Cost-Efficient Design of Occupational Exposure Assessment Strategies- A Review
Mahmoud Rezagholi, Svend Erik Mathiassen

To cite this version:

HAL Id: hal-00629471
https://hal.archives-ouvertes.fr/hal-00629471
Submitted on 6 Oct 2011

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Cost-Efficient Design of Occupational Exposure Assessment Strategies- A Review

<table>
<thead>
<tr>
<th>Journal:</th>
<th>Annals of Occupational Hygiene</th>
</tr>
</thead>
<tbody>
<tr>
<td>Manuscript ID:</td>
<td>AnnHyg-10-0120.R1</td>
</tr>
<tr>
<td>Manuscript Type:</td>
<td>Reviews</td>
</tr>
<tr>
<td>Date Submitted by the Author:</td>
<td>n/a</td>
</tr>
<tr>
<td>Complete List of Authors:</td>
<td>Rezagholi, Mahmoud; University of Gävle, Occupational and Public Health Science Mathiassen, Svend Erik; University of Gävle, Occupational and Public Health Science</td>
</tr>
<tr>
<td>Keywords:</td>
<td>error, information, performance, cost, optimization</td>
</tr>
</tbody>
</table>
Cost-Efficient Design of Occupational Exposure Assessment Strategies- A Review

Mahmoud Rezagholi\textsuperscript{1}  
Svend Erik Mathiassen\textsuperscript{2}

\textsuperscript{1}MSc, Centre for Musculoskeletal Research, Department of Occupational and Public Health Science, University of Gävle, Sweden
\textsuperscript{2}PhD, Centre for Musculoskeletal Research, Department of Occupational and Public Health Science, University of Gävle, Sweden

Address all correspondence to: Mahmoud Rezagholi, Centre for Musculoskeletal Research, Department of Occupational and Public Health Science, University of Gävle, SE-801 76 Gävle. Tel: +46(0)26648757.
Fax: +4626648686. E-mail: madrei@hig.se

Abstract

When designing a strategy for collecting occupational exposure data, both economic and statistical performance criteria should be considered. However, very few studies have addressed the trade-off between the cost of obtaining data and the precision/accuracy of the exposure estimate as a research issue. To highlight the need of providing cost-efficient designs for assessing exposure variables in occupational research, the present review explains and critically evaluates the concepts and analytical tools used in available cost efficiency studies. Nine studies were identified through a systematic search using two algorithms in the databases PubMed and ScienceDirect. Two main approaches could be identified in these studies: \textit{comparisons} of the cost efficiency associated with different measurement designs, and \textit{optimizations} of resource allocation on the basis of functions describing cost and statistical efficiency. In either case, the reviewed studies use simplified analytical tools and insufficient economic analyses. More research is needed to understand whether these...
drawbacks jeopardize the guidance on cost-efficient exposure assessment provided by the studies, as well as to support theoretical results by empirical data from occupational life.

**Keywords:** error, information, performance, cost, optimization.

**INTRODUCTION**

Acquiring sufficient information on occupational exposures is a persistent challenge in occupational epidemiologic studies. Imprecise and biased estimations of exposure averages may result in vague or even false conclusions regarding the exposure status of a group, and may thus even jeopardize groups or conditions, as in epidemiology and intervention research. Using biomechanical exposure as an example, guidance on *measurement designs* has therefore been developed during recent years to improve the information provided by occupational exposure assessments. This guidance includes considerations to the appropriateness of different measurement instruments, acknowledging possible systematic errors in using them (Burdorf and van der Beek, 1999; David, 2005; van der Beek and Frings-Dresen, 1998; Winkel and Mathiassen, 1994; Burdorf and van Riel, 1996; Stanton et al., 2005; Takala et al., 2010), and it includes discussions on sampling strategies focusing on how to deal with random sources of error (Burdorf, 1995; Mathiassen et al., 2002; Mathiassen et al., 2003; Nordander et al., 2004). The literature also includes an extensive discussion on which method is more accurate and most applicable when measuring different biomechanical exposures in working life (e.g. van der Beek and Frings-Dresen, 1998; Winkel and Mathiassen, 1994). The appropriateness and statistical efficiency of the employed measurement design, however, are not the only criteria determining whether or not a specific design will or should be employed. A measurement design should also be *cost-efficient* as pointed out and addressed decades ago by, e.g. Cochran (1977). While statistical efficiency concerns minimizing the variance of an unbiased estimator of the target exposure variable, the economic term of *cost efficiency* refers to either *technical efficiency*, i.e. generating the maximum possible “output” for the given “inputs” (measurement efforts), or *productive efficiency*, i.e. producing one unit of “output” at the lowest possible cost. In the context of exposure measurement, statistical efficiency is an appropriate measure of “output”, since it measures the amount of information generated by the measurement design. With this definition of output, cost efficiency is an appropriate comprehensive concept to use, because it emphasizes both economic and statistical performance. Notably, the concept of cost efficiency
when measuring exposures differs from the term “cost-effectiveness analysis” as frequently used in health economics. While cost efficiency analysis as discussed in the present paper addresses an economic evaluation of measurement designs that produce information on exposure variables, cost-effectiveness analysis is a methodology for economic evaluation of, in particular, treatment programs. Consequently, in cost efficiency, the term “efficiency” refers to a statistical concept focussing the quantity of information, while the term “effectiveness” in cost-effectiveness analysis refers to the outcomes of a treatment intervention on patients, for instance as measured by improved quality of life.

