Pipeline Variable Uncertainties and Their Effects on Leak Detectability

API TECHNICAL REPORT 1149
SECOND EDITION, SEPTEMBER 2015

AMERICAN PETROLEUM INSTITUTE

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Contents

Page

Contents

Contents

Page

Contents

Page

Contents

Page

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: $\bar{X} = \frac{1}{n}\Sigma X_i$.

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): $S^2 = \frac{1}{n-1}\Sigma(X_1 - \bar{X})^2$. 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	*Manual of Petroleum Measurements Standards*
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
$\sim$	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
$\sigma, \sum$	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.

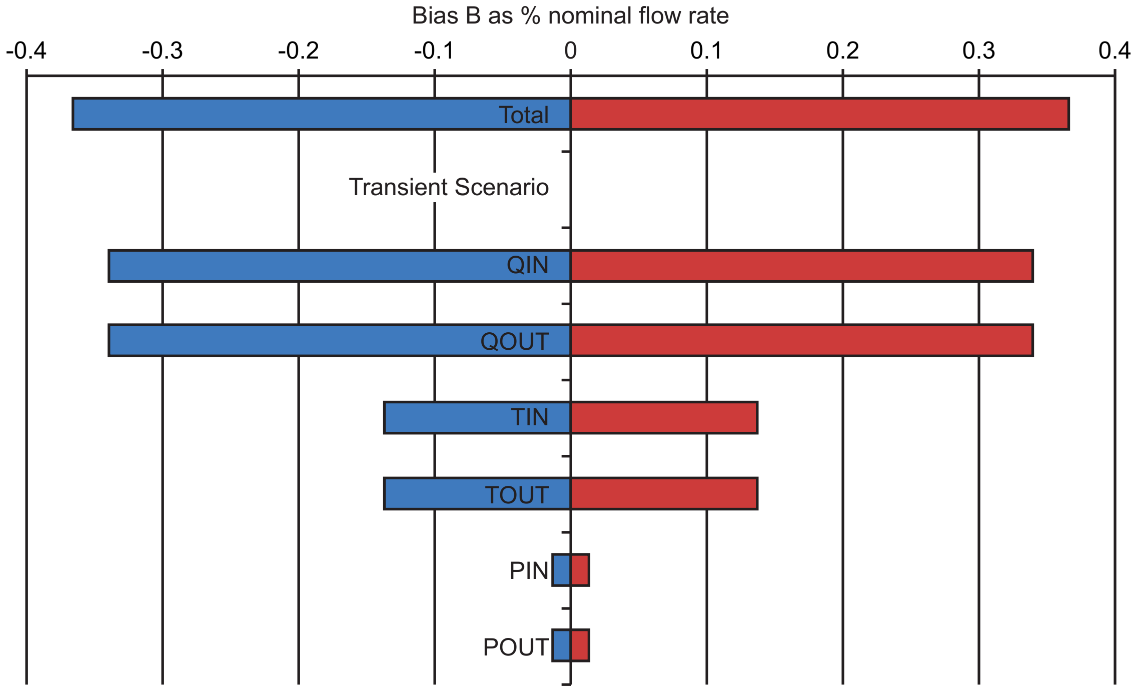


Figure 1—Example Summary Tornado Diagram

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

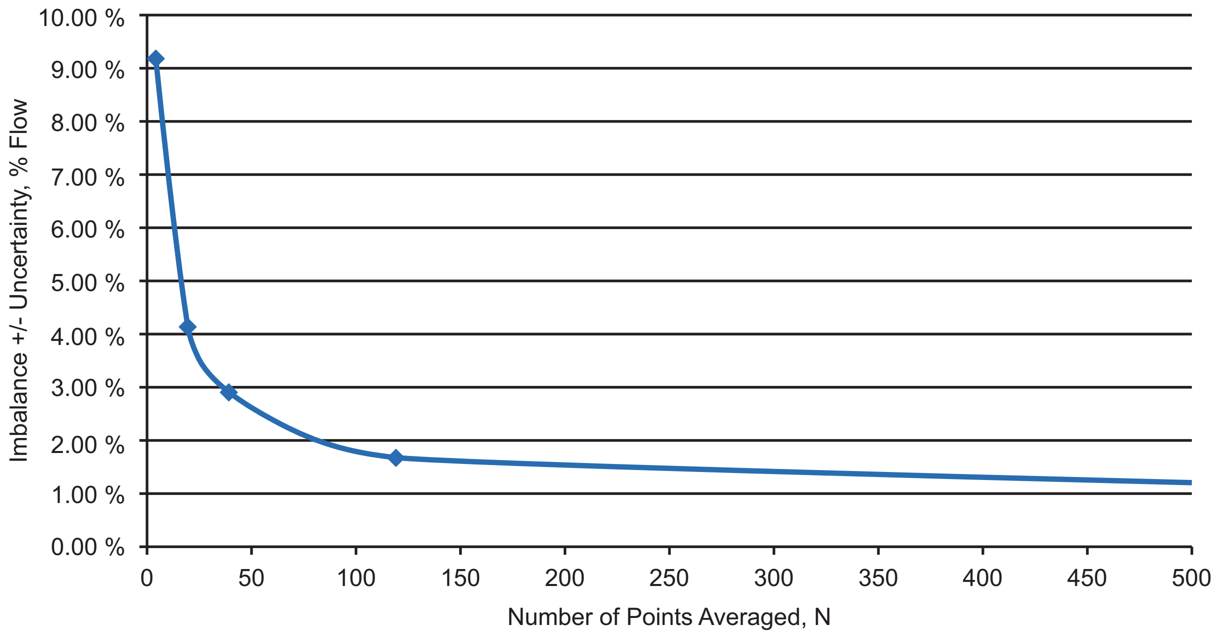


Figure 2—Example Summary Alarm Analysis

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

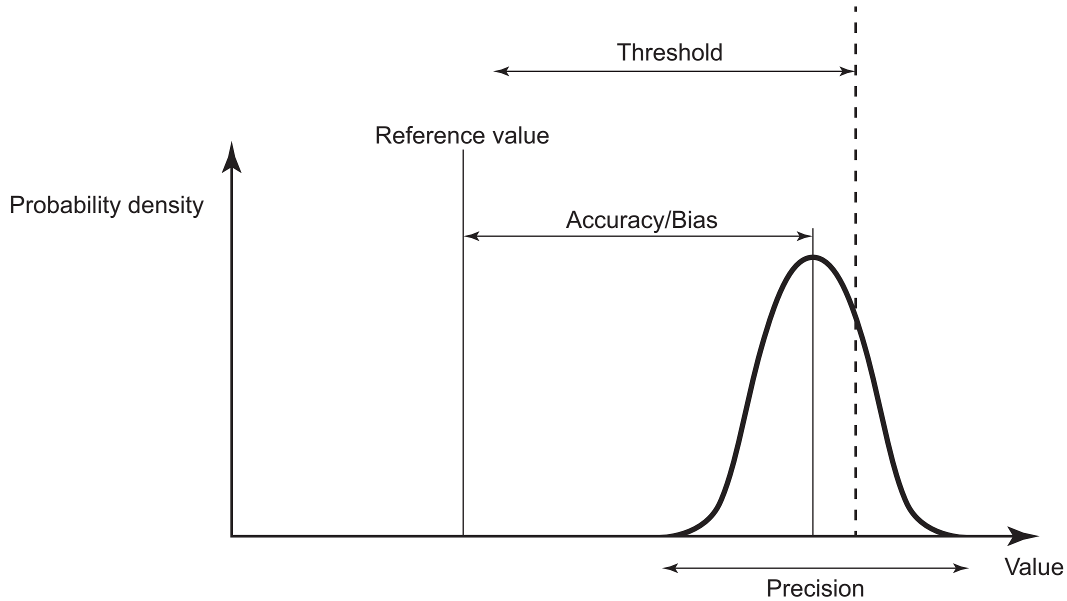


Figure 3—Basic Uncertainty Framework

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.

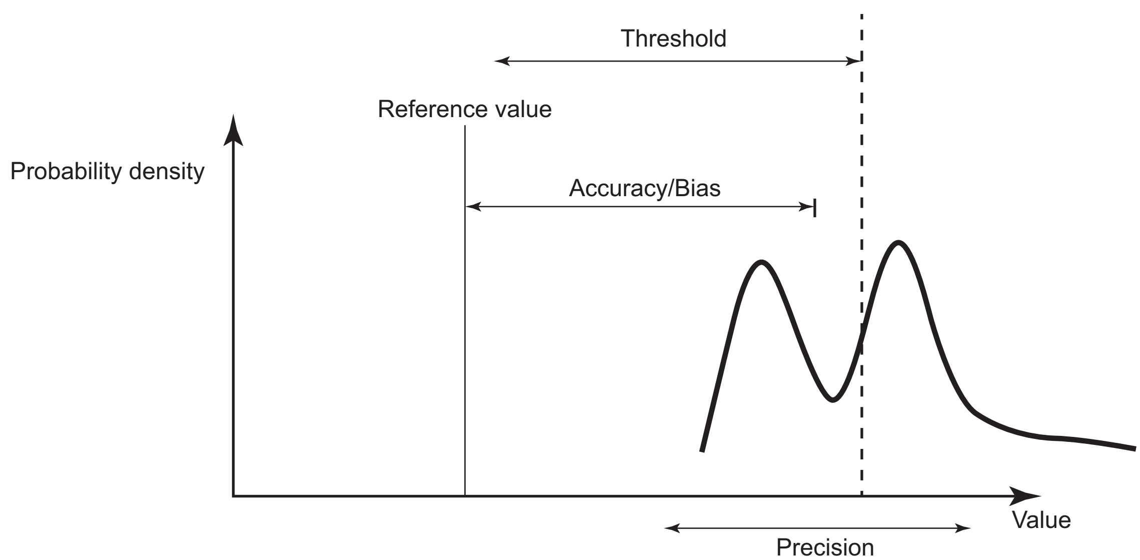


Figure 4—Non-Gaussian Distribution

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;

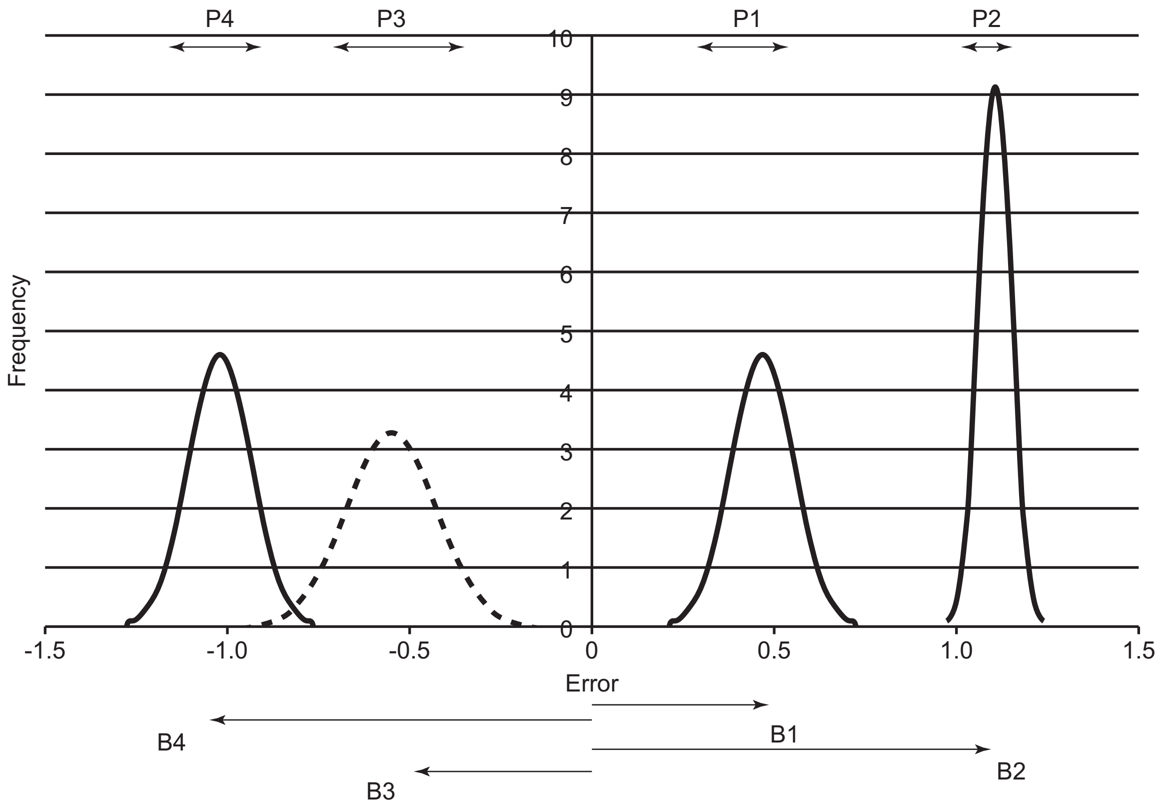


Figure 5—Multiple Uncertainty Assessments

— 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.

