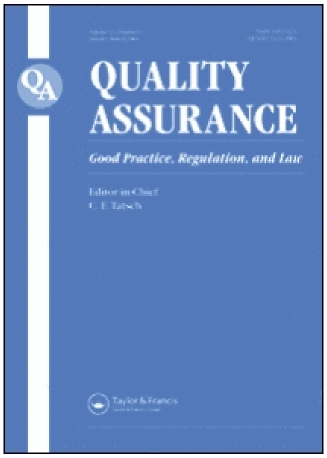

Quality Assurance
Good Practice, Regulation, and Law
Publication details, including instructions for authors and subscription information:
http://www.informaworld.com/smpp/title~content=t713775148

Application of Data Quality Objectives and Measurement Quality Objectives to Research Projects

Robert Wright [a]

[a] U.S. Environmental Protection Agency, National Risk Management Research Laboratory, Air Pollution Prevention and Control Division, Research Triangle Park, North Carolina, USA.

Online Publication Date: 01 July 2004
To cite this Article: Wright, Robert (2004) 'Application of Data Quality Objectives and Measurement Quality Objectives to Research Projects', Quality Assurance, 10:3, 177 - 192
To link to this article: DOI: 10.1080/10529410390892098
URL: http://dx.doi.org/10.1080/10529410390892098

Quality Assurance, 10:177–192, 2003

ISSN:1052-9411 print/1521-0677 online
DOI: 10.1080/10529410390892098

APPLICATION OF DATA QUALITY OBJECTIVES AND MEASUREMENT QUALITY OBJECTIVES TO RESEARCH PROJECTS

Robert S. Wright
U.S. Environmental Protection Agency, National Risk Management Research Laboratory, Air Pollution Prevention and Control Division, Research Triangle Park, North Carolina, USA

This paper assists systematic planning for research projects. It presents planning concepts in terms that have some utility for researchers. For example, measurement quality objectives are more familiar to researchers than data quality objectives because these quality criteria are more closely associated with the measurement systems being used. Because of the diverse nature of research, it is not possible to describe cookbook-style planning procedures to be used in all cases. Instead, several general concepts and techniques are presented and researchers can choose those techniques that best fit their specific projects. Examples are presented to illustrate the techniques.

INTRODUCTION

Systematic planning is used to develop programs and to link program goals with cost, schedule, and quality criteria for the collection, evaluation, or use of data. Under the U.S. Environmental Protection Agency's (EPA's) quality system, the data quality objective (DQO) process was developed to assist systematic planning (U.S. EPA, 2000; Batterman et al., 1999). While not mandatory, this process is EPA's recommended planning approach for many environmental data collection activities. It is based on the assumption that the ultimate goal for these activities is to make some decision (e.g., a regulatory compliance determination). This process uses a statistical approach to establish DQOs, which are qualitative or quantitative statements that clarify project objectives, that define the appropriate type of data, and that specify tolerable error levels for the decisions. The process finally develops a quality assurance (QA) project plan, including measurement quality objectives (MQOs), to collect data with uncertainties within these tolerable error levels.

Received 3 August 2004; accepted 25 September 2004.
Address correspondence to Robert S. Wright, U.S. EPA, mail code E343-03, Research Triangle Park, NC 27711. E-mail: Wright.Bob@epa.gov

DISTINCTIONS BETWEEN DQOs AND MQOs

There is some confusion about the difference between DQOs and MQOs, which also are called data quality indicator (DQI) goals. Although these terms refer to goals for the quality of information generated by a project, some people incorrectly regard them as being equivalent. One way to distinguish between them is that the former is associated with data users and the latter is associated with data collectors. Another way is that DQOs function at the level of project goals, while MQOs function at the level of measurement system capabilities.

For example, EPA has established a National Ambient Air Quality Standard for the maximum 8-hour mean concentration of ozone in the atmosphere. A reasonable DQO for this program might be that there can be no more than a 5 percent probability of making an incorrect decision (i.e., a false positive) based on ozone measurements that indicate an urban area has not attained the standard. In addition to the geographical and temporal variability of ozone concentrations in urban air, the decision makers must also consider the uncertainty of the ozone measurements. Appropriate MQOs for the measurements might be a bias of less than 10 percent of the mean concentration and a precision of less than 10 percent of the mean.

