

Pipeline Variable Uncertainties and Their Effects on Leak Detectability

API TECHNICAL REPORT 1149
SECOND EDITION, SEPTEMBER 2015



AMERICAN PETROLEUM INSTITUTE



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Introduction

General

Software-based leak detection systems (LDS), often loosely referred to as computational pipeline monitoring (CPM) rely upon field measurement and instrumentation. Systematic procedures are needed to allow rational design of CPM systems by providing an estimate of the sensitivity that can be expected given a CPM type and instrumentation, and given the engineering factors and operational environment of the pipeline.

CPM methods for LDS are not new, and early applications appeared almost as soon as useful computing power became available to the industry in the 1970's. It was realized very early on that a large number of factors contribute to the effectiveness of CPM. For a given pipeline, it is essential to understand the uncertainty in the prediction made by the CPM algorithm in use regarding the existence, or absence of leaks.

Modern internal LDS collects field data using supervisory control and data acquisition (SCADA) systems and provide the analysis in real time. There are a number of physical principles that can be used as the basis for a LDS technique. These can range from a simple monitoring of the rate of change of a single pressure reading, to the detailed computation of the complete physical state of the pipeline. Taken as a whole, including all the physical inputs, SCADA readings, and engineering assumptions, a modern, internal, CPM-based LDS is a complex system. Relating the uncertainties inherent in the inputs, configuration, and the technique itself to the uncertainty in the prediction of a leak is an equally complex task.

The first accepted industry publication for the numerical assessment of uncertainty in CPM techniques is the API 1149 (first published in 1993). This publication remains valid and extremely valuable within its range of applicability. Generally speaking, it is designed for crude oil and refined products pipelines. It also focuses on (while also discussing other ancillary issues) single, straight pipelines and on the material balance method of CPM, particularly under steady state conditions.

Purpose

This revision of procedures for the assessment of uncertainty in CPM techniques was undertaken in light of a number of recent technological developments and operational requirements. It is also directed at engineering uncertainty factors that prove, in practice, to have a significant effect on LDS uncertainty but that were not thoroughly addressed in the 1993 version.

While the 1993 API 1149 has proven to be useful to the industry, it is incomplete and has several shortcomings and gaps in justifying the sensitivity estimation metrics. The project team has identified these shortcomings and gaps that need to be addressed in the 2015 revision of the publication to improve the industry's ability to qualify sensitivities estimations of many CPM applications.

- 1) *The need to cover the complete range of CPM methods in current, practical use.* The original API 1149 only covers volume balance internally based CPM systems and not some of the other related CPM systems mentioned in the API 1130 (first published in 2002, revised September 2007, and reaffirmed in 2012).

A list of the techniques cited in API 1130 and covered in this document is provided in Table 1.

- 2) *The need to extend the assessment to highly volatile liquids (HVL) and natural gases.* In part because the uncertainties related to CPM in HVL and gas pipelines are not covered by the 1993 revision of API 1149, CPM is often dismissed too readily as a viable form of leak detection. The review therefore explicitly covers these two common pipeline fluids, in addition to low volatility liquids (LVL). The calculation of density—or, equivalently, the computation of volumes at standard conditions—is central to a number of lead detection (LD) techniques that rely on the principle of conservation of mass. Therefore, especially for these kinds of LD methods the equations

of state, and the calculation of density/standard volumes, are important. This is discussed in much more detail under the subsection on the reference model.

- 3) *Alignment of the definitions and approach to uncertainty with those used systematically in instrument and measurement engineering.* The intention is to provide a systematic and universally recognized framework for the definitions related to uncertainty. Specifically, the procedure refers to the American Society of Mechanical Engineers (ASME) *Validation and Verification Procedure (V&V)* number 20 (2009). A similar framework is used throughout metering and measurement engineering, including the *API Manual of Petroleum Measurement Standards (MPMS)* (2013), where far more technical detail can be found. The basic measures of uncertainty are bias and precision, and these are discussed at length.

This framework recognizes that there is no one fixed numerical value for uncertainty. Rather, it regards uncertainty as being fundamentally statistical in nature. Therefore, whatever threshold for detection is set using a given technology there remains a statistically defined probability that it will produce false alarms and miss actual leaks. The framework addresses and formalizes a number of issues, including:

- how to specify the uncertainties in the input variables and provide guidance on the uncertainties present in different types of sensors and measurement systems;
- how the presumed normally distributed errors in source measurement translate to strongly non-normal distributions in the uncertainty of the final leak alarm;
- issues related to the impossibility of systematically estimating false alarm rates by considering just the statistical measures of bias and precision.

The reader is also referred to the existing API 1130 as well as the 1993 API 1149 for discussion of the complex relationship between alarm sensitivity, alarm confidence, and false alarms. It is also discussed in Section 13.

- 4) *Recognition of the nonlinear and strongly time-dependent nature of certain engineering factors.* The motion of fluids in pipes, particularly with constantly and randomly variable boundary conditions, is difficult to predict systematically using simplified equations of motion. One of the most common and difficult issues in a pipeline is to estimate the impact of a fluctuating temperature of the fluid at its inlet. A simplified, steady state model of the flow tends to over-estimate, often by several orders of magnitude, the total effect on the fluid properties. Because of non-ideal thermal effects, the only effective approach is to use a full transient computation of the pipeline state with accurate inputs and boundary conditions.

There are a number of quasi-steady operations that vary with time due to the movement of temperature fronts, drag reducing agent (DRA) concentration variations, or product property variations (including those caused by batching) through the line. Again, the recognition that these effects can yield inaccurate results when simplified models are used makes the use of computer software for their assessment essential.

The 1993 API 1149 only produces an estimate curve for steady state conditions, limited to the impact of flow, pressure, and temperature. This approach aims to include any source of uncertainty within a consistent framework, including fluid properties, operational affects, and instrumentation analysis. It also addresses the implementation of the software to be used or developed.

Refer to Figure 7 and Figure 8 for example *overall* tornado diagrams that illustrate the relative impact of various engineering factors on the uncertainty of a LDS, for liquids and gas systems respectively.

- 5) *Inclusion, in detail, of a number of engineering factors that occur regularly in pipeline operations.* These are listed in detail, and represent issues that are addressed only at a fairly high level in the original 1993 API 1149 estimation procedures. In addition, the 1993 publication only quantifies the uncertainty effects of measured variables like flow, pressure, and temperature. The document examines in detail the calculation for uncertainties

in other fluid properties and their uncertainty affects, such as density, viscosity, bulk modulus, and thermal expansion coefficient.

Similarly, it aims to quantify the typical operational transient conditions experienced on a pipeline, including startup, shutdown, slack (channel flow) operations, and the effects of fluid properties from steady state to transient operations.

- 6) *Inclusion of the major telemetry (SCADA) uncertainties in measurement.* The procedure takes into account scan rate, communications, loss-of-data, data-time skew, and latency within the uncertainty calculation. Section 7 addresses these issues with an instrumentation guideline that couples the compounded effects of the scan rate, communications, loss-of-data, data-time skew, and latency on overall uncertainty.

Refer to Figure 9 for an example Tornado diagram that illustrates the relative impact of various SCADA factors on the uncertainty of a LDS.

- 7) *Section 7 provides update and improved guidance on the source uncertainties present in different types of sensors and measurement systems.* It also discusses what happens to the presumed normally distributed errors, pertaining to forecasting false alarm estimates, given that these alarms occur due to a failure in the telemetry system, which in turn would be outside of a normal statistical probability. In addition, it addresses the issues related to how this does not readily relate to false alarm rate, particularly with consideration of these statistical outliers.

Annex A is a high-level summary of the procedure, which can be used as a standalone document for non-technical readers, or for readers who only require an overview.

Annex B includes a set of worked examples that use actual operating pipeline data to illustrate the use of the procedure, with a range of engineering and operational factors present.

The reader is advised that a sound knowledge of basic fluid mechanics [appropriate to performing pipeline hydraulic modeling (see for example Wylie, Streeter, and Bedford, 2010 or Lurie, 2008)] as well as a knowledge of basic statistical theory [appropriate to performing instrument and measurement analysis (see for example Cox, 2006 or the 2013 API MPMS and references therein)] are pre-supposed in the presentation of these advanced LDS uncertainty assessment techniques.

Pipeline Variable Uncertainties and Their Effects on Leak Detectability

1 Scope

This document describes procedures for *predicting* uncertainties in the detection of leaks in pipelines using computational methods based upon physical hydraulic state measurements. This class of pipeline leak detection methods is commonly called computational pipeline monitoring (CPM).

Generally, CPM methods take physical measurements from a pipeline as an input, and calculate a *metric* that is used to assess whether a leak is likely to have occurred. The *uncertainty* in the CPM method is a fundamentally statistical measure of how likely an alarm is to be valid; equivalently, how often an alarm may be due to routine operational conditions or lie within the realm of known input uncertainty.

2 Normative References

The following referenced documents are indispensable for the application of this document. For dated references, only the edition cited applies. For undated references, the latest edition of the referenced document (including any amendments) applies. A list of other documents associated with API 1149 is included in the Bibliography.

API Recommended Practice 1130, *Computational Pipeline Monitoring for Liquids*, 1st Edition

API Publication 1149, *Pipeline Variable Uncertainties and their Effects on Leak Detectability*, 1993

3 Terms, Definitions, Acronyms, Abbreviations, and Symbols

3.1 Terms and Definitions

For the purposes of this document, the following definitions apply.

3.1.1

accuracy

Used to denote a standard deviation of an estimator of the mean uncertainty. If the sample mean is used, this is also the standard error $\sigma/\sqrt{n}$ of all the errors in the readings. This can itself be estimated by $\sqrt{S^2/n}$.

3.1.2

calibration

Process used to reduce the systematic bias to zero. A calibrated measurement has zero average error.

3.1.3

estimator

A function of a number of samples, used to estimate statistical parameters related to the distribution of U . Note that it is itself a random variable.

3.1.4

harmonic average/sum/product

The inverse of the average/sum/product of the inverses of a set of numbers.

3.1.5

mean uncertainty

The mean (unknown) of U .

NOTE In most statistical theory publications this is called the accuracy of the measurement.

3.1.6**precision**

The standard deviation (unknown) of U .

3.1.7**repeatability**

Formally, it is the test-retest reliability, i.e. the variation in measurements taken by a single person or instrument on the same item and under the same conditions. There are a number of ways of estimating this, within the framework of analysis of variance (ANOVA).

3.1.8**reproducibility**

Formally, it is the reliability between test methods, i.e. the variation in measurements taken by different people or instruments, but on the same item and under the same conditions.

3.1.9**sample mean**

Equals the average of the sample, is the maximum likelihood estimator of the mean: $\bar{X} = \frac{1}{n} \sum X_i$.

3.1.10**systematic bias**

Used to denote the mean of an estimator of the mean uncertainty. If the sample mean is used, this is just the average of all the errors in the readings.

3.1.11**unbiased sample variance**

S^2 equals the sum of squares of deviations from the average, divided by $(n - 1)$: $S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2$. It is the maximum likelihood unbiased estimator of the variance.

3.1.12**uncertainty in the accuracy**

Since the Accuracy is itself a random variable, it has a variance. If S^2 is used as the estimator, its behavior is given by the chi-squared distribution, and is equal to $1/n$.

3.1.13**underlying uncertainty**

A random variable representing the uncertainty U in a measurement, with a mean and variance that are unknown, to be estimated; with U being the difference between the reading or result and the *reference* or true value (see Figure 3).

3.2 Acronyms, Abbreviations, and Symbols

AGA	American Gas Association
ANOVA	analysis of variance
ASME	American Society of Mechanical Engineers
ASTM	American Society for Testing and Materials
CFD	computational fluid dynamics
CPM	computational pipeline monitoring
DRA	drag reducing agent
EOS	equation of state
GERG	European Gas Research Group
GPA	Gas Processors' Association
HVL	highly volatile liquid

IID	independent and identically distributed
ISA	International Society of Automation
ISO	International Standards Organization
LD, LDS	leak detection, leak detection system(s)
LVL	low volatility liquid
MFC	measurement of flow code
MPMS	<i>Manual of Petroleum Measurements Standards</i>
MTBF	mean time before failure
NIST	National Institute of Standards and Technology
PDF	probability density function
RM	reference model
RMS	root mean square
RTTM	real-time transient model
SCADA	supervisory control and data acquisition—generally, the data acquisition system being used
SLF	slack-line flow
SPRT	sequential probability ratio test
STBPH	standard barrels per hour
STP	stock-tank temperature and pressure (60 °F, 14.7 PSIA/16 °C, 100 kPa); also, fluid properties converted to their values at STP
TCF	front-end processing latency
TSM	data-time skew bias
TSS	data-time skew variance
~	varies as, has the distribution of
B	spread (confidence interval) of potential biases in a collection of samples
Δt	balancing period(s)
dt	time interval at which readings are sampled (s)
$\Delta l^{(r)}$	change in linepack, reference value, over a balancing period (lb or kg)
(dot)	superscript—rate of change with time (s^{-1})
$E()$, $Var()$	expected value and variance operators
i	subscript—inlet value
μ, M	mean
$N(\mu, \sigma)$	normal distribution
N, n, k	sample sizes
o	subscript—outlet value
P	mean precision in a collection of samples
P, T	(in context) pressure (PSI or kPa) and temperature (°F or °C)
ρ, v, μ, a	(in context) density, velocity, viscosity and speed of sound
Q_m	mass flow rate (lb.hr ⁻¹ or kg.s ⁻¹)
$Q, \dot{V}$	volume flow rate (BBL.hr ⁻¹ or m ³ .s ⁻¹)
(r)	superscript—reference (i.e. true, physical) value
R_k	residual or imbalance over k samples



S^2	sample variance: the maximum likelihood unbiased estimator of the variance
σ, Σ	variance
σ	standard deviation of a random variable; σ^2 is its variance
T, t	time periods
U	uncertainty (typically, in a measurement)
V	volume (BBL or m ³)
$\hat{X}$	estimator for the mean of X ;
X, Y	capital letters for random variables

4 Background

4.1 General

The method applies to CPM methods for leak detection systems (LDS). A large number of factors are known to contribute to the effectiveness of CPM and it is essential to understand the uncertainty in the prediction made by the CPM algorithm in use regarding the existence, or absence of leaks. The first accepted industry publication for the numerical assessment of uncertainty in CPM techniques is API 1149 (first published in 1993). Broadly speaking, it is designed for low volatility liquid (LVL) crude oil and refined products pipelines and focuses on single, straight pipelines and on the material balance method of CPM, under steady state conditions. It also includes only a few engineering uncertainty factors in its calculations. Nevertheless, the original 1993 API 1149 remains valid and is perfectly adequate within its stated scope of pipeline and fluid types, CPM methods, and uncertainty factors.

