## THE COEFFICIENT OF VARIATION IN INTERVAL ESTIMATION\*

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1. Introduction. In allocation problems, where the optimum sample size n is to be determined, the experimenter often wants to know how much he could deviate from the optimum solution without sacrificing the desired precision, nor increasing the cost, nor decreasing the profit angle substantially.

This study attempts specifically to use the coefficient of variation in obtaining confidence intervals for sample sizes  $n_h$  in a single-variable problem, and when there are many other characteristics of interest

In multipurpose surveys, since the characteristics behave differently, i.e., they have different population moments, the allocation of the sample size n to the strata would likewise differ according to the characteristic upon which the allocation was based. There is then need to get some compromise allocation such that the precision set would still be met.

2. The Coefficient of Variation and the Rel-Variance as Estimators. The coefficient of variation, (cv), of any sample estimate is defined as the standard error of the estimate divided by the value being estimated; while the rel-variance, RV, is equal to the square of the coefficient of variation. Thus,

$$cv = S/\bar{X}$$
,

RV = S²/
$$\bar{X}$$
², where S² = 
$$\frac{\sum\limits_{i=l}^{n} (X_1 - \bar{X})^2}{(n-1)}$$

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Although the coefficient of variation is neither an unbiased estimate nor an efficient statistic for non-normal distributions, it still remains a popular estimate (Norris). Its main utility lies in the fact that in a sample from a skewed population, the mean and standard deviation tend to change together, thus off-setting and compensating somewhat for any over estimation or under estimation that exist in the sample mean and standard deviation (Gutierrez 1965).

The rel-variance is not an unbiased estimate either, but this estimate  $v^2 = s^2 / x^2$  is a consistent estimate of the population rel-variance of the mean  $(V^2 = S^2 / X^2)$  and for reasonably large samples the bias will be trivial. (Hansen, Hurwitz, and Madow 1966).

## 3. Single Purpose Surveys.

3.1 Simple Random Sampling: Determination of Sample Size n and its Confidence Interval. The equation of the rel-variance of the mean in simple random sampling is

$$RV_{\overline{X}} = (1 - f) \frac{S^2/n}{\overline{X}^2} = (1 - f) \frac{RV_{\overline{X}}}{n},$$
 (1)

and if the finite population correction is ignored,

$$RV_{\overline{X}} = \frac{RV_{\overline{X}}}{n} = \frac{(cv_x)^2}{n}.$$
 (2)

Thus, if it is desired to have a degree of precision such that t times the coefficient of variation of the mean, cv\_, would be equal to d (where d is the relative difference between the estimated mean from a sample and the true mean), the equation becomes

$$t (cv_{\bar{x}}) = d$$
 (3)

and

$$(cv_{x})^{2} = d^{2}/t^{2}.$$
 (4)

Thus, substituting in equation (2);

$$\frac{d^2}{t^2} = \frac{(cv_x)^2}{n};$$

or

$$n = \frac{t^2(cv_x)^2}{d^2}.$$
 (5)

Actually, this is analogous to the equation for sample size n when the aimed-at precision is given in terms of the variance  $S^2$  instead of the rel-variance,  $(cv)^2$ .

Therefore, the variance of n, using equation (5), would be:

Var (n) = 
$$(t^2/d^2)^2$$
 Var  $(cv_x^2)$ .  
=  $(t^4/d^4)$  Var  $(RV_X)$ .

Inasmuch as the rel-variance of the estimated rel-variance based on a simple random sample of n units drawn with replacement is:

$$RV(RV) = \frac{\beta_2 - 1}{n} + \frac{4V_X^2}{n} - \frac{4 \mu_3 / \bar{X}^2 V_X^2}{n},$$

where

$$V^{2} = (N/N-1) \sigma^{2} / X^{2}$$

$$X$$

$$\beta_{2} = \mu_{4} / \sigma^{4}$$

The variance of the rel-variance, RV, is given by:

$$\begin{array}{rcl}
 & \text{Var } (\text{cv}_{x}^{2}) = [\ (\text{cv}_{x}^{2})]^{\ 2} \ [\text{Rel-Var } (\text{cv}_{x}^{2})] \\
 & = (\text{cv}_{x})^{4} \boxed{\frac{\beta_{2} - 1}{n} + \frac{4V^{2}}{n}} \\
 & - \frac{4\ \mu_{3}\ /\ X^{3}V^{2}}{n} \boxed{\frac{\beta_{2} - 1}{n}} \\
 \end{array}$$

The variance formula is just an approximation since simple random sampling without replacement is involved here. However, it is believed that this approximation is close to the true value whenever the number of sampling units in the population is large relative to the number in the sample.

