20) $$INDOVER(x,y)_i^j = \begin{cases} 1 & if \quad OVER(x)_i^j \; > \; y/100 \\ 0 & otherwise \end{cases}$$

(21) $$OVER(x)_i^j \; = \frac{1}{T_i}\sum_{t=1}^{T_i} LARGEx_{i,t}^j$$

and $PROPOVER(x,y)_j$ is the proportion of sites for which estimated consumption exceeds actual consumption by more than *x* percent for more than y percent of the metering cycles using estimation method *j*, where j indexes the various methods described in the previous section,

$INDOVER(x,y)_i^j$ is an index that is equal to 1 if, using method *j*, estimated consumption exceeds actual consumption for site *i* by more than *x* percent for more than *y* percent of the meter cycles for which estimates are made.

$OVER(x)_i^j$ is the proportion ($0 < OVER(x)_i^j < 1$) of estimates for site *i* using method *j* for which estimated consumption exceeds actual consumption by more than *x* percent,

x is the percentage by which the estimated consumption for site i in meter cycle period t must exceed actual consumption for that same site for the estimation error to be considered to be large.

y is the percentage of estimates for each site that must involve overestimates of x percent or more for that same site to be considered as being frequently overestimated.

In the empirical analysis we consider values for *x* of 5%, 10% and 25%, and values of y of 50%, 60%, 67%, and 75%. Thus, for example, $PROPOVER(10,60)_j$ would indicate the proportion of sites for which at least 60% of estimates obtained using method *j* exceed actual consumption by 10% or more. We only apply this measure to sites for which there are estimates for at least one year.

5.2 Aggregate Results:

The five estimation methods were applied, wherever applicable, to the full sample of Residential, Small Commercial, and Medium Commercial sites. However, due to the need to construct electricity consumption histories for each site, the total number of data points (*N*) used varies with each method. For each method the all applicable data points are used, although for comparison purposes each method is also applied using the subset of data points that can be applied to all methods.

First we consider the performance of the five estimation methods considered in terms of AEE and RMSPE. The results using these evaluation criteria are presented in Tables 1a, 1b, and 1c. The first three columns of these tables provide results using all available data points for each of the respective estimation methods, while the last three columns provide summary statistics for the group of observations for which there is sufficient data for all estimation methods to be applied.

While *Method A* appears to be unambiguously preferred for Residential sites, the results are mixed for Commercial sites.

5.2.1 Residential:

For Residential customers, *Method A* (the method currently used by EDI) always performs the best according to both standard statistical evaluation measures and using both comparison groups. The AEE measure of the average difference of the estimate from actual consumption indicates a very small tendency for *Method A* to overestimate, while *Method B* and *Method C* (which are the next best in terms of both average difference and RMSPE) both tend to underestimate by amounts that are 10 times larger in absolute value. The remaining two methods exhibit much larger average overestimates, and perform worst in terms of RMSPE. The RMSPE values indicate that the methods based on the previous metering period's information perform better than those based on a similar period from the previous year. By far the worst estimation method, according to both measures, is *Method E* which is based partially on projections of energy consumption for the entire upcoming year, opening up greater possibilities for error.

5.2.2 Small Commercial:

The results for Small Commercial sites are less clearcut than for Residential sites, although *Method E* always performs worst. No single method has the best performance. According to the AEE measure, *Method B* outperforms the other estimation strategies by a wide margin. Thus, according to the AEE criterion, basing the estimate purely on site-specific consumption in the preceding period is better than applying the customer's previous share of NSL to the current value of NSL. *Method B* tends to underestimate actual consumption, with the absolute value of the underestimate being approximately 5 times smaller than the overestimate from *Method A.*

In terms of the RMSPE criterion, *Method A* performs best when each method is evaluated using all observations for which that method can be applied. However, when the evaluation is based on the subset of observations for which all methods can be applied, *Method C* and *Method D* have the smallest RMSPE. Thus, for this subset of observations, estimation methods that take account of energy consumption patterns from the same general period of time in the previous year (without projecting annual consumption) perform the best. Even so, *Method A* is not outperformed by much, as its RMSPE value is similar in magnitude to those for *Method C* and *Method D*.

5.2.3 Medium Commercial:

As was the case for Small Commercial sites, *Method B* proves to be more accurate than the other methods in terms of the average difference between estimated and actual consumption (AEE). This is especially evident for the subset of observations for which all estimation methods can be applied, where the absolute values of the average errors for the other methods are all more than 100 times the value for *Method B.*

Depending on the set of observations being considered, *Method A* ranges from having the best RMSPE to the worst, although the RMSPE measures tend to be reasonably similar for all methods. Based on the subset of observations for which all methods can be applied, *Method A* is best, followed by *Method B* which also uses information from the previous metering period. However, when the evaluation is based on all available observations for each method, the ranking of methods according to RMSPE is opposite, with the methods based on information from the previous year performing the best in terms of RMSPE (but the worst in terms of average forecast error).

5.3 Robustness of Aggregate Results

It is only for Residential sites that a single method consistently outperforms the others for the aggregate data. To assess the robustness of this result, the analysis in the previous section was repeated on subsamples obtained by subdividing the residential sample into ten groups of approximately 50,000 meter-cycle observations. The AEE and RMSPE results for these various ten subsamples are presented in Tables 2a-2j.

These results indicate that the ranking of the different methods is somewhat sensitive to the sample metering cycles examined. *Method A* always has the smallest average estimation error (AEE) when the methods are evaluated using all observations for which each can be applied, and is always ranked first or second by this criterion when considering only those observations for which all methods can be applied.

However, the findings using RMSPE are not quite as robust. Using all observations for which each method can be applied, *Method A* has the smallest or second smallest RMSPE in 6 of the 10 subsamples, as is also the case with *Method B*, usually in the same subsamples. *Method E* has the smallest RMSPE using all observations for which it can be applied in 4 of the subsamples. When considering only those observations for which all methods can be applied, *Method A* has the smallest or second smallest RMSPE in 8 of the 10 subsamples, while the same result holds for *Method B* in 7 of these same 8 subsamples.

5.4 Patterns in Estimation Accuracy over Time:

In addition to comparing the performance of the different estimation methods using the entire sample of data points, it is instructive to consider their performance in different time periods or seasons, since it may be the case that some methods perform better or worse than others in particular circumstances. To investigate this issue, both AEE and RMSPE were calculated separately for each year of the sample (2001, 2002, and 2003), as well as for each month of the year (using all three years combined), where the year and month refers to the date at the midpoint of each meter reading cycle. These values are presented in Tables 3a-3f for the various estimation methods and customer types. Except for 2001, during which time there are sufficient data points to calculate estimates only for *Methods A* and *B*, the measures in each case are calculated using the subset of data points for which all estimation methods can be applied. Thus, the relevant comparisons that can be made are between the values in Tables 3a-3f and those in the final three columns of Tables 1a-1c, although the actual subset of observations used is not the same in the different tables.