DQOs establish the full set of specifications for the design of the data collection effort to ensure that data are of sufficient quality to make some decision. They typically incorporate requirements for total data uncertainty. These requirements are used, in turn, to establish quality criteria, stated as MQOs, for significant components of total variability. MQOs should be developed as an integral part of the QA project plan generated during the final step of the DQO process.

The DQO process is a formal balancing mechanism that uses statistical techniques for systematic planning. A decision maker balances the risk of making an incorrect decision against the cost of the data that allow the decision to be made. The products of this process are DQOs that are consistent with project goals.

A data collector balances the desired uncertainty of the data against the costs of the sample and analytical procedures that are used to collect the data in the project. Some scientifically defensible process must link the desired uncertainty with the capabilities of the procedures. The first step is the identification of DQIs, which are quantitative or qualitative parameters (such as bias, precision, and representativeness) that characterize the uncertainty of the project's measurement systems. The final step is the development of MQOs, which are specific goals for these DQIs. The MQOs are generally quantitative goals and must be verifiable by measurement during the project.

A feedback loop should occur between the establishment of DQOs and MQOs during planning and their reconciliation with the measurement data that have been collected during implementation. Both parts of the loop are necessary to establish the quality of data from the project. Performing this reconciliation while data are being collected can lead to improvements in the measurement systems during the project. Additionally, performing this reconciliation for one project can help with the development of DQOs and MQOs for a follow-on project.

APPLICATION OF DQOs TO RESEARCH PROJECTS

Under ideal circumstances, data users can be identified and their data quality needs can be determined. They then can participate in systematic planning by developing DQOs that are based on project goals. Data collectors design achievable MQOs for measurement systems and estimate the funding that will be needed to attain desired DQOs. The process balances the needs and capabilities of both groups. Several iterations may occur before a mutually acceptable set of DQOs and MQOs is established.

It is often a challenge to apply the DQO process to the development of quality criteria for research projects. It may be difficult to identify the data users or to establish a desirable level of uncertainty for the data. In many cases, there is no decision to make, although there may be some requirements for the uncertainty of measurements. For basic research projects, the measurement system may not be developed enough for its uncertainty to have been characterized, even for individual components of the system. Other procedures may be needed to develop the criteria. It may be necessary to develop DQOs and MQOs that are based only on the performance characteristics of the measurement systems. Nevertheless, researchers need to have quality control (QC) procedures that allow them to verify that the measurement systems are operating correctly and to estimate the uncertainty of the environmental data that they collect.

ACCOUNTING FOR SAMPLE VARIABILITY

If data will be collected from the environment, the DQO process must also develop a plan to select the number and location of the samples to be collected to attain some desired level of uncertainty due to the spatially or temporally heterogeneous nature of the sample population. For the purposes of this discussion, it will be assumed that the measurements to be made do not involve collecting samples from the environment and that the variability associated with the samples does not have to be considered in the systematic planning. In reality, both sample variability and measurement uncertainty must be considered in the systematic planning for a project and the development of its DQOs.

If sample variability is large relative to measurement uncertainty, efforts to reduce the total uncertainty by decreasing measurement uncertainty may not be cost-effective. It may be more fruitful in this instance to collect a larger number of more uncertain, inexpensive measurements than to collect a smaller number of less uncertain, expensive measurements. Conversely, if measurement uncertainty is large relative to sample variability, then efforts to decrease measurement uncertainty may be appropriate.

There are four principles that must be considered when developing sampling plans:

- Samples must be representative of the portion of the environment being investigated;
- Procedures for sampling and analysis influence each other, and so plans for sampling and analysis are codependent;
- QC samples must be representative of the samples being analyzed; and
- QC samples are used to provide an assessment of the kinds and amounts of bias and imprecision in data from analysis of the samples (Keith et al., 1996).