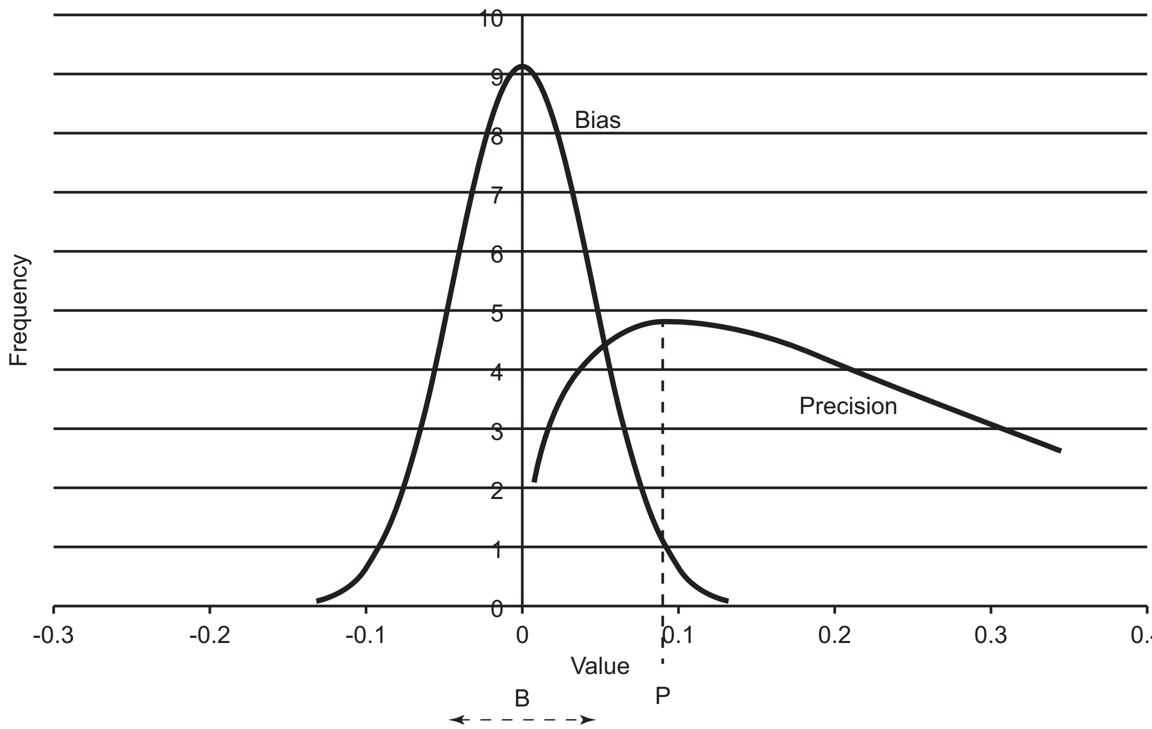


Figure 6—Distribution of Bias and Precision

— 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;

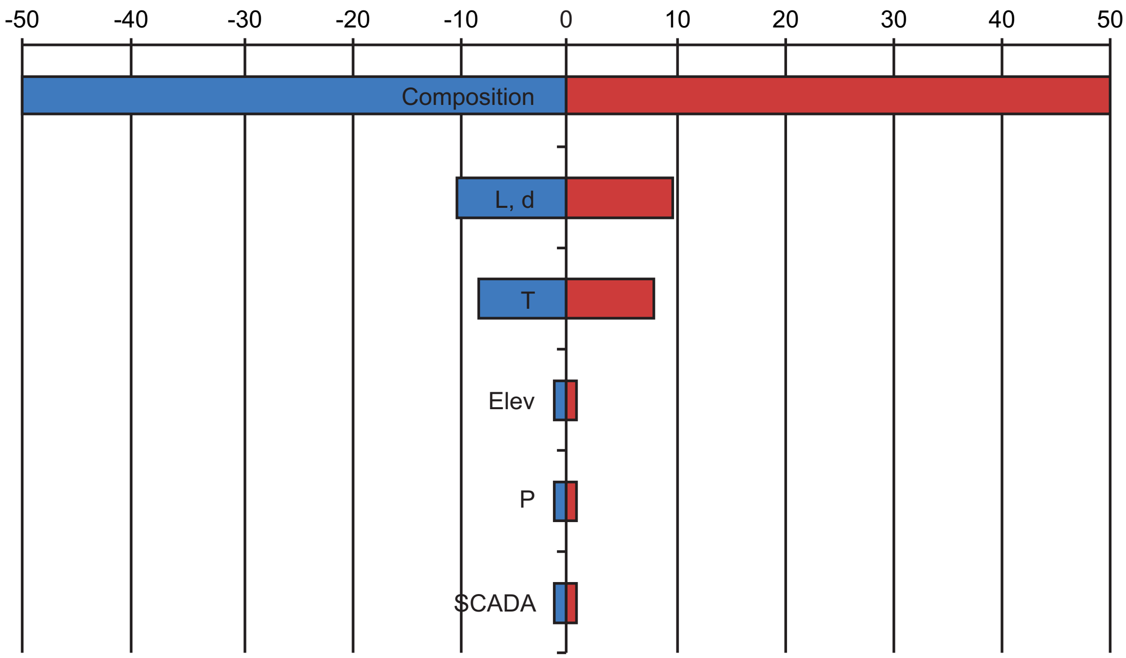


Figure 7—Typical Uncertainty Impact, Liquids Line

— *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

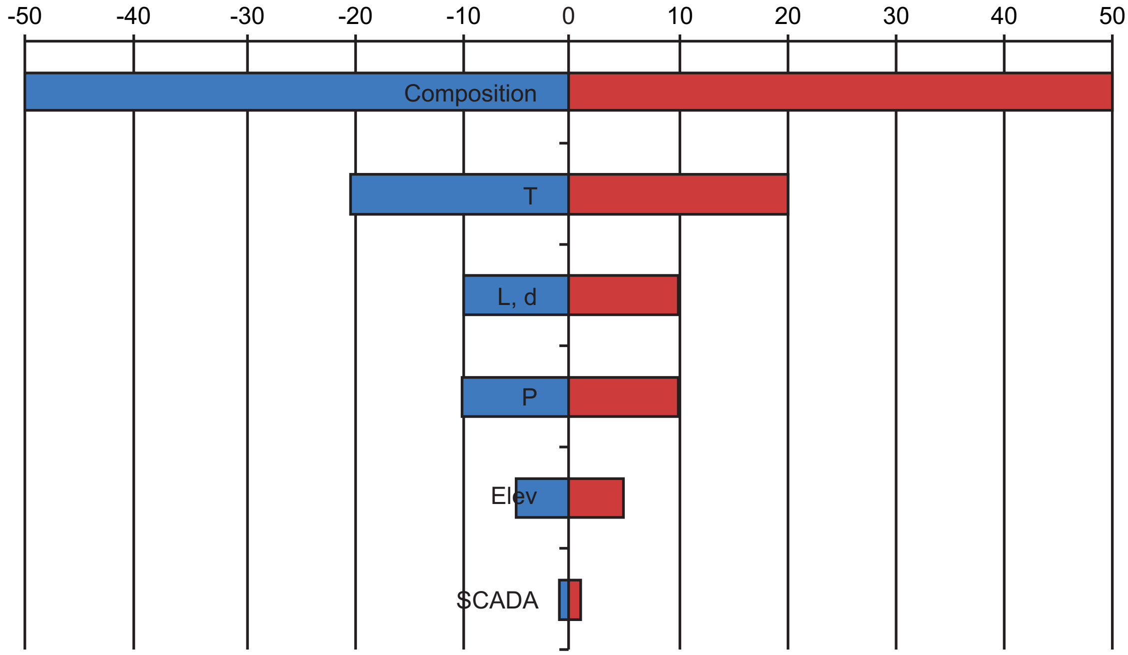


Figure 8—Typical Uncertainty Impact, Gas Line

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 availability = MTBF × 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 “± 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.

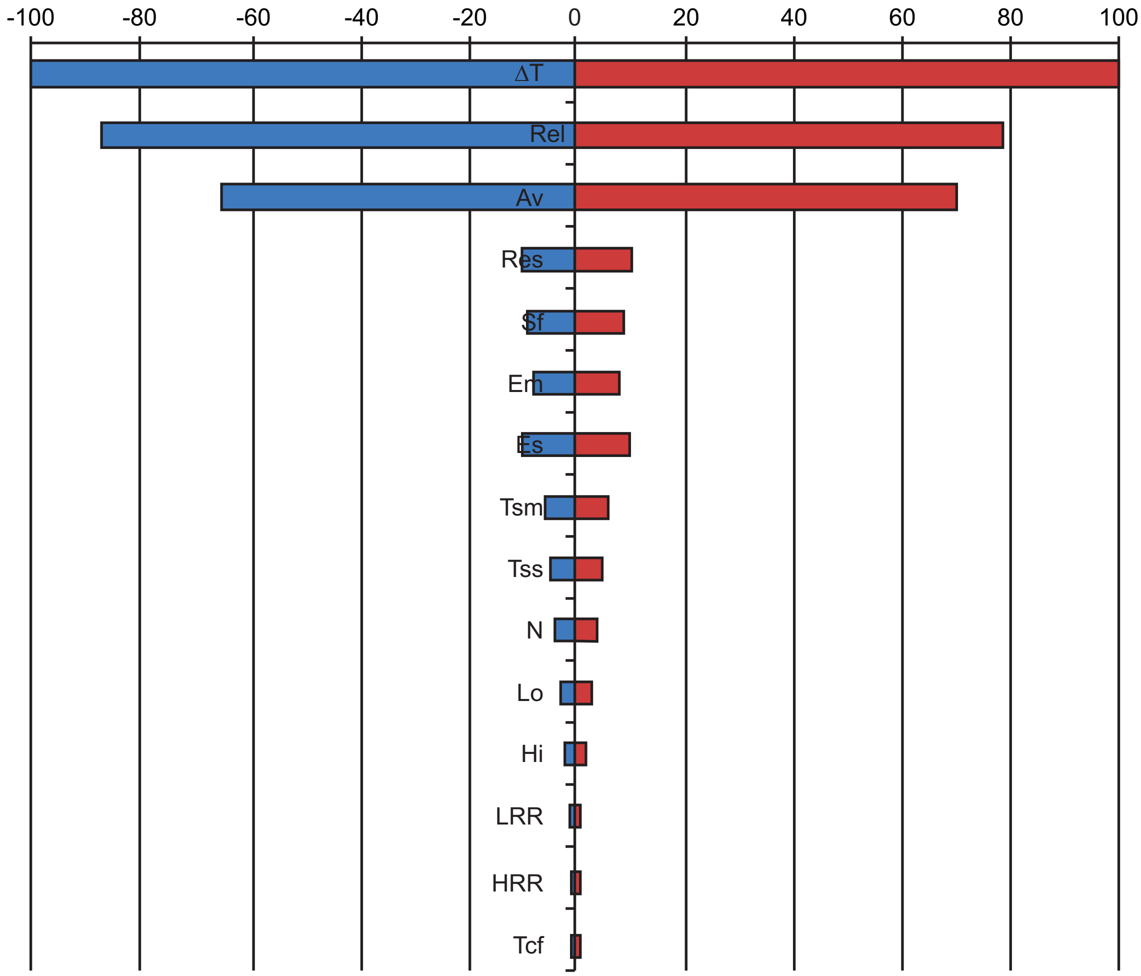


Figure 9—Typical Tornado Diagram for Telemetry Uncertainties

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):

$$U_{\mathrm{s}} = U_{\mathrm{input}} + U_{\mathrm{model}} + U_{\mathrm{num}} \tag{2}$$

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 CO_2 physical properties from the NIST *Reference Fluid Thermodynamic and Transport Properties Database* (*REFPROP*) V.9.1 (2013). However, high concentration dense-phase CO_2 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):

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

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 (m3/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.