5.4.1 Residential:

Although the average estimation error (AEE) is smallest for *Method A* in every year, this method does not provide the most accurate estimates for any particular month (season), as it is always outperformed by one or more of the other methods. It is only when averaged over the entire year (or sample) that *Method A* performs well. In fact, both methods (*Method A* and *Method B*) that are based on information on consumption in the previous meter-reading period tend to overestimate over the period from February through July, and underestimate over the period from August through January. Of the methods that make use of information on actual consumption from the previous year, *Methods D* and *E* tend to overestimate for every year and in every season, while *Method C* has a strong tendency to underestimate consumption.

With respect to RMSPE (Table 3a), when results are broken down by year or season, *Method A* is often (although not always) outperformed by *Method B*, and infrequently by the other methods that use information from consumption behaviour in the previous year. It is only when averaged across all years or seasons that the performance of *Method A* is ranked the highest (or second highest after *Method B*) of the various methods examined.

5.4.2 Small Commercial:

When averaged over all years and seasons (Table 1b), *Method B* is clearly more accurate in terms of average estimation error, while all but *Method E* have fairly similar RMSPE values (with *Method C* being the most accurate according to this measure). However, as was the case with the Residential sector, the aggregate results do not always hold across time or across seasons. While *Method B* has the smallest average error in every year (Table 3d), in most seasons, it is outperformed by *Method C* or *Method D*. Thus, in any particular season, a method that looks at the previous year's consumption for that site performs better in terms of having a smaller AEE value. *Method A* is found to exhibit behaviour that is similar to that observed for the Residential sites, except in this case it tends to overestimate, on average, for September through January, and underestimate for the remaining months.

From year to year, no single estimation method consistently performs best in terms of the RMSPE criterion (Table 3c), with the methods using information from the previous period performing better in 2003 but worse in 2002 than methods that use information from the previous year, although Method E has the smallest RMSPE of all methods in 2003. In terms of RMSPE in different months, *Methods A* and *B* which only consider consumption in the previous metering period perform better in most months, although one of the other three methods outperforms these in April, May and July.

5.4.3 Medium Commercial:

For the Medium Commercial sites, meter readings generally occur on a monthly basis, so that there are a sufficient number of observations to include 2004 in Tables 3e and 3f.

In 2002 and 2003, *Method B,* which performed best overall with respect to average estimation error (Table 1c), performs best on an annual basis, although *Method E* does better in the limited set of observations available for 2004. *Method B* occasionally performs best in terms of smallest AEE on a seasonal basis, although *Method A* is best in two months while *Method C* is best in five months and *Method E* is the best in January and November. Interestingly, we again observe that *Method A* exhibits a distinct pattern of overestimation and underestimation, with overestimates occurring from July through December, and underestimates in the remaining six months.

As with the other types of sites, RMSPE rankings vary across years and seasons, although *Method A* performs at least as well as other methods in the majority of months and in some years.

5.5 Proportion of Large Consumption Overestimates

As noted in Section 5 apart from standard statistical evaluation methods, such as AEE and RMSPE, the effectiveness of particular estimation methods can also be assessed in terms of the extent or frequency of the over- and under-estimates that are made. Specifically, as defined in Section 5.1.3.1, we calculate *PROPLARGEx* , the proportion of observations for which estimated consumption exceeds actual consumption by more than a specified percentage (x) using each estimation method. The specified percentages that are used in the calculations here are x = 5%, 10% and 25%. For each value of x, *PROPLARGEx* is calculated for all three types of customers. All calculations are based on the subset of observations for which all estimation methods can be applied, except for 2001 where we examine all observations for which *Methods A* and *B* can be applied. These results are presented in Tables 4a-4f.

5.5.1 Residential Customers

Table 4a shows that for residential customers, the lowest rate of substantial overestimates in any given year occurs using *Method A.* This method always performs best in terms of having the smallest proportion of estimates that exceed actual values by more than 10% or by more than 25%. Even so, approximately 10% of all estimates are over by more than 25%, even for the best performing method.

In general, the methods based on information from the previous year perform worse than those based on the previous metering period when it comes to the proportion of large overestimates of electricity use.

The superior performance of *Method A* continues to hold up in general when we examine proportions of overestimates by time of year (Table 4b). For 7 of the 12 months, Method A ranks best in terms of having the smallest proportion of large (>25%) overestimates, and only twice is it outside of the top 2 in this category. In both cases where *Method A* is 3rd best, it has rates of large overestimation that are very similar to the methods that outperform it.

There are distinct seasonal patterns for *Method A*. While generally the proportion of large (>25%) overestimates is at or below 0.09, this proportion is higher for April through July with values in the 0.11 to 0.17 range.

5.5.2 Small Commercial Customers

Tables 4c and 4d contain the results for small commercial customers. Proportions of large (>25%) overestimates are more similar across estimation methods than for residential customers, with proportions generally exceeding 0.15. There is no method that is unambiguously preferable in terms of this particular evaluation criterion. Furthermore, methods based on information from the previous year tend to do as well as those based on the previous metering period.

Seasonal patterns for *Method A* are also discernable for the small commercial customers, with the lowest proportions of large overestimates occurring in January through March, while the highest proportions occur during May, June, and July.

5.5.3 Medium Commercial Customers

The results for Medium Commercial customers are presented in Tables 4e and 4f. On a year-by-year basis, *Method A* tends to do quite well in terms of the proportion of large overestimates, although there is often not much difference in comparison to *Method B*. Large overestimates occur for only 5 to 6% of the observations. *Methods C* and *D* tend to perform worst, with 7% to 13% of the estimates generated via these methods involving substantial overestimates.

During some times of year *Methods A* and *B* outperform the methods based on information from the previous year by wide margins. This tends to occur in the January through March period where only 1% to 2% of estimates obtained using these two methods exceed actual consumption by more than 25%. It is more difficult to discern seasonal patterns in the proportion of large overestimates for these customers (who tend to have monthly meter readings anyway).

5.6 Proportion of Sites with Frequently Large Overestimates

For each category of customers (residential, small commercial, and medium commercial), we calculate the percentage of customers for whom more than 75%, 67%, 60%, or 50% of consumption estimates exceed actual consumption. This is repeated for estimates that exceed actual consumption by at least 5%, 10% and 25%. Only sites for which there are at least one full year’s worth of meter-reading cycles are included. In addition, we limit our comparison to the set of observations for which all estimation methods can be applied.

The results are reported in Tables 5a-5c. For almost all estimation methods and customer groups, a site is more likely to experience overestimates than underestimates. The only exceptions are *Method C* for Medium Commercial customers and *Method B* for Residential customers.

Some methods do much better than others in terms of the proportion of customers who are subjected to an 'inordinate' number of overestimates. For example, with residential sites, *Method C* would result in over 10% of the sites receiving overestimates more than 75% of the time. This is the case for fewer than 2% of the sites using *Method A*, and for fewer than 1% using *Method B*.

In general, methods using information from the previous metering cycle tend to perform better in terms of having a smaller 'inordinate' numbers of overestimates than those based on information from the same general time span during the previous year. *Method E*, however, does tend to perform in a manner that is comparable to *Methods A* and *B* according to this metric. These results hold over all customer types.