The website for the American Chemical Society's Division of Environmental Chemistry newsletter (www.envirofacs.org) has downloadable Windows software that allows one to calculate the number of samples that must be collected to attain three objectives: (1) determining the rate at which an event occurs; (2) determining an estimate of an average value within a tolerable error rate; and (3) determining the sampling grid necessary to detect localized points of contamination or hotspots.

DQOs AND MQOs NEED TO BE REALISTIC, MEASURABLE, AND AUDITABLE

QA project plans should contain DQOs and MQOs that represent realistic data quality needs and measurement system characteristics for the project. Generic DQOs and MQOs whose attainment cannot be verified during the project should not be included in a plan because they are meaningless. The project staff's hopes or unsubstantiated guesses regarding data quality are not adequate bases for DQOs and MQOs. Values for MQOs that are taken from the technical literature

TABLE 1 Measurement Quality Objectives for a Hypothetical Project

Measurement parameter	Analysis method	MQO for bias	MQO for precision	MQO for completeness
Parameter A	Method A	±5%	±10%	±90%
Parameter B	Method B	±20%	±20%	±90%

should be accompanied by information about the conditions under which the MQOs can be considered to be applicable.

Table 1 presents MQOs for a hypothetical project. These MQOs may or may not be realistic. One cannot tell from the table alone. The QA project plan needs to present mathematical formulas that define how project staff will determine by measurement whether the MQOs have been attained. The plan also needs to present specific QC check procedures that will be used to determine MQO attainment as well as the specific acceptance criteria for these procedures. For example, it does no good to establish an MQO for bias if there are no credible reference standards available for checking the bias of the method. If the plan describes such QC check procedures, acceptance criteria, and reference standards, then project staff will be able to determine whether measurement uncertainty is adequate for the intended use of the data. Additionally, an internal or external auditor can verify independently whether MQOs were attained by independent performance evaluations or by review of the paper trail of QC check results obtained by project staff.

QUALITATIVE DQOs

DQOs may be stated in quantitative or qualitative terms. Generally, quantitative statements are preferable, but acceptable qualitative DQOs are possible, such as the following:

> The project will produce data that will qualify to receive the 'A' rating with respect to the rating system described in Section 4.4.2 of the *Procedures for Preparing Emission Factor Documents* (EPA-454/R-95-015).

Although it is stated in qualitative terms, this DQO is measurable using specific data acceptance criteria that are referenced in the cited document. Because these criteria include whether EPA test methods were used for the measurements, reasonable MQOs for the project may include the QC check criteria specified in these methods. There is a direct link between quantitative MQOs and the qualitative

DQO. At the end of this project, data collectors and data users (e.g., stakeholders, regulators, and management) can determine whether the data quality is acceptable. In contrast, consider the following qualitative DQO, which is *not* acceptable:

> For this project, the qualitative DQO is to provide data to assess emissions related to the operations of the source. This QA project plan is a product of a systematic planning process and it contains the information needed to carry out the field operations and measurements in order to meet this DQO.

There is no way to tell whether the resulting data are suitable for the intended use because acceptable criteria have not been defined and a procedure for assessing data quality has not been developed. The best thing that project staff can do after data have been collected is to carefully characterize the uncertainty, but this process cannot be considered to be systematic planning.

INSTRUMENT PERFORMANCE SPECIFICATIONS AS MQOs

Lacking other information, project staff may wish to use instrument performance specifications taken from sales literature or operating manuals as MQOs. Such specifications must be viewed with some skepticism if it cannot be documented that they have been determined objectively and rigorously under conditions similar to the project. A vendor may feel compelled to present an instrument's performance in the best possible light relative to that of other instruments offered by competitors. Various uncertainty components may have been omitted from the specification or the specification may be based on measurements obtained under conditions not typical of routine service (e.g., daily calibrations of an instrument normally calibrated on a weekly basis or calibration of a field instrument under tight temperature controls). It is preferable that instrument performance be evaluated using objective and written procedures that are widely accepted for instruments of that type. The measurement of performance by an independent, objective evaluator is generally regarded as credible evidence.