The measurement method and the number of sampling units both affect the total cost of the measurement as well as the statistical efficiency of the estimated variable. A reduction of errors in exposure assessment, i.e. an improvement of statistical efficiency, can be achieved by using more suitable or advanced technical instruments and/or by increasing the number of sampling units. Such improvements, on the other hand, most often increase the total cost of the measurement. Thus, a measurement design that generates low error (high statistical efficiency) is not necessarily cost-efficient. A cost-efficient measurement design balances the cost and the amount of information produced according to either technical or productive efficiency criteria by, in principle, manipulating the number of sampling units at different stages as well as by considering which measurement methods to employ in the statistical production.

Analysis of the cost efficiency of producing information on exposure variables is an important field of research, yet so far with a limited body of literature. As an example, the literature on occupational biomechanical exposure assessment lacks studies devoted to the issue of how to supply “sufficient” information on exposures at a “low” cost. None of the measurement design studies cited above have considered cost efficiency criteria when assessing occupational exposures; all have focused on appropriateness and/or statistical performance.

An interesting study, however, by Trask et al. (2007) was devoted to classification and estimation of all important cost components associated with different methods of measuring low back injury risk factors. While this study clearly demonstrated that costs differ between exposure assessment technologies, it did not discuss statistical performance.

While our personal interests concern mainly biomechanical exposures in working life, the present review addresses all available studies devoted to the trade-off between “cost” and “efficiency” in assessment of any exposure variable. The purpose of the review is to analyse statistical and economical models suggested and/or applied in the literature for analysing cost efficiency in exposure assessment, so as to set a stage for future research. In order to aid the
discussions, the review even considers some studies devoted to cost-efficient assessments of response variables, and also points to usable methodologies from the literature on health economics. The review considers cost efficiency analysis in the two applications occurring in the literature: evaluation/comparison of alternative measurement designs and optimization of resource allocation in statistical production.

METHODS

A systematic search in the medical database PubMed and the cross-disciplinary scientific database ScienceDirect was conducted in February 2009, using two search algorithms:

1. \[ \text{cost} \cap (\text{precision} \cup \text{accuracy} \cup \text{power}) \cap \text{assessment} \cap \text{exposure} \],

2. (cost-efficient \cap \text{validation study}). These search algorithms identified 99 papers (78+21) in PubMed and 112 (22+90) papers in ScienceDirect, primarily in the areas of epidemiology, health economics and medical statistics. The relevance of the studies to the present review was judged using three criteria: 1) the analysis of cost efficiency should address assessment of exposure variables, 2) both “cost” and “efficiency” (or terms with equivalent meanings) must be considered, 3) the analysis of cost efficiency should be based on at least one mathematical model. First, the titles of all 211 papers were inspected. If the title suggested the paper to be relevant according to the inclusion criteria, the abstract was examined. Thus, the abstracts of 183 publications were examined. On the basis of this examination, nine papers were identified as relevant that fulfilled the inclusion criteria. Several other publications were considered relevant to the general topic of cost efficiency analysis in data collection. These papers are addressed when appropriate in the discussion below, but they were not included in the core review. Reviewing the reference lists of the nine included papers did not lead to the identification of additional relevant papers. Also, a citation report was retrieved for all nine papers using Google Scholar, but this did not reveal any additional studies either. Thus, a total of nine papers were accepted for a thorough review.

In examining these nine articles, we focused on three issues: 1) the indicator of statistical efficiency and the operational model applied to assess it, 2) methods used to assess “cost”, and 3) the general conclusion of the cost efficiency analysis. Some studies reported empirical data to illustrate their approach, but we considered these quantitative data not to be generalizable, and thus have not commented them in this review.
RESULT AND DISCUSSION

Early in the review process, we found that the identified papers employ concepts and tools that are specifically adapted either to evaluation/comparison of measurement designs or to their optimization. Since these two approaches are fundamentally different, conceptually as well as with respect to the applied methods, we chose to structure the review accordingly, and sort the nine identified papers into either category. Tables 1.a and 1.b summarize the nine studies by reporting their indicators of “efficiency”, the purpose in their cost efficiency analysis, and the underlying assumptions in the applied statistical and economical models.
### Table 1.a Basic characteristics of the identified studies on cost-efficient exposure assessment in comparison approach

