ABSTRACT. The Energy Information Administration (EIA) collects electric power generation and cost data from power plants in the United States. The purpose of this paper is to discuss results of applying model sampling and unequal probability sampling, and to compare these results to each other and to full census historical results where available. This may be used to help determine whether model sampling, or any sampling, is appropriate for some EIA applications. If some of the (smaller) plants are not included in future surveys, this removes some respondent burden, and reduces the number of records that need to be edited, thus possibly improving the quality of the editing and handling for those records that remain. Periodically, censuses may be conducted so that the continuing appropriateness of such methodologies, should any be found, may be examined. This paper represents work-in-progress which may be continued for some time. Also, additional analyses may be conducted.

Model Sampling to Estimate Net Generation For Hydroelectric Plants

Background. As at least a first step in investigating the possible use of model sampling for the collection of net generation information, three models described by Royall (1970) were used to study hydroelectric plant data. These three linear regression models consist of a more general model, and 2 others which adjust for heteroscedasticity (see Maddala (1977), pages 93-94, 259-261).
The models are (Royall (1970) page 378) such that $Y_i$ has mean $\beta x_i$ and variance $\sigma^2 v(x_i)$, where for Method 1, $v(x_i) = 1$, for Method 2, $v(x_i) = x_i$, and for Method 3, $v(x_i) = x_i^2$. Method 1 corresponds basically to ordinary regression estimation. Method 2 corresponds to ratio estimation and can be found succinctly described, among other places, in Cochran (1977), pages 158-160. Method 3 corresponds somewhat to unequal probability sampling where sampling is in proportion to some measure of size. However, unequal probability sampling is unbiased due to the nature of the design, whereas the purposive selection for this corresponding model is sometimes substantially biased. Cochran (1977), page 160, mentions that a good use of this method is found in Jessen, et.al. (1947). However, Jessen does not separate observed and unobserved $y$ values as Royall does. This can make a substantial difference in an establishment survey due to the predominance of a relatively few respondents.

Finally, a fourth method was applied. It is described in Cochran (1977), pages 199-200. It is even more general than Method 1 as, unlike the three methods taken from Royall (1970), it is not required that the regression pass through the origin. With this model, lowest variance occurs when $\bar{x} = \bar{y}$ (i.e., the sample is "balanced"), whereas Methods 1-3 have lowest variance when the $n$ observations with the largest $x$ values are chosen. Method 4 does not separate observed and unobserved $y$ values.

Note that a promising model may also lead to an imputation procedure. Also, another consequence of this study could be a study of the usefulness of sampling for nonutility generation.

### Equations

See Royall (1970), page 382, concerning variance estimation for Methods 1-3. Note that $\hat{Y}$ is an estimated total.

**Method 1:** If $v(x_i) = 1$, then $\hat{\beta} = \hat{b}_1 = \frac{\hat{Y}}{\hat{X}} = \frac{\hat{X}Y}{\bar{X}N}$, $\hat{Y}_b = \hat{b}_1X_N + \hat{Y}_o$, where $X_N$ is the total of the auxiliary variate values for the unobserved plants, and $\hat{X}_o$ is the total of the observed $y$ values ($Y = \sum y_i$), and $\hat{V}(Y_b) = \frac{\sigma^2(N-n)}{\sum x_i^2}$ where $\hat{\sigma}^2 = \frac{\sum (y_i - \hat{X})^2}{n-1}$.

**Method 2:** If $v(x_i) = x_i$, then $\hat{\beta} = \hat{R} = \frac{\hat{X}}{\bar{x}}$, $\hat{Y}_b = \hat{R}X_N + \hat{X}_o$, and $\hat{V}(Y_b) = \frac{\hat{\sigma}^2}{\sum x_i^2} + \frac{(X-n\bar{x})^2}{\bar{x}^2}$ where $\hat{\sigma}^2 = \frac{\sum (y_i - \hat{X})^2}{n-1}$, and $\hat{\sigma}^2 = \frac{\sigma^2}{x^2}$ in Cochran, et.al. (1947), page 370.