If the instrumentation vendor can provide credible evidence about how the performance specification was determined and about the measurements that were used in the determination, the use of such specifications as MQOs is reasonable. In these cases, the instrument's operating manual may yield QC check procedures and acceptance criteria that can be used directly by project staff. If these procedures are followed during the project and if the criteria are attained, one may conclude that the measurement uncertainty corresponds to the specifications.

GUIDE TO EXPRESSION OF UNCERTAINTY IN MEASUREMENTS

In recent years, the international metrology community has standardized the methods for calculating uncertainty in the *Guide to the Expression of Uncertainty in Measurement*, commonly referred to as GUM. In the United States, standards bodies such as American National Standards Institute (ANSI), National Conference of Standards Laboratories (NCSL), and National Institute of Standards and Technology (NIST) have adopted GUM as their official method for calculating uncertainty for metrology in testing and calibration laboratories (Taylor and Kuyatt, 1994; ANSI, 1997; NIST, 2004). The statistical techniques in GUM provide a standard basis for determining uncertainty in research projects. The statistical terminology that is used in GUM differs somewhat from customary statistical terminology.

ERROR ANALYSIS

For well-characterized measurement systems, project staff should be able to develop a functional relationship between the MQOs for a measurement system and the DQOs for the project. Error propagation techniques allow the uncertainties of individual measurement system components (expressed as standard deviations) to be combined into an estimate of the overall measurement uncertainty (Evans et al., 1984; Taylor, 1997; Coleman and Steele, 1999; Dieck, 2002; Kimothi, 2002). This approach assumes that the major sources of measurement variability have been identified, that bias can be controlled, and that relevant QC checks can be developed to characterize the variability. If a relationship exists, then one can demonstrate that DQOs have been attained if all QC check results fall within the corresponding MQOs.

If the functional relationship between the variables is of the form $Q = aX + bY - cZ$ where a, b, and c are constants and where X, Y, and Z are the variables and if the standard uncertainties (i.e., standard deviations) are S_X, S_Y, and S_Z, then the combined standard uncertainty of Q equals

$$u_c(Q) = \sqrt{(aS_X)^2 + (bS_Y)^2 + (cS_Z)^2}$$

If the functional relationship between the variables is of the form $Q = aX * (bY/cZ)$, then the combined standard uncertainty of Q is estimated by

$$U_c(Q) = (\bar{q})\sqrt{(S_X/\bar{x})^2 + (S_Y/\bar{y})^2 + (S_Z/\bar{z})^2}$$

where $\bar{q}$, $\bar{x}$, $\bar{y}$, and $\bar{z}$ are mean values of the measured variables, preferably based on a large number of observations. If the standard deviations are represented in terms of percentages of the measured values [i.e., as relative standard deviations $= 100(S_X/\bar{x})$], then the combined standard uncertainty can be calculated as the square root of the sum of the squared percentages.

It is often desirable to present combined uncertainties in terms of statistical confidence limits, which requires one to multiply the combined uncertainty by a coverage factor, k, to obtain the expanded uncertainty (U).

$$U = ku_c(Q)$$

The coverage factor is equivalent to the normal z-value in customary statistics. It relates the combined standard uncertainty to the probability that a single sample drawn from the parent population will fall within a multiple of u_C of the mean value. When the number of measurements contributing to the calculation of S_X, S_Y, and S_Z is large and when one seeks a 95 percent confidence limit for U, then k is set to approximately 2. This value is normally used when reporting the uncertainties of measurements. Statistical tables of the standard normal z-distribution should be consulted to obtain values of k for different values of the confidence limit.

Consult the references for detailed information about measurement uncertainty and error propagation calculations. The basic error propagation formulas have implicit assumptions such as the independence of the measurements, their randomness, and their variances being small. Significant deviations from these assumptions will lead to significant errors in the uncertainty estimates that are made using these formulas. Strictly speaking, the formulas apply to the statistics of the population of all possible measurements, rather than to the statistics of the smaller number of actual measurements. Any application of the formulas to the latter group is an approximation. When in doubt about the use of statistical calculations in specific applications, it's always a good idea to consult with a statistician.