<table>
<thead>
<tr>
<th>Reference</th>
<th>Indicator of statistical efficiency</th>
<th>Purpose</th>
<th>Statistical assumption</th>
<th>Economical assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lemasters et al. (1996)</td>
<td>Precision</td>
<td>Comparison of 32 alternative sampling strategies</td>
<td>Additive random error, three-stage sampling</td>
<td>Total cost directly proportional to the number of measurements</td>
</tr>
<tr>
<td>Shukla et al. (2005)</td>
<td>Precision</td>
<td>Comparison of alternative sampling strategies</td>
<td>Additive random error, three-stage sampling</td>
<td>Total cost directly proportional to the number of measurements</td>
</tr>
<tr>
<td>Armstrong (1995, 1996)</td>
<td>Accuracy</td>
<td>Comparison of two measurement methods</td>
<td>Existence of perfect measurement, single-stage sampling</td>
<td>One linear cost component differing between measurement methods, same fixed cost for both measurement methods</td>
</tr>
</tbody>
</table>

### Table 1.b Basic characteristics of the identified studies on cost-efficient exposure assessment in optimization approach

<table>
<thead>
<tr>
<th>Reference</th>
<th>Indicator of statistical efficiency</th>
<th>Purpose</th>
<th>Statistical assumption</th>
<th>Economical assumption</th>
</tr>
</thead>
<tbody>
<tr>
<td>Duan and Mage (1997)</td>
<td>Accuracy</td>
<td>Optimization of resource allocation between two measurement methods</td>
<td>Correlation between indirect and direct measurements, single-stage sampling</td>
<td>One linear cost component differing between direct and indirect measurement methods</td>
</tr>
<tr>
<td>Spiegelman and Gray (1991)</td>
<td>Discriminatory statistical power</td>
<td>Optimization of resource allocation between main and validation studies</td>
<td>Non-linear error model, single-stage sampling</td>
<td>One linear cost component differing between main and validation studies</td>
</tr>
<tr>
<td>Spiegelman (1994)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Stram et al. (1995)</td>
<td>Precision</td>
<td>Optimization of resource allocation between two sampling stages</td>
<td>Additive random error, two-stage sampling</td>
<td>Two linear cost components</td>
</tr>
<tr>
<td>Whitmore et al. (2005)</td>
<td>Precision</td>
<td>Optimization of resource allocation between three sampling stages</td>
<td>Additive random error, three-stage sampling</td>
<td>Three linear cost components, fixed cost addressed</td>
</tr>
</tbody>
</table>
Studies comparing measurement methods/strategies

Comparison of alternative sampling strategies

Based on variance components estimated by a random effect model, Lemasters et al. (1996) compared 32 possible alternative sampling strategies with various combinations of periods, weeks, and days that might be adopted in assessments of coal-dust exposure for an individual miner. Each of these alternatives is compared to a “pilot” strategy in terms of cost and precision. Gains or losses in “relative accuracy” are assessed using the expression \( \frac{\hat{\sigma}_\tau(\text{choice})}{\hat{\sigma}_\tau(\text{pilot})} \times 100 \), where \( \hat{\sigma}_\tau \) denotes the standard error of the mean. The assessed “relative accuracy” is evaluated together with the “cost saving”, which is set equal to the percentage reduction in the total number of measurements per person. The paper then identifies “the 10 best choices” among the 32 alternatives, for which the trade-off between cost savings and changed precision is most favourable. Thus, among “the 10 best choices”, the reader can identify the design that provides the highest precision for a particular budget, or the design that offers an acceptable precision at the lowest cost.

In a similar yet more advanced study, Shukla et al. (2005) also compared alternative sampling strategies in terms of cost and precision of the estimated mean, using the same structure as Lemasters et al. in assessing environmental exposure for periods, weeks, and days. In the paper by Shukla et al., the cost efficiency analysis is based on three concepts: “cost”, “precision” and “design efficiency”. Like Lemasters, the authors define “cost” as being directly proportional to the total number of measurements, while “precision” is quantified as the inverse of the standard error of the mean exposure estimate resulting from the sampling strategy. The “design efficiency” of a specific strategy is defined as its precision relative to the pilot strategy, divided by its relative cost. The alternative sampling strategies are then ranked according to their design efficiencies.

Unlike Shukla’s study, the Lemasters paper confuses the terms “precision” (reproducibility) and “accuracy” (unbiasedness) when it describes “relative accuracy” by standard errors in alternative designs. The two studies both use statistical models for estimating the precision of the mean that are based on the assumption of an additive random effect, while not discussing possible violations of this assumption. Neither of the studies considers fixed costs associated with the compared designs. Further, they equalize the cost and the number of measurements when estimating the cost of each design. This very simple approach of assessing costs has the advantage that it is easily employed for economic evaluation of different strategies. However,
it does not account for the fact that the cost of measurements is only part of the total cost of a strategy, and that it may vary over time. Thus, it seems improbable that the reduction of the total number of measurements per worker is equivalent to the “cost saving”. The Lemasters study identifies “the 10 best choices” among several investigated strategies, but the cost efficiency analysis does not introduce a general method for ranking alternative designs. Thus, Lemasters’ approach and results are not generally applicable in comparing measurement designs. The study by Shukla et al. solves this by introducing the concept of “design efficiency”.