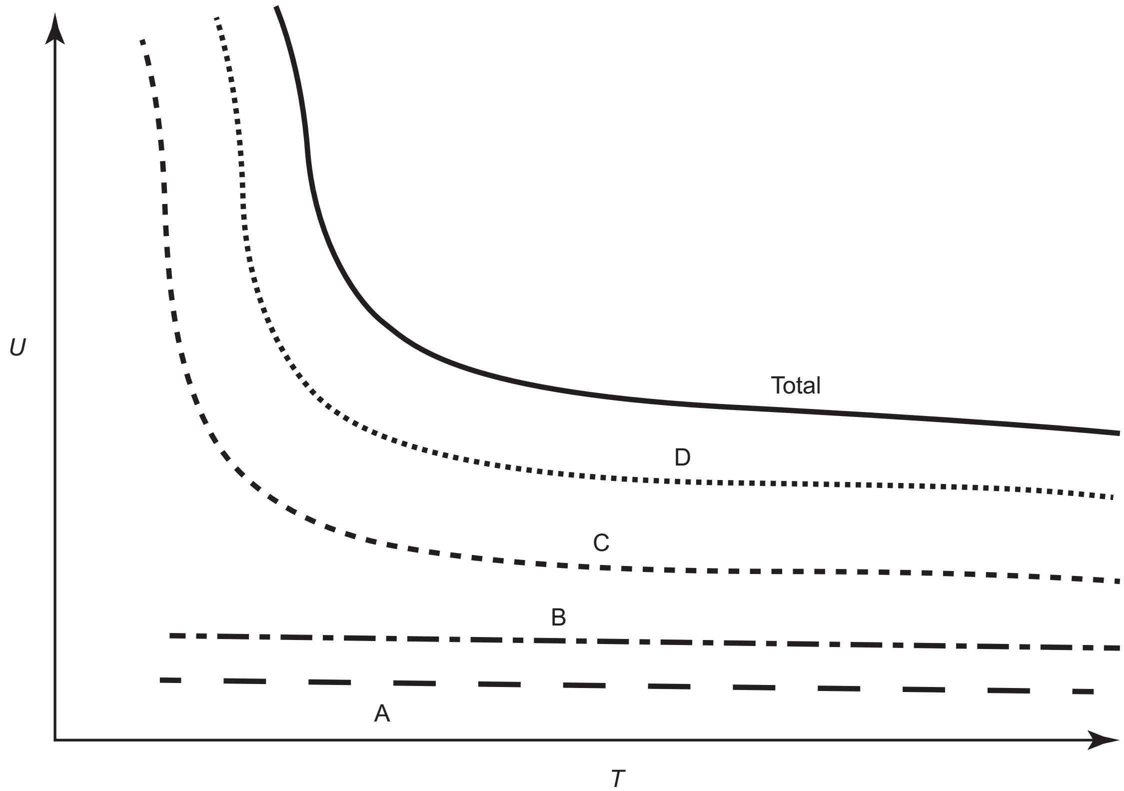


Figure 10—General Form of the Uncertainty, Imbalance LDS Techniques

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 ± 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):

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

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:

$$\bar{X} = \frac{1}{n}\Sigma X_i \tag{5}$$

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*:

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

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 $B_1 \ldots B_N$ 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:

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

Combining all the precisions $P_1 \ldots P_N$ 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.

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

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 ± *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:

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

Where, $\chi^2_{a/2}(n)$ 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 availability = MTBF x 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 x 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.

8.2.3 Preparing the Reference Model Simulations

The objective of the RM simulations is to estimate the resulting uncertainty in the physical pipeline state, due to an uncertainty in the complete set of input variables.

Recall also that for all balancing techniques, a balancing period Δt is set. Practically, this is set to a multiple N of the SCADA scan period $1/f$, so that $\Delta t = N/f$.

Uncertainties can either be in measurements (i.e. the input boundary conditions of the model) or in engineering factors, listed in the summary but generally items such as pipeline dimensions, fluid properties, etc. The method handles both of these in the same way.

The basic procedure can be summarized in the flowchart of Figure 12, due to Van Reet (2014). Essentially, it is a three-loop process.

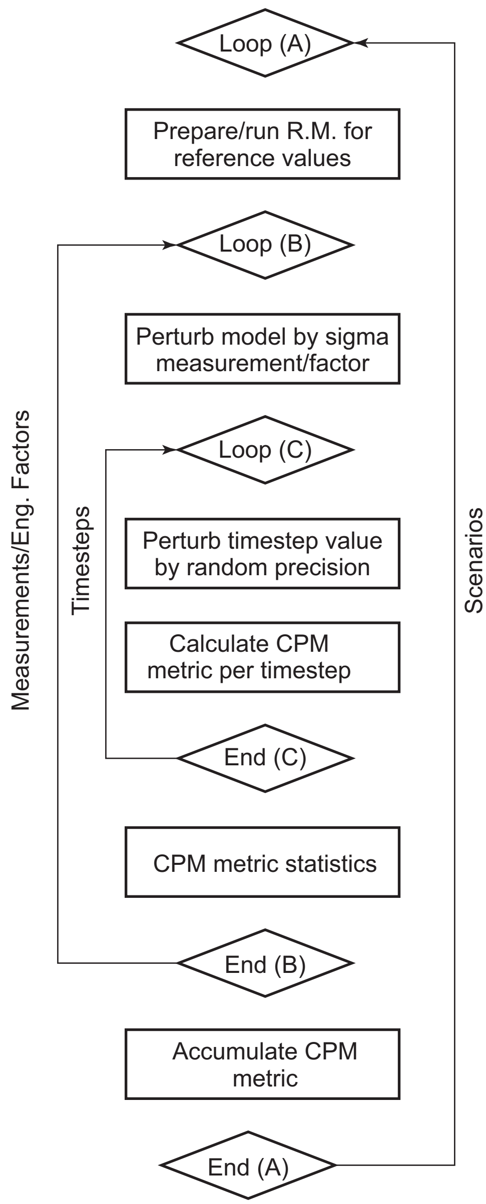


Figure 12—Flowchart of Overall Process

1) Loop (A) for clearly specified scenarios (i.e. each transient situation)—including, potentially, a steady state.

   a) Reference state—Prepare and run the RM to generate reference values for measurements, and for the reference pipeline state. This is the condition of the pipeline with zero uncertainty.

   b) Loop (B) for each measurement and engineering factor, and then once at reference conditions.

      i) *Perturbations*—Perturb model by plus one sigma "B" of bias of Item. The same model allows an assessment of the model at minus one sigma bias, and at one precision "P".

      ii) *CPM metric values*—Loop (C) time steps for scenario duration—calculating the CPM metric from the model at each time step. The loop has to be at least long enough for the metric to be assessed—for instance, if the metric is a one-hour material imbalance, then the simulation must last several multiples of an hour.

      iii) End loop for scenario length (C).

      iv) Capture metric statistics.

   c) End loop (B) for each measurement and engineering factor.

   d) Accumulate metric statistics. Statistics are recorded for ±B and P individually according to ASME *V&V* 20 (2009).

2) End scenario Loop (A).

3) *Scenarios*—The outermost loop (A) is for each scenario (steady-state, shutdown, startup, batch operation, slack (channel flow operations), pigging, etc.) that it is necessary to analyze. This is done so that the impact of the measurements and uncertainty factors on the CPM metric are specifically analyzed as close as possible to the actual operating conditions of the line. There is a strong physical and causal coupling between uncertainty due to the input variables and the pipeline operational scenario.

Naturally, one of these scenarios could be "quiescent" steady state. In fact, if the balancing period of the CPM is very much longer than the duration of the scenario, it is useful to perform a quasi-steady analysis in any case in order to extrapolate the metric to longer balancing periods.

For any of these scenarios it is important for the analyst to be precise about how the scenario is defined, and in particular how the physical hydraulic model is driven. For example, a single pipe can be driven by specifying flow at both ends and a pressure; however, it is also hydraulically feasible to specify pressures at both ends and a flow. This allows the results of the analysis to be reproduced unambiguously. The procedure is quite open to different boundary conditions being used, or other modeling techniques being used, so long as they are described in sufficient detail to be reproduced.

a) *Reference State*—The first step is to initialize and to run the reference model (RM) to generate the "true" *reference values* of all the pipeline variables. Thus all readings are set to nominal, as-expected values and all engineering factors are set to normal. This yields a reference pipeline state—including notably reference values for the CPM metric.

   i) *Perturbations*—The second loop (B) analyzes the impact of each of the input measurements and each of the engineering unknowns on the CPM metric during the course of the scenario, by simulation. Each parameter is varied individually to plus one confidence interval "B" of its bias—while holding the other parameters at expected values.

The justification for being able to perturb each parameter *individually* is that each of the parameters has an uncertainty that is statistically independent from all the other distributions. The impacts of each of the parameter's uncertainty are combined at the end of this loop.

One of these loops is also the reference state (i.e. no perturbations, zero uncertainty) in the first step.

ii) *CPM metric values*—The inner loop (C) simply runs the simulation with the RM, to generate the values of the pipeline variables with this uncertainty added to the base model. The pipeline variables are then used, with whatever CPM method is chosen, to predict the value of the CPM metric as a function of time. Each CPM method also includes, for example, the balancing period in an over/short comparison.

Typically, the simulation is performed to mimic the SCADA system and the CPM balancing periods being analyzed. For example, if the SCADA rate is 15 seconds, the time step is set to 15 seconds. If the scenario lasts up to one hour, for example, then balancing periods of 10 seconds, one minute, five minutes, ten minutes, and one hour are readily computed directly from the output of the simulation. If a much longer period is required it is not necessary to run, for example, a 24-hour scenario directly at 15-second time steps. Rather, a steady-state analysis or a short transient analysis at nearly steady conditions can be used to extrapolate the averages.

iv) *Capture metric statistics*—Generally, it is sufficient to perform the simulations only with perturbations of +B in each of the input parameters (measurements of engineering factors). However, it is recommended to calculate and capture, as a function of time:

— The baseline, *reference state* values of the CPM metric that corresponds to the reference physical error of the CPM method itself. Improvements in instrumentation or measurement cannot reduce this uncertainty. Rather, a more accurate CPM method is required—for instance, compensating a volume balance CPM for mass or using an RTTM to estimate linepack.

— The CPM metric values for a perturbation of –B. Assuming that the perturbations are sufficiently small, the response of the RM is taken to be approximately linear. These values will then be exactly the same perturbation from the CPM reference metric, but in the opposite direction.

— The CPM metric values for a perturbation of P. Again, assuming that the perturbations are sufficiently small, the response of the RM is taken to be approximately linear and these values will be the "+B" perturbation from the CPM reference metric multiplied by a factor of P/B.

The total uncertainty, due to the effect of all the parameter uncertainties, on a particular CPM metric (for example, 10-step accumulated over/short mass imbalance) is obtained by combining each of these curves by root-mean-square.

It is recommended to draw a time-series of at least the CPM metrics at the reference state and at each of the +B perturbation simulations. This is shown in Figure 13.

It is also recommended to record the *maximum* value of the CPM metric, for each perturbation, for the scenario. An example is given in the Table 5 template. 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 10.

The total uncertainty, due to the effect of all the parameter uncertainties, on this particular CPM metric is obtained by combining each of the 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. The values will be the same multiplied by the corresponding factors P/B.