This revision of procedures for the assessment of uncertainty in CPM techniques is directed at including a more complete set of CPM methods, operational scenarios, and pipeline types. It also includes multiple engineering uncertainty factors that prove, in practice, to have a significant effect on LDS uncertainty but that were not thoroughly addressed in the 1993 version.

An estimate of the *location* of a leak can often be made with some CPM methods, using an additional algorithm *independent* of the comparison technique and leak alarming. Uncertainty of leak location techniques is *not* within the scope of this document; nevertheless, there is a description of the most commonly used techniques. Location algorithms that are considered in this document include:

- pressure gradient intersection (for incompressible fluids);
- pressure wave speed.

In addition, certain *filters* are often used to pre-process measurement data, and are occasionally used to post-process the metrics. Filtering techniques are not within the scope of this document. Nevertheless, there is a discussion of how they affect the general uncertainty assessment procedure.

Metrics that are addressed in this document include:

- imbalance in volume flow, accumulated over time;
- imbalance in mass flow (or equivalently volumes at standard pressure and temperature), accumulated over time;
- state—a list of pipeline system (including fluid) physical properties;
- pressure measurement rate of change;
- flow measurement rate of change.

Only the first three of these are formally CPM methods in the sense of the API 1130. Point rate of change methods are listed in API 1130 under the category *Regular or Periodic Monitoring of Operational Data by Controllers* and are included here because of their widespread use.

Another dimension to the metric is how it is used in order to declare a leak alarm.

- For LDS using a pipeline state, the weighted root mean square (RMS) of the difference between the measured pipeline state and its expected, and reference state is used. The difference is used between the RMS and: (a) a constant threshold, or (b) against another computed function (often called a “dynamic threshold”) of given bias and precision.
- For all the other LDS using a single (scalar) valued metric, the difference is used against: (a) a constant threshold, or (b) against another computed function of given bias and precision.

Two LDS methods are listed in API 1130 under the categories of CPM and *data analysis*.

- Statistical identification of a change in a metric. Specifically, two methods are examined: student t-test; and sequential probability ratio test (SPRT).
- Pattern recognition measures of a metric or state variable. Specifically, two methods are examined: maximum entropy classifier and Naive Bayesian classifier.

The methods used, and how they relate to the API 1130, are shown in Table 1.

Table 1—CPM Methods According to API 1130

ID	API 1130 Description
1	Regular or Periodic Monitoring of Operational Data by Controllers:
a.	Volume balance (over/short comparison)
b.	Rate of pressure/flow change
c.	Pressure point analysis
d.	Negative pressure wave method
2	Computational Pipeline Monitoring (CPM):
a.	Mass balance with line pack correction
b.	Real time transient modeling
c.	Statistical pattern recognition
d.	Pressure/flow pattern recognition
e.	Negative pressure wave modeling/signature recognition
3	Data Analysis Methods:
a.	Statistical methods
b.	Digital signal analysis



Note that all methods that involve a balance rely upon an accumulation period Δt . The quantities being balanced (flow, mass, etc.) are rarely instantaneous values, but rather their values summed or accumulated over this time period. This is the same in principle to taking a moving average of the property in balance.

Three general classes of data filters are addressed in this document:

- moving average,
- high-pass filtering,
- outlier removal.

In principle, these filters can be applied at any stage of an LDS procedure. In practice, they are most often used—sometimes implicitly—on the raw input data and on the metric with a view to reducing the rate of false alarms.

API 1130 is in particular useful for a detailed discussion of the complex relationship between alarm sensitivity, alarm confidence, and false alarms. This document does not pursue these issues to the same level of already good detail, and the reader is referred to this recommended practice for these issues.

4.2 Prediction vs. Evaluation

An estimation of uncertainty can in general be made in one of two ways (Van Reet, 2014):

- *a posteriori* observation, by evaluating a recorded history of pipeline states and events that represent a collection of the majority of likely situations and scenarios where the LDS will be used, and assuming that the future will continue to be similar. This is generally accomplished by statistical analysis of recorded SCADA data; and
- *a priori* estimation, analytically from models and algorithms that seek to predict the performance of the LDS in as-yet unseen pipeline states and scenarios—for example, on an LDS that has not yet been installed and is in the planning stage, or in an improvement design study.

The first situation is discussed at length in API 1130 and refinements can be found in the specialized literature, as discussed in Section 13 and references therein. It is a powerful technique for assessing the performance of an LDS given historical performance, and assuming that in future no outlier situations not encountered to date will occur. Performance observation techniques are more appropriate where detailed knowledge of the asset, the operation, or the leak detection technology is not known or when the true performance of an existing asset needs to be determined.

However, the scope of the 1993 edition of API 1149 and of this update is to provide a *predictive estimation tool* that takes as inputs assumptions and parameters from the components of the LDS and seeks a systematic and physical model for deducing the uncertainty in the CPM method used. It allows a prediction of multiple potential future pipeline scenarios, as well as allowing multiple “what-if” improvement scenarios (additional instrumentation, different CPM algorithms, etc.) to be analyzed.

4.3 Performance Factors vs. Uncertainty

There are four main measures of performance of an LDS in current general industry practice:

- sensitivity: a composite measure of the size of a leak that a CPM system is capable of detecting and the time required for the system to issue an alarm in the event that a commodity release of that size should occur;
- accuracy: the precision with which the size and/or location of the loss can be estimated;
- reliability: the confidence that can be assigned to any reported loss;

- availability/robustness: the uptime that can be expected of the LDS under normal conditions; and also the resilience of the LDS to unexpected conditions.

These performance objectives are often at odds with each other; for example, higher LDS sensitivity generally leads to more false alarms, and therefore lower reliability. These issues are discussed at length in the API 1130 and the reader is recommended to follow Section 12 therein, particularly the summary in Figure 3.

This procedure is directed at establishing a more comprehensive Uncertainty measure of performance and does not aim to reproduce the API 1130 treatment. The aim is more to define the LDS as a *measurement device* with a bias and a precision as in the API *MPMS* (2013). However, it also emphasizes that availability is at least as important in the specification as the bias and precision during normal operations, particularly when the overall leak detection system is complex. The reader will therefore find in this document, in contrast to API 1130 and the original API 1149 (1993), three primary measures of performance: (1) bias, (2) precision, and (3) availability/robustness.

In this light, this specification generally relates to the measures of performance in four main areas.

- Sensitivity of the LDS is set at the discretion of the operator. However, it is limited absolutely by the assessed bias and precision of the LDS. The precision and bias of the LDS will then impact the number of false alarms, but in a complex manner. Note that if the bias of the LDS is known, it can be reduced to zero by calibration; unlike precision, which cannot.
- Size and leak location algorithms are not addressed. Therefore, their accuracy is not specified, except in passing in discussions contained in Section 12.
- Reliability is difficult to assess given a bias and precision, since the actual form of the uncertainty distribution is not known. This is discussed at length in Section 13. It is possible to infer a rate of false alarms from LDS uncertainty but the reader is warned that this estimation requires significant assumptions, often quite hard to justify, about the nature of the LDS uncertainty probability density function. It is also emphasized in Section 7 that the bias and precision effects are subject to the inputs to the CPM technique being *ideal* in the sense of the API *MPMS* (2013). Therefore, reliability of an LDS is often dominated in practice by imperfections in the measurement system, which should be tracked using an availability/robustness calculation.
- The availability of the LDS is assessed as a function of the *mean time before failure* (MTBF) of the overall system components. Similarly, robustness is defined as the overall MTBF of the complete system. This is discussed at length in Section 7.

5 Engineering Summary

5.1 General

The purpose of this engineering summary is to provide a rapid review of the overall algorithm for the engineering analyst, while deferring the complete discussion of the details to the remainder of the document.

Basic vocabulary—It is one of the aims of this study to standardize the procedure and vocabulary to follow industry instrumentation and measurement practices more closely. A key source for these terms is the API *MPMS* (2013).

Uncertainty is the deviation of a physical measurement, or any other value (including any that may be computed), from a known or expected *reference* value. It is treated as a probabilistic random variable.

Source uncertainties are first separated into a continuous component, which is assumed to have a normal (Gaussian) distribution (as in the *MPMS*), and a separate binary reliability component rated with a MTBF. The continuous, normal uncertainty distribution is additionally separated into a systematic *bias* (B) and a random *precision* (P).

The issue of how to estimate bias and precision for a variety of meters and instruments is beyond the scope of this document. However, a case study with commentary showing worked examples of possible approaches, both from field calibration/proving by the operator and from manufacturer specifications, is provided. The meters and instruments are all assumed to be *ideal*—with normally distributed uncertainties—throughout the calculations, according to the API MPMS (2013) model. In practice, this is not always the case and therefore any non-ideal behavior of the measurement system is assumed to lead to a failure of the LDS, and should be included in the estimates of MTBF.

Finally, some sources of uncertainty are *deterministic*—notably transient operations on the pipeline. They either are or are not, for example a pipeline may be in a steady state (no pumping); transient (pumps starting up); and steady state again (pressurized by pumps).

The leak detection system is a *system* with multiple components including, for example, input measurements, instrumentation, telemetry/SCADA, and computer calculations.

The multiple MTBF of the components of the leak detection system are combined using a “weakest link” approach to give an *availability* of the LDS, which is this minimum MTBF times the frequency of calculation of the CPM.

The combination of the continuous components of uncertainty is complicated by the nonlinear nature of the LDS. However, as in the API 1149 (1993) procedure, it is assumed that the uncertainties are small enough to allow their deviations to be combined by RMS. The justification and limitations of this assumption are covered in Section 7.

CPM methods—Any of the CPM methods listed in API 1130 can be defined by a *metric*, which is a number computed from the measured pipeline *state* (all the physical pressures, flow rates, and other hydraulic properties of the line). A LDS uses this Metric to declare an alarm—usually by comparing it against a *threshold*. For example, a typical metric for a material balance CPM might be the one-minute moving average of the imbalance between measured inlet and outlet flow, corrected to standard pressure and temperature conditions. When this averaged imbalance exceeds a certain threshold, the LDS calls an alarm. Pressures and single flow measurements are also used sometimes as CPM metrics in this sense.

Therefore, the uncertainty in the LDS is related closely to the uncertainty in the metric used, which is a nonlinear function of the pipeline state.

Reference model—To specify the uncertainty of the metric in terms of the reference—bias—precision measurement model, it is necessary to know the reference value of the metric. This requires knowledge of the *reference pipeline state* relevant to the computation of the metric. Similarly, it is necessary to compute how the metric changes as the uncertain input variables change.

In the API 1149 (1993) procedure, one metric is considered (material imbalance), one source of input uncertainty is considered (rate of change of line pack), flow is in steady state, and the fluids are LVL. This made it feasible to build a single hydraulic simulation model and then to run it just once to develop the published tables of results for the metric uncertainty.

Given the present mission of addressing a wide variety of sources of uncertainty, transient situations, fluid types, and even networked systems, it is impractical to build a single consistent and accurate set of lookup tables. Therefore, the procedure relies on the choice of a *reference model* (RM) that represents a computational engine for establishing reference values of the pipeline *state*.

The choice of this model is left to the discretion of the engineer. At one extreme, a highly detailed and accurate transient network pipeline simulator may be used, in order to provide the maximum flexibility in assessing the complete range of potential sources of uncertainty. However, if only the uncertainty due to a few parameters on a single incompressible fluid line is required then a far simpler model might be adequate. The only essential factor is that the engineer must be precise about which reference model was used, to ensure repeatability of the calculations, and should realize that the uncertainty of the calculations will be limited by the accuracy of the RM.



It is noted in Section 11 that an acceptable RM might well be recorded SCADA data from the actual pipeline itself. In this situation the only source of uncertainty that can be assessed systematically are historical transient operations (it is impossible to turn back the clock and examine what might have happened with different pressures and temperatures). Therefore, the drawback of this RM is clearly the inability to predict what might happen with any other engineering factors, transient scenarios, or measurement systems.

There is often confusion between the RM and the CPM metric. The RM calculates the *reference pipeline state* and is entirely separate from the *leak detection CPM method*. Multiple CPM metrics might be calculated from a single pipeline state, estimated by a single RM run.

5.2 Process

Data collection—Emphasis should be placed on being exact about the LDS, the pipeline, its operational scenarios, and the sources of uncertainty that are being considered. A basic report of the input data to an assessment would include the following.

- An engineering description of the pipeline—generally, this is equivalent to the minimum data set required to run the RM, including topology, fluid types, nominal system pressures and flow rates, etc.
- A statement of the operational scenarios that are to be considered—this might include, for example, (1) nominal flow steady state, (2) batch change, (3) pump start/stop, etc.
- A precise statement of the CPM method(s) (i.e. the metric) used—for example, “one-minute moving average of the imbalance between measured inlet and outlet flow, corrected to standard pressure and temperature conditions” or “rate of change of pressure at the sensor P1”. Several of these may be listed; indeed, for imbalance methods it is common to make a list of balancing periods for consideration.
- A statement of the RM being used, as well as its control modes—for example, a steady state might be estimated from two pressure measurements, or from a flow and a pressure, etc. Similarly, a transient scenario may be defined from recorded SCADA data, or from an idealized schedule of changes to boundary conditions.
- A statement of each source of uncertainty that will be considered—most typically this corresponds to the measurements used as inputs to the CPM method. For example, inlet and outlet flow rates, pressures, and temperatures. However, any source of uncertainty can be added to this list including fluid density, pipeline temperature, etc.
- Values for the assessed input uncertainties, for each source of uncertainty that are to be considered—in terms of a single bias “B” and precision “P” each. Similarly, an MTBF estimate must be provided for all components of the LDS for which an availability analysis is requested.

Availability—The cumulative availability of the LDS can be found first, using a critical path/weakest link approach as described in the document. Also, a total MTBF for the LDS can be reported by aggregating the separate component MTBFs.

Loop 1—Scenarios—In practice, by far the single largest contribution to changes in the CPM metric is due to the operational state of the pipeline. Therefore, it is recommended to structure the analysis around the operational scenarios first. So, for example, the analysis might include three separate subsets: (1) steady state; (2) batch change; and (3) pump start.