As the size of the overestimate that is considered increases, the same general patterns are observed across estimation methods. Overall, *Method A* appears to perform relatively well according to these criteria.

6. Proxied adjustments for weather and other seasonal factors

It is apparent, at least for *Method A*, that there are seasonal patterns associated with tendencies to over/underestimate electricity consumption.

In this section we report on a limited examination of the suitability of using NSL per day as a proxy for capturing factors such as hours of daylight and temperature in the estimation of Residential electricity usage. Variations in daylight and temperature are expected to affect the demand for lighting and heating. This will affect aggregate demand and manifest itself, along with other factors, in variations in NSL. We assume that there is some 'base' proportion (α) of energy use that is unaffected by fluctuations in seasonal factors, while remaining energy use is sensitive to temperature, hours of daylight, etc. A straightforward approach (that does not require the matching-up of weather data with the varying start dates and lengths of the periods involved) to proxy the weather/environmental factors that affect demand is to factor in relative NSL data from the current and previous periods. (This is similar to the method used by ATCO that uses degree day information. ATCO uses 0 .772 for the 'base load' component and 0.228 for the 'heat load' percentage weights).[8]

Our "weather-adjusted" estimates are calculated as

(22) $$EstimateWA_{it} = \alpha*Estimate_{it} + (1- \alpha)(NSLPD_t/NSLPD_{t-1})*Estimate_{it}$$

where $NSLPD_t$ = net system load per day corresponding to the relevant time period;

For *Methods A* and *B*, t-1 is the immediately preceding period. For the remaining methods, t-1 refers to the same 'period' in the previous year.

Since α is not known, we estimate it for early periods in the sample, and apply this estimate to later periods. The basic methodology we follow is:

(i) Use 'early' (observations with start dates up to and including December 2002) data to estimate α by finding the value that minimizes

(23) $$\Sigma(Cons_{it}-EstimateWA_{it})^2$$

- For *Method A* and *Method C* these yield values in the acceptable range of 0 to 1. The value obtained for *Method A* is also applied to *Method B*. The value obtained for *Method C* is also applied to *Method D*.

(ii) the values obtained in (i) are applied to estimates for the later period (observations with start dates during or after January 2003)

[8] As specified in the ENMAX document "Reasonability of Estimation Approaches for Settlement and Billing", dated August 31, 2004.

The results for these ‘weather-adjusted’ estimation methods appear in Table 6. In general, using a proxied ‘weather-adjustment’ does not lead to much improvement in performance. For *Method A*, although the adjustment leads to an improvement in RMSPE, there is a deterioration in the magnitude of the average difference between estimated and actual consumption when compared to the unadjusted estimates over the same set of observations. For *Method B*, the estimates improve according to both of our measures, with the improvement in the average estimating error being large enough to make its performance better than that of *Method A*. According to the RMSPE measure, *Method A* is still preferred over all of the other methods after the weather adjustments.

The remaining methods perform less well after the proxied weather adjustment. This may be due to a variety of factors including a limited ability of NSL to proxy accurately for weather-related factors (especially since the number of sites is steadily increasing) and possible shifts over time of the proportion of electricity usage that is sensitive to temperature or hours of daylight.

In further work it may be possible to improve upon these ‘weather-adjusted’ estimates by directly matching observed weather data (such as cooling degree days) with the meter-reading intervals.

7. Summary and Conclusions

We have examined several estimation methodologies that utilize electricity consumption information from previous periods, as well as – in some cases – additional information such as proxies for weather-related variables. These methodologies have been used to estimate electricity consumption over metering cycles for a random sample of residential, small commercial, and medium commercial sites in Edmonton, over a time span of approximately three and a half years. Furthermore, these methods have been evaluated according to a series of metrics ranging from standard statistical criteria such as average estimation error (AEE) and root mean square percentage error (RMSPE) to measures designed to capture potential customer 'disenchantment' that are based on the percentage of overestimates of various magnitudes. These evaluation criteria are examined in aggregate, by year, by time of year, and for the final criterion, by site.

Our findings indicate that no single estimation method performs best in all circumstances or according to all criteria. On aggregate, the current method used by EDI, which employs information from the immediately preceding metering cycle, performs best for residential sites and also performs well for small commercial sites. It does not fare as well for medium commercial sites, for which the number of observations available for analysis is much smaller. An alternative method, based as well on information from the immediately preceding metering cycle, also performs well with the aggregate data, and in some cases does better than or as well as the EDI method. However, particularly for small and medium commercial sites, estimation methods that utilize information on the electricity consumption history for the site from the same period in the previous year perform better according to some of the selected evaluation criteria.

Our analysis also indicates that the relative performance of the various estimation methodologies is somewhat sensitive to the sample of observations selected. Nevertheless, for residential sites, the two methods that utilize consumption history from the immediately preceding meter cycle generally perform the best. In terms of performance in different years or months, no single estimation method does well in all cases. For residential sites, the EDI method performs well regardless of the particular year, but not in all months, and is frequently outperformed by an alternative method that relies on information from the previous meter cycle. Interestingly, both of these methods exhibit strong seasonal patterns, tending to overestimate in some months and underestimate in others. This suggests that the performance of these methods may be enhanced by including additional seasonal information.

For residential sites the EDI method has the lowest rate of substantial overestimates of all estimation methods considered, although approximately 10% of all estimates exceed actual values by more than 25%, even for the best performing method. In general, for all types of sites, methods that utilize information from the previous meter cycle tend to yield better estimates according to this criterion than those utilizing information from the same period in the previous year. These same two methods also tend to result in smaller proportions of sites that receive overestimates in a large proportion of cases.

Future work of interest to firms who must invoice for electricity use in the absence of meter readings could involve the evaluation of the potential benefits that might accrue from the incorporation of supplemental information on weather such as cooling and heating degree days over the estimation period into the various methods considered.

References

"Appendix A: Estimation Methodology & Validation Thresholds"

Baraniecki, J.M. and S. Koehn (2002), "Proposed Billing Estimation Method Using Consumption Profiles", Working Paper, EPCOR Energy Services Inc, November.

ENMAX Corporation (2004), "Reasonability of Estimation Approaches for Settlement and Billing", mimeo, August.