LIMITATIONS OF ERROR ANALYSIS

Uncertainty estimates and MQOs derived from propagation of error calculations are useful as long as (1) one can determine the major sources of measurement error and (2) one can quantify the magnitude of the uncertainty associated with each source. In a research project, the measurement system may be so new that its performance is not yet characterized. In these circumstances, empirical approaches may be needed to determine measurement uncertainty and to establish MQOs for a project. For instance, collocated measurements can characterize the precision of measurement systems. Performance evaluations can characterize the bias of the systems. The results of such method evaluations can be used to establish defensible MQOs for future projects, even in the absence of knowledge of error sources and uncertainty magnitudes.

Error propagation calculations cannot be used to combine individual QC check results to yield an uncertainty estimate. One can't substitute a single measured value for a standard deviation. Random error will cause results from one QC check to be different from those of another check. By analogy, one can't pull a single red bead from a bag of beads and then conclude that all beads in the bag are red. The best that can be done is to use these QC check results to demonstrate that MQOs have been attained and to conclude that the uncertainty is within the acceptance criterion. The means and standard deviations for multiple QC checks can be combined to yield an uncertainty estimate.

UNCERTAINTY BUDGETS

One can use error propagation calculations to develop an uncertainty budget for the measurement system. Given a particular requirement for overall uncertainty, an appropriate portion of this uncertainty can be allocated to each component of the measurement system. Such an approach allows project staff to design measurement systems with MQOs that will allow attainment of DQOs or to assess whether it is technically feasible to attain the proposed DQOs. It also allows project staff to develop the most cost-effective method to reduce the overall uncertainty. They can determine which measurement system component has the largest effect on the overall uncertainty and then concentrate their efforts on improving the quality of the data from that component. They can also use uncertainty budgets to evaluate alternative measurement strategies and choose the most cost-effective strategy. For example, it may be less expensive to attain a DQO by making multiple measurements with a cheap, low precision method than to do so making a single measurement with an expensive, high precision method.

CONCLUSIONS

Although the application of DQOs and MQOs to research projects may seem to be difficult at first, the techniques presented in this paper can assist researchers in developing quality criteria that are meaningful to them while satisfying the quality requirements that are applicable to their projects. These criteria must be realistic for the project at hand, measurable during the course of the project, and auditable by external reviewers. Statisticians and QA specialists can assist researchers in developing these criteria.

REFERENCES

American National Standards Institute and National Conference of Standards Laboratories. 1997. *American National Standard for Expressing Uncertainty. U. S. Guide to the Expression of Uncertainty in Measurement*. ANSI-NCSL Z540–2–1997, 2nd ed. Boulder, CO: National Conference of Standards Laboratories.

Batterman, A.R., Batterman, S.L., Jensen, K.M., and Whiteman, F.W. 1999. Data quality objectives in environmental research planning. *Quality Assurance* 7:181–194.

Coleman, H.W. and Steele, W.G. 1999. *Experimentation and Uncertainty Analysis for Engineers*, 2nd ed. Hoboken, NJ: John Wiley & Sons, Inc.

Dieck, R.H. 2002. *Measurement Uncertainty: Methods and Applications*, 3rd ed. Research Triangle Park, NC: ISA-Instrumentation, Systems, and Automation.

ETS, Inc. and RTI International. 2001. *Generic Verification Protocol for Baghouse Filtration Products*. Prepared under EPA Cooperative Agreement No. CR826152-01-3. http://www.epa.gov/etv/verifications/protocols-index.html.

Evans, J.S., Cooper, D.W., Kinney, P. 1984. On the propagation of error in air pollution measurements. *Environmental Monitoring and Assessment* 4:139–153.

Keith, L.H., Patton, G.L., Lewis, D.L., and Edwards, P.G. 1996. Determining what kinds of samples and how many samples to analyze. *Principles of Environmental Sampling*, 2nd ed., 3–40, Washington, DC: American Chemical Society.

Kimothi, S.K. 2002. *Uncertainty of Measurements. Physical and Chemical Metrology. Impact & Analysis*, Milwaukee, WI: American Society for Quality.

National Institute of Standards and Technology. 2004. *NIST/SEMATECH e-Handbook of Statistical Methods*, Gaithersburg, MD: National Institute of Standards and Technology. http://www.itl.nist.gov/div898/handbook/.