Loop 2—Sources of uncertainty—Having fixed an operational scenario, a baseline estimate of the pipeline state is first made using the RM, using the reference values of all the inputs.

Then, for each identified source of uncertainty that will be considered, another pipeline state is found, using the RM, by perturbing that input by “B”. A second perturbation is also found, using the RM, by perturbing that input by “P”.

After this loop, if there are N stated sources of uncertainty, $2N + 1$ runs of the RM will have been made, and there will be $2N + 1$ perturbed pipeline states. As an example, if flow in (QIN) and out (QOUT); and pressure in (PIN) and out (POUT) are the sources of uncertainty, then the set of runs would be as shown in Table 2.

Table 2—Example Summary of Reference Model Runs

Run #	QIN	PIN	QOUT	POUT	State
Nominal	Reference	Reference	Reference	Reference	Nominal State
2	Ref. + B	Reference	Reference	Reference	State # 2
3	Reference	Ref. + B	Reference	Reference	State # 3
4	Reference	Reference	Ref. + B	Reference	State # 4
5	Reference	Reference	Reference	Ref. + B	State # 5
6	Ref. + P	Reference	Reference	Reference	State # 6
7	Reference	Ref. + P	Reference	Reference	State # 7
8	Reference	Reference	Ref. + P	Reference	State # 8
9	Reference	Reference	Reference	Ref. + P	State # 9

Metric analysis—At this stage, the specific CPM method(s) used is applied. This involves using the computed pipeline states, and calculating the corresponding metrics, to show what the impact of the “B” and “P” changes have on the CPM metric. This generates a table similar to Table 3.

Table 3—Example Summary of Metric Analysis

Run #	State	CPM Metric
Nominal	Nominal State	Reference Metric
QIN (B)	State # 2	Metric B # 2
PIN (B)	State # 3	Metric B # 3
QOUT (B)	State # 4	Metric B # 4
POUT (B)	State # 5	Metric B # 5
QIN (P)	State # 6	Metric P # 6
PIN (P)	State # 7	Metric P # 7
QOUT (P)	State # 8	Metric P # 8
POUT (P)	State # 9	Metric P # 9

Each row now represents a measure of the individual uncertainty due to each of the input uncertainties, both bias (B) and precision (P). The RMS of the individual components gives the total cumulative uncertainty.

The results are usefully presented graphically in a tornado diagram, as shown in Figure 1, where each bar of the tornado is simply a row of Table 3.

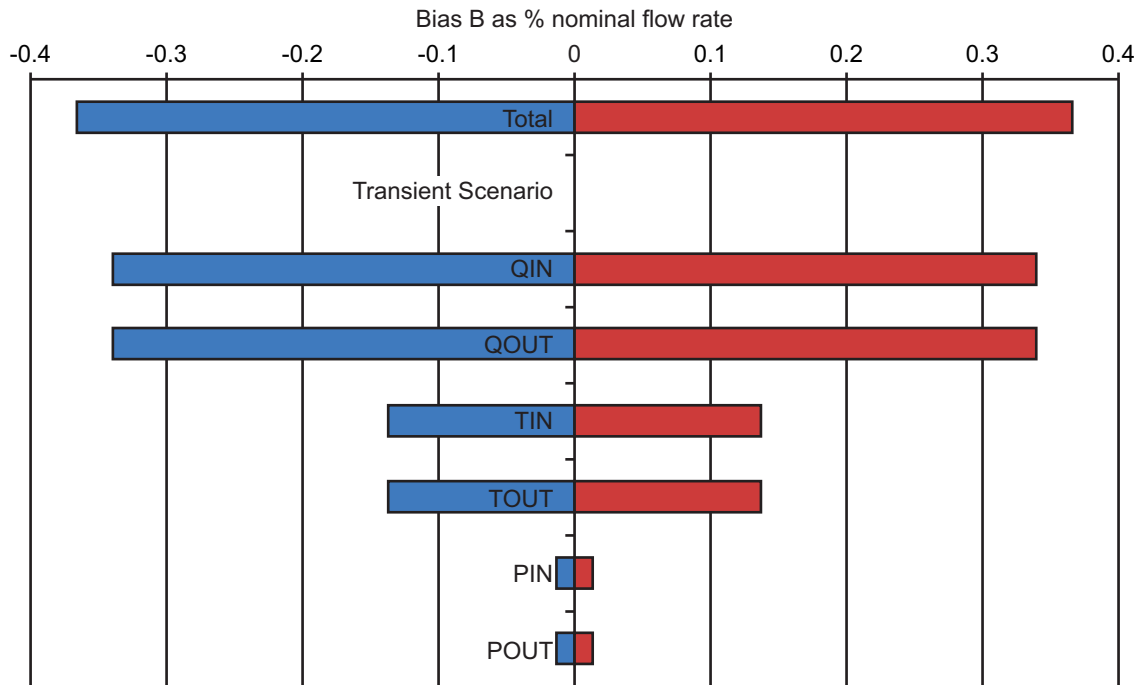


Figure 1—Example Summary Tornado Diagram

There may be multiple metric analyses that refer to different potential metrics corresponding to different CPM methods. Again, it might then be useful to draw tornado diagrams that compare the corresponding uncertainties against CPM method. Note that in this document, and in many practical situations, most tornado diagrams are symmetrical. This is not always necessarily the case, although generally the assumption that the input uncertainty sources are small will tend to make the resulting uncertainties symmetrical.

Alarm Analysis—When any CPM method that relies upon a balancing period (in other words, on a moving time average) of an instantaneous metric is used, then it is useful to draw a chart of uncertainty against time, in the style of the API 1149 (1993) procedure.

This generally requires computing several CPM metric columns in Table 3; however, it does not require re-running the RM. A typical results plot might look like Figure 2.

6 Procedure

6.1 General

The overall process to calculate the leak detection potential is summarized in Figure A.1 (see Annex A) and in the description immediately thereafter.

The overall process begins with data gathering and preparation. All available data is collected and the objectives of the study are defined—in other words, a decision is made about the selection of which potential sources of uncertainty are to be analyzed. The overall process allows for over fifty specific uncertainty parameters and it is by no means necessary or useful to analyze every one. This decision also includes which LD techniques are to be considered.

The first preliminary step is to perform a measurement analysis. This combines instrumentation and telemetry uncertainties into a composite set of input uncertainties for the LD technique. The second preliminary step is to build the Reference Model, which is a simulation of the pipeline hydraulics itself. Part of this activity is the calibration, and

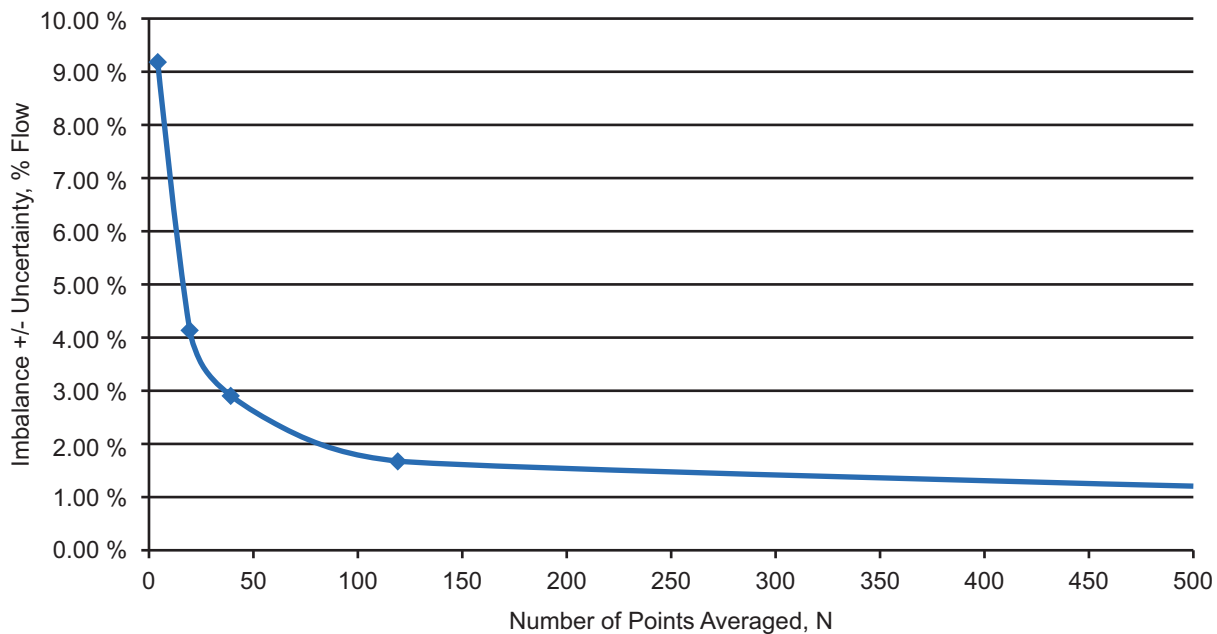


Figure 2—Example Summary Alarm Analysis

assessment of the accuracy, of the RM. The procedure can be accomplished even with very simple simulation models. However, the uncertainty in the RM represents the minimum level of uncertainty in the Metric that can ever be assessed.

Instrument uncertainty and telecommunications uncertainty (including the data gathering) is covered in Section 7—Measurement Model. The building of the reference model is covered in Section 8—Uncertainties Due to the Metric. Its calibration and guidance upon the modeling process are also covered in Section 11.

The use of the reference model for physical uncertainties is covered in Section 8. In particular, Figure 12 and subsequent discussions cover the procedure in much more detail.

The case study: *Worked Example Uncertainty Assessment*, performs an uncertainty assessment step-by-step. The reader may wish to refer to this example in order to see a summary of the procedure in practice.

6.2 Uncertainty Framework/Measurement Model

6.2.1 General Definitions

The uncertainty U in any measurement is a random variable. This framework is shown in Figure 3.

Therefore, in attempting to read a value that truly has a certain reference value, the measurement will over time produce values represented by the “bell curve” that has a systematic mean accuracy (or bias) shift, and a variance given by the precision. *Uncertainty* is specified by this probability density.

The area underneath the probability density function (PDF) corresponds to the probability of the value lying within a given range. If a given threshold is specified, then the area under the curve to the right of the threshold represents the total probability of the value being greater than this threshold. In measurement, this represents the probability of the meter reading *exceeding* the threshold value beyond the true value. Conversely, the area under the PDF to the left of the threshold represents the probability of the measurement being within the threshold value of the true value. This represents the probability of the meter reading *being less than* the threshold value beyond the true value. If there are

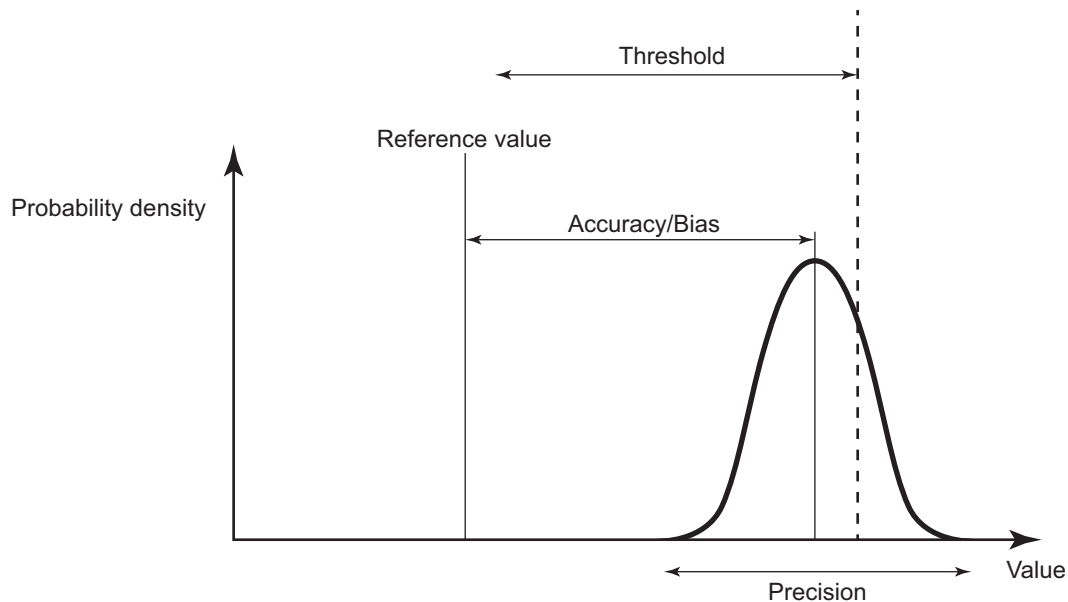


Figure 3—Basic Uncertainty Framework

two thresholds, a minimum and a maximum, then the area under the PDF between these two values represents the probability of the true value lying within this range.

6.2.2 Normal, Gaussian Distributions

Generally, it is assumed in accordance with the *MPMS* (2013) that all errors of measurement (or uncertainties) are Normal (Gaussian) distributions. In this situation, the *threshold* of uncertainty can be read from tables of confidence intervals for the Gaussian distribution in terms of a percent confidence.

Normal Gaussian distributions *do not generally apply to all uncertainties*—and in particular complex nonlinear transformations of uncertainties common in CPM. An example situation where the PDF has a long tail (i.e. there is substantially more area under the curve beyond one standard deviation) is shown in Figure 4.