Table 1a: Aggregate Results – Residential (26,990 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=199053)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	0.658 (N=460287)	6.510	1005.84	0.866	5.738	1042.09
Method B	-9.012 (N=460287)	6.662	1005.84	-10.345	6.104	1042.09
Method C	-10.682 (N=227356)	7.670	1045.56	-2.830	7.619	1042.09
Method D	30.400 (N=227356)	7.816	1045.56	33.136	7.772	1042.09
Method E	79.514 (N=199059)	9.842	1042.12	79.530	9.842	1042.09

Table 1b: Aggregate Results – Small Commercial (2,696 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N= 11395)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	28.37 (N=57089)	20.23	3738.95	34.88	24.88	3141.81
Method B	-4.82 (N=57089)	20.77	3738.95	-7.39	27.58	3141.81
Method C	-46.49 (N=13408)	22.94	3135.70	-33.63	23.17	3141.81
Method D	76.39 (N=13408)	23.95	3135.70	74.37	24.32	3141.81
Method E	3166.34 (N=11396)	203.67	3142.51	3167.05	203.67	3141.81

Table 1c: Aggregate Results – Medium Commercial (300 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N= 5224)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	107.23 (N=9480)	3.58	21022.47	108.91	1.85	21517.03
Method B	-33.85 (N=9480)	3.56	21022.47	1.06	1.89	21517.03
Method C	-131.01 (N=5686)	1.95	21397.88	-162.47	2.03	21517.03
Method D	726.51 (N=5686)	2.03	21397.88	664.02	2.11	21517.03
Method E	208.95 (N=5238)	2.22	21501.75	206.83	2.23	21517.03

Table 2a: Aggregate Results –Residential Sub-Sample #1 (2,632 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20284)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	1.808 (N=46844)	4.270	1019.31	1.544	1.488	1046.96
Method B	-7.512 (N=46844)	4.670	1019.31	-9.060	1.641	1046.96
Method C	-5.382 (N=23137)	2.709	1051.93	2.298	2.742	1046.96
Method D	36.503 (N=23137)	2.863	1051.93	38.680	2.867	1046.96
Method E	33.469 (N=20284)	0.766	1046.96	33.469	0.766	1046.96

Table 2b: Aggregate Results –Residential Sub-Sample #2 (2,630 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20478)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	2.034 (N=46779)	3.598	1000.04	2.632	2.400	1030.11
Method B	-7.182 (N=46779)	3.517	1000.04	-7.230	2.328	1030.11
Method C	-6.337 (N=23371)	3.265	1035.12	1.082	3.359	1030.11
Method D	35.076 (N=23371)	3.426	1035.12	37.126	3.531	1030.11
Method E	52.003 (N=20479)	2.775	1030.15	52.017	2.775	1030.11

Table 2c: Aggregate Results –Residential Sub-Sample #3 (2,627 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20471)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	1.809 (N=46758)	11.410	1009.26	0.845	1.705	1035.14
Method B	-7.607 (N=46758)	11.729	1009.26	-10.077	1.734	1035.14
Method C	-7.324 (N=23308)	12.178	1038.82	-1.851	10.664	1035.14
Method D	34.038 (N=23308)	12.545	1038.82	34.122	11.123	1035.14
Method E	39.114 (N=20471)	3.158	1035.14	39.114	3.158	1035.14

Table 2d: Aggregate Results –Residential Sub-Sample #4 (2,618 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20257)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	3.125 (N=46715)	3.436	1018.97	0.721	2.283	1054.68
Method B	-6.606 (N=46715)	3.277	1018.97	-10.420	2.105	1054.68
Method C	-6.756 (N=23068)	3.397	1057.51	-1.812	3.260	1054.68
Method D	35.354 (N=23068)	3.482	1057.51	34.907	3.333	1054.68
Method E	36.767 (N=20258)	2.649	1054.71	36.781	2.649	1054.68

Table 2e: Aggregate Results –Residential Sub-Sample #5 (2,619 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20462)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	1.577 (N=46793)	2.952	1003.36	0.961	3.775	1034.25
Method B	-7.706 (N=46793)	2.816	1003.36	-10.020	3.510	1034.25
Method C	-6.641 (N=23335)	3.563	1039.64	-0.161	3.801	1034.25
Method D	34.694 (N=23335)	3.629	1039.64	35.840	3.870	1034.25
Method E	31.956 (N=20462)	8.829	1034.25	31.956	8.829	1034.25

Table 2f: Aggregate Results –Residential Sub-Sample #6 (2,623 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20081)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	2.146 (N=46806)	7.873	1009.34	2.008	11.489	1038.83
Method B	-7.027 (N=46806)	8.284	1009.34	-8.935	12.089	1038.83
Method C	-7.264 (N=23067)	10.161	1043.98	-0.146	10.861	1038.83
Method D	34.407 (N=23067)	10.381	1043.98	36.124	11.096	1038.83
Method E	52.595 (N=20182)	23.369	1038.85	52.605	23.370	1038.83

Table 2g: Aggregate Results –Residential Sub-Sample #7 (2,623 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20301)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	2.014 (N=46785)	7.937	1011.70	1.404	11.851	1050.92
Method B	-7.357 (N=46785)	8.789	1011.70	-9.619	13.155	1050.92
Method C	-7.862 (N=23142)	10.334	1055.47	0.094	11.023	1050.92
Method D	34.006 (N=23142)	10.438	1055.47	36.545	11.131	1050.92
Method E	46.357 (N=20301)	11.341	1050.92	46.357	11.341	1050.92

Table 2h: Aggregate Results –Residential Sub-Sample #8 (2,625 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20689)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	2.245 (N=46852)	2.736	1012.13	1.040	3.049	1055.05
Method B	-7.035 (N=46852)	2.622	1012.13	-9.828	2.813	1055.05
Method C	-4.523 (N=23527)	8.339	1058.08	2.585	8.134	1055.05
Method D	37.584 (N=23527)	8.571	1058.08	39.155	8.412	1055.05
Method E	44.492 (N=20689)	3.372	1055.05	44.492	3.372	1055.05

Table 2i: Aggregate Results –Residential Sub-Sample #9 (2,624 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=20545)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	2.121 (N=46721)	5.740	1016.99	2.383	3.087	1055.98
Method B	-7.323 (N=46721)	5.626	1016.99	-8.392	3.107	1055.98
Method C	-7.461 (N=23389)	9.390	1058.36	0.281	9.346	1055.98
Method D	34.403 (N=23389)	9.308	1058.36	36.816	9.175	1055.98
Method E	176.593 (N=20546)	10.866	1055.99	176.567	10.866	1055.98

Table 2j: Aggregate Results –Residential Sub-Sample #10 (3,369 sites)

	Based on all observations for which individual Estimation Method can be applied.			Based on subset of observations for which all Estimation Methods can be applied (N=15385)		
	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption	Average Difference between Estimated and Actual Consumption	Root Mean Square Percentage Error	Average Consumption
Method A	-14.787 (N=39234)	9.072	948.04	-6.754	1.409	1011.41
Method B	-27.796 (N=39234)	8.589	948.04	-22.990	1.247	1011.41
Method C	-57.969 (N=18012)	4.618	1008.36	-39.932	4.568	1011.41
Method D	-24.473 (N=18012)	4.760	1008.36	-8.154	4.724	1011.41
Method E	346.614 (N=15387)	7.550	1011.60	346.841	7.550	1011.41