Knowing Var (n), it is now possible to obtain confidence intervals for sample size n from the following relation:

$$n \pm t' \sqrt{Var n} = n \pm t' \left\{ (t/d)^4 e v_x^4 \left[ \frac{\beta_2 - 1}{n} + \frac{4V_x^2}{n} - \frac{4 \mu_3 / \bar{X}^3 V_x^2}{n} \right] \right\}^{\frac{1}{2}}$$
(6)

where t' will take the value corresponding to the degree of confidence one wants to achieve.

3.2 Stratified Random Sampling: Determination of stratum s ample size  $n_h$  and its Confidence Interval.

In simple random sampling, the equation for the relvariance of the original variate,  $\mathrm{RV}_{_{\mathrm{X}}}$  is

$$RV_{X} = \frac{(N-n)}{n(N-1)} \frac{S^{2}}{\bar{X}^{2}} = \frac{(N-n)}{n(N-1)} \frac{RV}{X}$$
 (7)

Suppose that the population is divided into several strata, and that independent estimates of  $RV_{\perp}$  are obtained for these L strata. The sum

$$\sum_{h=1}^{L} RV_{h}(X) = \sum_{h=1}^{L} \frac{(N_{h} - n_{h})}{n_{h}(N_{h} - 1)} RV_{h}(X)$$
 (8)

can be taken. If  $\sum_{h=1}^{L} RV_h(X)$  is set equal to a certain desired precision, say  $RV_{oh}$ , for the  $h^{th}$  stratum,

$$\sum_{h=1}^{L} RV_{oh} = \sum_{h=1}^{L} \frac{(N_h - n_h)}{n_h(N_h - 1)} RV_h(X)$$
 (9)

To estimate  $n_h$  for  $h=1,\ldots,L,\sum\limits_{h=1}^{L}RV_{oh}$  is to be minimized with the constraint

$$n = \sum_{h=1}^{L} n_h$$

imposed. With the use of Lagrange multiplier,

$$F = \sum_{h=1}^{L} \frac{(N_h - n_h)}{n_h(N_h - 1)} RV_h(X) + \lambda (n_1 + ... + n_L - n)$$

is minimized with respect to  $n_h$ ,  $h = 1, \ldots L$ .

The results of the minimization of this function as obtained by Sinsioco (1969) are:

$$n_h = \frac{cv_h}{\sum_{h=1}^{L} cv_h} n \tag{10}$$

and

or, if the finite population correction is ignored,

$$n = \frac{(\sum\limits_{h=1}^{L} cv_h)^2}{\sum\limits_{h=1}^{L} RV_{oh}}.$$

From equation (10), a variance formula for sample size  $n_h$  can be formulated. However, there would arise several different cases dependent upon the assumptions made with regard to the coefficients of variation. As:

Case I. Let (  $\frac{cv_h}{\sum\limits_{h=1}^{L} cv_h}$  ) be constant. Therefore,

$$\operatorname{Var} n_h = \begin{bmatrix} & cv_h & & \\ & \underline{\Sigma} & cv_h & & \\ & \underline{h} = 1 & & \end{bmatrix} \operatorname{Var} (n).$$

$$n = \frac{(\sum_{h=1}^{L} cv_h)^2}{\sum_{h=1}^{L} RV_{oh}},$$

$$\text{Var } n = \text{Var} \begin{bmatrix} \frac{L}{(\sum\limits_{h=1}^{L} cv_h)^2} \\ \frac{L}{\sum\limits_{h=1}^{L} RV_{oh}} \end{bmatrix}$$

$$= \begin{bmatrix} 1 \\ \sum_{h=1}^{L} RV_{oh} \end{bmatrix}^{2} Var \begin{bmatrix} L \\ \sum_{h=1}^{L} cV_{h} \end{bmatrix}^{2}$$
(11)