**Method 4:**

$$\hat{Y}_b = N(\bar{X} + \hat{b}_4(X - \bar{X}))$$

$$\hat{V}(Y_b) = \frac{\sigma^2}{\sum x_i^2} \frac{N-n}{n} + \frac{(\bar{X} - \bar{X})^2}{\sum x_i^2}$$

where $\sigma^2 = \frac{\sum (y_i - \bar{X})^2}{n-2}$, and $\sigma^2 = \frac{1}{\bar{X}^2}$

in Cochran (1977), pages 199-200, and

$$\hat{\sigma}^2 = \frac{\sum (y_i - \hat{X})^2}{n-1}$$

As another aside, note that from Cochran (1977), page 158, when the ratio estimator is a BLUE:

1. The relation between $y_i$ and $x_i$ is a straight line through the origin.
2. The variance of $y_i$ about this line is proportional to $x_i$.

Thus, $x_i$ and $y_i$ should be highly positively correlated, and therefore their signs should often be identical.

What happens if $x_i=0$ is zero (or nearly zero) and so is $y_i=0$? The $k$th term of $\lambda$ should then be zero if the variance of $y_i$ is to be proportional to $x_i$. We have

$$\lim (1 / x_k)(y_k - \hat{X}x_k) / (n-1)$$

and

$$\lim (1 / x_k)(y_k - \hat{X}x_k) / \bar{x}^2$$

since $\hat{x}_k$ should approach zero much faster than $x_k$ does. However, what if $y_k$ is not near zero when $x_k$ is zero? L'Hospital's rule gives us that the $k$th term of $\lambda$ should be $-2Ry_k/(n-1)$.

**Results.** The relative performances of Methods 1-4 were studied by several means. Each estimator, $\hat{Y}$, was compared with $\hat{Y}$, using the signed rank test. Additional methodology is also described. Some of the data for these comparisons are given in the table below. $Y$ and $\bar{X}$ are the estimated total net generation and estimated CV (percent) values for each method. $D$ is the percent difference between $Y$ and $\bar{X}$, and $z$ is the approximately standard normal variate derived in the fol-
lowing assuming that a given CV estimate is viable. (Also, \( \hat{Y} \) is the estimated total when \( Y \) is not treated separately from the unobserved \( Y_s \). This only affects Methods 1 and 3. In the 11 cases that were studied here, \( Y_s \) was a very large portion of \( Y \). It seems reasonable that treating \( Y_s \) separately would reduce variance, but the table below also indicates that Method 3 is a poor model for these data unless \( Y_s \) is separated. When this is done using Royall (1970), Method 3 performs very well for these data. Apparently the smallest plants related differently to the auxiliary data.)

Now,
\[
D = \left( \frac{\hat{Y} - Y}{\hat{Y}} \right) \times 100 \%, \text{ and } \widehat{CV} = \left( \frac{\hat{Y} - Y}{\hat{Y}} \right) \times 100 \%.
\]

\[
\left[ \frac{\left( \frac{\hat{Y} - Y}{\hat{Y}} \right) \times 100 \% \right] \left/ \left[ \left( \frac{\hat{Y} - Y}{\hat{Y}} \right) \times 100 \% \right] \right. = \left( \frac{\hat{Y} - Y}{\hat{Y}} \right) \times 100 \%.
\]

Thus, for each sample estimate, \( \hat{Y} \), and the census value, \( Y \) (where a total is indicated), a number, \( z \), can be estimated as a standard normal variate. This is done for each methodology for purposes of comparison.

The Wilcoxon Signed Ranks Test is employed according to Conover (1980), pages 278-292, where the raw data are the values \( (Y/Y)_s \) and \( (Y/Y)_o = 1 \), for each matched-pair. This also is done for each method to be compared.