**Comparison of two alternative measurement methods**

In two similar studies, Armstrong (1995, 1996) formulated principles for comparing the cost efficiency of two exposure assessment methods. His approach is based on the concepts asymptotic relative efficiency (ARE), validity coefficient (\( \rho_{xz} \)) and reliability (\( \rho_{xz}^2 \)). In the context of Armstrong’s studies, asymptotic relative efficiency is given an extended definition as the ratio of the total costs of two measurement designs that achieve equal statistical power, i.e. that yield the same precision of an estimated mean exposure. The validity coefficient of an approximate exposure measure \( Z \) is its correlation with the “true” exposure \( X \), and the reliability of \( Z \) as a measure of \( X \) is the square of the validity coefficient. In comparing an “approximate” and a “perfect” exposure measurement, Armstrong suggests the following model:

\[
ARE_{Z/X} = \rho_{xz}^2 [(C_I + C_X)/(C_I + C_Z)]
\]

[1]

In this equation, \( c_I \) denotes the basic cost of including a subject, while \( c_X \) and \( c_Z \) refer to the cost of getting a perfect and an approximate measurement, respectively, from that subject. Armstrong states that \( Z \) and \( X \) are equally efficient when \( ARE = 1 \), and that \( X \) is preferable if \( ARE < 1 \), which occurs when \( \rho_{xz}^2 < [(C_I + C_Z)/(C_I + C_X)] \). For comparing an approximate exposure measure \( Z_1 \) with a more accurate one \( Z_2 \), he suggests another model:

\[
ARE_{Z_1/Z_2} = (\rho_{xz_2}^2 / \rho_{xz_1}^2) [(C_I + C_{Z_2})/(C_I + C_{Z_1})]
\]

[2]

The more accurate measure \( Z_2 \) is preferable if \((\rho_{xz_2}^2 / \rho_{xz_1}^2) > [(C_I + C_{Z_2})/(C_I + C_{Z_1})] \). Armstrong (1996) concludes, therefore, that “investment in increased precision is worthwhile up to the point at which the proportional increase in the total cost per subject exceeds the proportional gain in \( \rho_{xz}^2 \), the square of the validity coefficient (reliability)”.

Further, he
stresses that the expression \( \rho_{XZ} / \rho_{XZ} \) in [2] cannot generally be replaced by \( (\rho_{Z_1 Z_2}) \), which means that it is always necessary to have access to a perfect measurement when comparing two alternative methods, if both are approximate.

The terms “power” (the probability of rejecting a null hypothesis that is, in fact, false), “accuracy” and “precision” as indicators of statistical efficiency are interchangeably employed by Armstrong, which is confusing, given the sources of error actually addressed by the study. Armstrong’s suggested models for comparing the cost efficiency of alternative measurement methods are based on the concept “asymptotic relative efficiency”, which is theoretically advantageous. However, it presents difficulties in practice, since it involves the terms “validity coefficient” and “reliability”, which are principally unknown whenever the “true exposure” is inaccessible. Thus, in principle, Armstrong’s comparison approach cannot clearly identify the most cost-efficient measurement method when “the true exposure” is not available. Despite the development of advanced instruments during recent years, perfect measurements are not possible in most situations. Realizing this, Armstrong (1996) relaxes the requirement for a “perfect measurement” to the “most accurate” when exemplifying his approach in an assessment of exposure to nitrogen dioxide. Armstrong’s model for calculating total cost for each measurement method includes a fixed cost, which is important when comparing alternative designs. However, as Lemasters et al. and Shukla et al., Armstrong assumes that the cost associated with using either method is linearly related to the number of measurements.

Studies optimizing resource allocation

Optimal allocation of resources between two measurement methods

Duan and Mage (1997) have addressed the approach of combining direct and indirect methods for assessment of pollution exposure. The direct measurement method is superior in precision but expensive, while the indirect exposure estimation is cheaper but associated with a larger error. The combined approach is a way to balance the drawbacks of either method. The sample of subject is principally separated into two sub-samples: a dual sample and an indirect-only sample. Both measurement methods are used simultaneously in the dual sample, while only the indirect method is used in the indirect-only sub-sample. The dual sample is used to estimate the relationship between the direct measurements and the indirect estimates. The estimated relationship is then applied to the indirect-only sample to calibrate the indirect estimates, thus predicting the direct measurements that were never carried out. Finally, the
direct measurements in the dual sample and the predicted direct measurements in the indirect-only sample are combined into an estimate of mean exposure in the entire target population. Duan and Mage provide an algorithm that can be used to determine the optimal allocation of subjects between the dual and the indirect-only samples, in the sense that it minimizes the measurement error subject to a linear budget constraint. The optimal fraction of direct measurements, \( f_{(D)}^* \), depends on the costs of collecting the indirect data and the direct data for each individual in the dual sample, \( c(I) \) and \( c(D) \), and the correlation between the direct measurements and indirect estimates, \( \rho_T^2 \), as follows:

\[
f_{(D)}^* = \sqrt{\frac{c(I)(1-\rho_T^2)}{c(D)\rho_T^2}}
\]

[3]

The formula states, as could be expected, that if an indirect measurement is a good predictor of the direct measurement, i.e. if \( \rho_T^2 \) is large, and if the cost of the indirect measurement is low compared to that of the direct measurement, then the optimal sample allocation will call for a small number of expensive direct measurements.