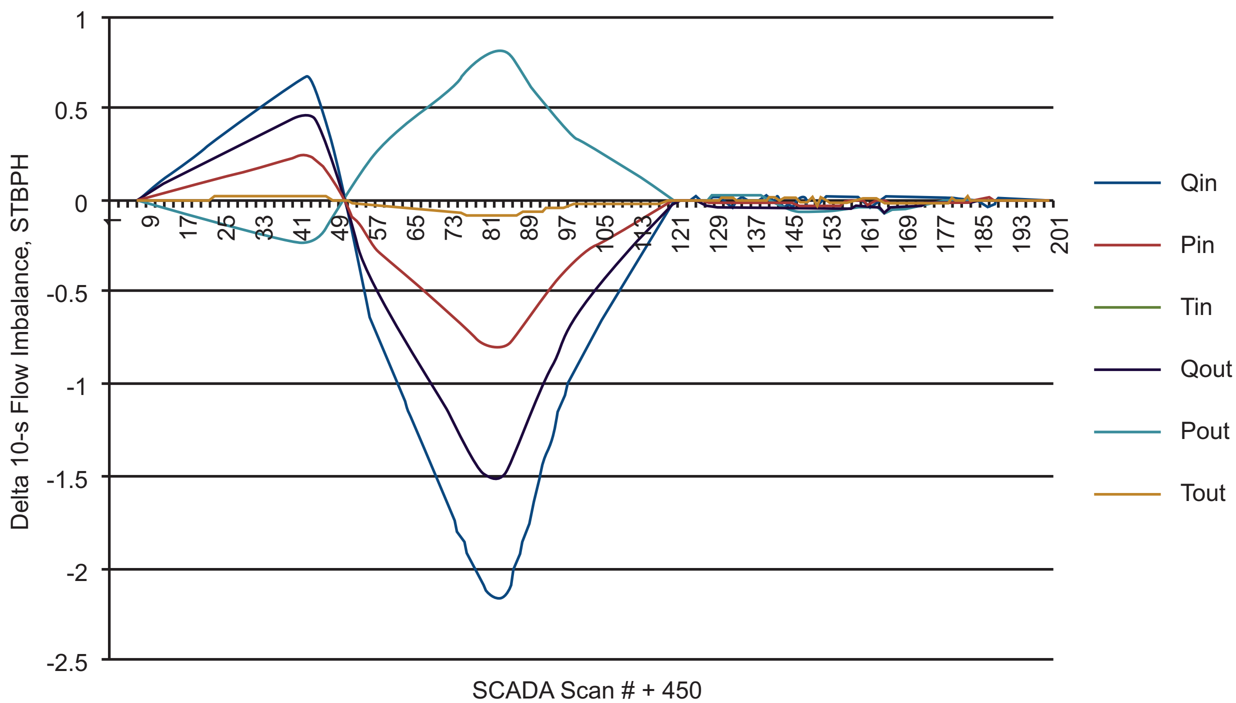


Figure 13—Impact of Individual Parameters on CPM Metric

Table 10—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				

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 ± the value of the imbalance B for each row in the table. An example is shown in the example problem.

8.2.4 Longer Averaging Periods

Averaging periods for the CPM metric can be extended to be much longer than the scenario period, if periods of quasi-steady flow before and after the transient are analyzed as well.

In general periods of stable flow are present both before and after a transient (pressure change, batch change, etc.). Values of the imbalance deltas (constant on average) during these periods can then be averaged with the values during the transient.

8.3 Algorithms

The metrics can be computed using differing degrees of model error. For a much more detailed treatment of the methods and physical principles that are presented here, the reader is referred to: Wylie, Streeter, and Bedford (2010); Geiger (2012); or Geiger (2006), from where the equations in this section and the notation are taken.

In the case of imbalance in mass flow, the algorithms differ in the degree of detail devoted to the estimation of material in the pipe (linepack). The three levels of detail are:

1) Computing the imbalance using mass rate of change at the inlet and outlet only. This may either be using a direct density measurement at the pipe ends, or it may be using correlations for density using pressure and temperature readings.

2) Computing the mass in the pipe using correlations for density using pressure and temperature estimates. The intermediate densities are estimated using a fixed, assumed linear pressure and exponential temperature profile.

3) Model-compensated mass balance, where essentially a complete RTTM is used to estimate the mass in the pipe, potentially using a number of intermediate pressure and temperature readings.

The pressure and flow rate of change techniques use only current reading values. The “computation” in these CPMs is therefore very simple. Note that often, in practice, current instantaneous readings are not used and the readings are usually smoothed using, for example, a moving average. Refer to the section on filtering for the procedure to add the effects of using these additional steps.

8.4 Particular Engineering Factors

8.4.1 General

The general process can be used to analyze the impact of *any* source of uncertainty on the algorithm. However, the discussion covers particular engineering factors that are of primary concern and represent an update on the factors that are included in the API 1149.

8.4.2 System Size, Complexity, and Batch Operations

This discussion concentrates on two main classes of pipeline models:

— A piecewise linear deviated and/or 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 in 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.

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.

8.4.3 Existence of Pre-existing Leaks

Any technique that includes an estimate of line pack (and makes a direct comparison against its value) can potentially be used to detect a pre-existing leak. Suppose that there is no leak, then:

$$\dot{Q}_1 - \dot{Q}_o = \frac{d}{dt} M_{LP} \tag{11}$$

However, suppose that there is an intermediate leak at an arbitrary location X, and denoting 1 for upstream and 2 for downstream of X:

$$\dot{Q}_1 - \dot{Q}_x = \frac{d}{dt} M_{LP,1}$$

$$\dot{Q}_x - \dot{Q}_o = \frac{d}{dt} M_{LP,2} \tag{12}$$

Adding:

$$\dot{Q}_1 - \dot{Q}_o = \frac{d}{dt}(M_{LP,1} + M_{LP,2}) \tag{13}$$

In short, there will always be a minimum discrepancy in the material balance calculation. This will show up as an extra mass flow imbalance. This can be used in a comparison algorithm—including biases from metering and SCADA—to assess whether a pre-existing leak is evident.

8.4.4 Sensitivity to Flow Conditions

Five categories of flow condition are identified.

— Steady state, in which none of the boundary conditions on the pipeline (including inlet and outlet pressures, flows, and temperatures) change.

— Shut-in, where there is no flow but the line is maintained tight, at above atmospheric pressure.

— Transient, in which one or more of the boundary conditions on the pipeline is varied from an initial to a final value over a given period of time, with a ramp profile.

— Including shut-down transient operations, start-ups.

— Slack-line flow (SLF), where the pressure in a liquid line falls locally below its vapor pressure so that there are sections with free gas present.

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

Only leak detection methods that rely purely upon pressure measurements can reliably detect leaks at shut-in conditions. It is sufficient to set the inlet and outlet flows to zero to analyze this situation.

SLF is a very special case, where most classic leak detection systems fail outright. A separate section is devoted to how to model a SLF situation. At this point note that the focus is on the dominant uncertainty due to SLF, not necessarily on how to reduce it.

8.4.5 Multiphase Flow

There is a distinction between truly mixed multiphase flow, and SLF. SLF is defined as being piece-wise continuous: there are sections of tight (liquid only) and channel (segregated liquid-vapor) flow.

Fully mixed multiphase flow leads to substantial uncertainties. These uncertainties are generally much higher than the few percent thresholds that are assumed consistently throughout, and therefore are beyond the scope of this approach. It is generally accepted that any correlation-based multiphase estimate of linepack will be accurate to at best ±5 %. The dominant uncertainties will be: mass flow at the meters at the inlet and outlet; and linepack estimation. Even with purely pressure-based techniques, the variability in pressure in normal multiphase flow can regularly be in the ±5 % range or more.

It is therefore generally impractical to provide a reference model, or a reliable CPM metric, during multiphase flow either. For all these reasons, multiphase flow is beyond the scope of this method.

8.4.6 Gas and High- and Low-volatility Liquids

The RM specifically models these effects. Where bulk modulus, speed of sound, and other fluid properties are required by the LD technique, it is assumed that precisely the same correlations are used as by the reference model.

The RM also uses Bulk Modulus $K = -V\,{}^{dP}/_{dV}$ coefficient of thermal expansion $C_T = {}^{1}/_{V}\,({}^{dV}/_{dT})_P$ and coefficient of pressure expansion $C_P = {}^{1}/_{V}\,({}^{dV}/_{dP})_T$ to calculate the actual in-situ volumes of fluid in the pipeline, which affects the linepack and overall pipeline physical state.

8.4.7 Temperature Effects

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.

The RM models temperature using a number of specific approximations—generally quite accurately—in computing temperature, as described in the earlier section.

8.4.8 Drag Reducing Agents (DRA)

Recall that the RM includes the effects of DRA, using a simplified parameterized DR equation. The two parameters in the equation are themselves potentially uncertain, but are subject to bias (i.e. actually constants, even if unknown).

8.4.9 Pig Tracking

The RM provides a basic pig tracking method that mimics the behavior of an online pig tracking system.

— Pig tracking instruments can, at any time, signal the passage of the pig.

— Between these “synchronization” measurements, the model estimates the position of the pig using an estimate of the pressure differential—generally done by moving the pig with the liquid flow, accounting for some slippage factor—across the pig. A perfectly free-moving pig would have no pressure differential, so this represents a resistance to movement.

Both of these are time-varying parameters.

8.5 Other Common Sources of Uncertainty

8.5.1 Pipeline Configuration and Dimensions

There is no reason why the pipeline lengths, deviations, elevations, diameters, etc. cannot all be treated as any of the other parameters within this framework, and assessed using an estimated bias spread B. With the one exception of SLF this rarely adds any significant uncertainty, and costs an additional N runs of the RM.

However, note that for SLF any uncertainty in elevation translates directly to a pressure uncertainty that may be significant.

8.5.2 Fluid Composition

Generally, the fluid in the pipeline is of a fairly constant grade—i.e. specific gravity. Also, the uncertainty impact on linefill due to gravity is generally very slight with liquids, while with gases the gas composition is very carefully controlled. However, there is also no reason why uncertainty in the purity of the fluid—or of the batch product in the pipeline—cannot be treated as any other parameter within this framework subject to a potential bias "B". Recall that this requires at least one extra transient simulation run.

8.6 Summary of Model Uncertainties

The nature and observations on the covered sources of model uncertainty are summarized in Table 11.

8.7 Leak Detection Metrics and Techniques

8.7.1 General

The leak detection techniques and their associated metrics are summarized in Table 5.

8.7.2 Volume Balance

A balancing period $T_o = N\,\Delta T$ is set. Practically, this is set to a multiple of the SCADA scan period, so that $T_o = N\,\Delta T$. Over this period, at each SCADA scan the volume into and out of the system is accumulated:

$$V_{T_o} = \frac{1}{T_o} \Sigma_{t=1}^{N} \dot{V}_t \, \Delta T \tag{14}$$

Here V denotes volume at current pressure and temperature, and the superscript dot denotes rate of change with time.

If density is constant and the linefill is constant then volume into the system should equal the volume out.

The metric used is outlet, minus inlet, accumulated volume: $V_{T,o} - V_{T,i}$.

Here subscript "i" and "o" denote inlet and outlet conditions, respectively.

8.7.3 Procedure

8.7.3.1 General

The baseline RM is prepared with expected values:

— one of inlet or outlet volume flow rate specified;

Table 11—Major Uncertainty Factors

Uncertainty Factor	Nature	Observations
System physical dimensions/ configuration	Bias	Except for SLF, very small uncertainties in dimensions, deviation and elevation generally have small impact.
System complexity	Fixed	1. Single pipe, one inlet, one outlet. 2. Simple network, containing no internal flow control.
Batch Operations	Bias	The uncertainty variable is time ramp of batch change.
Pre-existing leaks	Fixed	This will manifest itself as a consistent bias in any mass-balance technique.
Flow Conditions	Fixed	1. Steady-State 2. Shut-in 3. Transient 4. Startups 5. Slack Line Flow
Multiphase Flow	N/A	Multiphase flow uncertainties are greater than “very small”; >5 %. Therefore, the general methodology fails and they are out of scope.
Fluid type: LVL, HVL and Gas	Fixed/Bias	The type of fluid is Fixed, and is handled within the RM. The gravity of the fluid may be uncertain, although this is rare.
Temperature effects	Bias and Precision	Any variability in the boundary conditions on the pipeline is potentially both subject to a B and a P variability.
Drag Reducing Agents	Bias	DRA is handled within the RM using a two-parameter model. These two parameters are subject to a potential bias.
Pig Tracking	Bias	Pig tracking uses two variables: PD across the pig and pig sensor transit time.
Transient Effects	Fixed	Any parameter or boundary condition can be varied during the RM simulation. Typically, a parameter has an initial value, final value and a ramp time. However, any transient schedule can in principle be used.

— one of inlet or outlet pressure specified;

— one or both inlet and/or outlet temperatures are specified;

— the model tuned to match outlet/inlet pressure and temperature.

In this method, the only instrumentation used is inlet and outlet volume flow rate.

8.7.3.2 Uncertainty in the Metric

Any of the boundary conditions can be varied in order to analyze their impact on the metric.