Now 
$$\operatorname{Var}\left[\left(\begin{array}{c}L\\\Sigma\\h=1\end{array}\operatorname{cv_h}\right)^2\right] = \operatorname{Var}\left[\begin{array}{c}L\\\Sigma\\h=1\end{array}\operatorname{cv_h}^2 + 2\begin{array}{c}L\\\Sigma\\i< j\end{array}\operatorname{cv_i}\operatorname{cv_j}\right]$$

$$= \operatorname{Var}\left[\begin{array}{c}L\\\Sigma\\h=1\end{array}\operatorname{cv_h}^2\right] + 4\operatorname{Var}\left[\begin{array}{c}L\\\Sigma\\i< j\end{array}\operatorname{cv_i}\operatorname{cv_j}\right]$$

$$+ \operatorname{covariance\ term}$$

$$= \sum_{h=1}^{L}\operatorname{Var}\operatorname{cv_h}^2 + 4\operatorname{Var}\sum_{h=1}^{L}\operatorname{cv_i}\operatorname{cv_j}\ (12)$$

+ covariance term

An approximation of the above equation can be obtained by dropping the covariance term. It is believed that such procedure will not affect much the final equation for  $Var\ n_h$  since the order of the covariance term is  $1/n^2$ . Inasmuch as it was also assumed that the samples drawn from each stratum are independent, the stratum coefficients of variation are likewise expected to be independent.

Hansen, Hurwitz, and Madow (1966) give the formula for the variance of a product of two random variable  $U_1$ ,  $U_2$  as

$$Var (U_1U_2) = (U_1U_2)^2 \left[ \frac{Var U_1}{U_1^2} + \frac{Var U_2}{U_2^2} + 2 \frac{Cov(U_1U_2)}{U_1U_2} \right]$$

Let  $U_1 = cv_1$  and  $U_2 = cv_2$ . The third term of the above equation will drop out since the strata coefficients of variation were assumed to be independent.

If the variance for each pair of  $cv_h$ ,  $h=1,\ldots L$ , are summed, the second term of equation (12) becomes:

$$Var (cv_1cv_2) = (cv_1cv_2)^2 \left[ \frac{Var cv_1}{cv_1^2} + \frac{Var cv_2}{cv_2^2} \right]$$

$$\sum_{i < j}^{L} Var (cv_i cv_j) = \sum_{i < j}^{L} \left\{ (cv_i cv_j)^2 \right] \left[ \frac{Var cv_i}{cv_i^2} + \frac{Var cv_j}{cv_j^2} \right] \right\}$$

Simplifying, the result is:

$$\sum_{i < j}^{L} Var (cv_i cv_j) = \sum_{i < j}^{L} Var cv_h (\sum_{i < j}^{L} cv_j)$$

where, for a particular stratum h, the subscript j will take on all values, 1, ... L, except h.

Therefore equation (12) becomes:

$$\operatorname{Var}\left[\left(\sum_{h=1}^{L} \operatorname{cv}_{h}\right)^{2}\right] = \sum_{h=1}^{L} \operatorname{Var} \operatorname{cv}_{h}^{2} + \sum_{h=1}^{L} \left[\operatorname{cv}_{h}^{2} \cdot \operatorname{RV}(\operatorname{cv}_{h}^{2}) \left(\sum_{h=1}^{L} \operatorname{cv}_{j}^{2}\right)\right]$$

$$\operatorname{Var}\left[\left(\sum_{i < j}^{L} c v_{h}\right)^{2}\right] = \sum_{h=1}^{L} \left\{\operatorname{Var}\left(c v_{h}^{2}\right)\left[1 + \frac{1}{c v_{h}^{2}}\left(\sum_{j=1}^{L} c v_{j}^{2}\right)\right]\right\}$$

where  $j \neq h$ .

If the above is substituted in equation (11), the variance of n is:

$$Var \ n = \left[ \frac{1}{\sum_{h=1}^{L} RV_{oh}} \right]^{2} \sum_{h=1}^{L} \left\{ Var(cv_{h}^{2}) \left[ 1 + \frac{1}{cv_{h}^{2}} \left( \sum_{j=1}^{L} cv_{j}^{2} \right) \right] \right\} (13)$$

The formula for the variance of a stratum sample size is

$$Var n_h = \begin{bmatrix} cv_h \\ L \\ S \\ cv_h \end{bmatrix}^2 Var n$$
 (14)

where Var n is given as in equation (13).