Duan and Mage’s study constitutes a step forward as compared to the results by Armstrong in introducing analytical tools to optimize the fraction of direct measurements. The confusion between “precision” and “accuracy” found in the Lemasters and Armstrong studies is also seen here, since the authors measure the “precision” of the mean exposure estimate by its mean square error, which also includes the bias of an estimator. Duan and Mage’s statistical modeling of “approximate mean square error” is thus potentially advantageous, provided that the sub-sample selected for direct measurements is representative to the entire population. Surprisingly, the optimal sample allocation fraction is allowed to exceed one without imposing the additional constraint \( f_{(D)}^* \leq 1 \).

**Optimal allocation of resources between main and validation studies**

In two similar studies of cost-efficient designs for assessing exposure and response variables in epidemiologic research, Spiegelman and Gray (1991), and Spiegelman (1994) suggested a complicated error model for determining optimal sample sizes for a main study, \( n_1 \), and a validation study, \( n_2 \). The optimization problem involves minimizing \( (r_D + r_X)n_1 + (r_X + r_Y)n_2 \) for a specified discriminatory statistical power, \( \pi \), determining constraints

\[
1 - \Phi \left( \frac{z_{1-\alpha/2} \sqrt{V_L(n_1,n_2)} - \beta_U + \beta_L}{\sqrt{V_U(n_1,n_2)}} \right) \geq \pi \quad \text{and} \quad \Phi \left( \frac{-z_{1-\alpha/2} \sqrt{V_U(n_1,n_2)} - \beta_L + \beta_U}{\sqrt{V_L(n_1,n_2)}} \right) \geq \pi ,
\]
where \( r_p, r_x, \) and \( r_s \) are the unit costs for assessing the (binary) response variable, the imperfect exposure measurement, and the superior exposure measurement, respectively. \( z_{1-\alpha/2} \) is the \( 1-\alpha/2 \) (confidence level) percentile of the standard normal distribution, and \( V_L(n_1, n_2) \) and \( V_U(n_1, n_2) \) are the variances of the estimated regression coefficient \( \beta \) between exposure and response under the two alternative values \( \beta_L \) and \( \beta_U \), respectively. In a simple explanation, the power constraints reflect an epidemiologic study designed to discriminate between two values of relative risk obtained by two different measurement methods. Spiegelman’s optimization approach thus attempts to provide a cost-minimized, yet powerful epidemiologic study, where both superior and imperfect measurement methods are used to assess a continuous exposure variable, similar to the dual sampling idea also addressed by Duan and Mage (1997). As expected, the optimal resource allocation between the main study and the external validation study depends on many parameters, such as the desired confidence level, unit cost components, distance between two alternative values of relative risk, magnitude of hypothesized values of parameters, and the specified non-linear model of measurement error.

The choice of “discriminatory power” as an indicator of efficiency is highly relevant when assessing relationships between response and exposure variables using approximate and more accurate methods for measuring exposures. However, the constraint inequalities in the Spiegelman papers results in the optimization problem having no closed-form mathematical solution for \( n_1 \) and \( n_2 \). This is unfortunate, since closed-from solutions provide elementary demand functions for the number of sampling units, which are discrete and offer the potential for sensitivity analysis. An alternative approach in epidemiologic studies is to assume a fixed or maximized precision of regression coefficients instead of inequalities, which can lead to closed-form solutions (Reilly, 1996). Like in the studies by Armstrong and by Duan and Mage, Spiegelman’s cost model is based on the assumption of the measurement costs for each method being linearly related to the number of measurements; that is, the cost does not vary with replicate measurements or between subjects.

**Optimizing a two-stage sampling strategy**

For the purpose of sampling diet records in a nutrition study, Stram et al. (1995) suggest an analytical tool for determining a cost-efficient strategy in terms of the number of subjects, \( n \), and the number of recording days per subject, \( m \). In optimizing this two-stage sampling
strategy, the authors minimize the variance \( \frac{1}{n} \left( \frac{\sigma^2}{m} + \sigma^2_{\varepsilon} \right) \) of the mean exposure subject to a fixed total cost, \( C = n(S + R(m-1)) \), and an implicit constraint, \( m \geq 1 \), where \( \sigma^2 \) and \( \sigma^2_{\varepsilon} \) are the variabilities in nutrient consumption within and between subjects, respectively, \( S \) is the cost of recruiting a new subject and obtaining the first 1-day record, and \( R \) is the cost of making an additional measurement on a subject who has already been measured once. The optimal number of recording days when \( S > R \) depends on the ratios of variances and costs as follows:

\[
m = \frac{\sigma^2_{\varepsilon} \left( \frac{S}{R} - 1 \right)}{\sigma^2_{\varepsilon}} \]

The unusual specification of the cost model in Stram’s study leads to an optimal allocation that has a global solution only in the case of \( S > R \). If \( S < R \) or \( S = R \), for instance if the cost of recruiting a subject is negligible, the variance has a local minimum when \( m \) takes its smallest possible value, i.e. \( m = 1 \). Stram et al. do not state whether any economical assumptions or theories can explain that they separate the cost of the first-day recording from the cost of additional recordings, and instead add it to the cost of recruiting a subject. When optimizing a two-stage sampling strategy, the costs of primary and secondary sampling units usually appears as separate parts of the total sampling cost (Cochran, 1977). In that case, the cost model could take the form \( C = n[S + Rm] \), where \( S \) denotes the average cost of recruiting a subject and \( R \) stands for the average cost of one measurement from a subject. The demand function for \( m \) would then be \( m = \sqrt[2]{\frac{S}{R}} \), which has a global solution also in the case of \( S < R \) and \( S = R \).