Recall that, even in a steady-state calculation, a transient run with a time-step of ΔT must be run, with the specified inlet and outlet rates, pressures and/or temperatures sampled at reference +B, and +P. This yields a mean and variance estimate of $\dot{V}_t$.

In steady state, expect the mean and variance of the metric to be constant. The expected value is:

$$E(V_{\text{T,o}} - V_{\text{T,i}}) = \frac{1}{T_{\text{o}}} \Sigma_{\text{t}=1}^{\text{N}} E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})\,\Delta T = \frac{N\Delta T}{T_{\text{o}}} E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}}) = E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}}) \quad (15)$$

In short, the bias is constant and equal to any one of the SCADA time-step biases. On the other hand, for the variance:

$$Var(V_{\text{T,o}} - V_{\text{T,i}}) = \left(\frac{\Delta T}{T_{\text{o}}}\right)^2 \Sigma_{\text{t}=1}^{\text{N}} Var(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}}) = \frac{1}{N}(Var(\dot{V}_{\text{t,o}}) + Var(\dot{V}_{\text{t,i}})) \quad (16)$$

In other words, the precision increases by a factor of N times any one of the SCADA time-step variances.

In transient simulations, this is not necessarily the case. In this case, a transient run of at a minimum of N time steps must be run. Since the balancing period itself is a performance factor in this method, it is practical to set N to the maximum period under consideration, and the appropriate averages for shorter periods can be calculated from the single dataset.

8.7.3.3 General Behavior of the Uncertainty

The bias is a fixed value:

$$E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{meters}} + E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{model}} \quad (17)$$

Note that whereas the meter biases are essentially fixed, the RM biases will depend strongly on all the engineering factors being considered.

The precision varies inversely with the balancing period:

$$\frac{1}{N} Var(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{meters}} + \frac{1}{N} Var(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{model}} \quad (18)$$

This behavior is sketched in Figure 14.

— The x-axis is $N = T_{\text{o}}/\Delta T$ and the y-axis is the cumulative uncertainty.

— The line A represents the meter bias effect, $E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{meters}}$.

— The line B adds any physical bias estimated from the Reference Model, $E(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{model}}$. Note that this is generally small except in highly transient situations.

— The line C is set by the precision of the meters. This line is set at the discretion of the user. For example, one standard deviation would be the square root of the variance. A 90 % confidence interval would be 0.9785 of the variance (if the uncertainty is assumed normally-distributed), etc. It is recommended to use one standard deviation, which makes no assumption about the nature of the distribution.

— The line D adds any physical variability estimated from the reference model, $\frac{1}{N} Var(\dot{V}_{\text{t,o}} - \dot{V}_{\text{t,i}})_{\text{model}}$. Again, recommended practice is drawing one standard deviation as the curve.

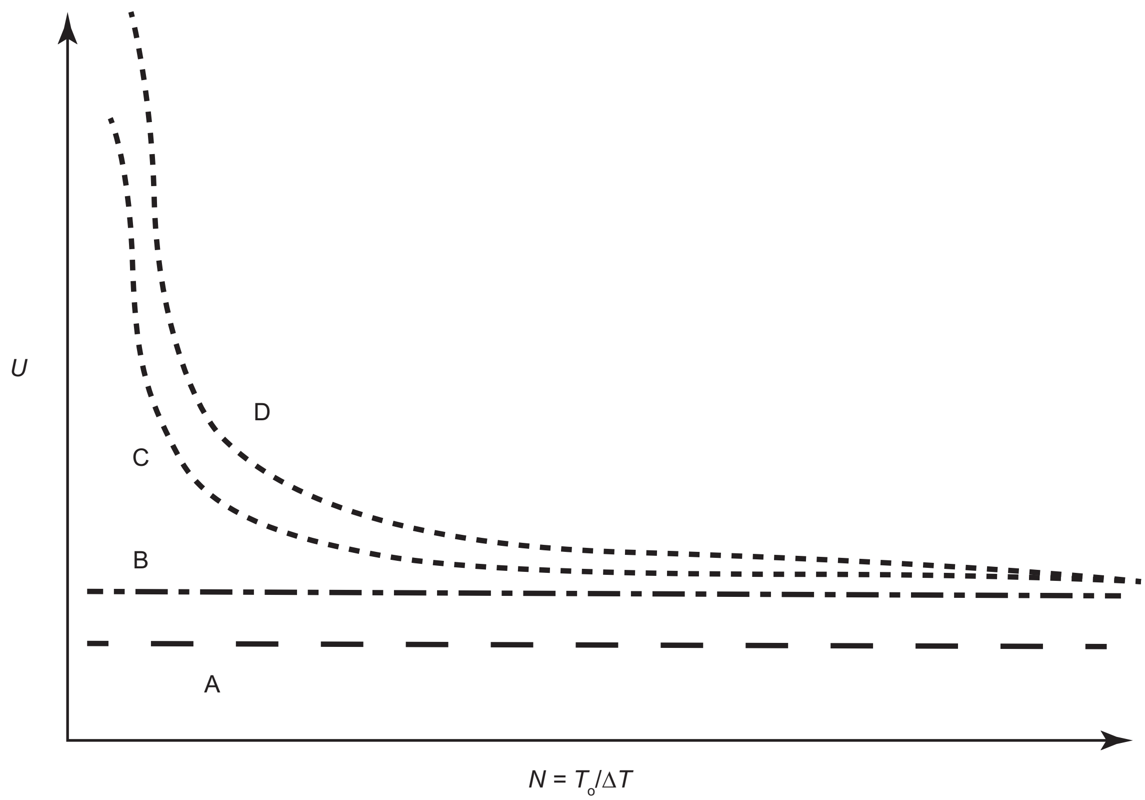


Figure 14—Volume or Mass Balance Uncertainty Behavior

8.7.4 Rate of Pressure Change

8.7.4.1 General

A pressure reading is taken at an arbitrary point on the pipeline. The basic version of this method works by assuming stable, steady state flow, or zero flow, and therefore a zero pressure change is expected.

The derivative is taken over a single SCADA scan: $(P_{t+1} - P_t)/\Delta T$, where P is the pressure reading.

Two parameters directly affecting the metric are the location “x” of the pressure sensor, and ΔT.

This method provides very good results on gas pipelines, and also provides for leak location estimation—see 12.5.2.

8.7.4.2 Procedure

The baseline RM is prepared with expected values.

— Inlet and outlet pressure specified. Equivalently, a nominal flow rate can be specified with one pressure.

— One or both inlet and/or outlet temperatures are specified.

— The model tuned to match flow rate (or pressure) and temperature.

In this method, the only instrumentation used is the one pressure sensor.

8.7.4.3 Uncertainty in the Metric

Any of the boundary conditions can be varied in order to analyze their impact on the metric. The bias of this metric is by definition zero. Its variance is $2Var(P_{RM})/\Delta T^2$.

— The measurement bias in the rate of pressure change is again zero, by definition.

— The variance is $2Var(P_m)/\Delta T^2$.

These two are added to the metric uncertainty.

8.7.5 Rate of Flow Change

A flow rate reading is taken at an arbitrary point on the pipeline. The basic version of this method works by assuming stable, steady state flow, and therefore a zero flow rate change is expected.

Most of this method works exactly like the pressure rate of change method, but with two main differences:

— It will not work when the pipeline is shut-in; and

— It is normal to prepare the RM with a mean rate, and one pressure setting.

8.7.6 Mass Balance

Recall that there are three levels of detail for this technique:

1) outlet mass minus Inlet mass, from rates and local inlet/outlet density totalized over a given time;

2) as i, but with linepack estimated from a given (but varying along the pipeline) pressure/temperature profile;

3) linepack estimated from a RTTM.

8.7.7 Basic Mass Balance

8.7.7.1 General

A balancing period T_o is set and much of this method is similar to the Volume Balance method, except that the Volumes $V_{T,o}$; $V_{T,i}$ are replaced by the local mass flow rate Q_m:

$$Q_{m,i} = \rho_i \dot{V}_i;\ Q_{m,o} = \rho_o \dot{V}_o \tag{19}$$

***Metric*—**The measure used is outlet, minus inlet, accumulated mass: $M_{T,o} - M_{T,i}$ where, as before:

$$M_T = \frac{1}{T}\Sigma_{t=1}^{N} Q_{m,t}\,\Delta T \tag{20}$$

8.7.7.2 Uncertainty in the Metric

Write *a* and *b* for the precision and bias of the inlet and outlet flow meters. Then if ρ is the local density:

$$E(M_{T,o} - M_{T,i}) = \frac{1}{T_o}\Sigma_{t=1}^{N} E(\rho_o \dot{V}_{t,o} - \rho_i \dot{V}_{t,i})\,\Delta T = \frac{N\,\Delta T}{T_o} E(\rho_o \dot{V}_{t,o} - \rho_i \dot{V}_{t,i}) = \hat{\rho}_o b_o - \hat{\rho}_i b_i \tag{21}$$

For the variance:

$$Var(M_{\mathrm{T,o}} - M_{\mathrm{T,i}}) = \left(\frac{\Delta T}{T_{\mathrm{o}}}\right)^2 \Sigma_{\mathrm{t}=1}^{\mathrm{N}} Var(\rho_{\mathrm{o}}\dot{V}_{\mathrm{t,o}} - \rho_{\mathrm{i}}\dot{V}_{\mathrm{t,i}}) = \frac{1}{N}(\alpha_{\mathrm{o}}^2 Var(\rho_{\mathrm{o}}) + \alpha_{\mathrm{i}}^2 Var(\rho_{\mathrm{i}})) \tag{22}$$

Note that if the inlet and outlet densities can be estimated accurately, and N is large, then the variance of the metering uncertainty can therefore be made very small.

8.7.7.3 General Behavior of the Uncertainty

The general assessment is very similar to volume balance, except that the advantage of this method is that the line marked C is generally much lower in value, if the densities can be estimated accurately.

8.7.8 Corrected Mass Balance

8.7.8.1 General

The metric adds an estimate of the linepack as well. This is based upon an assumed linear pressure profile and an assumed exponential temperature profile. These pressures and temperatures are then used to estimate density throughout the pipe, and therefore the mass in-place in the line.

The physical principle of conservation of mass reads:

$$\int_{\mathrm{t}-\Delta\mathrm{t}}^{\mathrm{t}} Q_{\mathrm{m,i}}^{(\mathrm{r})}\,\mathrm{d}t_{\mathrm{m,i}}^{(\mathrm{r})} = \int_{\mathrm{t}-\Delta\mathrm{t}}^{\mathrm{t}} Q_{\mathrm{m,o}}^{(\mathrm{r})}\,\mathrm{d}t_{\mathrm{m,o}}^{(\mathrm{r})} + \Delta l^{(\mathrm{r})}(\Delta t) \tag{23}$$

where

Q_{m} is the mass flow rate, in kg.s^{-1};

t is the time at which the balance is made, in s;

Δt is the balancing period, in s;

$\mathrm{d}t$ is the time interval at which readings are sampled, in s;

$\Delta l^{(\mathrm{r})}$ is the change in linepack, reference value, over the balancing period, in kg;

(r) superscript—reference (i.e. true, physical) value;

i subscript—inlet value;

o subscript—outlet value.

This is approximated by:

$$M_{\mathrm{T,o}} - M_{\mathrm{T,i}} + \frac{1}{T_{\mathrm{o}}}\Sigma_{\mathrm{t}=1}^{\mathrm{N}}\frac{\Delta l}{\Delta T}\Delta T \approx 0 \tag{24}$$

Therefore, the original metric is modified by the addition of an estimated rate of change of linepack.

8.7.8.2 Metric

The pressure and temperature is estimated point-by-point along the pipe, but the actual linepack is estimated numerically by discretizing the line:

$$l = \int A(x)\,\rho(x)\,dx \approx \Sigma_{i=1}^{M} A(x_i)\,\rho(x_i)\,\Delta x_i \tag{25}$$

To the metric of the basic material balance method, add:

$$\frac{1}{T_o}\Sigma_{t=1}^{N}\frac{\Delta l}{\Delta T}\Delta T \tag{26}$$

Its expected value (with constant, A, for simplicity) is just the expected total linepack rate of change:

$$V\,E\left(\frac{\partial\rho}{\partial t}\right) \tag{27}$$

Therefore, in steady state this bias in the estimate is zero. The variance is:

$$\frac{\Delta x}{L}\left(\frac{v}{T_o}\right)^2 Var(\rho) \tag{28}$$

In short, the precision is as good as the precision in the density and improves, as the discretization is refined.