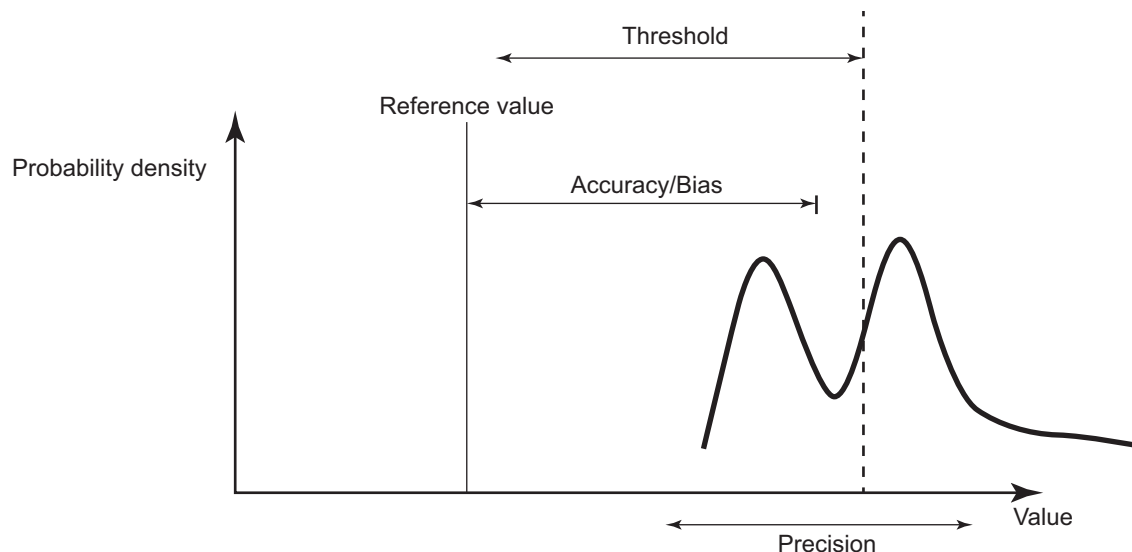


Figure 4—Non-Gaussian Distribution

This illustrates how the precision does not translate directly to a probability, unless (rarely) the precise nature of the PDF is known. In this sketch, a much greater area lies under the curve to the right of the threshold than with a Gaussian PDF, despite the distributions having the same mean and variance. This is particularly significant when assessing *rate* of false alarms (and misses) in an LDS, which technically means a probability. The uncertainty is expressed rigorously with a bias and precision, but without assumptions as to the form of the distribution of the LDS uncertainty, it is generally impossible to calculate a rate.

6.2.3 Binary Uncertainties

Of particular interest to leak detection systems, many instruments provide a binary, on/off indication. It is possible to define accuracy and precision for binary uncertainties, and in this case,

Accuracy = (number of true positives + number of true negatives)/(number of all measurements)

Precision = (number of true positives)/(number of true positives + number of false positives)

It is extremely unlikely that binary measurements follow a normal distribution. They follow instead the binomial distribution, and only when a very large set of binary measurements is taken does this approximate a normal distribution, due to the central limit theorem. Since the number of alarms is not expected to be extremely large, this approximation is not likely to be appropriate. This is just another example of situations where it is necessary to handle non-Gaussian statistics.

In order to use terminology that is more familiar to leak detection engineers, this document slightly modifies the word *accuracy* used in the API *MPMS* (2013) to *bias*; or *systematic bias* when it is useful to be explicit. In order to be precise, for the purposes of this document the following applies.

- The bias is a value, in the physical units of measurement of the meter (or computation). By contrast, it is usually expressed as a percentage in the API *MPMS* (2013).
- Similarly, precision is a value corresponding to *one standard deviation* of the uncertainty—again, in the units of measurement of the instrument or computation. In general industry practice, two or three standard deviations may be specified depending on circumstances.

Finally, since the assumption in the API *MPMS* (2013) that measurement uncertainties are normally distributed is not always true in practical situations, it is best to include situations where measurement uncertainties do not follow the API *MPMS* model as failures, and to include estimates of the frequency of these non-ideal measurements in the MTBF or availability estimate.

6.2.4 Practical Estimation of Bias and Precision

In practice, it is difficult to assess a realistic value for the bias and precision for every given measurement (Van Reet, 2014). In a pipeline system with perhaps dozens or hundreds of meters and instruments, it becomes practically impossible. The biases and precisions are themselves estimated from experiments on a number of similar devices or, in the case of flow meters, on the same meter several times. Generally, the bias of a given reading is estimated from a population sample mean (the average) of a number of readings, and the precision from a population sample variance. When the statistics of a number of readings taken from a number of instruments—or the same instrument over a range of conditions or times—are collected, the results are typically as shown in Figure 5.

In this very simple example, with just four independent tests on a measurement, four separate biases (B1 to B4) are measured, and also four different precisions (P1 to P4). The uncertainty on the x-axis is the error, the difference between the measured value and the true value. The y-axis gives the number of times a particular measured value was observed. The separate assessments might be, for example:

- on the same flow meter, during separate proving runs at different times;

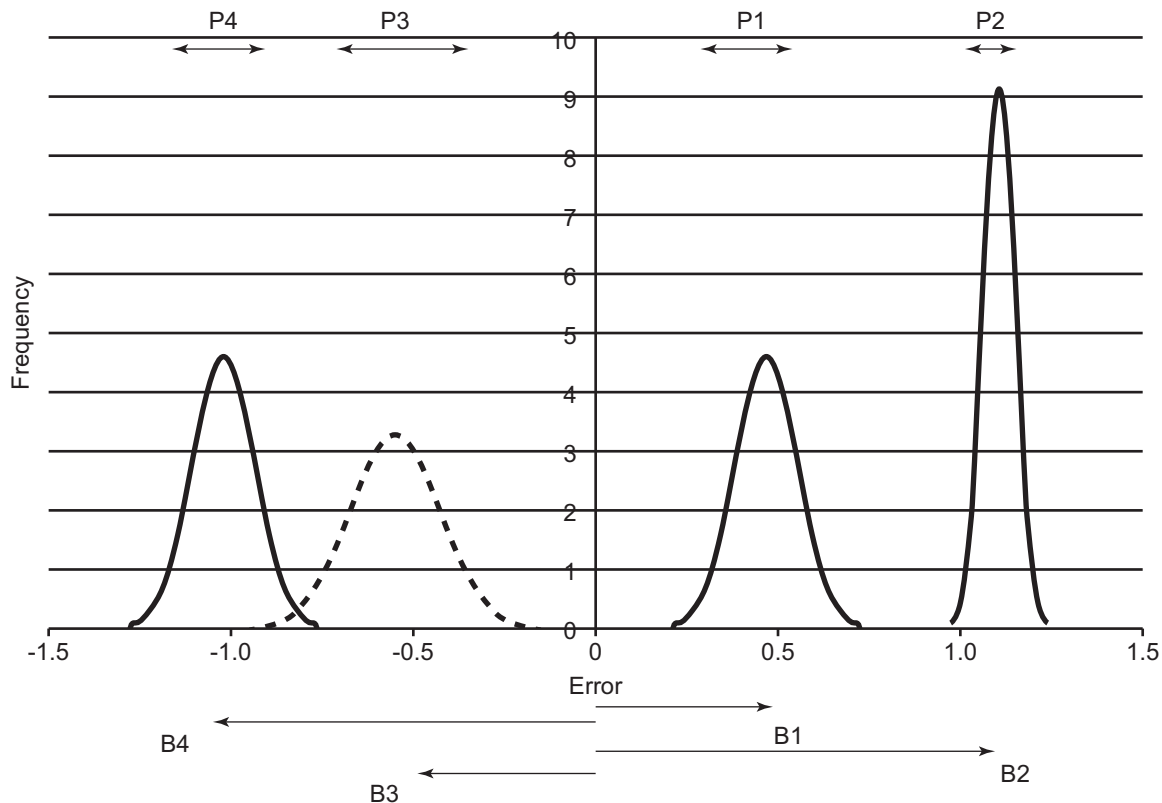


Figure 5—Multiple Uncertainty Assessments

- on different pressure transducers, but of the same kind and make, during separate calibrations; or perhaps;
- on the same instrument but over a range of operating conditions (e.g. fluid type, temperature, or pressure) that might be encountered during a transient scenario.

The result is that there is an uncertainty in the bias and precision figures themselves, related to the cumulative uncertainty in the sample means and sample variances that are used. It is therefore more useful to think of the *distributions* of biases and precisions, as shown in Figure 6.

The diagram in Figure 6 is exaggerated for clarity. In practice, the mean precision will be rather less than the standard deviation of the bias (although there may conceivably be situations where this is not the case). Also, in practice, it is quite common to take or estimate P to be exactly zero.

In this procedure, the essential metrics are:

- a chosen multiple of the standard deviation—or alternatively a specified confidence interval—of the bias (marked as B in the diagram); and
- the mean precision (marked as P in the diagram).

6.2.5 Assumptions

A systematic procedure is used in the procedure to accumulate and to transform the bias and precision of uncertainties. *No attempt is made to calculate the distribution of the combined uncertainties.* Throughout the study, the following is assumed.

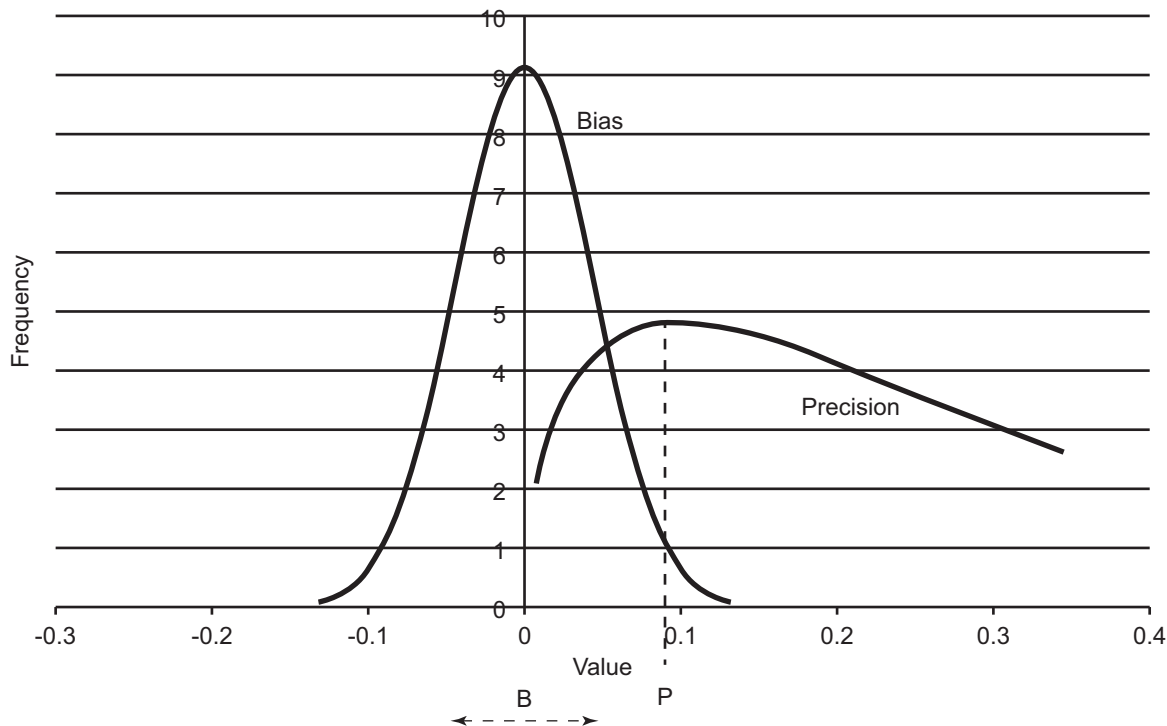


Figure 6—Distribution of Bias and Precision

- Separate sources of uncertainty are independent (uncorrelated) from each other. For example, any inaccuracy in the measurement of the length of the pipeline is unrelated to errors in the density measurement of the gasoline. This is also the case for engineering factors; for example, the uncertainty due to the pipeline starting up is statistically independent of the uncertainty in fluid density.
- The values of precision are very small compared with the reference value. It is hard to be more precise, but many of the transformation algorithms generally begin to be inaccurate when the precisions are greater than about 5 % of the reference value. For example, any inaccuracy in the measurement of the length of a 100-mile pipeline is assumed to be of the order of a small fraction of one mile.

These are strong assumptions, but generally allow uncertainties to be combined and transformed very simply.

- Adding two uncertainties sums their biases and sums their variances (the square of their precision).
- Multiplying two uncertainties multiplies their biases. The combination of their variances is more complicated, but still an explicit single-line expression.
- Any transformation of an uncertainty by a smooth function multiplies the bias and precision by the value of the derivative of this transformation, evaluated at the mean.

This generally allows for a simple “accumulating sum” approach to combining new sources of uncertainty. Every time an additional source of uncertainty is assessed, it can independently add its bias and variance to the current totals. There is no need for these individual sources of uncertainty to be added in any particular order or any differently—provided that the basic independence and smallness assumptions are respected and the categories of uncertainty are tracked. With reference to the general form of CPM leak detection approaches, the two main categories of uncertainty are *measurement* and *metric*.

6.2.6 Approach

Metric Uncertainties are assessed for the metric specifically used by the LDS. This is accomplished by use of a reference model that is designed to assess the impact of both: (a) uncertainty in the inputs; and (b) uncertainty due to engineering factors, particularly any transient effects. Each *independent* source of uncertainty is listed, and the impact of each source on the metric itself is computed, independently of the others (i.e. holding all other factors at their expected value). As each uncertainty is added, biases and variances are accumulated, using the assumptions regarding statistical independence and small variance. At the end of this process, there is a total uncertainty in the metric—in terms of a bias and precision per CPM scan. For most LDS that are based on a balancing principle, an accumulation time period is used. A final adjustment provides a resulting precision that takes this accumulation time period into account.

Various comparison methods could be used, and the approach is to assess them as an added source of uncertainty. Typically, this results in a final PDF with a bias and precision in the same measurement units as the metric. This represents a measure of the final compound uncertainty of the LDS. Extreme care needs to be exercised when attempting to take the bias and precision; and availability and robustness; and then attempting to represent them as rates of misses and false alarms. *This is generally impossible*, and is discussed at length.

Even though the language used is different, these approximations are practically equivalent to the deviations analysis procedure used throughout the 1993 API 1149. If the “accuracies” used by the 1993 API 1149 are systematically treated in terms of a multiple of a standard deviation, then the resulting computed accuracies will again be in the same terms. It is nevertheless worth recalling the fundamental assumptions of smallness and independence of the sources of uncertainty.

Finally, define two general categories of uncertainty:

- 1) known uncertainty, typically from instrumentation, where a bias and precision can be assigned from repeated experiments or calibrations; and
- 2) spurious uncertainty from factors that are only estimated. An example might be the ambient temperature of the pipe, if not measured. It will have a value that may have a significant impact on the hydraulics, but the average value and variance will need to be estimated.

Generally, the approach will accommodate both types of uncertainty—the requirement is that a bias and variance is measured, assessed, or estimated.