Other studies besides the one by Stram et al. have addressed optimization of a resource allocation between two sampling stages, either when assessing a continuous response variable (Shoukri et al., 2003) or when addressing two different treatment conditions (Allison et al., 1997). As in Stram’s study, these papers optimize a two-stage sampling strategy by manipulating the number of subjects and the number of replicates per subject. However, rather than addressing the precision of a mean value, they express statistical performance through the size of the intraclass correlation coefficient (Shoukri et al.) or through the correlation between replicate measurements (Allison et al.) The estimated total cost in the studies consists of costs associated with recruitment and observations (Shoukri et al.) or treatments (Allison et al.). The optimization model in Shoukri’s study is appropriate for
assessing continuous variables in two-stage sampling procedures, but does not apply to sampling at three stages, for instance subjects, days and units within days. The study by Allison et al. identifies solutions to a number of additional basic optimization problems with applications in health economics, besides the two-stage allocation issue. Another similar study is available, addressing how to optimize a general two-stage sampling strategy for conducting a reliability study (Eliaziw and Donner, 1987). However, the results of this study are not directly applicable to sampling strategies for mean exposure assessment.

Optimizing a three-stage sampling strategy

Using a three-stage sampling procedure (county, \(n_1\), census block, \(n_2\), household, \(n_3\)) for assessment of human environmental exposure to metals and volatile organic compounds, Whitmore et al. (2005) aimed at determining the optimal numbers of sampling units to achieve a given level of precision at a minimum cost. The analytical tools applied in sampling optimization consisted of a linear cost model \(C = C_0 + n_1C_1 + n_2\bar{n}_2C_2 + n_3\bar{n}_3\bar{n}_2C_3\) and a variance model assuming random effects \(\text{Var}(\bar{y}) = \frac{\sigma_1^2}{n_1\bar{n}_2} + \frac{\sigma_2^2}{n_3\bar{n}_2\bar{n}_3}\); where \(\sigma_1^2, \sigma_2^2, \sigma_3^2\) are the variance components at the three stages; \(C_1, C_2, C_3\) are the variable costs of adding one more county, census, and household, and \(C_0\) is a fixed cost, which, while not specified in Whitmore’s work, could include equipment costs or the salaries of the key executives that run the research. The authors transform the variance formula above to an error model based on intraclass correlations for the first and second sampling stages, \(\rho_1\) and \(\rho_2\). The authors then provide the optimal sample sizes for the second and third stages, \(\bar{n}_2\) and \(\bar{n}_3\), as functions of variance components (or intraclass correlations) and unit costs:

\[
\bar{n}_{2,\text{opt}} = \sqrt{\frac{C_1(1-\rho_1)\rho_2}{C_2\rho_1}} \quad \bar{n}_{3,\text{opt}} = \sqrt{\frac{C_2(1-\rho_2)}{C_3\rho_2}} \quad \bar{n}_{3,\text{opt}} = \sqrt{\frac{C_3\sigma_3^2}{C_3\sigma_3^2}}
\]  

The authors conclude that greater variability and/or lower costs at a certain sampling stage calls for a larger sample size at that stage.