8.7.8.3 General Behavior of the Uncertainty

The general assessment is very similar to Volume Balance, except that:

— as with the basic mass balance technique, the line marked C is generally much lower in value, if the densities can be estimated accurately;

— similarly, the line marked B generally is much lower since the linepack estimate will be closer to the reference model values.

8.8 Real-Time Transient Model (RTTM)

8.8.1 General

If RTTM is used in the CPM LDS, it is generally practical to use the exact same model that is used for real time transient modeling as the reference model.

One of the underlying assumptions is that any RTTM that is used for the leak detection is at least as accurate as the reference model. in an ideal case, all the engineering factors that are considered for leak detection are already being modeled by the RTTM. In that case, the assessment of the uncertainty due to transient effects or any of the engineering factors will be precisely zero.

In a less than ideal case, some of the engineering factors are not included in the RTTM. In that case, a comparison will again be needed against another reference model, except that only those engineering factors that are left out need to be considered.

However, this still leaves:

1) metering uncertainty;

2) numerical inaccuracy of the RTTM. These include the factors that can be estimated using the techniques described under calibration of the reference model; and

3) physical inaccuracies of the RTTM (modeling errors) in the modeling of the engineering properties and factors on the pipeline.

Metering uncertainty is handled separately using the measurement model, and numerical inaccuracy is discussed systematically in 11.7. However, there is no systematic way of predicting the extent and frequency of modeling errors, due for example to the quality and accuracy of correlations for fluid density or temperature effects. One approach is to accept this and tacitly assume the RTTM model as perfect. Another alternative is to assess, within the MTBF calculation, a proportion of the number of times the RTTM model provides poor results and then to categorize that as a failure of the total LDS.

8.8.2 Model-compensated Mass Balance

This method is therefore, in the ideal case, just as the mass balance technique free from any RM comparisons. The lines B and D on the general behavior chart are no longer present.

8.8.3 Deviations Analysis

8.8.3.1 General

A subset of the pipeline state, which may include pressures, flow rates and temperatures, is computed using a subset of the metering on the system as boundary conditions. This set of state variables is then compared against other metering and instrumentation on the pipeline. Practically speaking, the set of state variables is therefore limited to values that are also metered.

The metric is therefore generally a list of pipeline state variables, denoted by N values $\{S_i\}$.

8.8.3.2 Procedure

The baseline RM is prepared using the expected values of all the boundary conditions that are themselves being used by the RTTM.

8.8.3.3 Uncertainty in the Metric

Any of the boundary conditions can be varied in order to analyze their impact on the metric.

Again, there is generally no purpose in assessing any engineering factors that are already accounted for in the RTTM. However, all metering uncertainty effects and transient effects as appropriate will lead to an uncertainty in the state.

8.8.3.4 Use of the Metric

This state is then used directly in specialized comparison algorithms.

8.9 Leak Location Algorithms

8.9.1 General

There are two major location algorithms:

1) pressure gradient intersection;

2) using pressure wave speed.

The first two methods are designed as practical solutions for steady state liquid flow. The second method implicitly requires the use of an RTTM so that multiple leak location scenarios can be analyzed.

8.9.2 Pressure Gradient Intersection

The method is designed for steady state liquid flow. The corresponding Darcy-Weisbach pressure drop equation is then:

$$\frac{dP}{dx} = f\,\frac{\dot{M}|\dot{M}|}{2\,D\,A^2\,\rho} \qquad (29)$$

Here f is the Moody friction factor. If there is a leak at a point x along the pipe, then downstream of this leak the gradient will instead be:

$$\frac{dP_{\text{down}}}{dx} = f\,\frac{(\dot{M}-\dot{M}_{\text{leak}})|\dot{M}-\dot{M}_{\text{leak}}|}{2\,D\,A^2\,\rho} \qquad (30)$$

The location of the leak can be found from the point of intersection of the two pressure gradients, as illustrated in Figure 15.

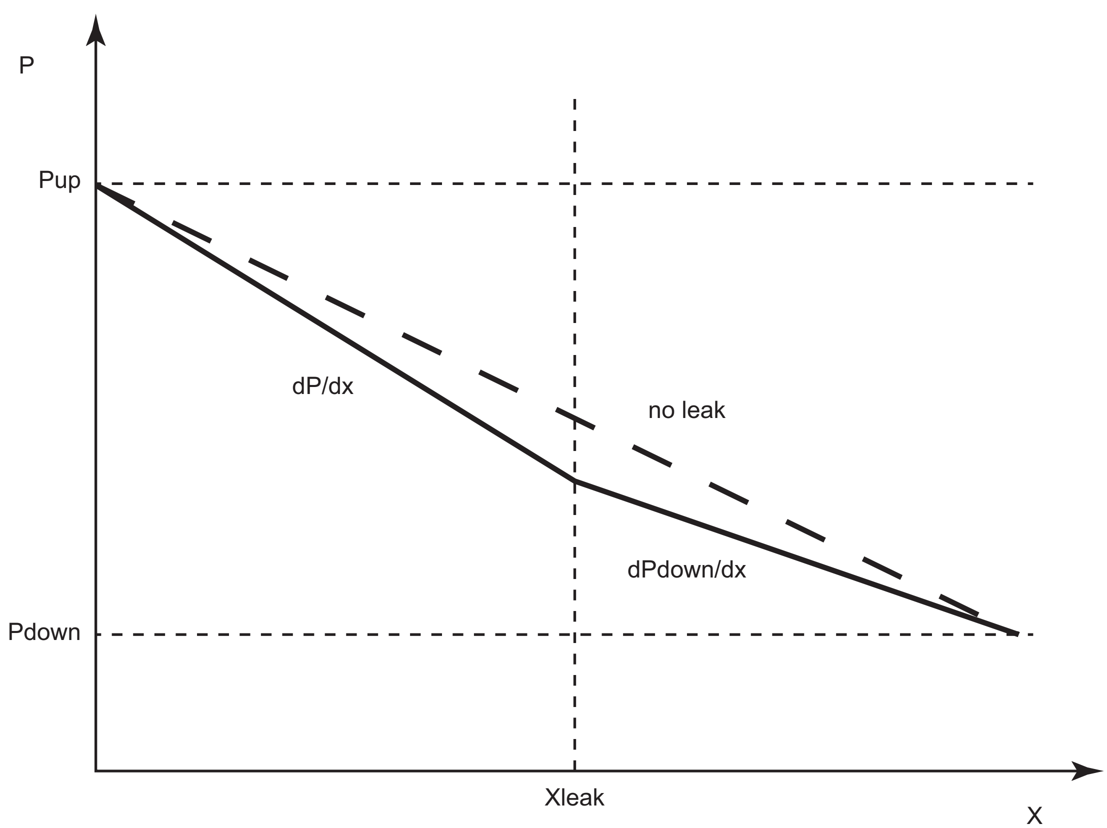


Figure 15—Gradient Intersection Method

This is conveniently coupled with a material balance method, since if there is an imbalance then the first equation can be used with the inlet mass flow rate, and the second with the (different) outlet mass flow rate.

If the gradients are *g* then the point of intersection is:

$$\Delta P - L\,g_2 = x\,(g_1 - g_2) \tag{31}$$

Formally, the precision of this estimate is given by:

$$Var(x) = (Var(\Delta P) + a^2 L^2\,Var(\dot{M}_{\text{up}}))/a^2 L^2 (Var(\dot{M}_{\text{up}}) + Var(\dot{M}_{\text{down}}))$$

$$a = f/2\,D\,A^2\,\rho \tag{32}$$

This can be (and is often) used with each of the inputs (including $Var(\Delta P)$, $Var(\dot{M}_{\text{up}})$, and $Var(\dot{M}_{\text{down}})$ assessed using the reference model.

There are essentially four inputs to the algorithm: inlet and outlet pressure, and inlet and outlet mass flow rate. The procedure can be used with the location of the predicted leak as the metric. This yields four partial derivatives, and these can then be used to calculate a compound uncertainty as a function of the uncertainties in these four inputs.

However, recall that this entire method is contingent upon constant density and the Darcy-Weisbach equation. In practice this precision is completely dominated by uncertainties in density and the pressure drop, making Equation (29) largely irrelevant.

8.9.3 Pressure Wave Speed

In isentropic flow, a pressure change will be induced by a sudden volume change, equal to:

$$\Delta p = -\frac{1}{A}\,c\,\dot{M}_{\text{leak}} \tag{33}$$

Here c is the speed of sound of the fluid. The pressure change can be used from this equation to estimate the mass flow rate of the leak. It is common to use this technique in combination with pressure rate of change monitoring for Δp.

If two pressure transducers are upstream and downstream of the leak, then:

$$x_{\text{leak}} = 0.5((x_2 - x_1) + c(t_2 - t_1)) \tag{34}$$

Formally, the idealized precision of this estimate is then:

$$Var(x_{\text{leak}}) = 0.5\;Var(c)\;Var(t) \tag{35}$$

To use this equation, generally it is necessary to obtain the precision of *c*. This can be achieved using the procedure from all the measurement uncertainties under consideration.

An uncertainty analysis of pressure rate of change monitoring is also necessary in order to provide levels of confidence in Δp.

However, the isentropic flow assumption is very weak for HVLs and for gases. Therefore the practical applicability of this estimate is generally poor.

8.10 Slack Line Flow (SLF)

8.10.1 General

SLF occurs when the pressure drops below the vapor pressure at a point in a liquid line. At this point, segregated vapor-liquid channel flow will begin (Nicholas, 1995). The pressure may then increase further downstream, in which case the flow will re-attach to form single-phase liquid flow again.

This situation is often just as uncertain for leak detection as multiphase flow. However, it is at least piecewise single-phase up- and down-stream of the vapor region. There are two objectives.

— Identifying the onset of SLF in a pipeline. It is then a choice between ceasing to rely upon installed LDS, and modifying the technique in order to compensate.

— Analyzing all of these CPM techniques to assess reliability during SLF.

There are some immediate observations for a pipeline in slack line flow.

Frictional pressure drop in SLF is far greater than under normal conditions. At the onset of SLF, there is therefore a noticeable and immediate downstream pressure decline, just as for a leak.

The flow rate of the pipeline is completely defined by the upstream pressure of the line, and the elevation (i.e. head) at the point at which SLF first occurs.

Any pressure changes downstream of the slack region will be completely invisible upstream—the slack region absorbs transients.

8.10.2 Traditional Methods vs. RTTM

There is a significant difference between attempting to use a monitoring or balancing technique, and using an RTTM. With an RTTM, there is at least an attempt to model the channel flow region physically and this yields significant advantages. The simpler methods can yield very uncertain results.

8.10.3 Estimating the Location of Slack Flow

The reference model is used as a tool, simply to identify the location of the first point where SLF occurs. The RM is not set up to model SLF at all; rather it is run as a normal simulation without consideration of potential vaporization. Quite simply, the line pressure is then compared against vapor pressure and the location of this point is regarded as a metric.

8.10.4 Pressure and/or Flow Monitoring

If SLF occurs, it is suggested that single-point pressure or flow monitoring yield uncertainties that are well beyond the few percent range that are considered. Therefore, this becomes more of a robustness/reliability issue. The recommendation is to use the likelihood of slack line flow occurring as essentially the probability of this form of leak detection failing altogether.

8.10.5 Balancing Techniques

Similarly, either volume, or basic or compensated mass balance, will suffer from uncertainties in the linepack well beyond the few percent range that are considered.

This can be verified by running the RM with slack-line flow modeling turned on. In that situation, even just crude comparisons with the basic balancing techniques will typically show discrepancies over 10 %.

Therefore, the recommendation is to use the likelihood of slack line flow occurring either as a measure of:

— the probability of the LDS being inoperative (availability); or

— the probability that performance will be seriously degraded (reliability).

8.10.6 RTTM

Recall that with a RTTM, a core assumption is that the RTTM itself is at least as accurate as the reference model. What instead is the case is that a number of inputs to an RTTM that attempts to model SLF become far more sensitive. It is therefore recommended to analyze explicitly:

— Elevation profile (a factor with a potential bias). Regions of slack line flow always begin at an elevation peak, so rather than necessarily evaluating the sensitivity with regard to every elevation point, these should be examined in most detail.