6.2.7 Graphical Representations

A *tornado diagram* is designed to illustrate the impact of uncertainty of each input variable or engineering factor on the final uncertainty. The base line is the value of the metric when all inputs are at their reference values. The left of each bar represents the value of the metric with a given input uncertainty at plus (or minus, depending on the relationship between variable and output) one deviation “B” and all other inputs held constant. Correspondingly, the right of each bar represents the value of the metric with the given input uncertainty at minus (or plus, depending on the relationship) one “B” and all other inputs held constant. The value of this diagram is that it illustrates at a glance which variables have the most impact on the result, and conversely which inputs have negligible effect.

For uncertainty calculations, the x-axis of the tornado diagram typically indicates deviations from the reference.

As a practical matter, a typical liquids pipeline will generally have an *overall* tornado diagram similar to the one shown in Figure 7 (with the x-axis representing deviations in percent of the nominal flow rate, or imbalance in BBL).

In Figure 7:

- composition refers to the fluid specific gravity, or its composition in the case of mixtures of liquids or gases;

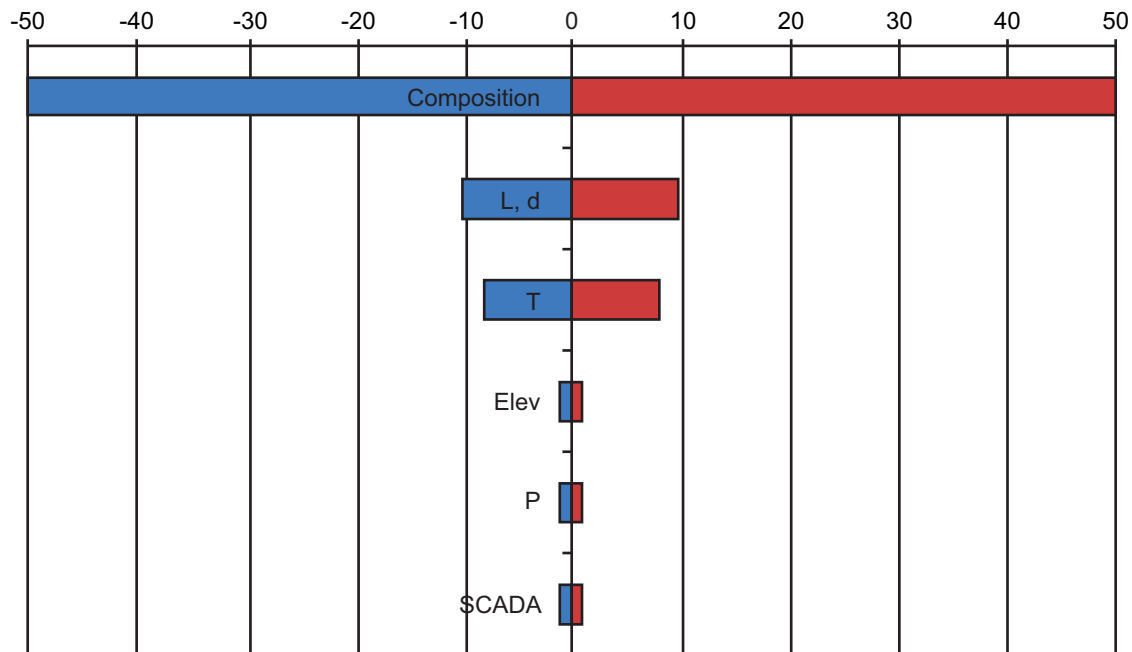


Figure 7—Typical Uncertainty Impact, Liquids Line

- *L, d* refers generally to the pipeline physical dimensions, including length, diameter, and wall thickness;
- “elev” refers to the pipeline elevation profile;
- *P, T* refers to pressure and temperature measurements;
- SCADA refers to uncertainties in the data due to telemetry.

This diagram was developed as one of the main results of applying this procedure to an example batched products pipeline. The uncertainty due to *composition* is therefore specifically related to the uncertainty in the product type actually present in the line. Also note that this diagram relates to a quasi-steady state situation, where there is no large physical change in linepack. In transient scenarios, the transient effect alone dominates any one of these physical factors.

This illustrates how an uncertainty of 0.1 %, for example, in the reference density or composition of the fluid has by far the largest impact on total uncertainty. This includes, for example, uncertainty in the position or content of the batches in a multiple-product pipeline. Configuration measurements like Length and diameter has the second biggest relative impact. Temperature measurements are then the next most important, followed by elevation measurements, pressure measurements and SCADA uncertainties. The general lessons learned from this kind of an analysis are that LD techniques will benefit most from improvements in knowledge about the fluid properties first, followed by the pipeline configuration and temperature measurement.

The typical tornado diagram of a gas pipeline is quite different (with the x-axis representing deviations in percent of the nominal flow rate, or imbalance in SCF). See Figure 8.

Because of the importance of the density/specific volume correction in most mass-balance techniques, the impact of temperature and pressure (and measurements that affect pressure) are much greater.

This diagram was developed as one of the main results of applying this procedure to an example natural gas pipeline. Therefore, the uncertainty due to *composition* is related specifically to the uncertainty in the gas density actually

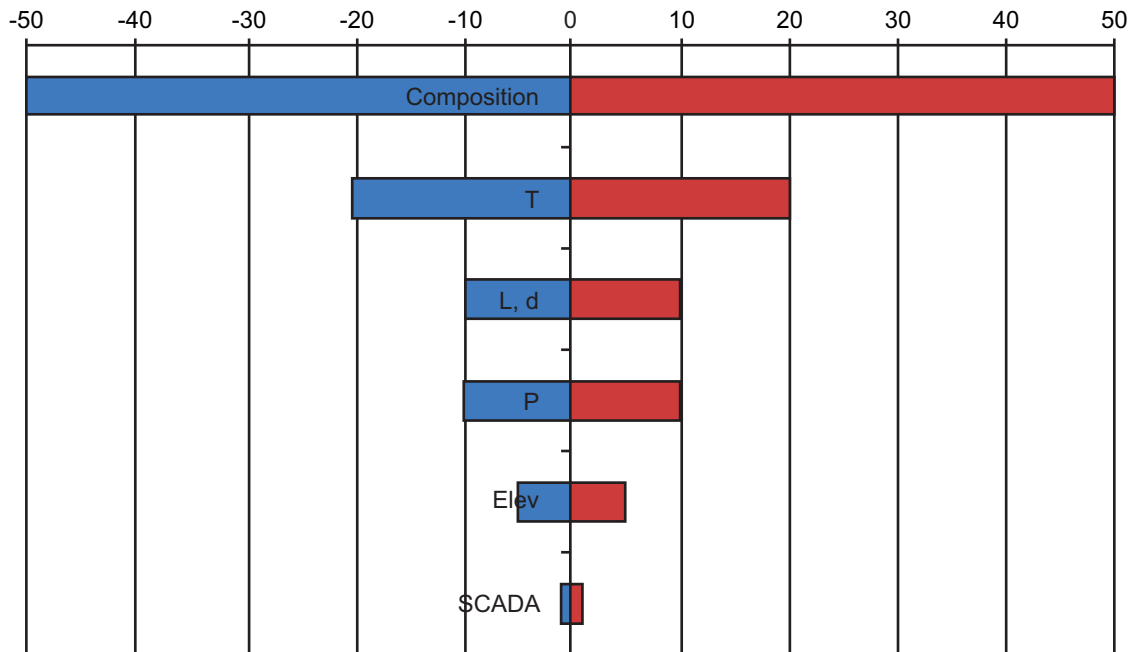


Figure 8—Typical Uncertainty Impact, Gas Line

present in the line. Also note that this diagram relates to a quasi-steady state situation, where there is no large physical change in linepack. In transient scenarios, the transient effect alone dominates any one of these physical factors.

6.2.8 Availability and Robustness

The standard definitions of the API *MPMS* (2013) are modified slightly, again in order to avoid confusion among leak detection engineers (Salmatanis, 2014).

Availability is defined as the *probability* that a product or system will perform its *intended function* for a *specified period of time* under a *given set of conditions* (Lewis, 1995).

For the purposes of this document, availability is the “useful number of CPM scans between failures of the LDS” (time definition) or “ratio of successfully executed CPM scans to failures” (probability definition) under normal operations of the pipeline. This relates to the standard definition of MTBF via $\text{availability} = \text{MTBF} \times f$ monitoring computations, where f is the frequency with which the CPM is invoked. This is a *probability* (no units):

$$\text{MTBF} = \frac{\Sigma(\text{start of downtime} - \text{start of uptime})}{\text{number of failures}} \quad (1)$$

The *robustness* figure is chosen to represent the mean proportion of times (i.e. the probability) when the instrument is read, that the reading deviates substantially from its rated uncertainty. Note that this means a reading no longer within the definition of normal, Gaussian error. Generally, the assumption is that this unreliable reading will cause false alarms from the LDS. For the purposes of this document, this is measured as an overall system MTBF. The overall system MTBF is the *harmonic sum* of all the MTBFs in the system. It is a *time* (in seconds, or other convenient time measure).

Note that LDS that are redundant can have substantially lower MTBF values, since redundant subsystems combine by *harmonic product* to give a much smaller value. However, this is not the subject (prediction of performance of a single CPM LDS) of this document.



Availability and robustness are tracked separately, for the most part, from bias and precision. The one time that they interact is when any filtering is used, in which case precision is improved at the expense of availability.

6.2.9 Measurement Uncertainty

The cumulative uncertainty of all the inputs to the CPM algorithm is calculated. The first step is to assemble all the instrumentation that is used with the CPM LDS and to assign a bias spread, B, and mean precision, P, to each of these. It is not the purpose of this document to specify precisely how these biases and precisions are evaluated, and the operator is asked to use industry or corporate standards during their evaluation. Nevertheless, guidance is provided in the corresponding section, which applies specifically when these data are to be used in the procedure for assessing uncertainty.

Very often, bias and precision are not the specifications that are provided by the manufacturer or by a calibration report. A figure for “accuracy” is often quoted in specifications, and this is usually in terms of a “ $\pm$ percentage”. The basis for the percentage is often unclear. The first step is to convert this accuracy into an absolute value, and then to clarify the following.

- If this accuracy may be a range of potential biases in measurement, in which case there is a figure for worst-case bias, but precision still needs to be assessed. The manufacturer may cite this as a “repeatability” figure.
- If this accuracy may be a measure of precision. In this case, it is important to specify how many standard deviations this accuracy represents; the procedure asks for one standard deviation, but manufacturers and testing facilities often differ on this. The bias can be estimated from the average of the accuracy limits.

A figure for “repeatability” is often quoted in specifications and can generally be understood to represent a measure of precision. The bias still needs to be assessed, but will usually be quoted as “accuracy”.

When a proving report is used, at least it is known that the API *MPMS* (2013) standards, Chapter 4: *Proving Systems*, have probably been followed: the repeatability will specifically be an estimate of the variance and accuracy will be an estimate of bias. Nevertheless, it is important to note that:

- the measurements must be entirely independent of each other, and be raw, unprocessed;
- the accuracy of these estimates itself depends on the number of independent samples used in the tests. This number must be large enough for the estimates to be useful.

Recall that one of the central assumptions is that separate sources of measurement are statistically independent. This is one common area where hidden assumptions may be made. As an extreme example, a single measurement at a manifold may be allocated to several points on a system, in which case all these measurement points actually have the very same statistical distribution—quite the opposite of independence. If several apparently separate measurement points are actually connected, it is usually best to consider them as one.

Another example might be when various temperature measurements from the same meter temperature transmitter are used to determine the meter factor, the correction for the effect of temperature on the metered liquid and the correction for the effect of pressure on the metered liquid.

Finally, instrumentation is assumed to be raw, physical measurement in the sense of the API *MPMS* (2013). There can be no filtering—including outlier removal, accumulation or averaging—without some thought given to the impact that these data manipulations may have on the uncertainty statistics.

6.2.10 Impact of SCADA

The raw measurements are then combined and transformed via a SCADA system. The factors that are explicitly considered are listed in Table 4.

Table 4—Telecommunications Uncertainties

SCADA Parameters		Units
ΔT	Total scan period, average—includes delays, etc.	s
Rel	Reliability—fraction of bad data points	(fraction)
Av	Availability—fraction of dropouts	(fraction)
Res	Resolution of measurement	(fraction)
Sf	Scale factor variance	(fraction)
Em	Transmission noise—systematic bias	(fraction full-scale)
Es	Transmission noise—sigma	(fraction full-scale)
Tsm	Data-time skew (bias)	s
Tss	Data-time skew (sigma)	s
Processing Parameters:		Units
N	Averaging chain number (smoothing)	#
Lo	Low cutoff	(fraction full-scale)
Hi	High cutoff	(fraction full-scale)
LRR	Low reliable reading range (RR)	(fraction full-scale)
HRR	High reliable reading range (RR)	(fraction full-scale)
Tcf	Front-end processing latency	s
Unknowns (Spurious Uncertainties):		Units
UN	PLC/DCS/Flow computer access latency (skew)	s

Note particularly that in most practical applications the first three items—an analysis of SCADA effective scan period, reliability and availability have the greatest impact on total measurement uncertainty. In addition, if there is any data processing at the SCADA system level, the most important factor is any smoothing or dead banding. A typical Tornado diagram illustrating the general relative impact of each SCADA/telecommunications parameter is shown in Figure 9 (with the x-axis representing deviations in percent of the nominal flow rate, or imbalance in BBL).

This diagram was developed as one of the main results of applying this procedure to an example crude oil pipeline. Typical values for each of the SCADA uncertainties were applied, and their impact on a standard mass flow imbalance LDS was recorded.

Recall that in any case, the relative impact of SCADA uncertainties is usually small compared with many other physical uncertainties—see Figure 7 and Figure 8.

The impact of the number of, and distance between measurement points is particularly significant, however. This is particularly important for pressure wave detection where very many pressure instruments may be required. The technique can be used to regard the number and distance between measurement points as any other engineering factor.

Any other inputs to the CPM algorithm (spurious uncertainties) are assigned a mean value and a variance as well, using the experience and engineering judgment of the operator.