If the assumption in Case I is not made, the variance of  $n_h$  can be obtained thus:

$$Var n_h = Var \begin{bmatrix} \frac{cv_h}{L} & n \\ \frac{\Sigma}{h=1} & cv_h \end{bmatrix}$$

where

$$n = \frac{(\sum_{h=1}^{L} cv_h)^2}{\sum_{h=1}^{L} RV_{oh}}$$

$$Var \ n_h = \left[ \frac{cv_h \ .n}{\sum\limits_{h=1}^{L} cv_h} \right]^2 \left[ \frac{Var \ cv_h}{cv_h^2} + \frac{Var \ (\ n/\sum\limits_{h=1}^{L} cv_h \ )}{(\ n/\sum\limits_{h=1}^{L} cv_h \ )^2} \right]$$

$$+ 2 \frac{\text{Cov ( cv}_{h}, n' / \sum_{k=1}^{L} \text{cv}_{h})}{\sum_{h=1}^{L} \text{cv}_{h}}$$

Simplifying the numerator of the second term

$$\begin{array}{c|c} Var & \frac{n}{L} & Var & \begin{bmatrix} (\sum\limits_{h=1}^{L} & cv_h)^2 / & K_o \\ \sum\limits_{h=1}^{L} & cv_h \end{bmatrix} \\ \sum\limits_{h=1}^{L} & cv_h \end{bmatrix} ,$$

where 
$$K_0 = \sum_{i=1}^{I_i} RV_{oh}$$

$$= \operatorname{Var}\left[\frac{\sum_{h=1}^{L} \operatorname{cv}_{h}}{K_{0}}\right]$$

$$= \frac{1}{|K_o|^2} \left[ Var \left( \sum_{h=1}^{L} cv_h \right) \right]$$

$$= \frac{1}{|K_o|^2} \left[ \sum_{h=1}^{L} Var cv_h \right]$$

and likewise the numerator of the third term,

Cov (cv<sub>h</sub>, 
$$\frac{n}{\sum\limits_{h=1}^{L} cv_h}$$
) = Cov (cv<sub>h</sub>,  $\frac{\sum\limits_{h=1}^{L} cv_h}{K_o}$ )
$$= \frac{1}{K_o} \left[ Var cv_h \right],$$

the variance formula for nh becomes

$$+2\frac{\operatorname{Var} \operatorname{cv}_{h} \left(\sum_{h=1}^{L} \operatorname{cv}_{h}\right)}{\operatorname{K}_{0}.\operatorname{cv}_{h}.n}.$$
 (15)

Cases II and III employ the above equation in getting confidence intervals for  $n_h$ , where different assumption about the coefficients of variation are made.

Case II. Specify the precision by making the supposition that

$$\sum_{h=1}^{L} cv_h = \sum_{h=1}^{L} (all upper limits of cv_h)$$

$$= \sum_{h=1}^{L} cv_{hu}$$

where  $cv_{hu}$  is obtained from  $cv_h + t \sqrt{Var cv_h}$ 

Case III. For this case, it is assumed that

$$\sum_{h=1}^{L} cv_h = K \text{ (largest } cv_h)$$

where K = number of strata.

Confidence limits for the stratum sample sizes  $n_h$  can then be obtained by using either equations 14 or 15, and taking into account the different assumptions made in the three methods of estimating Var  $(n_h)$ .