Like Stram’s solution, the solution in Whitmore’s sampling optimization problem does not provide the optimum sample size for first-stage sampling units, i.e. counties in the case of Whitmore. However, the optimal number of samples at this stage can be obtained from the variance model in the optimization problem. Whitmore et al. chose to describe the precision of the mean exposure estimate also by using intraclass correlations because “intraclass correlations tend to be more stable for similar outcomes than the variance components

```
themselves”. Obviously, optimization based on intraclass correlations will give the same result as optimization using raw variance components, and the authors do not present empirical evidence to support that optimization will be easier or more correct if using intraclass correlations, to compensate for the increased difficulties in translating results into practical sampling advice.

Addressing continuous response variables, Foster and Asztalos (2001) also developed a methodology for optimizing a three-stage sampling strategy based on the same cost and variance models as in Whitmore et al. The authors optimized sampling strategies both in terms of minimizing cost at a constant precision, and in terms of maximizing precision under a budget constraint. The cost and precision of the optimal strategies are compared with some non-optimal sampling strategies. The principles for optimization are useful also for exposure studies.

GENERAL DISCUSSION

Strikingly, most of the cost efficiency studies identified in this review were published more than ten years ago. This shows that while the interest in identifying exposure measurement designs worth their price is obvious in both research and practice, little effort has been devoted to developing this issue. However, the few identified and reviewed studies are very valuable as a basis for further research in that they offer the initial necessary theories and methods. They clearly demonstrate the need of developing cost-efficient designs of exposure assessment strategies by analysing their economic and statistical performance in a systematic fashion. This requires data on cost components and sources of error, and also well-behaved economical and statistical models. The review also demonstrated that additional theories and experiences within microeconomics and sampling statistics, including empirical data, will be necessary to further develop cost efficiency analysis.

As noted previously, cost efficiency analyses, regardless of their specific approach and application, strive to achieve a balance between the cost and statistical performance of a measurement design. However, the specific concepts and methods chosen for the cost efficiency analysis depends on whether the aim is to evaluate and compare alternative designs, as pursued by some of the reviewed studies, or to determine an optimal allocation of resources between different measurement efforts as attempted by others. Since the reviewed papers are so few and disparate, it is not justified to derive any more specific guidelines for
what might be the optimal exposure measurement design in a particular occupational setting. The concept of “efficiency” in the reviewed studies was expressed by indicators such as “precision”, “accuracy” or “statistical power”. Some studies suffered from confusion in the definition and operationalization of these indicators of “efficiency”. Such confusion can be observed in the work of Lemasters et al. (1996), Armstrong (1995, 1996), and Duan and Mage (1997), as explained in the specific reviews of these studies. Which indicator of “efficiency” to select in a particular study depends on the specific purpose and limitations of the study. For optimization of a resource allocation, the most useful indicator of efficiency is “precision”, as employed by Whitmore et al. (2005) and Stram et al. (1995), since a possible bias of a particular exposure assessment method does not influence how to optimally allocate samples. The concept of “statistical power” can only be employed in an optimization approach with some difficulty, as in the studies by Spiegelman and Gray (1991) and Spiegelman (1994). For evaluating and comparing different measurement methods, on the other hand, it is appropriate to use indicators that include both systematic and random sources of error or, as a minimum, to assume that exposure assessment is non-biased only after assuring that the possible bias is negligible compared to the uncertainty associated with data. Likewise, including fixed costs associated with exposure measurement is important when evaluating or comparing measurement designs. In their comparisons, Armstrong (1995, 1996) did consider fixed costs, while Lemasters et al. (1996) and Shukla et al. (2005) did not. In studies addressing optimal resource allocation, on the other hand, fixed costs do not need to be included in the proposed cost model, as all fixed costs will disappear in the differentiation contained in the optimization procedure and thus do not influence optimal allocation.

Modern mixed-model statistics has, in the past decade, gained increasing intention as a tool for identifying exposure determinants with a satisfying predictive ability, mainly for the purpose of exposure control and intervention (Burdorf, 2005). However, determinants that are “cheap” to obtain and, at the same time, correlate well with “true” exposures also represent a potentially cost efficient avenue for exposure assessment. Besides the studies addressing cost efficient allocation of subjects to indirect/imperfect and direct/superior exposure measurements (Duan and Mage, 1997; Spiegelman, 1994; Spiegelman and Gray, 1991), none of the studies in the present review discuss this possibility of modeling “expensive” exposure variables by “cheap” determinants. Various ideas for exposure modeling have been analyzed with regards to statistical performance (e.g. Chen et al., 2004; Mathiassen et al., 2005; Preller et al., 1995), while the possible and probable economic benefits of exposure modeling remains an issue for future research.
All together, the reviewed studies showed two typical and common characteristics:

**Simplification**

All of the reviewed studies assume that the total cost of data collection is linearly related to the number of subjects and measurements per subject. In the studies by Lemasters et al. (1996) and Shukla et al. (2005), this linearity is particularly simplified in assuming a straightforward equivalence between the number and the cost of measurements. However, the recruitment costs may well differ between subjects, for instance because they live at different distances from researcher’s laboratory and thus cause different travelling cost, or because different efforts need to be invested in convincing them to participate. The cost of measurements for a particular subject can also vary, for instance as a result of subjects getting more familiar with measurement procedures, and thus saving working time. Costs can also vary over time not only due to the effect of economical factors as inflation rate but also due to changes of exposure patterns. An appropriate economic model should therefore allow for cost variations. A linear development of input costs exhibits a constant return to scale for exposure measurements irrespective of the applied measurement technique, because the marginal cost, i.e. the cost of one additional unit of measurement, is equal to the average cost at each level of output. This assumption is a simplified view of statistical production. When adopting a linear cost function, the optimized sampling strategy will be the same irrespective of whether marginal costs of sampling units or their average costs are addressed in the cost model (Whitmore et al., 2005). However, calculation of the total cost of a study would be incorrect if the statistical production does not exhibit constant return to scale.