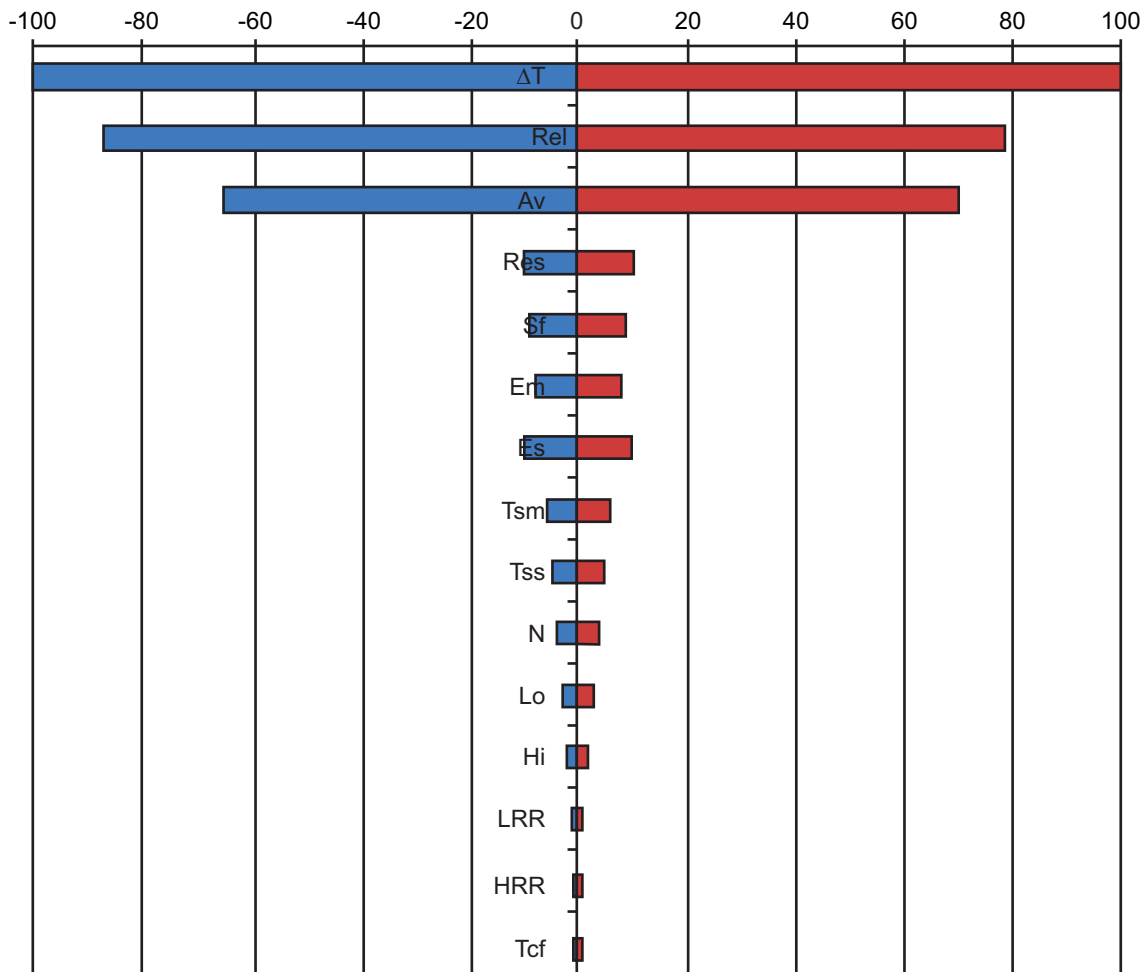


Figure 9—Typical Tornado Diagram for Telemetry Uncertainties

The frequency f with which the CPM is invoked is generally $f = 1 / \Delta T$. This strong relationship with the CPM method itself is among the reasons why ΔT has such a strong impact.

6.3 The Reference Model (RM)

6.3.1 General

A major feature of this procedure is that it relies upon software, and in particular upon a reference model, which calculates the reference physical state of the pipeline. The purpose of this reference physical state is to allow an estimate of the bias and precision due to assumptions in the CPM method (steady state hydraulics in a line balance, engineering factors, etc.), beyond the effects of instrument uncertainty on the CPM method.

This is a numerical model of the pipeline that calculates an estimate of the unknown true reference physical state of the line and the contained fluids, and its variation with time. The reference model includes as much of the physical detail of the pipeline being analyzed as feasible. The reference physical state of the pipeline includes “virtual” reference values for any instruments used in the CPM method—allowing an estimation of a reference CPM metric. However, note that the RM is completely independent of the LDS technique used; it only provides a reference state of the pipeline.

The RM itself is subject to model and numerical uncertainty. The additional uncertainty introduced by modeling to the actual reference conditions is, according to ASME V&V 20 (2009):

$$U_s = U_{\text{input}} + U_{\text{model}} + U_{\text{num}} \quad (2)$$

These three terms are:

- 1) Input uncertainty—in this treatment, this is analyzed under measurement uncertainty and it is assumed that there is no additional input uncertainty beyond measurement and telemetry itself.
- 2) Model uncertainty—this is due to physical assumptions and approximations. It is useful to separate this into two: physical effects that are ignored entirely, and other physical estimates and approximations.
- 3) Numerical uncertainty—that is due to the numerical solution of the equations.

The ASME V&V 20 (2009) is normally used to estimate model uncertainty, given a total uncertainty that is assessed by comparisons against physical experiments. This situation is different: an estimate of model uncertainty is provided so that an impact on total error with respect to physical reality can be calculated.

It is useful to divide model uncertainty further into two:

- a) physical effects that are ignored entirely, and
- b) physical estimates and approximations.

The user estimates, or at least provides bounds for, both of these, using experience and engineering judgment. By contrast, the numerical error can be estimated rigorously with a procedure that varies the time and space discretization of the numerical method used by the simulator. The estimation of the numerical uncertainty is called *verification* and is usually split into two categories: code and solution verification.

Code verification evaluates the mathematical correctness of the code and is typically accomplished by simulating a problem that has an exact solution and verifying if that solution is obtained. For the purposes of this document, proceed assuming that code is verified. In other words, there are no errors of code in the leak detection algorithm being used.

Solution verification is the process of estimating the numerical uncertainty for a particular solution of a problem of interest. The two main sources of errors here are: (a) the discretization, and (b) the iteration processes. The discretization error is the difference between the result of a simulation using a finite grid and that obtained with an infinitely refined one. The iteration error is present in codes that use iterative solvers, where the result must converge to the exact value as the iterations develop.

It is important to remember that the reference model uncertainty is the absolute least level of precision that the overall leak detection uncertainty estimation procedure can estimate. This critically means that if a fairly coarse or inaccurate RM is used during the procedure, it is quite possible that it will simply be unable to assess a higher-fidelity leak detection algorithm. For this reason, any analysis that uses an RM must report the baseline estimate of the RM's own bias and precision.

Of particular note is the approach to leak detection algorithms that use computational fluid dynamics (CFD) themselves—these techniques are often referred to as real-time transient models (RTTMs); otherwise the approach utilizes simple Bernoulli's. Since all the estimates are with respect to a CFD model as well, the default assumption is that the operator's RTTM is at least as accurate as the reference model. Therefore, the assessed RTTM modeling error for leak detection is precisely the minimum uncertainty in the reference model.

The RM is then used to calculate the reference values of the metrics used by each of the CPM methods. It can assess their variability with respect to a number of engineering factors, and also major issues (or gaps) within the 1993 API 1149, which are summarized which are summarized in 6.3.2 through 6.3.9.

6.3.2 System Size, Complexity, and Batch Operations

This discussion concentrates on two main classes of pipeline models.

- A single, straight (perhaps inclined) pipe of general dimensions. This model can be analyzed for behavior against all the other engineering factors.
- A generalized network of pipes with the restriction that there is no flow control or pumping/compression within the interior of the network. This model can be analyzed for transient behavior and a number of the other engineering factors.

Any network that does contain flow control can be decomposed into appropriate sub-networks if discharge and/or intake pressures, and flow rates, are being monitored. Also note that not necessarily all engineering factors can be analyzed consistently in a network due to non-uniqueness of several results.

While extrapolation to other piping configurations such as gathering networks, looped or branched distribution systems may be possible under certain simplifying assumptions, it is generally beyond the scope of this document.

6.3.3 Existence of Pre-Existing Leaks

Any technique that includes a line balance can potentially be used to detect a pre-existing leak. Few other methods are suitable for detecting pre-existing leaks. A related issue is leak detection during shut-in conditions.

6.3.4 Sensitivity to Flow Conditions

Five categories of flow condition are identified.

- 1) Steady state, in which none of the conditions on the pipeline (including inlet and outlet pressures, flows, and temperatures) change.
- 2) Shut-in, where there is no flow but the line is maintained tight, at above atmospheric pressure.
- 3) Transient, in which one or more of the conditions on the pipeline is varied from an initial to a final value over a given period of time, with a ramp profile.
- 4) Shut-down transient operations, and start-ups transient operations
- 5) Slack-line flow (SLF), where the pressure in a liquid line falls locally below its vapor pressure so that there are sections with vapor present.

In the analysis of transient conditions, the impact of the change in one pipeline measurement is studied and then, if several of them are changed, these individual effects are combined.

Note also at this stage that, even in steady state conditions, the uncertainties can be transient in nature. The small, random fluctuations in the boundary conditions (particularly temperature) inherently lead to transient effects.

6.3.5 Multiphase Flow

Mixed multiphase flow is not considered in this document. It generally leads to uncertainties in measurement and modeling of magnitudes that are beyond the present scope.

6.3.6 Gas and High- and Low-volatility Liquids

Single-phase gas and single-phase of high and low volatility liquid flow in the pipeline of industrial petroleum hydrocarbons are explicitly considered. Their main effect on leak detection calculations is in the estimation of the fluid bulk modulus (and, to a lesser extent, other fluid properties). In this regard, this document adopts the other applicable standards from the API, AGA, and GPA—specifically:

- API 2540, taken from Chapter 10 and Chapter 11 and other appropriate sections of the API *MPMS* (2013);
- AGA Standard #8 (1992), for gases. Also widely used is the GERG-2008 equation of state model, also adopted as ISO 20765;
- GPA Technical Paper TP-27 for LPG and NGL from *MPMS*, Chapter 11—*Physical Properties Data*—Section 2, Part 4—*Temperature Correction for the Volume of NGL and LPG*—Table 23E, Table 24E, Table 53E, Table 54E, Table 59E and Table 60E.

Carbon dioxide pipelines are also considered, using the tables for CO₂ physical properties from the NIST *Reference Fluid Thermodynamic and Transport Properties Database (REFPROP)* V.9.1 (2013). However, high concentration dense-phase CO₂ systems may exhibit dramatic density changes with the presence of minor concentrations of light hydrocarbons such that Equation of State methods yield better results. Operators of systems with these characteristics should evaluate the fluid property trends for any discontinuities in the range of operating conditions.

It is generally recommended to use these references in favor of more complex equation of state (EOS) or other equation-based procedures, especially when the fluids transported are almost pure single-phase hydrocarbons. In most typical midstream, industrial applications there is very little benefit in using an EOS, especially considering the added complexity. The use of EOS becomes more important when hydrocarbon mixtures are considered, which the case is often in upstream gathering systems. However, in these situations multiphase hydraulics effects generally dominate and the added accuracy in density becomes less significant. Furthermore, their reliability is reduced by considerations of their range of applicability, critical points, etc.

For several leak detection methods an estimation of pressure drop is also necessary. The Colebrook (1939) equation for friction factor is used, primarily because it is widely adopted in the industry. This still has one free parameter, the roughness ϵ , which is an unknown length and is related to the mean roughness height of the internal wall of the pipe.

6.3.7 Temperature Effects

Uncertainty in end-point boundary conditions, but particularly temperature, can have unpredictable effects on the hydraulics of a pipeline. Even in an apparently steady-state condition, where the average temperatures are constant, both the value and the stability of the temperature reading is generally uncertain.

Observe that—certainly for short times—the disturbance to the overall average temperature in the pipe is far smaller than simply perturbing a fully steady-state model. This is because any local temperature change will diffuse only at a finite rate along the pipeline and its fluids. Therefore, any local temperature uncertainty is by its nature a transient effect.

In calculating the temperature profiles, a piecewise constant thermal conductivity is generally assumed. The ambient temperature profile is at most a piecewise linear profile between two end point ambient temperatures.

6.3.8 Drag Reducing Agents (DRA)

The treatment is limited to situations where the operator can express the drag reduction (as a percentage of frictional pressure drop) takes the form, when DRA is added at a concentration of ppm (Burger, Munk, and Wahl, 1982):

$$\text{Drag reduction} = \frac{\Delta P \text{ with DRA}}{\Delta P \text{ no DRA}} = A / (\text{ppm} + B) \quad (3)$$

An estimate of A and B magnitude and uncertainty are therefore required. Note that other forms of Equation (3) are often used as well.

6.3.9 Batch and Pig Tracking

Both Batch and Pig tracking are a form of added uncertainty due to a transient effect.

Batch tracking uncertainty enters the analysis as an uncertainty due to a change, of uncertain timing, of the entry or exit of a new fluid type in a pipeline.

Pig tracking leads to a combination of two effects:

- an uncertainty in the position of the pig. Pigs often either “stick” or “leak” which means that their actual position is often quite far behind where expected; and
- an uncertainty in the pressure differential across the pig due to varying friction with the pipe wall.

6.4 Metrics

The CPM will calculate a metric, which is an indicator used to assess the likelihood of a leak in the pipeline. These metrics are summarized in this table (compare with Table 1) and are further explained in Table 5.

It is useful to summarize the required data for each of these techniques in Table 6.

It is the primary purpose of the RM to assess the uncertainty in the metric, by providing the procedure with a reference pipeline state with which to compare. Evidently, the uncertainty in the metric can only be assessed up to the level of uncertainty in the RM that is used.

This procedure assumes that there is uncertainty in the measurements, but it ignores any variability in the time of occurrence of a transient. In other words, the measurements as made may be subject to a bias and error, but they physically occur within the small interval of time defined by telemetry uncertainties.

Each time a separate parameter is assessed, and the bias and precision of its impact on uncertainty is calculated, the additional bias and precision is tracked with a running total.

6.5 Rate of False Alarms and Misses

At this point, a bias and precision estimate is available for the metric from the running total of the biases and precisions due to each parameter assessed.

The reader is warned again that without knowledge of the precise nature of the PDF, a bias and precision do not translate to a *probability* beyond a certain threshold. This is relevant when one attempts to translate the final bias and precision of the LDS into a rate (i.e. a probability) of false alarms. This probability is, just as in Figure 3, the area under the PDF greater than the threshold. Without knowledge of the exact form of the PDF, this is impossible. Rule of thumb and estimates are to be avoided in this regard since they can be very misleading.