4. Multipurpose Surveys. In sampling practice it is quite unusual if only one population characteristic is being estimated. Without loss of generality, it will be assumed that interest lies on the estimates of the population means of several characteristics. The notations to be used are:

 $\bar{x}_{ij}$  — mean of the i<sup>th</sup> stratum of the j<sup>th</sup> variable

 $n_{ij}$  — sample size for the i<sup>th</sup> stratum of the j<sup>th</sup> variable

 $N_{ij}$  — number of elements of i<sup>th</sup> stratum of j<sup>th</sup> variable

 $cv_{ij}$  — coefficient of variation of  $i^{th}$  stratum of  $j^{th}$  variable

RV<sub>ij</sub> — rel-variance of the i<sup>th</sup> stratum of j<sup>th</sup> variable

 $U_{ij}$  — the reciprocal of the sample size  $n_{ij}$ 

For each characteristic, the sum of the rel-variances over all the L strata is desired to be less than or equal to a specific value, say  $RV_{oj}$ , for the j<sup>th</sup> characteristic.

$$RV_{1j} + RV_{2j} + \ldots + RV_{Lj} \leq RV_{0j}$$
;  $j = 1, \ldots p$ 

So, all in all, there would be p constraints of the above type and L restrictions of the form

$$0 \le n_i \le N_i;$$
  $i = 1, ... L$ 

4.1 Linear Programming: Charnes and Lemke's Method.

The linear programming technique is to minimize or maximize an objective function subject to certain restrictions. In this study, since each stratum sample size  $n_{ij}$  estimated has a com-

puted confidence interval, there would arise restrictions of the form

$$n_{ijv} \le n_{ij} \le n_{iju}; i = 1, ... L$$
  
 $j = 1, ... p$ 

where  $n_{ijv}$  is the lower limit of  $n_{ij}$  and  $n_{jiu}$  the upper limit.

For this bounded-variable problem as it is known in literature, the interest is not in getting higher precision than that already guaranteed by the stratum sample size  $n_{iu}$ , where  $n_{iu}$  is the largest upper bound for a particular stratum i among all  $n_{iju}$ ,  $j=1,\ldots p$ . Neither is the interest on any decrease in precision by reducing sample size  $n_i$  such that it is less than  $n_{jv}$ , where  $n_{iv}$  is the least lower bound among all  $n_{ijv}$ ,  $j=1,\ldots p$ .

If it is assumed that the problem is that of maximization, the bounded-variable problem can be written as follows:

a) Maximize 
$$f(U) = c_1U_1 + ... + c_LU_L$$
,

b) subject to: 
$$a_{11}U_1 + ... + a_{L1}U_L \leq b_1$$

$$d_{vj} \quad \ = \quad U_j \quad \ = \quad d_{uj} \qquad \quad j \, = \, 1, \, \ldots \, p$$

and

$$d) \qquad \qquad J_j \; \geq \; O \qquad \qquad j = 1, \; \ldots \; p$$

where  $d_{vj}$  is the lower bound of the variable  $U_j$  and  $d_{uj}$ , the upper bound. The lower bound  $d_{vj}$  may all be zero.

By adding the necessary slack variables  $(U_{L+1} \dots U_{L+p})$ ,  $(X_1, \dots X_L)$ , the problem becomes:

a) Maximize 
$$f(U) = c_1U_1 + ... + c_LU_L$$
;

b) subject to: 
$$a_{11}U_1 + \ldots + a_{L1}U_L + U_{L+1} = b_1$$

$$a_{1p}U_1 + \ldots + a_{Lp}U_L + U_{L+p} = b_p$$
;

and

$$\mathbf{U}_{i},\,\mathbf{X}_{i} \geq \mathbf{0} \qquad \qquad \mathbf{i} = 1,\,\ldots\,\mathbf{L}$$

All in all, there are p + L constraints (p structural and L upper-bound constraints.)

- 5. Application. The data used throughout are the results of a research (1967) conducted by the Department of Varietal Improvement of the International Rice Research Institute. The objective of the experiment was to determine the association between grain yield and agronomic traits in Peta X T(N) Backcrosses. Table 1 shows the coefficients of variation of the 5 different strata and characteristics.
- 5.1 Single Purpose Survey: Stratified Random Sampling. Using equations 10, 14, and 15 (section 3.2), and taking into account the different assumptions of each method, stratum sample size  $n_h$ ,  $h=1,\ldots L$  and its confidence limits were estimated for the first characteristic  $X_1$  in Table 1. The precision set in terms of  $RV_{oh}$  were:

$$RV_{01} = RV_{02} = RV_{03} = .05$$
  
 $RV_{04} = RV_{05} = .0045$ 

The results are presented in Tables 2 and 3.