Generally, the reviewed studies do not discuss whether the underlying assumptions of the statistical models used for assessing precision of the mean exposure estimates were met; and all studies employ a standard additive random effect model. It should be investigated more thoroughly whether errors at different stages of sampling are, indeed, additive, and which consequences a violation might have for the cost efficiency analysis. Further, variabilities at the different stages of sampling are assumed to be homogeneous in the exposure studies as well in the response and intervention studies, which may also in many cases be a critical assumption.

In studies aiming at sampling optimization, the selection of simple cost and error models may be the result of a strive to obtain easy mathematical solutions to the optimization problem. With complex cost and error models, the mathematical form for optimizing sample sizes is
also more complicated, so that operations may not lead to closed-form optimal solutions without the use of additional assumptions. In many cases, numerical analysis, such as “non-linear multiparameter constrained optimization subroutine” in the studies by Spiegelman et al. (1991, 1994), may then be the most viable alternative.

**Incompleteness**

The reviewed studies have given much less attention to the cost model and economic analyses than to error models and statistical interpretations. It is often not clear which cost curves (unit cost, average cost or marginal cost) or which input costs (capital cost, labor cost, energy cost or material cost) are considered and estimated in the cost models. The social costs of biased and imprecise estimates of exposures, i.e. the *opportunity costs* of not using the most productive measurement design, have never been modelled, since the outcomes have been limited to statistical performance of the exposure measurement design. Further, systematic methods for estimating the actual costs have not been discussed in the studies, and hence not either the reliability of assessing various cost components, even though mathematical techniques are available for this purpose. These techniques include approaches based on Bayesian statistics (Lambert et al., 2008) or regression analysis (Lin, 2003), by which costs can be estimated reliably in spite of uncertainty and incomplete data. Also, non-parametric estimation methods are available to address the distributional form of measurement cost data (Cooper et al., 2003).

No studies have given attention to the cost and productivity associated especially with the labour inputs or to further analysis of associations between (minimized) total cost and statistical performance. A fundamental issue to consider when making economic decisions for exposure assessment, which has not been addressed by any of the reviewed studies, is the various *elasticities* associated with statistical production. Elasticities measure the dynamic behaviour of cost and efficiency by a ratio of the percent change in one variable to the associated percent change in another variable. Elasticities include, for instance, cost *elasticity of output*, $E^c_y$, and *price elasticity of demand*, $E^p_D$, measuring the responsiveness of an optimized function to changes in the required output and input cost, respectively. $E^c_y$ would, for instance, show the percentage change in the (minimized) cost as a result of a one percent change in the required precision of the mean exposure estimate, and $E^p_D$ would measure the percentage change in demand of a measurement input, e.g. the optimal number of subjects,
resulting from one percent change in its cost. Both these type of elasticities could be useful as a basis for decision-making when designing exposure measurement.

Also, methodologies developed for economic evaluation of competing treatment interventions in the field of health economics (Tompa et al., 2008; Goossens et al., 1999) could be useful when providing cost-efficient exposure measurement designs. The basic purpose of an economic evaluation in this case is to ensure that the opportunity cost of implemented interventions is compensated by their (positive) effects on health. In contrast to cost efficiency analysis of exposure assessment, economic evaluation of alternative health care interventions has a long scientific history. Since the generic issue of how to optimize economic resource consumption with respect to a desirable output is shared by cost efficiency analysis and health economics, research in exposure assessment could benefit from consulting the health economics literature; for instance on approaches for modelling cost data, comparing the cost efficiency of alternative measurement designs where the “perfect measurement” does not exist, and/or optimizing resource allocation if the cost of measurement inputs, but not the variabilities, are taken into consideration. Adopting approaches from health economics into exposure science will present challenges in terms of replacing various dimensions of health outcomes by appropriate indicators of statistical performance, while it will, at the same time, offer opportunities of expressing the success of measurement designs in wider terms than mere statistical performance.

Distinct and well defined concepts, well-specified models for costs and error, complete cost analysis, and estimation of elasticities should all be emphasized when attempting to econometrically model the production of information on different exposure variables. Our suggestion for future research devoted to cost efficiency analysis of exposure assessment is to first formulate appropriate indices for measuring the quantity of information produced on the exposure variable according to the specific need of a study, and then to construct a statistical production function and its corresponding cost function, i.e. its dual cost function in economics terms, so as to provide the basis for a comprehensive economic analysis. The measure of the quantity of information produced should account for all sources of error and not assume an “unbiased estimation” or the existence of a “perfect measurement”. Methods should also be developed for evaluating the output of statistical production, e.g. statistical performance, in monetary terms, so as to make it directly comparable to the total cost of data collection and processing. The production and cost functions should give all information
about the marginal effects of inputs on statistical production in order to facilitate decisions about how to invest an increased budget or implement a saving. Another area for future cost efficiency related research concerns the influence of the specifications of the statistical and economical models applied on the results from comparison or optimization of measurement designs. The results and principles developed by the reviewed studies might have been different if other models had been applied, but the sensitivity of, for instance, an “optimal” allocation to the principles and algorithms used for optimization is not known so far. This includes research into the practical need of using well-specified, though complex, models for estimating costs and errors, and the loss of performance when designing exposure assessment strategies that deviate from the optimal choice.

Acknowledgements

Professor Eva Vingård, Occupational and Environmental Medicine, Uppsala University, and Dr. Apostolos Bantekas, Group of Economics, University of Gävle, are gratefully acknowledged for their support in writing this review. Parts of the study were supported by a grant from the Swedish Council for Working Life and Social Research (FAS DNr. 2005-0183).

References