Rhodes, R.C. 1983. *Guideline on the Meaning and Use of Precision and Accuracy Data Required by 40 CFR Part 58 Appendices A and B*. EPA Publication No. EPA-600/4-83/023.

Rhodes, R.C. 1990. *Limits of Uncertainty of Environmental Measurements (Using as an Example, the Dichotomous Particulate Sampler)*. EPA Publication No. EPA/600/D-90/014.

Taylor, B.N. and Kuyatt, C.E. 1994. *Guidelines for Evaluating and Expressing the Uncertainty of NIST Measurement Results*, NIST Technical Note 1297, Gaithersburg, MD: National Institute of Standards and Technology. http://physics.nist.gov/cuu/Uncertainty/.

Taylor, J.R. 1997. *An Introduction to Error Analysis. The Study of Uncertainties in Physical Measurements*, 2nd ed. Sausalito, CA: University Science Books.

U.S. Environmental Protection Agency. 2000. *Guidance for the Data Quality Objectives Process, EPA QA/G-4*, EPA Publication No. EPA/600/R-96/055.

EXAMPLE 1: COMPARISON OF TWO DIFFERENT METHODS TO ESTIMATE THE UNCERTAINTY OF FINE PARTICULATE CONCENTRATIONS IN AMBIENT AIR USING A DICHOTOMOUS SAMPLER

This example is adapted from a report by Rhodes (1990), who compared two different methods to determine the uncertainty of fine particulate measurements. The first method used error propagation techniques and the precision of measurement system components to obtain the combined standard uncertainty. The second method used the results from collocated measurements to estimate precision and flow sensor performance evaluations to estimate bias.

EPA established MQOs for measurements that are used to determine whether ambient air quality attain the National Ambient Air Quality Standards (Rhodes, 1983). State and local air pollution control agencies are required to conduct periodic assessments of their ambient air quality monitors and to report precision and bias estimates for the data that they report to EPA. To reduce the probability that decision makers will make an incorrect decision about whether a specific area has attained or not attained the standards, acceptance criteria were established for the precision and bias of the data. Current EPA MQOs for measurements of fine particulates in ambient air specify that the agency-average precision be no more than a 10 percent coefficient of variation and the agency-average bias be no more than ± 10 percent. (Note that these MQOs pertain to samplers that had not yet been developed at the time of Rhodes' 1990 report.)

The dichotomous sampler collects fine and coarse particulate matter from ambient air, which is drawn into the sampler for 12 or 24 hours and passes through an impactor that separates it into one air stream containing fine particles and another air stream containing coarse particles. The two flow rates are 15 L/min and 1.67 L/min, respectively. Fine particles are collected on one filter and coarse particles are collected on another filter. Each filter is weighed before and after sampling to determine the mass of particles that have been deposited on the filter. The equation for calculating the fine particulate concentration is

$$[F] = (W_e - W_u)/Qt$$

where

$[F]$ = fine particulate concentration ($\mu g/m^3$)
W_e = weight of exposed filter (μg)
W_u = weight of unexposed filter (μg)

TABLE 2 Uncertainty of Fine Particulate Concentration Based on Error Analysis

Measurement variable	Symbol	Value	Uncertainty (u_i)*
Weight of exposed filter	W_e	99,412 µg	7.1 µg (0.007%)
Weight of unexposed filter	W_u	99,211 µg	5.7 µg (0.006%)
Fine particulate mass on filter	$W_e - W_u$	201 µg	9.1 µg (~5%)
Flow rate through filter	Q	0.015 m^3/min	0.00045 m^3/min (3%)
Sampling time, min	t	705 min	2.5 min (~0.03%)
Fine particulate concentration	[F]	19 µg/m^3	1.7 µg/m^3 (~6%)

*u_i is the standard deviation of the listed value. Normally it is multiplied by a factor of approximately 2 to obtain a 95 percent confidence interval for the value.