5.2 Multipurpose Survey: Charnes and Lemke's Method. The objective function in terms of  $U_i = 1^i/n_i$  is:

Maximize  $K=c_1U_1+c_2U_2+\ldots+c_LU_L$  while the structural constraints become

$$\sum_{\substack{j=1\\i=1}}^{L} RV_i(X_j)U_i \leq RV_{0j}. \qquad j=1, \ldots p$$

Recal that RV(X) = RV(X)/n, and thus, the above result.

TABLE I. STRATA COEFFICIENTS OF VARIATION FOR FIVE VARIABLES

| CV for X       | stratum | 2      | 3      | 4      | 5      |
|----------------|---------|--------|--------|--------|--------|
| $X_1$          | .33348  | .38894 | .36191 | .45658 | .41414 |
| $\mathbf{X_2}$ | .21850  | .19586 | .20640 | .19720 | .19708 |
| $X_3$          | .20958  | .21380 | .20022 | .19784 | .21044 |
| $X_4$          | .12024  | .06486 | .04039 | .09303 | .08407 |
| $X_5$          | .05429  | .09509 | .07205 | .06518 | .05804 |

| Variables:                       | Strata:                 |
|----------------------------------|-------------------------|
| X <sub>1</sub> — Leaf angle mean | 1 — P/2 Semi-dwarf Line |
| $X_2$ — Panicle number           | 2 — P/3 Semi-dwarf Line |
| X <sub>3</sub> — Tiller number   | 3 — P/4 Semi-dwarf Line |
| $X_4$ — Plant height             | 4 — P/3 Tall Line       |
| $X_5$ — Grain yield              | 5 — P/4 Tall Line       |

TABLE 2. COMPUTED VALUES OF n and  $n_h$  (FOR  $X_1$ ) FOR THE THREE METHODS

|            | n <sub>1</sub> | $n_2$ | $n_3$ | n <sub>4</sub> | $n_5$ | n     |
|------------|----------------|-------|-------|----------------|-------|-------|
| Method I   | 13.04          | 15.21 | 14.15 | 17.85          | 16.19 | 76.44 |
| Method II  | 7.98           | 9.30  | 8.66  | 10.92          | 9.91  | 46.77 |
| Method III | 11.17          | 13.02 | 12,12 | 15.29          | 13.87 | 65.47 |
|            |                |       |       |                |       |       |

TABLE 3. CONFIDENCE INTERVALS FOR  $n_{\rm h}$  FOR THE THREE METHODS (FOR  $\chi_1$ )

|            | CI n <sub>1</sub> |       | CI n <sub>2</sub> |      | CI n <sub>3</sub> |      | CI n <sub>4</sub> |      | CI n <sub>5</sub> . |      |
|------------|-------------------|-------|-------------------|------|-------------------|------|-------------------|------|---------------------|------|
| Method I   | 10.4              | 15.70 | 12.1              | 18.3 | 11.3              | 17.0 | 14.2              | 21.5 | 12.89               | 19,5 |
| Method II  | 3.9               | 12.0  | 4.7               | 14.0 | 2.3               | 15.0 | 5.6               | 12.3 | 3.4                 | 16.7 |
| Method III | 5.6               | 16.7  | 6.7               | 19.3 | 2.2               | 22.0 | 8.3               | 22.3 | 4.2                 | 23.5 |

The upper and lower bounds restrictions become:

$$1/n_{i\mathfrak{u}} \leq U_i \leq 1/n_{i\mathfrak{u}}; \qquad \qquad i=1,\,\dots\,L$$

Let the desired precision be:

$$RV_{01} = .1125$$
  
 $RV_{02} = NV_{03} = .05$   
 $RV_{04} = RV_{05} = .0045$ 

Confidence intervals for  $n_i$ ,  $i=1,\ldots L$ , are computed for all 5 variables and are shown below in Table 4. (Only confidence limits obtained by using Method I will be employed in this illustration.)