Wilcoxon Signed Ranks Test Results on \( D \)
(See Conover (1980), Table A13):

- For Method 1: \( T_+ = 13 \), so fail to reject (two-tailed) at 5 percent, but reject at 10-percent level.
- For Method 2: \( T_+ = 10 \), so fail to reject (two-tailed) at 2 percent, but reject at 5-percent level.
- For Method 3: \( T_+ = 28 \), so fail to reject (two-tailed) at 60 percent, but reject at 80-percent level.
- For Method 4: \( T_+ = 47 \), so fail to reject (two-tailed) at 20 percent, but reject at 40-percent level.

From these results, \( \hat{Y} \) appears to be the most biased estimator for \( Y \). However, bias is not of any real importance here compared with variance in terms of relative size. The ratio estimate actually appears to be very good, since the absolute difference between \( Y \) (census), and \( Y \) (sample) is least for the ratio estimate, usually by far, for 11 out of 11 data sets. \( \hat{Y} \), however, can only be said to be best, or second best in this way, 10 of 11 times. \( \hat{Y} \) for Method 3 usually did a little better here.

Table 1. Net Generation Data for Five Example Cases

<table>
<thead>
<tr>
<th>State</th>
<th>Method</th>
<th>( \hat{Y} )</th>
<th>( \hat{CV} )</th>
<th>( Y )</th>
<th>( D )</th>
<th>( z )</th>
<th>( \hat{Y} )</th>
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<td>A</td>
<td>1</td>
<td>1,807</td>
<td>11.5</td>
<td>1,826</td>
<td>-1.1</td>
<td>-0.09</td>
<td>834</td>
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<td></td>
<td>2</td>
<td>1,818</td>
<td>1.1</td>
<td>1,826</td>
<td>-5</td>
<td>-45</td>
<td>-</td>
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<tr>
<td></td>
<td>3</td>
<td>1,830</td>
<td>2</td>
<td>1,826</td>
<td>2</td>
<td>.81</td>
<td>2,930</td>
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<tr>
<td></td>
<td>4</td>
<td>2,414</td>
<td>10.5</td>
<td>1,826</td>
<td>32.2</td>
<td>2.33</td>
<td>-</td>
</tr>
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<td>B</td>
<td>1</td>
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<td>594.0</td>
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<td>594.0</td>
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<td>-</td>
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<td>1.1</td>
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<td>11.1</td>
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<td>1.9</td>
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<td>-66</td>
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<tr>
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<td>.5</td>
<td>6.713</td>
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<td>6.713</td>
<td>7.0</td>
<td>1.03</td>
<td>-</td>
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</tbody>
</table>

Note: For State A, \( \Sigma_{Y_1} = 1797 \); for State B, \( \Sigma_{Y_1} = 572.9 \); for State C, \( \Sigma_{Y_1} = 128.1 \); for State D, \( \Sigma_{Y_1} = 37.9 \); and, for State E, \( \Sigma_{Y_1} = 6631 \).
Kolmogorov-Smirnov (K-S) Testing on z also indicated a substantial bias for the CV estimate for \( \hat{Y}_R \). However, again this is a small problem compared with variance.

The graphs below are for the K-S test for Methods 2 and 4.

![Graph for Method 2](image1)

**Method 2**

\[ T = 0.40 \Rightarrow \text{Attained two-sided} \}

\text{“significance” level approximately 5\%}

(See Conover (1980), Table A14.)

![Graph for Method 4](image2)

**Method 4**

\[ T = 0.26 \Rightarrow \text{Attained two-sided} \}

\text{“significance” level greater than 20\%}

(See Conover (1980), Table A14.)

It is concluded that although both \( \hat{Y}_R \) and \( \hat{CV}(\hat{Y}_R) \) appear to be slightly biased, deviations from census based values are generally low -- especially maximum deviations -- for this method. For the cases shown in the table given in this paper, however, Method 3 performs somewhat better, indicating substantial heteroscedasticity dealing with smaller plants.