Table 3a: Variations in RMSPE over Time – Residential

	Number of Observations	Method A	Method B	Method C	Method D	Method E
Year						
2001	139263	8.41	8.36	n.a.	n.a.	n.a.
2002	90665	2.40	2.30	6.51	6.80	7.42
2003	108381	7.46	8.00	8.44	8.50	11.48
Month						
January	18633	3.56	3.24	11.38	11.92	3.36
February	8586	0.39	0.38	1.88	1.98	0.61
March	9727	3.56	3.77	10.44	10.59	3.38
April	15863	4.54	5.28	2.94	2.95	2.77
May	18825	10.95	12.38	10.81	10.89	10.58
June	17804	11.93	12.66	10.58	10.28	6.21
July	17652	1.76	1.70	4.17	4.29	4.88
August	18302	2.95	2.86	4.82	5.07	11.55
September	18639	1.02	1.01	3.44	3.58	2.44
October	18307	3.57	3.53	7.29	7.38	5.77
November	18637	1.90	1.71	6.65	6.89	3.61
December	18078	5.46	4.69	7.42	7.73	26.00

Table 3b: Variations in Average Estimation Error over Time – Residential

	Actual Consumption	Method A	Method B	Method C	Method D	Method E
Year						
2001	997.34	-6.73	-24.72	n.a.	n.a.	n.a.
2002	1027.89	-2.49	-16.48	-15.26	36.59	109.35
2003	1054.01	3.64	-5.24	7.55	30.24	54.55
Month						
January	1321.15	-28.91	-121.71	-13.39	38.27	47.50
February	1157.55	31.73	13.66	-1.69	41.88	-6.09
March	1115.33	50.64	133.73	29.82	39.71	103.62
April	952.24	29.41	159.86	-8.04	24.12	49.18
May	931.62	41.80	176.31	-17.90	20.30	39.18
June	897.22	55.44	95.20	-5.62	29.01	73.51
July	965.32	35.22	1.11	-14.09	30.42	91.71
August	944.99	-8.79	-25.57	-8.22	27.46	197.58
September	967.48	-28.14	-22.15	-0.039	24.58	108.84
October	986.51	-35.31	-82.73	7.76	39.73	82.58
November	1105.14	-43.12	-165.20	1.07	38.06	71.58
December	1238.27	-43.19	-182.81	11.78	50.95	58.30

Table 3c: Variations in RMSPE over Time – Small Commercial

	Number of observations	Method A	Method B	Method C	Method D	Method E
Year						
2001	17037	21.53	21.94	n.a.	n.a.	n.a.
2002	5119	30.40	34.18	17.82	18.66	303.74
2003	6275	19.25	20.71	26.76	28.10	8.18
Month						
January	954	2.59	2.44	4.17	4.36	3.08
February	551	0.56	0.55	1.10	1.16	0.67
March	496	2.10	2.24	2.41	2.44	2.53
April	941	14.73	17.02	21.11	22.49	5.27
May	1073	72.59	82.18	2.88	3.02	3.37
June	1082	16.04	17.13	18.30	20.07	17.18
July	928	28.50	27.38	3.95	4.08	80.58
August	1136	2.11	2.17	41.81	43.73	17.37
September	960	0.48	0.48	2.52	2.56	1.91
October	1156	0.63	0.60	1.69	1.74	5.99
November	942	1.13	1.00	1.59	1.64	3.53
December	1176	11.30	10.13	52.94	55.28	629.43

Table 3d: Variations in Average Estimation Error over Time – Small Commercial

	Actual Consumption	Method A	Method B	Method C	Method D	Method E
Year						
2001	3769.20	48.87	-11.17	n.a.	n.a.	n.a.
2002	3076.54	40.35	-5.42	-41.37	118.13	6291.29
2003	3195.14	30.45	-8.96	-27.21	38.78	618.42
Month						
January	3248.59	97.98	-142.01	18.23	149.34	300.18
February	3454.36	-68.24	-77.36	-84.57	34.72	46.63
March	2946.77	-144.74	51.03	55.53	83.67	60.58
April	3071.82	-105.83	290.49	-111.05	-21.80	219.75
May	2720.11	-139.64	216.90	-0.38	126.25	250.69
June	3337.81	-271.58	-167.98	-114.03	2.87	195.08
July	3060.66	-99.60	-200.55	10.07	155.16	33346.54
August	3380.81	-4.71	-70.09	-118.38	2.10	1344.21
September	2838.85	175.53	195.58	64.52	138.39	267.82
October	3102.84	355.21	182.28	-71.57	21.79	423.13
November	2886.10	218.74	-135.77	47.28	145.90	256.34
December	3575.01	228.93	-221.57	-44.09	71.80	1359.95

Table 3e: Variations in RMSPE over Time – Medium Commercial

	Number of observations	Method A	Method B	Method C	Method D	Method E
Year						
2001	2798	2.33	2.21	n.a.	n.a.	n.a.
2002	2419	1.43	1.36	1.42	1.54	2.20
2003	2619	2.22	2.33	2.52	2.57	2.33
2004	185	0.14	0.14	0.57	0.60	0.25
Month						
January	412	0.31	0.31	0.55	0.58	0.38
February	396	0.11	0.11	0.31	0.33	0.15
March	427	0.28	0.29	0.51	0.54	0.36
April	445	0.21	0.25	2.08	2.29	4.10
May	445	5.36	5.63	6.03	6.17	5.57
June	437	0.20	0.20	1.47	1.63	0.49
July	436	0.22	0.21	0.74	0.79	0.21
August	436	0.21	0.23	0.64	0.66	0.47
September	425	0.33	0.33	0.91	0.91	0.31
October	478	0.27	0.25	0.59	0.60	0.24
November	451	3.27	3.11	1.63	1.69	3.02
December	436	0.16	0.14	0.50	0.53	0.23

Table 3f: Variations in Average Estimation Error over Time – Medium Commercial

	Actual Consumption	Method A	Method B	Method C	Method D	Method E
Year						
2001	20503.97	336.94	126.69	n.a.	n.a.	n.a.
2002	21413.85	200.46	78.45	-187.66	1051.95	191.05
2003	21515.68	129.43	32.88	-122.06	316.63	246.08
2004	22882.16	-1371.46	-1457.07	-397.61	514.19	-140.77
Month						
January	22643.50	-428.15	-955.71	-506.54	526.58	-310.97
February	22167.17	-632.36	3.04	-360.09	661.35	105.71
March	20988.52	-170.17	456.99	-343.48	882.69	181.75
April	20738.24	-712.15	1227.09	41.04	939.06	642.64
May	19599.93	-1035.34	-25.55	209.55	905.89	258.94
June	22296.04	-883.07	-1391.13	-104.61	736.48	249.34
July	22914.54	227.75	-680.77	-714.19	477.91	-382.31
August	22039.04	528.45	1061.83	-333.05	352.74	488.93
September	20523.15	699.14	768.77	24.07	443.70	466.98
October	20619.12	1038.27	-64.03	235.23	758.45	347.13
November	21260.37	779.24	-920.01	-176.79	585.07	-108.15
December	22649.56	1737.14	524.89	-6.69	672.27	497.42