This topic is quite extensive, and applies to many areas of uncertainty and reliability analysis. For this reason, Section 13 is dedicated to a fuller discussion of rate of false alarms and misses.

Table 5—Leak Detection Techniques and Their Metrics

ID	Description	Metric
1	Regular or Periodic Monitoring of Operational Data by Controllers:	
a.	Volume balance	Outlet volume minus Inlet volume, from rates totalized over a given time.
b.	1.b.i—Rate of pressure change	Rate of change of a single pressure reading, over a given time.
	1.b.ii—Rate of flow change	Rate of change of a single flow rate reading, over a given time.
2	Computational Pipeline Monitoring:	
a.	Mass balance	i. Outlet mass minus Inlet mass, from rates and local density totalized over a given time. ii. As i, but with linepack estimated from a fixed pressure/temperature profile.
b.	RTTM: 2.b.i—Model-compensated mass balance	As 2.a.ii, but with linepack estimated from a RTTM
	RTTM: 2.b.ii—RMS analysis	A subset of the pipeline state, estimated from a RTTM

Table 6—Leak Detection Techniques and Required Data

ID	Description	Minimal Required Data
1	Regular or Periodic Monitoring of Operational Data by Controllers:	
a.	Volume balance	Inlet and Outlet volume flow rates (m ³ /s or Bbl/hr)
b.	1.b.i—Rate of pressure change	A pressure (kPa or PSIA)
	1.b.ii—Rate of flow change	A volume flow rate (m ³ /s or Bbl/hr).
2	Computational Pipeline Monitoring:	
a.	Mass balance	Inlet and Outlet volume flow rates (m ³ /s or Bbl/hr), plus: i. Inlet and outlet pressure (kPa or PSIA). ii. Inlet and outlet temperature (C or deg.F).
b.	RTTM: 2.b.i—Model-compensated mass balance	Multiple flow rates (m ³ /s or Bbl/hr); pressures (kPa or PSIA); and temperatures (C or deg.F).
	RTTM: 2.b.ii—RMS analysis	
3	Leak location	
a.	Leak location via gradient intersection	At least two pressures (kPa or PSIA)
b.	Leak location via pressure wave speed	
c.	Leak location via scenario testing/optimization	As for RTTM

6.6 Filtering

Data and calculated values are often filtered, either explicitly or implicitly via data processing. A good example of implicit filtering is time-smoothing or using a moving average. This is very common in SCADA system processing, and results in a low-pass filter.

A particular issue with all filtering is that it can make the data physically and hydraulically inconsistent, despite the apparent statistical advantages.

The approach to filtering is to define formulas that relate the bias and precision before and after filtering. In general, this results in a reduction in variance. This is at the expense of two items:

- 1) time horizon to detection; and
- 2) reliability.

The reduced reliability results from the fact that outliers that are filtered out still represent a sample of readings that might have resulted in an alarm. There is therefore a trade-off between improved precision and reduced reliability.

6.7 Outputs

The general form of the results of an uncertainty calculation is illustrated, by using as an example one of the balancing CPM methods, corresponding to 1.a or 2.a in Table 3. The general observation is that any uncertainty that is constant—i.e. has a fixed bias greater than zero—does not decay with time; whereas, any random uncertainty with zero mean does decay with time. In an ideal case, where the uncertainty is constant with time, the bias of the moving average is unchanged, constant; the precision of the moving average decays as N , the number of samples used in the average. Very often, though (particularly when dealing with uncertainties due to a transient hydraulic effect) the uncertainty is *not* constant with time, and the decay of the precision is not proportional to N .

With most CPM balancing methods, a balancing period T is set. The general behavior of CPM uncertainty is sketched in Figure 10.

- The x-axis is T and the y-axis U is the cumulative uncertainty at one standard deviation (or any specified multiple/fraction).
- The line A represents the flow measurement (i.e. meter + SCADA) bias effect, which is constant.
- The line B represents flow measurement (i.e. meter + SCADA) precision effect, which is constant.
- The line C represents the precision effects of the measurement system. It decays with time but can be significant for short times.
- The line D includes any physical variability (notably, linepack effects) estimated from the reference model and all the remaining instrumentation. Its tail represents the underlying reference model numerical and model uncertainty.
- These lines sum, to give a total standard deviation in uncertainty.

It is also recommended to record the impact of each of the input variables, for each perturbation, for each scenario. As an example, where the uncertainties are in the Upstream (IN) and Downstream (OUT) Pressures (P) Rates (Q) and Temperatures (T)—and the CPM is a mass balance over/short averaged over 10, 60, 120, and 1200 seconds—this might create a table like Table 7.

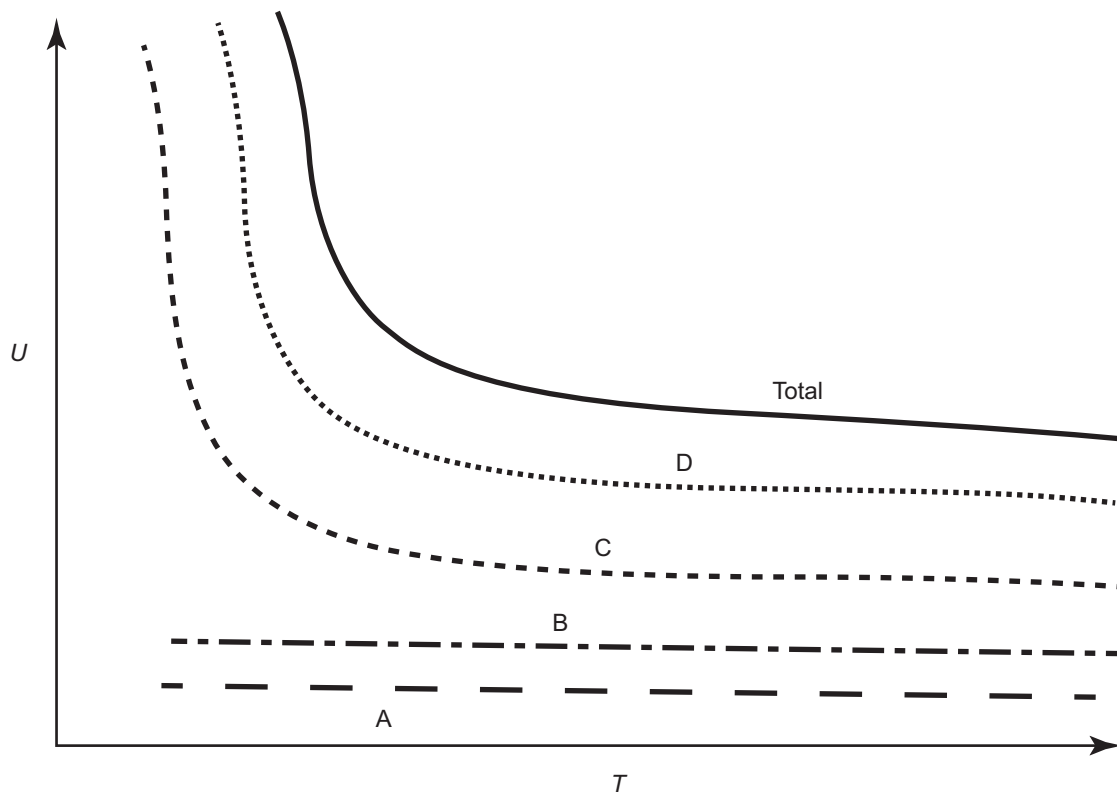


Figure 10—General Form of the Uncertainty, Imbalance LDS Techniques

Table 7—Template Uncertainty Table

Inputs						Max STP Imbalance B			
QIN	PIN	TIN	QOUT	POUT	TOUT	10 s	60 s	120 s	1200 s
Ref	Ref	Ref	Ref	Ref	Ref				
Ref + B	Ref	Ref	Ref	Ref	Ref				
Ref	Ref + B	Ref	Ref	Ref	Ref				
Ref	Ref	Ref + B	Ref	Ref	Ref				
Ref	Ref	Ref	Ref + B	Ref	Ref				
Ref	Ref	Ref	Ref	Ref + B	Ref				
Ref	Ref	Ref	Ref	Ref	Ref + B				

Here, the abbreviation *Ref* stands for the Reference or expected value of each of the individual uncertainties. The total uncertainty, due to the effect of all the parameter uncertainties, on this particular CPM Metric is obtained by combining each of Imbalance columns by root-mean-square.

If tracking of the precision is also desired (as recommended by ASME V&V 20, 2009) then a similar table for the “*P*” perturbations can be produced.

A tornado diagram of variability due to each individual parameter can be built from the CPM metric table. Each bar in the diagram will simply be $\pm$ the value of the Imbalance B for each row in the table. An example is shown in Figure 7 and Figure 8.

6.8 Outline of the Document

The next three sections provide a sequential approach to estimating uncertainty. They follow the process Input-Model-Numerical Algorithm [see Equation (1)]:

Section 7 describes how uncertainties due to measurement are found. This includes the components of instrument and metering uncertainty, and components of telemetry uncertainty. At the end of this process the inputs to a leak detection algorithm are assessed a bias, precision, robustness, and availability.

Section 8 describes how uncertainties due to the metric are estimated. For most LDS techniques, this includes a comparison with the reference model described in Section 6. The methods of using the reference are covered in detail in this section, and at the end of this process the measures used by the leak detection algorithm are assessed an uncertainty.

Section 9 provides a brief reference on the impact of filtering on an uncertainty distribution. Filtering can in principle be used at any stage of the input-model-comparison chain, so the objective of this section is to highlight how the general uncertainty estimation process can take this into account in specific circumstances.

The final sections are reference material.

Section 10 covers the uncertainty model. To understand and to use the algorithms, it is only necessary to read 5.2. Nevertheless, the justifications and derivations that are used throughout the method are discussed. There is also a brief set of citations to the ASME, API, and ISO that the reader can use for alternative discussions.

Section 11 describes the techniques used in the reference model. it discusses only the reference itself—the actual utilization of the model in order to assess the uncertainty in the metric of the LDS is discussed in Section 6.

Section 12 provides exact definitions of the LDS technologies that are covered in this work. Again, it only provides their specification—the discussion of how to assess their uncertainty is covered in Section 7 and Section 8.

All published references that are made in the document are consolidated at the end.

Three more extended discussion sections are also included.

- 1) Section 13—Rate of False Alarms and Measurement Uncertainties. This emphasizes the difficulty, and emphasizes the practical impossibility of finding a rate of false alarms from the assessed precision of an LDS. It also discusses at more length important considerations in measurement uncertainties, used as inputs to the LDS, which are not covered in the API *MPMS*.
- 2) Case Study: Using Meter Data and Reports for Bias and Precision. A practical assessment of metering uncertainty is made using meter proving reports and manufacturer's specifications, in order to illustrate the ambiguities in these sources for estimating bias and precision.
- 3) Case Study: Worked Example Uncertainty Assessment. This worked example covers all the steps in the uncertainty assessment for a simple pipeline.

7 Measurement Model

7.1 General

As explained in the Introduction, and in Section 10—Uncertainty Model, it is useful to divide sources of uncertainty in computing the LD metric systematically into:

— instrumentation and measurement,

- telemetry,
- model error—Type A,
- model error—Type B,
- numerical errors,
- filtering.

This section focuses on the first two elements, which are central to Measurement and Instrumentation. The assumption is that the flow rates, pressures and temperatures (and, perhaps, densities, viscosities, or fluid quality) are measured at the pipeline and then transmitted to the LDS with a given reference period ΔT (i.e. frequency $f = 1 / \Delta T$).

Where appropriate, the measurement uncertainty is divided into two components:

- continuous variability due to uncertainty while in normal operation; and
- a mean time between failure (MTBF) that represents the likelihood of failure of the component.

These two can be tracked separately, until potentially a final roll-up calculation is performed to assess availability and reliability from the sub-system MTBFs. Note that in many practical applications the MTBF dominates the uncertainty values during normal operation. It is not unusual for instrument accuracy to contribute ~0.1 % uncertainties, while the overall LDS availability can be in the 99 % range—i.e. perhaps ten times as significant.

Uncertainty due to measurement is the first step in a three-step process for estimating the total uncertainty in a leak alarm. It takes as inputs the instrument and telemetry uncertainties and it transforms them into an Input uncertainty in the leak detection technique. For example, suppose a given LDS relies on measurements of pressure, flow, and temperature at the inlet and outlet of a pipeline. The process followed in this section will be:

- assess a bias and precision of all the instruments and meters providing the readings.
- combine these with the telemetry uncertainties associated with each instrument.
- apply any filtering that may have been introduced during measurement (see Section 9).
- at this point, there is a list of uncertainties in pressure, flow, and temperature used as input to the reference model and the calculation of the LDS metric.

There is also a Case Study: Using Manufacturer Specifications and Meter Proving Reports, using this section in a practical example.

7.2 Instrument Uncertainty

7.2.1 General

The aim is to follow the standard ASME/ASTM presentation (2013 API *MPMS*, 2013) of meter and instrument uncertainty. The *reference value* is the unknown, true physical value that is being measured; *accuracy* refers to any systematic bias in the measurement; and *precision* refers to the variance of the measurement.

To avoid confusion, another terminology convention is adopted: *accuracy* will be replaced by the term *bias*, or *systematic bias* for emphasis.

Therefore, the measurement is a random variable with a distribution (API MPMS, 2013):

$$\text{Measurement} \sim \text{Reference Value} + U_m = \text{Reference Value} + b + X(0, a^2) \quad (4)$$

Here, X is a random variable with an unknown probability distribution of mean 0, and unknown standard deviation a . Equate b with the bias, and a with the precision.

In following the API MPMS (2013), it is reasonable to assume that the unknown probability distribution with meters and instruments is Gaussian. The unknowns a and b are estimated from a collection of k independent, unrelated trials using the sample mean (average) and sample variance (mean sum of squares deviation) as unbiased maximum likelihood estimators. If the underlying probability distribution is Gaussian then the estimators, too, will be Gaussian.

It is not the purpose of this leak detection publication to specify how the operator estimates the instrument and metering parameters. Nevertheless, this guidance applies specifically when these data are to be used in the procedure for evaluating uncertainty.

7.2.2 Bias Variance/Mean Precision

It is noted in the summary how, in practice, it is difficult to assess a realistic value for the bias and precision for every given measurement. Generally, the bias of a given reading is estimated from a population sample mean (the average) of a number of readings, and the precision from a population sample variance. When the statistics of a number of readings taken from a number of samples are collected, the results are typically as sketched in Figure 5.