The upper and lower bounds restrictions are then:

Making a simple transformation of variables,  $Y_i = U_i - a_i$ , where  $a_i$ ,  $i = 1, \ldots L$  are the lower limits of  $U_i$ , and adding the necessary slack variables  $(Y_6, \ldots, Y_{10})$  to the structural constraints and  $(X_1 \ldots X_5)$  to the upper bounds restrictions, the resulting equations are:

TABLE 4. CONFIDENCE INTERVALS FOR  $n_h$  FOR ALL CHARACTERISTICS

| X              | CI n <sub>i</sub> |       | CI n <sub>2</sub> |      | CI n <sub>3</sub> |      | CI n <sub>4</sub> |       | CI n <sub>5</sub> |      |
|----------------|-------------------|-------|-------------------|------|-------------------|------|-------------------|-------|-------------------|------|
| Х,             | 4.61              | 6.98  | 5.38              | 8.14 | 5.01              | 7.57 | 6.32              | 9.55  | 5.73              | 8.66 |
| X <sub>2</sub> | 3.15              | 5.72  | 2.82              | 5.13 | 2.98              | 5.40 | 2.84              | 5.16  | 2.84              | 5.16 |
| $X_3$          | 3.07              | 5.58  | 3.13              | 5.70 | 2.93              | 5.34 | 2.89              | 5.27  | 3.08              | 5.61 |
| X              | 8.23              | 13.19 | 4.49              | 7.12 | 2.80              | 4.43 | 6.44              | 10.21 | 5.84              | 9.20 |
| $X_5$          | 3.38              | 4.94  | 5.91              | 8.65 | 4.48              | 6.56 | 4.05              | 5.93  | 3.61              | 5.28 |

$$\begin{array}{c} 1112.1077\ Y_1\ +\ 1512.7466\ Y_2\ +\ 1309.8195\ Y_3 \\ +\ 2084.6130\ Y_4\ +\ 1715.1431\ Y_5\ +\ Y_6\ =\ 302.2838 \\ 477.4024\ Y_1\ +\ 383.6209\ Y_2\ +\ 426.0298\ Y_3 \\ +\ 388.8670\ Y_4\ +\ 388.4213\ Y_5\ +\ Y_7\ =\ 282.9094 \\ 439.2446\ Y_1\ +\ 457.1132\ Y_2\ +\ 400.8799\ Y_3 \\ +\ 391.4253\ Y_4\ +\ 442.8478\ Y_5\ +\ Y_8\ =\ 274.4618 \\ 144.5808\ Y_1\ +\ 42.0737\ Y_2\ +\ 16.3162\ Y_3 \\ +\ 86.5443\ Y_4\ +\ 70.6741\ Y_5\ +\ Y_9\ =\ 10.8659 \\ 29.4740\ Y_1\ +\ 90.4254\ Y_2\ +\ 51.9083\ Y_3 \\ +\ 42.4828\ Y_4\ +\ 33.6892\ Y_9\ +\ Y_{10}\ =\ 17.6371 \end{array}$$

$$Y_1$$
 +  $X_1$  = .2503632302  
 $Y_2$  +  $X_2$  = .2386267554  
 $Y_3$  +  $X_3$  = .2256560783  
 $Y_4$  +  $X_4$  = .2538367670  
 $Y_5$  +  $X_5$  = .2433034905  
 $Y_i$ ,  $X_i \ge 0$ ;  $i = 1, ... 5$   
 $j = 1, ... 10$ 

Applying Charnes and Lemke's method to the above problem.

The solution arrived at gives the following sample size allocations:

$$\begin{array}{rcl}
 n_1 & = & 7.7 \\
 n_2 & = & 8.6 \\
 n_3 & = & 3.2 \\
 n_4 & = & 10.2 \\
 n_5 & = & 9.2
 \end{array}$$

6. Conclusions. The results obtained indicate that the values of the sample size n and stratum size  $n_{\rm h}$  (in stratified sampling), and its confidence limits are in proportion to the values of the corresponding coefficient of variation.

If a comparison is made among the three methods proposed for obtaining confidence intervals for  $n_h$ , Method III is observed to give the widest interval in all the strata and for all the characteristics, while Method I, the least. It has been likewise noted that in all cases, Method II has the lowest confidence limits, whether in the lower or upper bounds.

Charnes and Lemke's Method was used to get a compromise allocation in a multipurpose survey where several different allocations are possible. Herein, because of the upper and lower bounds constraints, not only is the over-allprecision satisfied, but each stratum sample size  $n_h$  also meets the precision requirements.

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