Table 4a: Proportion of Overestimates by Year: Residential

	Method A	Method B	Method C	Method D	Method E
2001-2004 (N=199053)					
over	0.50542	0.47618	0.48329	0.56947	0.51559
>5% over	0.36668	0.37640	0.36745	0.44656	0.38815
>10% over	0.25692	0.29169	0.28092	0.34120	0.28959
>25% over	0.10051	0.12865	0.14860	0.17313	0.13577
2001 (N=139263)					
over	0.49564	0.46516	n.a.	n.a.	n.a.
>5% over	0.34527	0.35614	n.a.	n.a.	n.a.
>10% over	0.23439	0.26524	n.a.	n.a.	n.a.
>25% over	0.09053	0.10859	n.a.	n.a.	n.a.
2002 (N=90665)					
over	0.49523	0.45133	0.45708	0.58712	0.54505
>5% over	0.35871	0.35473	0.34393	0.46339	0.41598
>10% over	0.25185	0.27609	0.26189	0.35300	0.31166
>25% over	0.10042	0.12717	0.13777	0.17535	0.14559
2003 (N=108381)					
over	0.51392	0.49694	0.50521	0.55470	0.49093
>5% over	0.37332	0.39449	0.38712	0.43247	0.36485
>10% over	0.26112	0.30470	0.29681	0.33129	0.27110
>25% over	0.10053	0.12986	0.15763	0.17125	0.12754

Table 4b: Proportion of Overestimates by Time of Year: Residential

	Method A	Method B	Method C	Method D	Method E
January (N=18633)					
over	0.44421	0.22975	0.47389	0.57522	0.47459
>5% over	0.28026	0.13863	0.35421	0.44695	0.33747
>10% over	0.17662	0.09118	0.26802	0.33553	0.24054
>25% over	0.06183	0.04165	0.14142	0.16970	0.10760
February (N=8586)					
over	0.58805	0.53413	0.49849	0.58945	0.44025
>5% over	0.41847	0.37794	0.37584	0.46949	0.31249
>10% over	0.28302	0.25099	0.28360	0.35057	0.22502
>25% over	0.09050	0.08386	0.14826	0.17529	0.09318
March (N=9727)					
over	0.62702	0.81875	0.55289	0.57099	0.54806
>5% over	0.44741	0.69312	0.42397	0.44063	0.40896
>10% over	0.29392	0.53418	0.32867	0.34368	0.29053
>25% over	0.09551	0.17138	0.16850	0.17529	0.12841
April (N=15863)					
over	0.56818	0.86301	0.47412	0.55809	0.53653
>5% over	0.41247	0.77615	0.36639	0.43390	0.40100
>10% over	0.28986	0.64773	0.28242	0.33335	0.29685
>25% over	0.11208	0.28437	0.14903	0.17197	0.13572
May (N=18825)					
over	0.60223	0.86465	0.44356	0.55076	0.51384
>5% over	0.46502	0.78778	0.32961	0.42640	0.38444
>10% over	0.34194	0.68542	0.25131	0.32064	0.28382
>25% over	0.14215	0.34560	0.13344	0.16069	0.13163
June (N=17804)					
over	0.64081	0.73169	0.46950	0.55768	0.53173
>5% over	0.51696	0.61801	0.36217	0.45029	0.41446
>10% over	0.39794	0.49590	0.28280	0.35537	0.31931
>25% over	0.17350	0.23040	0.15783	0.18653	0.16069
July (N=17652)					
over	0.63494	0.53807	0.46142	0.57342	0.52736
>5% over	0.49405	0.39231	0.35027	0.45406	0.39837
>10% over	0.35883	0.27759	0.27034	0.35344	0.29532
>25% over	0.13709	0.10622	0.14486	0.17783	0.13732
August (N=18302)					
over	0.47323	0.40996	0.47071	0.55923	0.50535
>5% over	0.32193	0.26418	0.35799	0.44361	0.38504
>10% over	0.21167	0.17441	0.27576	0.34051	0.29439
>25% over	0.07786	0.06895	0.14878	0.17637	0.14392

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Table 4b (continued) Proportion of Overestimates by Time of Year: Residential

	Method A	Method B	Method C	Method D	Method E
September (N=18639)					
over	0.37089	0.38854	0.48930	0.55416	0.53651
>5% over	0.25398	0.26589	0.37405	0.43157	0.41622
>10% over	0.17898	0.18762	0.28188	0.32459	0.31461
>25% over	0.07758	0.08058	0.15081	0.16589	0.15510
October (N=18307)					
over	0.37838	0.27312	0.49751	0.57961	0.53040
>5% over	0.27378	0.19801	0.37740	0.45261	0.40476
>10% over	0.19681	0.14781	0.28863	0.34397	0.31223
>25% over	0.09128	0.07238	0.14918	0.17414	0.15235
November (N=18637)					
over	0.41004	0.15995	0.49992	0.58556	0.50856
>5% over	0.29280	0.10967	0.37688	0.45737	0.38241
>10% over	0.19853	0.07673	0.28363	0.34609	0.28470
>25% over	0.07308	0.03724	0.14530	0.16972	0.12888
December (N=18078)					
over	0.44640	0.15134	0.50769	0.58978	0.51328
>5% over	0.30451	0.10084	0.39202	0.46073	0.38516
>10% over	0.19875	0.07080	0.29887	0.35358	0.28654
>25% over	0.07086	0.03701	0.15582	0.17740	0.12944

Table 4c: Proportion of Overestimates by Year: Small Commercial

	Method A	Method B	Method C	Method D	Method E
2001-2004 (N=11395)					
over	0.52190	0.49829	0.50189	0.58008	0.51031
>5% over	0.42229	0.39017	0.37964	0.46327	0.38315
>10% over	0.33857	0.30838	0.30004	0.36218	0.29495
>25% over	0.17016	0.17376	0.16428	0.19158	0.16253
2001 (N=17037)					
over	0.53014	0.50420	n.a.	n.a.	n.a.
>5% over	0.39473	0.35957	n.a.	n.a.	n.a.
>10% over	0.28555	0.26484	n.a.	n.a.	n.a.
>25% over	0.13101	0.12819	n.a.	n.a.	n.a.
2002 (N=5119)					
over	0.53292	0.50303	0.49873	0.61125	0.52080
>5% over	0.43602	0.39519	0.37878	0.49932	0.39715
>10% over	0.35085	0.31686	0.29635	0.39265	0.31237
>25% over	0.18031	0.18324	0.16175	0.20649	0.17347
2003 (N=6275)					
over	0.51299	0.49450	0.50454	0.55474	0.50167
>5% over	0.41116	0.38614	0.38040	0.43394	0.37163
>10% over	0.32861	0.30151	0.30311	0.33737	0.28064
>25% over	0.16191	0.16606	0.16637	0.17944	0.15347