The result is that there is an uncertainty in the bias and precision figures themselves, related to the cumulative uncertainty in the sample means and sample variances that are used. It is therefore more useful to think of the *distributions* of biases and precisions, as sketched in Figure 5.

In the procedure, the essential metrics (and in practice usually the only data available to the analyst) are:

- a chosen multiple of the standard deviation—or alternatively a specified confidence interval—of the bias (marked as B in Figure 6); and
- the mean precision (marked as P in Figure 6).

The curve in Figure 6 of distribution of the precisions is chi-squared, while that of the biases is Gaussian—assuming: (a) API MPMS Gaussian errors and no outliers; and (b) that *sample variances and averages* were used, respectively.

The mean readings are estimated using the *sample mean* (or the *average*) of these readings:

$$\bar{X} = \frac{1}{n} \sum X_i \quad (5)$$

The bias is then estimated as the difference between the sample mean and the reference value.

The variance of the readings is estimated using the *sample variance*:

$$S^2 = \frac{1}{n-1} \sum (X_i - \bar{X})^2 \quad (6)$$

The sample variance is then used as an unbiased estimate of the precision.

By design, the mean bias is zero. It is unlikely that known uncalibrated instruments would be used, and certainly most specifications assume that the device is calibrated. The variance of the biases all the samples can be estimated from

the multiple biases $B_1 \dots B_N$ in Figure 1 by using their population variance—which is equivalent to taking the root mean square (as is customary) since the mean bias is zero:

$$B^2 \sim \frac{1}{n} \sum_{i=1}^N (B_i - E(B))^2 = \frac{1}{n} \sum_{i=1}^N B_i^2 \quad (7)$$

Combining all the precisions $P_1 \dots P_N$ in Figure 5 is rather less straightforward. Generally, the most accurate approach is to use a total sample made up of the aggregated individual samples, and perform a sample variance calculation on the complete set (as in the Worked Examples). Otherwise, it is important to know the individual sample sizes for each of the curves. Then, the combined P is the *weighted* RMS average of the samples, weighted by the individual sample sizes.

$$n_1 P_1^2 + \dots + n_n P_n^2 \sim \sum_{i=1}^{n_1} (a_i - E(A))^2 + \dots + \sum_{i=1}^{n_n} (a_i - E(A))^2 = \sum_{i=1}^N (a_i - E(A))^2 \sim NP^2 \quad (8)$$

This is discussed in the ASME V&V 20 (2009) where, apart from other reasons, this explains why it is recommended to record the degrees of freedom (i.e. the sample size) of any precision estimate.

When speaking of flow meters, manufacturer specifications often assume a proved meter: therefore, the mean bias is zero. The quoted $\pm$ *accuracy* (not to be confused with accuracy in the API MPMS [2013] sense, see Figure A.1) is a specified number of standard deviations of the mean bias curve. The quoted *repeatability* is the mean of the mean precision curve.

When speaking of pressure and temperature instruments, manufacturer specifications usually assume a calibrated meter: therefore, the mean bias is zero. The quoted *accuracy* is a specified number of standard deviations of the mean bias curve. A mean precision is rarely quoted—it is generally taken to be so small as to be negligible.

That the sample mean and variance are valid, unbiased estimators is quite independent of the nature of the probability distribution of the readings $\{X\}$. However:

- The readings must be statistically independent and identically distributed (IID). This means that the error in any one reading cannot be correlated with any other reading—in short, each reading must occur as if no other readings had taken place. In practice this means that the system must be allowed time to recover from any prior readings. That the readings are identically distributed means that there can be no artificial processing of the results, or gradually changing errors, due for example to the telemetry system.
- The degree of confidence in both these estimators increases as the sample size increases. If n is only fairly small, then the uncertainty in the bias and precision becomes greater, and generally the assessed precision becomes greater.

Meter proving is generally not designed to provide data to uncertainty analysis. Meters flow at a nearly constant rate throughout the prove cycle and might exhibit significant correlation (non-independence). For example, if one were to bring the flow to zero and then back to rate between each cycle one might get a very different result. This appears hardly ever to be studied or verified; it is not covered in the API MPMS (2013) standards.

With regard to the second observation, it is useful to be able to estimate the degree of confidence in the estimates, as a function of the number of sample readings n . The discussion *assumes that the readings are distributed normally*. This assumption is made in the API MPMS (2013) standards, Chapter 4: *Proving Systems*.

The sample variance S^2 (times $n - 1$) has a *chi-squared distribution* if and only if the underlying distribution of $\{X\}$ is normal, since it is then the sum of n squared normal distributions. It has one parameter— k the degrees of freedom. In the case of the sample variance times $n - 1$, of n normally distributed random variables, $k = n$.

Using this fact, an interval within which it is α -certain that the true variance of the sample will lie is:

$$\left[\frac{S^2}{\chi_{a/2}^2(n)}, \frac{S^2}{\chi_{1-a/2}^2(n)} \right] \quad (9)$$

Where, $\chi_{a/2}^2(n)$ is the $a/2$ confidence interval of the chi-squared distribution with n degrees of freedom. In our application, the general interest is in the worst-case precision, so it is the upper bound that is used. As an example, if a 95 % level of confidence is required in estimating the precision then instead of using the sample variance S^2 , use the *multiples* of S^2 listed in Table 8.

Table 8—Adjustments to the Sample Variance by Desired Confidence

n	95 %	97.5 %	99 %
2	19.75	39.75	99.75
3	9.27	14.95	27.89
4	6.19	8.98	14.49
5	4.81	6.55	9.71
10	2.77	3.32	4.17
15	2.24	2.57	3.04
20	1.98	2.22	2.56
25	1.83	2.02	2.28
50	1.51	1.62	1.75
100	1.33	1.39	1.47

Note particularly that if n is small, around 5, the actual variance might be nearly five times the sample variance, to a 95 % certainty. Even with a sample size of 20, twice the sample variance should be used.

If and only if the underlying distribution of X is normal, then the normalized sample average statistic:

$$T = \frac{\bar{X} - \mu}{S/\sqrt{n}} \quad (10)$$

has a Student- t distribution, with $(n - 1)$ degrees of freedom. As an example, to work to a 95 % level of confidence in estimating the bias then instead of using the sample mean, use the factors listed in Table 9, multiplied by the sample standard deviation S .

Note particularly that if n is small, around 5, the actual mean might be nearly the whole sample variance lesser or greater than the sample mean, to a 95 % certainty.

7.2.3 Instrument Availability/Reliability

As with most industrial devices, metering systems are rated with a MTBF. It is common to combine this with a mean time to repair (MTTR) in order to compute an *availability* figure.

This definition is modified, again in order to avoid confusion among leak detection engineers (Salmatanis, 2014).

For the purposes of this document, *availability* is the “useful number of CPM scans between failures of the LDS” (time definition) or “ratio of successfully executed CPM scans to failures” (probability definition) under normal operations of the pipeline. This relates to the standard definition of MTBF via $\text{availability} = \text{MTBF} \times f$ monitoring computations, where f is the frequency with which the CPM is invoked. This is a *probability* (no units).

Table 9—Confidence Intervals for the Mean, in Multiples of S

n	95 %	97.5 %	99 %
2	2.06	3.04	4.92
3	1.36	1.84	2.62
4	1.07	1.39	1.87
5	0.90	1.15	1.50
10	0.57	0.70	0.87
15	0.45	0.55	0.67
20	0.39	0.47	0.57
25	0.34	0.41	0.50
50	0.24	0.28	0.34
100	0.17	0.20	0.24

The *robustness* figure is chosen to represent the mean proportion of times (i.e. the probability) when the instrument is read, that the reading deviates substantially from its rated uncertainty. Note that this means a reading no longer within the definition of normal, Gaussian error. Generally, the assumption is that this unreliable reading will cause false alarms from the LDS. For the purposes of this document, this is measured as an overall system MTBF. The overall system MTBF is the *harmonic sum* of all the MTBFs in the system. It is a *time* (in seconds, or other convenient time measure).

Also to avoid confusion among leak detection engineers, note that this robustness is usually called *reliability* among instrument engineers. This term is “overloaded” in LDS engineering, where reliability is usually considered to be a measure of the rate of false alarms, rather than the probability of outright failure of the system.

7.2.4 Approach

It is recommended to track and tabulate four elements separately for the pipeline system:

- the systematic bias of the system;
- the precision of the system;
- the system availability (MTBF $\times f$);
- the system robustness.

Biases and precisions (variances) add; the lowest component availability is used; and robustness combines by harmonic sum.

7.2.5 Instrument Telemetry

Additional inaccuracies due to data transmission must be added to the source uncertainties of the instruments at the pipeline. These major factors are considered.

Resolution of measurement—this is sometimes already reflected in the accuracy of the instrument itself, and sometimes—if the instrument has an analog output—in the telemetry system. Essentially, the digital transmission

system will have to round off the reading to the nearest figure that it represents digitally. It is known (Bennett, 1948) that this introduces an additional random uncertainty with a zero bias, but a variance equal to $\Delta^2/12$ where Δ is the resolution or rounding interval.

Scale factor—it is very common for telemetry system to scale the raw readings. This process creates additional uncertainty via a numerically not perfect (finite digital word length) multiplication. This additional variance is represented by SF . Multiplication does not add bias.

Transmission noise—although most digital telemetry adds negligible noise (beyond the quantization effect from resolution) certain components of the system may be analog. This adds a bias EM and a standard deviation ES .

7.2.6 Data-Time Skew

It is often the case that the measurement interval is itself inaccurate. In that case, it is useful to regard it as itself a random variable and the uncertainty analysis in later sections allows for this.

In this case $\Delta t^{(r)}$ is actually the uncertain Δt plus a bias and a random variable with zero mean and a variance.

From Table 2 the bias is the sum of: data-time skew bias TSM and front-end processing latency TCF. The variance is data-time skew variance, TSS squared.

7.2.7 Spurious Uncertainties

The term “spurious” is intended in the statistical sense, where it is meant that the nature of the uncertainty is not well known and its parameters are not well estimated.

In these situations the approach is to assess a minimum and maximum value for this particular uncertainty. The fundamental assumption with these unknowns is that they are distributed uniformly between these values. Then the mean (bias) is the average of the minimum and maximum, and the variance is one-twelfth ($1/12$) of their difference squared $\Delta^2/12$.

7.3 Summary

In summary, it is useful to develop a table, for each input to the LDS algorithm that is similar to the example shown in Figure 11.

Each instrument (in this example, inlet and outlet flow and pressure) is assessed a bias and precision. Each of the telemetry factors is added, to give a total bias B, precision P, availability, and reliability.

Note that in general, and with most modern measurement systems, *only* the bias and precision is a significant factor. As noted in the Introduction, their impact is typically two orders of magnitude that of any other factor. If any of the other factors are unknown then they can generally be assessed a zero value.

Any other inputs to the LDS technique (in this example, ambient and fluid temperature) is simply estimated a minimum and maximum spread. This results in a bias and precision according to the estimate described under spurious uncertainties.

8 Uncertainties Due to the Metric

8.1 General

Computational pipeline monitoring (CPM) leak detection methods are defined by their approach, which is to compute a metric that is used as an indicator of the likelihood of a leak being present.

	Instrument 1	Instrument 2	Instrument 3	Instrument 4	Unknown 1	Unknown 2
Data	Inlet Pressure	Outlet Pressure	Inlet Flow	Outlet Flow	Ambient Temperature	Fluid Temperature
Bias						
Precision						
Min						
Max						
Resolution						
Scale Factor						
Noise Bias						
Noise Var						
TSM						
TSS						
TCF						
Totals:						
Bias						
Precision						
Availability						
Reliability						

Figure 11—Measurement Uncertainty Table

Metrics that are considered in this document include:

- imbalance in volume flow, accumulated over time;
- imbalance in mass flow, accumulated over time;
- state—a list of pipeline system (including fluid) physical properties;
- pressure measurement rate of change (operational);
- flow measurement rate of change (operational).

Only the first three of these are formally CPM methods in the sense of the API 1130. Point rate of change methods are listed in API 1130 under the category *regular or periodic monitoring of operational data by controllers* and are included here because of their widespread use.

Another dimension to the metric is how it is used in order to declare a leak alarm.

- For LDS using a complete pipeline state, the weighted root mean square (RMS) of the difference between each state variable and a fixed threshold, and the RMS difference between the state variables and another computed function of given bias and precision.
- For all the other LDS using a single (scalar) valued metric, the difference against a constant threshold and against another computed function of given bias and precision.

Also an estimate of the *location* of a leak can be made from the metric, using an additional algorithm. Location algorithms that are considered in this document include:

- 1) pressure gradient intersection;
- 2) pressure wave speed.

Each of the metrics that are used present different advantages and weaknesses. The estimation of uncertainty due to the calculation of a metric is among the more difficult steps in the assessment of an LDS.

A summary of a typical example application of this section can be found in the Case Study: Worked Example Uncertainty Assessment.

8.2 General Approach

8.2.1 General

Recall that in order to assess uncertainties in the high-accuracy (few percent and smaller) range, the recommended approach is to compare the method against an RM.

The reference will itself have uncertainties—both due to the model and numerical approximations—and this must be combined with the uncertainty that is estimated from comparisons with the model. Refer to Section 7 for a description of how the reference model uncertainties are estimated. Therefore, the bias and variance of the reference model is always added to the biases and variances as estimated.

This means that the assessed uncertainty will always be at best that of the reference model and therefore the better the reference, the tighter the uncertainty estimates.

It is important to note that it is assumed that all real-time transient model (RTTM) algorithms rely upon a transient hydraulic simulator that is at least as accurate as any reference model. Any comparison between two identically implemented numerical models will show zero discrepancy. Therefore, the only uncertainty estimation is of model and numerical inaccuracy in the RTTM itself. While there is a systematic procedure for estimating numerical inaccuracy (see Figure 16) model inaccuracy is difficult.

8.2.2 Setting Up a Comparison with the Reference Model

The performance of any technique will depend on measurement uncertainties, and a number of listed engineering factors.

The general, underlying assumption is that the uncertainty due to each of these measurements and factors are statistically independent. With this assumption, it becomes possible to assess the uncertainty due to each of the factors individually (holding the other factors at their mean value) and then to combine the resulting biases and variances by addition.

Each time a separate parameter is assessed, and the bias and precision of its impact on uncertainty is calculated, the additional bias and precision is tracked with a running total.