Note that if we denote \( P_\gamma(\mid z \mid) = 2P[Z < -\mid z \mid] \), and \( \gamma = \prod P_\gamma \) then for the cases studied, \( \gamma(\text{Method 1}) > > \gamma(\text{Method 2}) > > \gamma(\text{Method 3}) > > \gamma(\text{Method 4}). \) Method 4 sometimes provided poor CV estimates.

In 7 of 11 cases, ranking \( |D| \) from smallest to largest for these methods, yielded the order 3, 2, 1, 4. There are only approximately 15 chances in 10,000,000 that 1 of 24 possible orderings would occur 7 of 11 times. Thus, for these data, a pattern is shown.

The ratio estimate (Method 2) may be best for general purposes of estimating generation. Note that if the assumptions of this model are strictly correct, estimation may proceed as well with the smaller plants as with the larger ones, as long as more plants are sampled if the smaller ones are used. Suppose the plants in one data set are divided into two groups -- the larger plants and the smaller ones -- and we let \( \bar{X}_1 \) be \( \bar{x} \) for the larger plants, \( n_1 \) be the size of that part of the overall sample, and \( \bar{X}_2 \) and \( n_2 \) correspond to the smaller plants. One then \( n \) wants \( n_1 + n_2 = n \) such that \( (X - n_1 \bar{X}_1) / (X - n_2 \bar{X}_2) = (n_1 \bar{X}_1) / (n_2 \bar{X}_2) \) implies that \( n_2 \bar{X}_2 = n_1 \bar{X}_1 \). Establishing two groups of plants accordingly. If \( \bar{X}_2 \) is the same in each group, variances will be equal. If \( \hat{Y}_R \) estimates from these two groups are nearly equal, and variance estimates are nearly the same, then this is excellent evidence in support of the model. If a complete census is not available for testing a model, then, in addition to graphical procedures, this method could be adopted to the extent data are available, as a check of the model. Experience on these data, however, shows that it would probably take a rather large data set for enough stability for the above equations to hold approximately true, even if the model works well. Therefore, if these equations do hold approximately true, we have very good evidence that the model is good, and the smaller the sample sizes, the better is such evidence. For the data used in, four cases studied, the \( \hat{Y}_R \) and \( \hat{CV} \) values varied greatly, but the absolute values of D did not. This seems to indicate some difference due to plant size, and therefore some model failure, but from the size of the D values in Table 1 for Method 2, the model failure does not appear to be serious. Sample sizes in Table 1 range from less than 50 to more than 200. In some cases, very few plants had most of the net generation. Under such conditions, it is not surprising that the \( \hat{CV} \) estimator will be tenuous for the \( n_1 \) group described above.

**Sampling to Estimate Generation Expense for Major, Privately Owned Coal-Fired and Nuclear-Powered Electric Generating Plants**

**Background.** No census results are available for some of the cost components of generating electricity. These costs are therefore estimated through sampling. The most readily apparent stratification criterion in this
new effort was size (net generation, or nameplate capacity), so unequal probability sampling was used and net generation was chosen as the measure of size. Also, model sampling results, using $Y_R$ with first net generation and then generator nameplate capacity as the auxiliary variate were studied. For preliminary samples, from which required additional sample sizes were calculated, 4 sets of results were provided: 2 design-based, and the 2 model-based mentioned above. The first design-based method was unbiased, and the second one was built upon that. The 2 model-based methods make use of the model-unbiased ratio model shown earlier as Method 2.

For the design-based analyses, cost estimates and estimates of their CV's were calculated under the design requirement of sampling in proportion to net generation and with replacement. (Negative net generation cases were handled separately.) Next a without replacement design-based set of estimates was calculated by not using any duplications of observations, adjusting the inclusion probabilities according to the methodology of Van Beeck and Vermetten shown in Konijn (1973), pages 259-261, and multiplying by the usual finite population correction factor of equal probability sampling, as may be justified by the findings in Cochran (1977), pages 267-270, and Bayless and Rao, as described there by Cochran, and seen to extend to larger sample sizes by comparison to the Rao, Hartley, Cochran Method.