Table 4d: Proportion of Overestimates by Time of Year: Small Commercial

	Method A	Method B	Method C	Method D	Method E
January (N=954)					
over	0.62264	0.39623	0.50524	0.61111	0.45912
>5% over	0.48218	0.22642	0.37841	0.48008	0.33543
>10% over	0.32600	0.14361	0.29874	0.36688	0.24423
>25% over	0.08386	0.04927	0.16771	0.19392	0.11740
February (N=551)					
over	0.41016	0.39564	0.48457	0.57895	0.43557
>5% over	0.27405	0.26860	0.34483	0.44102	0.31579
>10% over	0.21053	0.19056	0.26316	0.32486	0.22505
>25% over	0.08348	0.07986	0.15426	0.17241	0.11797
March (N=496)					
over	0.40726	0.59476	0.56048	0.58669	0.54637
>5% over	0.28226	0.44960	0.45968	0.46573	0.38105
>10% over	0.20968	0.32258	0.36895	0.39113	0.27419
>25% over	0.09879	0.15726	0.20565	0.21169	0.15524
April (N=941)					
over	0.43571	0.73326	0.46440	0.51647	0.51753
>5% over	0.34006	0.60043	0.36557	0.43677	0.39107
>10% over	0.28374	0.48247	0.29224	0.35069	0.28480
>25% over	0.15728	0.28587	0.16153	0.18385	0.14772
May (N=1073)					
over	0.44548	0.70270	0.49767	0.58900	0.48742
>5% over	0.37558	0.61044	0.37372	0.48555	0.36160
>10% over	0.32060	0.51445	0.30289	0.38397	0.27679
>25% over	0.19478	0.32246	0.16869	0.20317	0.14818
June (N=1082)					
over	0.51294	0.56100	0.46303	0.52773	0.49815
>5% over	0.43068	0.49076	0.35305	0.43068	0.38447
>10% over	0.36691	0.42237	0.29113	0.35397	0.30961
>25% over	0.22643	0.25970	0.16451	0.19593	0.18577
July (N=928)					
over	0.62392	0.56466	0.50647	0.58944	0.52047
>5% over	0.53017	0.46444	0.39009	0.49569	0.40841
>10% over	0.43750	0.34698	0.31358	0.40409	0.32220
>25% over	0.23491	0.19935	0.16379	0.20905	0.18103
August (N=1136)					
over	0.48680	0.42254	0.46743	0.55370	0.49384
>5% over	0.34595	0.29930	0.34947	0.43486	0.39085
>10% over	0.25528	0.23327	0.27641	0.33099	0.31690
>25% over	0.12852	0.12852	0.15317	0.17606	0.18574

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Table 4d (continued): Proportion of Overestimates by Time of Year: Small Commercial

	Method A	Method B	Method C	Method D	Method E
September (N=960)					
over	0.47604	0.48646	0.52604	0.62292	0.54063
>5% over	0.37708	0.38229	0.40521	0.45417	0.41354
>10% over	0.30417	0.31563	0.33542	0.37083	0.32188
>25% over	0.15833	0.16875	0.18646	0.21563	0.17708
October (N=1156)					
over	0.53979	0.44983	0.50606	0.57699	0.55450
>5% over	0.46280	0.38235	0.37370	0.45242	0.39965
>10% over	0.39619	0.32699	0.27941	0.35208	0.31574
>25% over	0.24394	0.19810	0.14014	0.16263	0.17128
November (N=942)					
over	0.54034	0.33333	0.56688	0.63800	0.52442
>5% over	0.46921	0.26539	0.42463	0.52123	0.40764
>10% over	0.38004	0.21444	0.32484	0.39278	0.30892
>25% over	0.20382	0.12951	0.16667	0.20276	0.16136
December (N=1176)					
over	0.64626	0.36650	0.50595	0.58333	0.52636
>5% over	0.55102	0.23639	0.37415	0.46344	0.37840
>10% over	0.43793	0.15221	0.28486	0.33588	0.29252
>25% over	0.14626	0.06037	0.16156	0.18282	0.17007

Table 4e: Proportion of Overestimates by Year: Medium Commercial

	Method A	Method B	Method C	Method D	Method E
2001-2004 (N= 5224)					
over	0.50766	0.49943	0.47473	0.60528	0.49904
>5% over	0.31585	0.29230	0.31145	0.43434	0.30475
>10% over	0.18817	0.17764	0.20463	0.28905	0.18224
>25% over	0.05532	0.05398	0.08078	0.10356	0.06011
2001 (N=2798)					
over	0.54753	0.52216	n.a.	n.a.	n.a.
>5% over	0.33881	0.31523	n.a.	n.a.	n.a.
>10% over	0.20944	0.18585	n.a.	n.a.	n.a.
>25% over	0.07076	0.07005	n.a.	n.a.	n.a.
2002 (N=2419)					
over	0.52956	0.51509	0.47458	0.66887	0.50434
>5% over	0.33444	0.31087	0.32327	0.50351	0.31170
>10% over	0.20215	0.18768	0.21993	0.34808	0.18479
>25% over	0.06077	0.06160	0.08847	0.12774	0.06284
2003 (N=2619)					
over	0.50630	0.50630	0.47614	0.54868	0.49561
>5% over	0.31615	0.29133	0.30279	0.37113	0.30661
>10% over	0.18633	0.17946	0.19359	0.23597	0.18671
>25% over	0.05384	0.05040	0.07446	0.08247	0.05995
2004 (N=185)					
over	0.24324	0.20000	0.45946	0.57838	0.48108
>5% over	0.07027	0.06486	0.28108	0.42703	0.18919
>10% over	0.03243	0.02162	0.16216	0.27027	0.08649
>25% over	0.00541	0.00541	0.07027	0.08649	0.02703

Table 4f: Proportion of Overestimates by Time of Year: Medium Commercial

	Method A	Method B	Method C	Method D	Method E
January (N=412)					
over	0.41505	0.27913	0.45631	0.61893	0.46117
>5% over	0.20388	0.14563	0.26456	0.43204	0.22087
>10% over	0.11165	0.08010	0.16019	0.26214	0.12136
>25% over	0.01214	0.00971	0.06068	0.07767	0.02913
February (N=396)					
over	0.33333	0.56313	0.45202	0.62626	0.47980
>5% over	0.13384	0.21717	0.28535	0.44192	0.22727
>10% over	0.06313	0.09596	0.18182	0.27778	0.12374
>25% over	0.01263	0.01768	0.05303	0.07323	0.03283
March (N=427)					
over	0.41686	0.60656	0.47307	0.63466	0.47307
>5% over	0.16862	0.29040	0.29742	0.45667	0.29977
>10% over	0.08431	0.12412	0.16862	0.34426	0.16862
>25% over	0.02108	0.03513	0.06089	0.09836	0.05621
April (N=445)					
over	0.29213	0.70337	0.47191	0.62921	0.55281
>5% over	0.18427	0.43146	0.32135	0.45618	0.35281
>10% over	0.10787	0.29438	0.21348	0.31236	0.20000
>25% over	0.04045	0.07416	0.08764	0.12135	0.06966
May (N=445)					
over	0.29888	0.50787	0.48764	0.61798	0.53034
>5% over	0.17303	0.31236	0.33708	0.44270	0.31461
>10% over	0.10562	0.17303	0.24270	0.32135	0.19101
>25% over	0.04944	0.06742	0.10562	0.13258	0.07640
June (N=437)					
over	0.41648	0.35240	0.49199	0.60870	0.49886
>5% over	0.28146	0.21281	0.33410	0.45080	0.31350
>10% over	0.17391	0.15332	0.23570	0.29977	0.20137
>25% over	0.05492	0.05034	0.09840	0.13272	0.07780
July (N=436)					
over	0.50229	0.36468	0.39679	0.60780	0.42890
>5% over	0.30046	0.21789	0.27752	0.42202	0.29358
>10% over	0.19266	0.14450	0.18578	0.27523	0.18349
>25% over	0.09404	0.08028	0.07569	0.10550	0.06651
August (N=436)					
over	0.57798	0.66972	0.48624	0.56881	0.55275
>5% over	0.34633	0.46789	0.32110	0.43119	0.38761
>10% over	0.20413	0.27982	0.21789	0.27294	0.24771
>25% over	0.06193	0.07569	0.09862	0.11468	0.06422