— Vapor pressure itself (a factor with a potential bias).

— Pressure measurements (a factor with a potential bias and also a potential Variance P).

However, beyond these three particular recommendations, the quality of the uncertainty assessment is essentially directly related to the quality and fidelity of the reference model itself.

This makes a careful analysis of model and numerical error in the RM, as discussed in the reference model section, equally important. If any one of these uncertainty factors exceeds the 5 % range, the process should be abandoned.

8.11 Constant Threshold

The most common comparison technique in steady state conditions is against a constant threshold. The comparison then made is whether the uncertain metric M is greater than a constant threshold T. This situation is illustrated in Figure 1.

The uncertainty analysis has been assessing the total uncertainty of M in terms of a bias b and its precision a^2, as explained in the last section.

The most precise expression of the likelihood of a false alarm being called is in terms of standard deviations. The random variable $M - b$ has zero mean, and therefore a threshold set at $b + a$ will have one standard deviation likelihood of being valid. Setting a higher threshold—for example, at $b + 2a$—will reduce the uncertainty of the likelihood of the alarm being valid, at the possible expense of missing actual alarms that occur in the tail of the PDF.

8.12 Two Metrics

Occasionally, two random variables need to be compared, and their difference compared against a threshold.

The distribution of the difference between two random variables has the property:

$$E(U_1 - U_2) = b_1 - b_2$$

$$Var(U_1 - U_2) = a_1^2 - a_2^2 \tag{36}$$

By using a random variable *M* with this distribution reduces the problem to one metric as just discussed. Note that this approach increases the variability by addition of the metrics' values. However, its true purpose is that the biases subtract—therefore, by choosing these metrics carefully it is possible to reduce (or eliminate) the bias substantially.

8.13 Root Mean Square

The RMS difference between two vectors S and T is defined as:

$$R^2 = \Sigma\, a_i\, (S_i - T_i)^2 \tag{37}$$

Here, the constants a_i represent arbitrary weighting factors. This new random variable has the expected value:

$$E(R^2) = \Sigma\, a_i\, [Var(S_i) + Var(T_i) + E^2(S_i) + E^2(T_i)] \tag{38}$$

Note that, even if all the individual elements have zero bias, the RMS will in general have a bias driven by their individual precisions. Its variance is complicated and requires higher-order moments in the general case. However, assuming that the distributions are approximately normal:

$$Var(R^2) = \Sigma\, 2a_i^2[(Var(S_i) + Var(T_i))][Var(S_i) + Var(T_i) + 2(E(S_i) + E(T_i))^4] \tag{39}$$

As before, one standard deviation of having a valid alarm from an RMS is at a threshold of $E(R^2) + \sqrt{Var(R^2)}$.

8.14 Student *t*-test

8.14.1 General

The Student t-test is specifically designed to assess whether the mean of a normally distributed random variable has a value (in this case, usually zero or the assessed bias) specified in a null hypothesis.

The classical version uses the statistic:

$$t = \frac{\overline{M} - b}{S/\sqrt{N}} \tag{40}$$

Here $\overline{M}$ is the sample mean and S is the sample variance over N successive samples of M.

Assuming that M is normally distributed, the variable t has a Student's Distribution. Percentiles and confidence intervals can be found readily for this distribution. These then correspond to actual rates (probabilities) of false alarms.

Note how this test makes no use of a priori estimates of precision at all. Rather, the readings themselves are used to estimate precision. This is very useful when it is too difficult to assess the variability of leak detection metrics.

This method can also be used to detect a change in a reading (or a metric). The readings $p(k)$ are sampled discretely in time via SCADA or locally, and are treated over two different time windows. Each moving window contains a different fixed number of sample points at any one time: N_o, N_1.

This gives two estimates of the average measurement at any time, using the moving average estimator:

$$\hat{\mu}_o(k) = \hat{\mu}_o(k-1) + \frac{p(k) - p(k - N_o + 1)}{N_o}$$

$$\hat{\mu}_1(k) = \hat{\mu}_1(k-1) + \frac{p(k) - p(k - N_1 + 1)}{N_1} \tag{41}$$

If it is assumed that the original readings are normally distributed, then the moving average is also normal. To test whether these two are statistically different, then use the statistic:

$$t = \frac{(\ddot{\mu}_o(k) - \ddot{\mu}_1(k))}{\sqrt{\frac{N_o - N_1}{N_o - 1} \times \frac{S}{N_1}}} \tag{42}$$

This also has a student's distribution.

Note how, in this version, not even an assessment of the bias is needed. Rather, the bias is also estimated directly from the data.

8.14.2 Uncertainty with a *t*-test

The t-tests are rigorous and allow a specified certainty in the leak alarm to be set. However, two remarks should be made:

Note how a factor of $\sqrt{N}$ appears in both equations. While it is attractive that an estimate of bias and/or precision may not be needed from physical principles, this does mean that the uncertainty can be quite large if the number of readings is small. Sometimes, perhaps hundreds of samples are needed in order to provide useful confidence intervals. This fact can lead to a relatively long response time.

Also, the number N is the number of samples taken from an *identical population*. If anything changes, for normal reasons, on the pipeline then N starts again from zero. This can lead to false alarms if N is left at the value in the former state, and a correspondingly tight error bar is left in place.

8.15 Sequential Probability Ratio Test

8.15.1 General

This approach asks the question: is the value of a normally distributed reading or metric R_t at this time t likely to be, on average, the old value μ or has it increased to $\mu + \Delta\mu$? This is a statistical hypothesis question, and is approached using the sequential probability ratio test (SPRT). The ratio is:

$$\lambda_k = \log\left(\frac{R_k}{R_{k-1}}\right) \tag{43}$$

An alarm is definitely called if $\lambda > A$—there is certainly no alarm if $\lambda < B$—and no decision is made if $B < \lambda < A$; where A and B are fixed thresholds.

Define:

$$A = \frac{\alpha}{1-\beta}$$

$$1/B = \frac{\beta}{1-\alpha} \tag{44}$$

then α, β represent the confidence intervals for identifying a change, and of missing a change, respectively. No special assumptions about normality are made about the distribution of the readings.

To estimate the magnitude of the change—i.e. what is $\Delta\mu$—the theoretical result that assumes all errors are normally distributed can be used:

$$\lambda(k) = \lambda(k-1) + \frac{\Delta\mu}{\sigma^2}\left(R(k) - \mu - \frac{\Delta\mu}{2}\right) \tag{45}$$

To use this formula, values of σ,μ have to either be assumed, or estimated from the sample variance:

$$S^2 = \frac{1}{N-1}\sum(X-\bar{X})^2 \tag{46}$$

and sample mean (i.e. the average) of the $R(k)$.

Note how this method requires no estimate of the bias or precision of R_k. You do need to estimate these, either from theory or from the sample data, in order to calculate the magnitude of the actual change.

8.15.2 Uncertainty with a SPRT

Similar remarks apply to those made earlier, for statistical techniques:

The SPRT is designed to detect *changes* over time, and has no reference to the actual mean value of a sample. This makes it particularly insensitive to gradually increasing variables. If the thresholds A and B are low enough to allow small systematic increases then quite a large metric can pass undetected unless other measures are in place to avoid this effect.

Also, in using Equation 45 with σ,μ estimated from the sample variance and mean, the number N is the number of samples taken from an *identical population*. If anything changes, for normal reasons, on the pipeline then N starts again from zero. This can lead to false alarms if N is left at the value in the former state, and a correspondingly tight error bar is left in place.

9 Filtering

9.1 General

Filtering is quite often applied to leak detection systems, either purposely or implicitly.

— In situations where data is known to be poor, or perhaps there are common, known very short-term hydraulic transients in the pipeline; explicit acceptable data bounds are set.

— Very often, data acquisition systems either sample in time, or perform moving average calculations, or have implicit reliable reading bounds set.

Many leak detection algorithms also implicitly apply a filter within their calculations as well. For example, line balance calculations often use a moving average of imbalances as their metric as well as the instantaneous balance.

The general model for treating a filter on data or the computed metric is that it narrows the precision of the uncertainty, at the expense of the availability. In short, it will reduce tolerances but increase the rate of misses. Generally, a well-designed filter does not introduce systematic bias to the data. These are the most relevant filters:

— moving average;

— high-pass filtering;

— outlier removal:

— upper and lower bounds;

— upper and lower percentiles.

9.2 Moving Average

A very common implicit filter is the moving average (technically, a form of low-pass frequency filter on a time-series):

$$X_j^{(N)} = \frac{1}{N} \Sigma_{i=j-N+1}^{j} X_i \tag{47}$$

As written, Equation (47) represents a backward-looking moving average of the last N samples. There are also forward-looking and centered moving averages as well, but their statistical nature and uncertainty structure is very similar.

The mean of the moving average is still equal to the mean of the time-series, but the variance is reduced by a factor of N.

Technically, this also introduces a time-data shift of one-half the chain length times the rate: $N^{\Delta t}/2$.

This is at the expense of a reduction in the frequency of readings that deviate from the mean. One standard deviation of a distribution contains $F(1)$ of all possible samples, while a standard deviation of the moving average (reduced by a factor of N) will contain only $F(1/N)$. Therefore, a measure of the ratio of dropped readings is:

$$\text{Availability} = 1 - \frac{F(1)}{F\left(\frac{1}{N}\right)} \tag{48}$$

The longer the chain length N the more points will tend to be dropped. The numerical values of $F(x)$ can be found from tables for the normal distribution, or they are simply a linear $x\ \Delta^2/12$ for the uniform distribution.

9.3 High-pass Filter

The intention of a high-pass filter is the opposite of the moving average. It is meant to eliminate gradual, long-term drift in the data or an imbalance that is normal.

This kind of filtering is commonly achieved using Fourier transforms or other digital signal processing. There is a minimum time resolution at the data-sampling rate (the maximum rate at which data is collected) and there is a maximum period over which the analysis is performed. If there is a frequency cutoff f_c then:

— the mean is not affected: the first term in the Fourier series is not modified;

— the availability is now: $(\Sigma_1^c a_i / \Sigma_1^N a_i)$;

— the variance is now: $1 - (\Sigma_1^c a_i^2 / \Sigma_1^N a_i^2)$ times the former variance.

9.4 Outlier Removal

9.4.1 Upper and Lower Percentiles

The simpler case for outlier removal is when the filter is set only to pass the central *S* standard deviations of the time-series.

The mean is not affected, and the availability is now:

$$\text{Availability} = 1 - \frac{F(1)}{F(S)} \tag{49}$$

The standard deviation of the new distribution is $F(1)/F(S)$ times the original standard deviation.

9.4.2 Upper and Lower Numerical Cutoff

When working with a numerical cutoff Y it is useful to normalize this against the mean and variance of the underlying distribution:

$$y = \frac{(Y - \mu)}{\sigma} \tag{50}$$

This is then analyzed using the cumulative distribution function $P(x)$, which measures the probability of the sample being less than x. The numerical values of $P(x)$ can be found from tables for the normal distribution, or they are simply a linear x/Δ for the uniform distribution.

The mean is not affected, and the availability is now:

$$\text{Availability} = P(y) \tag{51}$$

The standard deviation of the new distribution is $P(y)$ times the original standard deviation.

9.5 Comment on Usage

Note how in general the effect of a filter is to reduce the original variance by a given factor. Therefore, generally a filter can be applied at any stage, or to any component of the uncertainty calculation by:

— leaving the bias unchanged;

— multiplying the precision by one of the factors described;

— taking the minimum of the current availability, and the availability due to the filtering.

Note especially that deliberately filtering input data to LD techniques that are based on physical principles—such as most of the balancing techniques—can be dangerous since the filtered data no longer necessarily represent the true physical measurements expected by the method. As an example, if the flow into a pipe is filtered, but not the flow out, there is no longer a physical reason why the two should necessarily balance—particularly if readings outside a pass-band are removed.

10 Uncertainty Model

10.1 General

Recall that any uncertainty has a mean value called the bias, and a standard deviation called the precision. It is systematically assumed that:

— 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.

— 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 begin to be inaccurate when the precisions are greater than about 5 %.

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.

Finally, returning to the discussion of Table 2, without knowledge of the precise nature of the PDF, a bias and precision do not translate to a *probability* beyond a certain threshold.

The statistical principles presented in this section are taken from ASME *V&V* 20 (2009), API *MPMS* (2013) are references therein. Essential introductory statistics can be found in, for example, Cox (2006).