There are a number of more exact methods, but they are often quite cumbersome either to calculate or administer, and may not easily accept secondary sampling when the initial sample is found to be inadequate.

The Van Beeck and Vermetten Method resulted in increased relative probabilities of selection for smaller plants over what they were when replacement was allowed. Since the smaller plants may have disproportionately high costs, this could help to lower variance since variance approaches zero as proportionality becomes more exact. If this is an over-adjustment, then at least the result might be like a Type B population (found in Cochran, 1977), pages 268-269), thus helping to keep variance relatively small. This is apparently because the next best situation to complete proportionality is to have positive correlation between the probability of selection and the mean per element.

Let us consider that $n$ distinct plants were selected, some perhaps multiply, so that the with replacement sample size $n'$ is such that $n' \geq n$. If $n' > n$, then systematically chosen subsets of $n$ of the $n'$ observations were used for variance estimation. The mean of such results, using the finite population correction factor (as in Rao-Hartley-Cochran sampling with no remainder term) was used as a without replacement type estimate. As stated above, the Van Beeck and Vermetten Method provides inclusion probabilities that may help insure that this correction factor is not too optimistic.

A big advantage of this sampling methodology is the ease with which additional observations may be incorporated. This is convenient if a preliminary sample is taken and the remaining required sample size is then calculated, as was done here. (This procedure is sometimes called double sampling.) Also, as was contemplated in this application, this works well if additional observations are wanted in conjunction with poststratification. Also, the model sampling results could be calculated for every corresponding situation.

Note that although only costs are discussed here, costs per kilowatthour have the same CV estimates since kilowatthours generated is considered a constant in this application.

In summary, for estimation of generation expense, unequal probability sampling did not remain strictly sampling with probability proportional to size (PPS) after the first observation was drawn, but became proportional to the size of the remaining population on each draw. However, this may have tended to insure (for these data) that variance estimation was not too optimistic, and also means that drawing additional observations was easy. In addition, model sampling was done to see if similar results would follow, bringing the advantages of purposive sample selection to future efforts, and also as a way of comparing the use of net generation and generator nameplate capacity as variates correlated with costs. Results of a poststratification study to separate plants by those with at least one relatively new unit were marginal. Perhaps other criteria may be found. Note also that for the design-based estimates, using the without replacement scheme was of limited help since $n' > n$.

**Equations and Results**

**Required sample sizes.** Do a preliminary sample to estimate the total size needed. For ratio model sampling, i.e., Method 2, found earlier, let $c$ be a particular CV value. Then, $c Y_R$ equals the square root of the variance.

Solving for $c$: \[
    c \approx \frac{\delta}{\Phi} \left[ \frac{(X \cdot n \bar{x})}{n \bar{x}^2} \right]^{1/2}
\]

Solving for $n$: \[
    n \approx \frac{s_x^2 x^2}{(\bar{x}^2)^2 + s_x^2 x \bar{x}}
\]

For the without replacement design-based sampling found here:

Solving for $c$: \[
    c \approx \frac{\delta}{\Phi} \left[ \frac{N - n}{n(N - 1)} \right]^{1/2}
\]

Solving for $n$: \[
    n \approx \frac{N}{(N - 1) c^2 \bar{Y}^2 / s^2 + 1}
\]

If, as happened in the generation expense estimation project, a certainty stratum is used (to account separately for two plants with negative net generation totals for a given year), the last two equations become

\[
    c \approx \frac{\delta}{\Phi} \left[ \frac{N - n}{(n - n_2)(N - n_2 - 1)} \right]^{1/2}
\]

\[
    n \approx \frac{N - n_2}{(N - n_2 - 1) c^2 \bar{Y}^2 / s^2 + 1}
\]

where $n_2$ is the number of units (here plants) selected with certainty, $n$ is the total sample size, and $N$ is the size of the population.
An example encountered in generation expense estimation follows:

For \( N = 63 \), \( g^2 = 2 \) and \( n = 14 \), the estimate for \( s \) was 12,593, and \( \bar{Y} = 17,245 \). This yields \( c \approx 19.1 \) percent. If, however, we set \( c = 10 \) percent, and solve for \( n \), \( n \approx 30.7 \). Therefore, a total sample size of 29 plus the two certainties was estimated to be needed to bring the CV down to 10 percent. (Thus, there was a lot of variability in the data. Either a better stratification criterion, or set of criteria, must be found, or relatively large sample sizes will continue to be needed. A lot of this variability may actually be due, however, to nonsampling error.)

Let \( \hat{V}(PPXWOR) \) be the variance estimate under the without replacement unequal probability scheme described above. If we set \( \hat{V}(R) = \hat{V}(PPXWOR) \) when sample sizes are equal, and the unequal probability sampling scheme is used, then
\[
n = \frac{f(\bar{X})}{((\bar{X}) - \bar{X} - Nb)/(a - b)), \text{ where } a = s^2\bar{X}, \text{ and } b = s^2/(N - 1). (\text{Notice that if } \bar{X} = X/ N = \bar{X}, \text{ then } n = N. \text{ This is not likely, however. More likely, } \bar{X} > X.)
\]

Let \( g = Xa/(a - b), \text{ and } h = Nb/(a - b) \), then
\[
n = \frac{f(\bar{X})}{g / \bar{X}}, \text{ and } n > f(\bar{X}) \text{ implies that } n + h > g / \bar{X}.
\]

Example: \( N = 61, \ n = 22, \ \bar{X} = 453,380, \ \text{mean of} \ s^2 = 120,976,900, \ s^2 = 6,3006, \ \bar{X} = 19,432. \text{ then, } n + h \leq 168, \text{ and } g / \bar{X} \leq 168.4, \text{ so, } V(R) < V(PPXWOR). \text{ However, } E_n = 22(\bar{X}) \approx 9,329, \text{ found using Van Beeck-Vermten inclusion probabilities, thus } g / E_n = 22(\bar{X}) \approx 165.2, \text{ and } n + h \approx 168.4.
\]

Since 168.4 > 165.2, \( \hat{V}(R) \) and \( \hat{V}(PPXWOR) \) would be expected to be nearly equal on average, but with \( V(R) < V(PPXWOR) \) in general, when \( n = 22 \). The graph which follows shows that the point where \( n + h \) and \( g / E_n \) cross is near \( n = 11 \).

Therefore, in the future, the model sampling approach could be at least partially verified by taking an unequal probability sample of (approximately) size 11 as a preliminary sample, and if results are encouraging, only the "largest" plants would be selected to complete the desired sample using a model sampling approach. Little efficiency is lost in this case by waiting until after the preliminary sample selection to decide on the final sampling methodology.

Alternatively, perhaps a census could be used to determine, among other things such as a better stratification possibility, more accurate values for \( g \) and \( h \) (using generation nameplate capacity as that now appears to be a little better than net generation as a measure of size), and establish an improved estimate of the preliminary sample size for future years. (Variability of \( s^2 \) and \( s \) estimates for this sample size could be studied also.)

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References


Addendum to References

- **I. Hypothesis Testing**
- **II. Design-Based Sampling**
- **III. Model-Based Sampling**

1 Another EIA survey is used to estimate revenue to the utility per kilowatt-hour of electricity sold for various (ultimate consumer) sectors of the economy at the State level. Those estimates are made using a double ratio estimate (see Knaub (1989a)) which is design-based rather than model-based. (The author has made plans to investigate the possibility of modeling by comparing design-based results, as they are acquired, to results that are obtained through modeling and the use of data from certainty strata (i.e., generally large utilities only).)