Q = flow rate (m^3/min)
t = sampling time (minutes)

Under the first method, error propagation techniques were used to calculate the combined standard uncertainty of the fine particulate concentration. The standard uncertainties for each measured variable and the combined standard uncertainty are presented in Table 2.

The combined standard uncertainty of F was calculated using the following equation:

$$u_c(F) = \sqrt{(5)^2 + (3)^2 + (0.03)^2} \approx 6\%$$

In this example, the uncertainty associated with the fine particulate mass is the largest contributor to the uncertainty of the fine particulate concentration. If the sampling time were longer or if the concentration were greater, the flow rate might become the largest contributor because the increased mass collected on the filter would decrease the relative magnitude of the weighing uncertainty.

Under the second method, collocated measurements and performance evaluations were used to estimate the combined standard uncertainty. The precision of the dichotomous sampler was obtained from analysis of a large number of collocated measurements. The standard deviation of difference of the two paired measurements yielded an estimate of the uncertainty associated with the random error (i.e., precision) component of the measurement. There is no practical way to measure the systematic error (i.e., bias) of the fine particulate concentration. Because the flow measurement was considered to be the main source of error, performance evaluations of the flow sensor were used to estimate the bias component of the measurement. Table 3

TABLE 3 Uncertainty of Fine Particulate Concentration Based on Empirical Measurements

Measurement variable	Symbol	Value	Uncertainty (u_i)*
Collocated fine particulate concentrations (precision)	$[F]_{collocated}$	19 µg/m^3	1.9 µg/m^3 (10%)
Performance evaluation of flow sensor (index of bias)	Q_{audit}	0.015 m^3/min	0.0015 m^3/min (10%)
Fine particulate concentration	[F]	19 µg/m^3	2.5 µg/m^3 (~14%)

*u_i is the standard deviation of the measurement. Normally, it is multiplied by a factor of approximately 2 to obtain a 95 percent confidence interval for the value.

shows that these two error components yield an estimate of the combined standard uncertainty for [F].

In this calculation, the bias component was treated as an uncertainty. Rhodes (1990) states that if bias is believed to be very persistent and has been determined from a large number of values and if it is to be used only for a limited data set from which bias is estimated, then the bias would be added as a constant value to the uncertainty associated with the precision. However, if the bias has been estimated from a limited number of audits (therefore not exactly known), if the bias itself may be considered as having variability in time and if the limits are to be generally applied to the measurement method, then the bias can be treated as an uncertainty. There is no universal agreement as to which procedure is more appropriate.

The combined standard uncertainty estimate using the second method (14%) is considerably larger than the corresponding value obtained from the first method (5%). There appears to be unknown sources of error in the dichotomous sampler measurements that were not considered by the error propagation technique. Rhodes indicated that some of these error sources could be:

- Variation in flow rates during the sampling period and their separate effects on the particle separation by the dichotomous impactor;
- Drifts in the weighing measurement system;
- Losses in particulate during handling prior to final weighing;
- Losses of filter fibers during sampling, sample handling, and prior to final weighing; and
- Variation in the effects of filter conditioning prior to weighing.

Rhodes concludes by stating that the most realistic combined standard uncertainty estimates are those obtained from the collocated measurements and the performance evaluations because the error propagation techniques did not reveal some sources of variability.

Rhodes recommends that bias and precision data for the various measurement systems should be used more effectively in the determination of the uncertainty of ambient air monitoring data. More analyses should be performed to determine the relative contributions to variation and to indicate more quantitatively the importance of errors of particular variables. Further efforts should be made to reduce the magnitude of the errors.

EXAMPLE 2: UNCERTAINTY ANALYSIS FOR LABORATORY TESTING OF BAGHOUSE FILTRATION PRODUCTS

This example is adapted from a generic verification protocol for baghouse filtration products that was prepared for EPA's Environmental Technology Verification Program (ETS, Inc. and RTI International, 2001). Forthcoming EPA regulations may require particulate emission sources that use baghouse filters to control fine particulate emissions. However, fine particulate control efficiencies have generally not been measured for commercially-available baghouse filtration products (BFPs). A laboratory testing program was established to measure BFPs using a modified German method. Fine particulates passing through the BFP are sampled in triplicate on filters mounted in a sampler. Fine particulate mass that is collected on the filters is determined by weighing the filters before and after sampling.