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Table 4f (continued): Proportion of Overestimates by Time of Year: Medium Commercial

	Method A	Method B	Method C	Method D	Method E
September (N=425)					
over	0.64471	0.60471	0.48706	0.56706	0.54118
>5% over	0.42353	0.44000	0.30824	0.37882	0.33882
>10% over	0.29176	0.31294	0.20706	0.24706	0.20235
>25% over	0.07765	0.08471	0.08000	0.08941	0.07294
October (N=478)					
over	0.70293	0.48536	0.49791	0.59833	0.50628
>5% over	0.51464	0.30544	0.35146	0.42678	0.34100
>10% over	0.32636	0.19874	0.24477	0.28870	0.21548
>25% over	0.09414	0.06276	0.10042	0.11088	0.07741
November (N=451)					
over	0.63636	0.25721	0.48337	0.60532	0.44568
>5% over	0.42129	0.11530	0.30820	0.43681	0.24834
>10% over	0.21286	0.05987	0.18847	0.27273	0.15965
>25% over	0.04656	0.03104	0.07095	0.08426	0.04435
December (N=436)					
over	0.82110	0.60321	0.50688	0.58257	0.51376
>5% over	0.59862	0.34174	0.32110	0.43578	0.30505
>10% over	0.35780	0.20413	0.19954	0.29128	0.16055
>25% over	0.08945	0.05275	0.07110	0.09633	0.04816

Table 5a: Percentage of Sites with Frequent Overestimates – Residential

	Percentage of estimates for each site that are overestimates			
	more than 75%	more than 67%	more than 60%	more than 50%
over				
Method A	1.69	9.17	23.70	55.68
Method B	0.94	5.62	15.14	44.66
Method C	12.52	23.17	33.79	50.03
Method D	22.60	36.03	48.24	64.24
Method E	2.41	10.58	25.61	58.43
at least 5% overestimate				
Method A	0.18	1.40	3.95	16.74
Method B	0.19	1.29	3.43	16.42
Method C	5.57	11.60	18.49	30.54
Method D	9.89	18.66	27.87	42.64
Method E	0.47	2.56	5.92	21.32
at least 10% overestimate				
Method A	0.06	0.31	0.79	4.72
Method B	0.04	0.40	0.92	6.01
Method C	2.98	6.71	11.06	19.93
Method D	4.85	9.99	15.75	26.43
Method E	0.20	0.94	1.89	8.37
at least 25% overestimate				
Method A	0.01	0.03	0.04	0.39
Method B	0.01	0.05	0.07	0.53
Method C	0.88	2.15	3.63	7.95
Method D	1.20	2.70	4.76	9.65
Method E	0.01	0.17	0.24	1.34

Note: Number of Sites =18031. Only sites with at least 6 estimates are included.

Table 5b: Percentage of Sites with Frequent Overestimates – Small Commercial

	Percentage of estimates for each site that are overestimates			
	more than 75%	more than 67%	more than 60%	more than 50%
over				
Method A	2.19	10.07	26.22	58.72
Method B	1.00	8.28	20.14	50.75
Method C	16.55	25.32	36.39	52.84
Method D	25.92	38.48	49.05	64.51
Method E	1.69	9.97	24.73	56.43
at least 5% over				
Method A	0.50	2.79	5.98	27.62
Method B	0.20	2.09	5.28	18.44
Method C	8.18	14.56	20.94	32.80
Method D	13.16	20.94	29.41	43.87
Method E	0.50	2.49	6.28	23.03
at least 10% over				
Method A	0.30	1.00	2.09	11.76
Method B	0.00	0.90	1.79	8.47
Method C	5.18	8.87	13.76	23.33
Method D	7.08	12.96	18.74	29.81
Method E	0.40	1.00	2.79	11.37
at least 25% over				
Method A	0.00	0.30	0.30	2.09
Method B	0.00	0.30	0.40	2.89
Method C	1.50	2.69	4.09	9.47
Method D	1.99	3.89	11.57	11.57
Method E	0.00	0.50	0.90	3.49

Note: Number of Sites =1003. Only sites with at least 6 estimates are included.

Table 5c: Percentage of Sites with Frequent Overestimates – Medium Commercial

	Percentage of estimates for each site that are overestimates			
	more than 75%	more than 67%	more than 60%	more than 50%
over				
Method A	0.86	3.00	13.73	58.37
Method B	0.43	1.72	12.02	55.79
Method C	11.589	19.74	26.61	43.78
Method D	30.04	40.34	48.50	70.39
Method E	0.00	1.29	11.16	59.23
at least 5% over				
Method A	0.00	0.00	0.00	3.43
Method B	0.00	0.00	0.43	3.43
Method C	3.00	6.01	8.58	17.60
Method D	7.73	14.16	21.03	38.20
Method E	0.00	0.00	0.43	3.43
at least 10% over				
Method A	0.00	0.00	0.00	0.43
Method B	0.00	0.00	0.00	0.43
Method C	0.86	3.00	4.29	8.15
Method D	2.58	4.72	8.58	13.73
Method E	0.00	0.00	0.00	0.43
at least 25% over				
Method A	0.00	0.00	0.00	0.00
Method B	0.00	0.00	0.00	0.00
Method C	0.43	1.29	1.72	2.15
Method D	0.86	1.29	1.72	2.58
Method E	0.00	0.00	0.00	0.43

Note: Number of Sites =233. Only sites with at least 6 estimates are included.

Table 6: Comparison of Adjusted and Unadjusted Estimates for Residential Customers, 2003-2004

	Unadjusted			Adjusted		
	N	Average Difference	RMSPE	N	Average Difference	RMSPE
Method A	161378	2.10776	6.79097	161378	5.19230	6.72802
Method B	161378	-5.18394	7.20263	161378	-3.75111	7.11836
Method C	113258	6.13671	9.09150	113258	8.62574	9.09827
Method D	113258	28.56949	9.15441	113258	31.16458	9.16216
Method E	108393	54.54816	11.48069	108393	57.15390	11.53480

Notes: For method A and B, alpha=.803499
For methods C and D, alpha=.889045

CBEEDAC
Department of Economics
University of Alberta
8-14 Tory Building
Edmonton, Alberta
Canada
T6G 2H4
cbeedac@ualberta.ca