A group of data users established DQOs, shown in Table 4, for a number of performance characteristics for the BFP. Because the testing method had been already established in Germany, the measurement system and its MQOs were already defined. The task then became one of showing that the MQOs would allow for DQO attainment. This example focuses on the mean outlet fine particulate concentration, $\overline{C}_{op}$which has a DQO of 15 percent.

The equation for calculating each outlet particulate concentration is as follows:

$$C_{op} = \left(\sum PM_{filter}\right) \Big/ (Q_{filter})(t)$$

where

PM_{filter} = the fine particulate mass collected on a filter
Q_{filter} = the sample flow rate through the filter
t = the sampling period

The uncertainty of the mean concentration can be expressed as:

$$u_c(\overline{C}_{op}) = u_c(C_{op}) \big/ \sqrt{3} \leq 15\%$$

TABLE 4 Data Quality Objectives for Testing of Baghouse Filtration Products

Verification parameter	DQO	Method MQO for residual pressure [cm water column]	Method MQO for flow rate, raw gas [L/min]	Method MQO for flow rate, clean gas [L/min]	Method MQO for mass gain [milligrams]	Method MQO for time (seconds)
Weight gain of reference fabric [grams, relative to reference value]	±10%				±50 (lo res)	
Maximum pressure drop [with respect to reference fabric value]	±10%	±0.25				
Mean outlet $PM_{2.5}$ particulate concentration, $\overline{C}_{op}$ [mg/L]	±15%		±4	±1	±0.05 (hi res)	±1
Average residual pressure drop [cm water column]	± 5%	±0.25				
Mass gain of filter sample, PM_{filter} [milligrams]					±0.05 (hi res)	
Average filtration cycle time [seconds]	± 1%					±1

TABLE 5 Uncertainty of Outlet Particulate Concentration by Error Analysis

Measurement variable	Symbol	Value	Uncertainty (u_i)*
$PM_{2.5}$ mass on each impactor stage (filter weighed twice)	PM_{filter}	~2 mg	~0.07 mg (~4%)
Total $PM_{2.5}$ mass on five filters (each filter weighed twice)	$\sum PM_{filter}$	~10 mg	~0.16 mg (~2%)
Flow rate thru all five filters	Q_{filter}	20 L/min	~1 L/min (5%)
Sampling time, min	t	35 min	~1 sec (0.04%)
Outlet fine particulate concentration	C_{OP}	0.014 mg/L	~0.001 mg/L (~ 5%)

*u_i is the standard deviation of the listed value. Normally, it is multiplied by a factor of approximately 2 to obtain a 95 percent confidence interval for the value.

The uncertainty of the individual concentrations is made up of uncertainty components associated with the short-term and long-term variability of the BFP testing method.

$$[u_c(C_{op})]^2 = [u_c(long-term)]^2 + [u_c(short-term)]^2 \leq (26\%)^2$$

The short-term variability is associated with the variability on each test date and the long-term variability is associated with the variability between tests, which may be months apart. The two components are assumed to be statistically independent. The ±10 percent DQO for the reference fabric weight gain will be used as an index of the maximum acceptable long-term variability. By substituting terms and rearranging the equation above, we obtain an acceptance criterion for the uncertainty of each of the three outlet particulate concentrations:

$$u_c(short-term) \leq \left(\sqrt{26^2 - 10^2}\right) \leq \sim 24\%$$

The standard uncertainty for each variable (based on the method's MQOs) and the combined standard uncertainty of the outlet particulate concentration is presented in Table 5.

The estimated uncertainty of C_{OP} was calculated using the following equation:

$$u_c(C_{op}) = \sqrt{(2)^2 + (5)^2 + (0.004)^2} \approx 5\%$$

This value is less that the acceptance criterion of ± 24 percent that is derived from the DQO. On this basis, the modified German method should meet the data quality needs of the data users. In other words, the DQO for the project will be attained if the MQOs for the method are attained. As in the previous example, one error source (i.e., flow rate) dominates the uncertainty calculations.