10.2 Model Details

10.2.1 General

Uncertainty is no more than a random variable representing the distribution U of a measurement, or calculated value based upon measurements, with a mean and variance that are unknown, to be estimated. Refer to the mean of the random variable as the bias, and its standard deviation as the precision. The object of uncertainty analysis is the estimation of the total bias and precision based upon all the inputs, which are also uncertain.

The approach is to separate sources of uncertainty so that they are mutually uncorrelated. With uncorrelated random variables the expected values and variances of sums and products combine particularly simply. Therefore, if a measure of uncertainty is "± one standard deviation" these can be combined relatively easily.

By contrast, an x % confidence interval requires not only knowledge of the standard deviation, but also the nature of the underlying distribution over time. This is difficult to assess in most cases.

There are closed form transformations that convert an uncertainty into the uncertainty of a function. There are also simple approximations for the effect of the transformation on the mean and variance that can be used *when the variance of the underlying uncertainty is small*. In most cases, proceed throughout this work with the assumption of numerically small variances in all the uncertainties.

10.2.2 Vocabulary

The *underlying uncertainty* in any measurement, parameter or calculated value is a random variable with a mean and variance *that are unknown*, to be estimated, as well as an underlying probability distribution function. It has a *mean uncertainty* (its mean) and a *precision* (its variance).

Note that statistical and information theory call the mean of the uncertainty the accuracy of measurement. This might be confusing, since in engineering measurement, accuracy is generally the sample variance of measurements.

Estimators are used to estimate the mean and variance of the underlying uncertainty, from a set of n samples X_i. These are often labeled "sample" quantities: for example, the *sample mean* and the *sample variance*.

The estimated mean of the underlying uncertainty is called the (estimated) *systematic bias*. The maximum likelihood estimator for the mean is the simple average (also called the *sample mean*):

$$\bar{X} = \frac{1}{n} \Sigma X_i \tag{52}$$

Note that a *calibrated* meter or instrument is assumed to have a zero systematic bias.

The standard deviation (the square root of the variance) of the estimator of the mean of the underlying uncertainty is called the *accuracy*. Note that this is not standard statistical practice (accuracy = mean uncertainty). It is, however, common vocabulary in engineering measurement theory.

The maximum likelihood and unbiased estimator for the variance of the sample is the average sum of squares deviation (also called the *unbiased sample variance*):

$$S^2 = \frac{1}{n-1}\Sigma\,(X-\bar{X})^2 \tag{53}$$

Note that, if n is used in the denominator instead of (n – 1) then the estimator is biased and systematically underestimates the variance. As n increases, this bias decreases and is often practically negligible when $n > 10$ or so.

Repeatability 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). The most common are the Fisher test, Pearson correlation, and Chronbach alpha (Cox, 2006).

Reproducibility is part of the precision of a test method. It is used to emphasize that the uncertainty is due to the test method or calculation algorithm—rather than a measurement or similar inaccuracy.

An example might be the testing of metering equipment. If the same meter is used for all experiments, and all samples relate to the same meter, one might talk of the reliability of this meter. If, on the other hand, multiple meters are used to make the same measurement or if different test scenarios were used in the experiments, one might talk about reproducibility of the meters as a group or the test method.

10.2.3 Uncertainty Distributions

Normal distributions—are appropriate for smooth uncertainties with a large number of components (law of large numbers—also it maximizes entropy). Note that the large majority of meter and instrument specifications assume that their uncertainty is Gaussian. This kind of uncertainty is also called additive white noise (AWN).

Lognormal distributions—are continuous probability distributions of random variables whose logarithm is normally distributed (i.e. if X is a random variable with a normal distribution, then Y = exp (X) is lognormal). Note that the errors of many temperature and pressure sensors tend to be lognormal.

Binomial distribution—is the discrete probability distribution of the number of successes in a sequence of n independent yes/no experiments, each of which yields success with probability p, and failure with probability (1 – p). This distribution is appropriate for measures of reliability and robustness.

Poisson Distribution—is a discrete probability distribution that expresses the probability of a given number k of events occurring in a fixed interval of time; space; volume, etc. if these events occur with a known average rate and independently of the interval since the last event. This also is useful in assessing the number of failures of a system in a given time period.

The sample variance S^2 has a *chi-squared distribution* if and only if the underlying distribution of X is normal. It has one parameter—k the degrees of freedom. In the case of the sample variance of normally distributed random variables, $k = n$. This fact is useful in calculating confidence intervals of estimates of repeatability.

For a (normalized) chi-squared distribution, the variance is 2k. Therefore, in estimating the uncertainty in the accuracy (as one standard deviation of the uncertainty) it is critical to record how many samples were used in the estimate (the degrees of freedom).

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

$$T = \frac{\bar{X} - \mu}{S/(\sqrt{n})} \tag{54}$$

has a student-t distribution, with (n – 1) degrees of freedom. This fact is useful in calculating confidence intervals of estimates of systematic bias.

Again, for a (normalized) student-t distribution, the variance is (n – 1)/(n – 3). Therefore, in estimating systematic bias it is critical to record how many samples were used in the estimate (the degrees of freedom).

Often a useful approximation is that, as n becomes large, the student-t distribution approximates the normal distribution. In many practical applications, "large" may only be greater than ten or so.

10.2.4 Classification of Sources of Uncertainty

Generally, the aim is to decompose the sources of uncertainty in any LDS algorithm into these main categories, each of which is mutually statistically independent and each of which is typically individually small.

Metric uncertainty:

— instrument,

— telemetry,

— model error—Type A,

— model error—Type B,

— numerical errors,

— filtering.

Where appropriate, also divide the errors 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.

Recall from the Introduction that it is useful to divide model uncertainty into two:

1) physical effects that are ignored entirely; and

2) estimates and approximations.

In order to estimate the magnitude of these errors, the process makes use of a RM that (it is assumed) has a minimal model error itself (although it will have a numerical error). Filtering is applied either to the inputs of the algorithm (i.e. after telemetry) or to the metric itself.

The metric is then used in a comparison technique in order to assess whether a threshold, or perhaps another metric or measurement, has been crossed. Comparison uncertainty is therefore a function of one or more metric uncertainties.

Location uncertainty is similarly a function of the uncertainties of the metrics that are used to estimate leak location.

10.2.5 Combining Uncertainties

10.2.5.1 General

In order to combine uncertainties more simply, assume that they are *independent* random variables (i.e. a variation in one of them has no impact on the other).

10.2.5.2 Addition

The probability distribution of the sum of two or more independent random variables is the convolution of their individual distributions. In some particular cases—especially the normal distribution—this simply reproduces the original distribution. The sum of two normal distributions is again normal.

For any two *independent* random variables, regardless of distribution:

$$E(X+Y) = E(X) + E(Y) \tag{55}$$

The variance of a sum of *independent* random variables is equal to the sum of their variances:

$$Var(X+Y) = Var(X) + Var(Y) \tag{56}$$

In other words, standard deviations combine in quadrature.

10.2.5.3 Multiplication

The probability distribution function of the product $V = XY$ of two random variables is given by:

$$f_{\mathrm{v}}(v) = \int_{-\infty}^{\infty} f_{\mathrm{X,Y}}\left(x, \frac{v}{x}\right) \frac{1}{|x|}\, dx \tag{57}$$

The distribution of the product of two random variables, which have lognormal distributions, is again lognormal. However, this is an unusual special case.

If X and Y are *independent*:

$$E(XY) = E(X)\, E(Y)$$

$$Var(XY) = (E(X))^2\, Var(Y) + (E(Y))^2\, Var(X) + Var(X)\, Var(Y) \tag{58}$$

In particular, for uncertainties with zero systematic bias the standard deviations combine as a product.

10.2.6 Transforming Uncertainties

10.2.6.1 General

Often in the analysis of uncertainty it is necessary to study the effect of a complicated functional transformation of an uncertain measurement. A common rule in probability theory is that for a random variable X with *any* probability distribution function $f_X(x)$—if $Y = g(X)$ is any function of the random variable X *that is monotonic* then:

$$f_{\mathrm{y}}(y) = \left|\frac{d}{dy}(g^{-1}(y))\right| f_{\mathrm{x}}(g^{-1}(y)) \tag{59}$$

In short, one only needs to multiply by the derivative of the transformation function in order to compute the probability distribution of the transformed variable.

The requirement that g should be monotonic (therefore, to have a unique inverse) is commonly accomplished in practice by restricting the range of x and y to regions where this is the case. Usually a reasonable interval around the mean of X can be found for uncertainty analysis. Note that, with many physical transforms and especially with complicated transforms that are implicit in form, it is often easier to work with the derivatives rather than g itself, in any case.

With multiple random variables, $f_Y(y)$ is:

$$\int_{y=g(x_1,\ldots,x_n)} \frac{f(x_1,\ldots,x_n)}{\sqrt{\sum_{j=1}^{n} \frac{\partial_g}{\partial_{x_j}}(x_1,\ldots,x_n)^2}}\, dV \tag{60}$$

This can often be estimated usefully, when the distribution f has a sharp peak, i.e. it has a small variance and the confidence interval is small, to give:

$$f_Y(y) \approx f_x(g^{-1}(y)) \Big/ \sqrt{\Sigma \frac{\partial_g}{\partial_{x_j}}(\mu)^2} \tag{61}$$

This corresponds to a very simple linear scaling, with a scale factor equal to the RMS of the partial derivatives of g at the mean. The mean and the variance—and therefore the resulting confidence interval—will similarly transform linearly as well.

In order to transform uncertainties more simply, assume that their variance (i.e. their precision) is numerically small. This simplifies the transformation formulas considerably.

10.2.6.2 Expected Value

The expected value of a function is *not* in general the function's value at the expected value of X:

$$E(g(X)) = \int g(x) f_x(x)dx \neq g(E(X)) \tag{62}$$

In practice, the simplifying assumption that the distribution $f_X(x)$ is sharply-peaked at its mean, μ is often made. Then the expected value of a function is *approximately* the function's value at the expected value of X:

$$E(g(X)) \approx g(E(X)) \int f_x(x)dx = g(\mu) \tag{63}$$

A good example is when the distribution is normal with a very small standard deviation.

10.2.6.3 Variance

The variance of a function can be found from the formula:

$$Var(g(X)) = E(g^2(x)) - E(g(x))^2 \neq g(Var(X)) \tag{64}$$

However, with the same sharply-peaked (small standard deviation) approximation for $f_X(x)$ it is possible to estimate (provided that g is twice differentiable and that the mean and variance of X are finite):

$$Var(g(X)) \approx (g'(\mu))^2\ Var(X) \tag{65}$$

11 Reference Model

11.1 General

This section describes the reference model that is recommended in the procedure for estimating the metric errors in each leak detection algorithm. A central assumption in this process is that the Reference Model that is used has itself negligible model error compared with the leak detection algorithm itself (particularly when the CPM in question involves a Bernoulli and/or a RTTM itself), and represents the actual behavior of the pipeline accurately (although it may have numerical error).

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 might be used, in order to provide the maximum flexibility in assessing the complete range of potential source of uncertainty. However, if only the uncertainty (for example) 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.

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 the transient operations themselves (it is impossible to turn back the clock and examine what might have happened with different pressures and temperatures) but the entire method can still be applied using this approach.

With these observations in mind, this section describes a *minimal* RM that will cover all the uncertainty factors and engineering factors listed as objectives in the Introduction at the beginning.

The equations presented here can be found in, for example, Wylie, Streeter, and Bedford (2010), Lurie (2008), or Geiger (2012). Many of the procedures—notably, the estimation of modeling uncertainties—are taken from the ASME *V&V* 20 (2009).

11.2 Model

11.2.1 General

Leak detection methods that are subject to density (in particular, line pack fluid compressibility, or speed of sound), pressure and/or flow profile uncertainties require an estimate of the reference values of these physical properties along the pipe. For this reason, a reference pipe model is used to provide an accurate set of physical values.

The reference pipe model can be based upon this set of simplifications.

11.2.2 Temperature Effects

Recall that all *variations* in inlet and/or outlet pressure and temperature values will be treated as fully transient effects. As a simplification of the full enthalpy model, the definition will be used:

$$\delta h = c_{\mathrm{P}}\,\delta T + V(1 - \alpha T)\delta P \tag{66}$$

The additional assumption that variations in V are relatively small simplifies these equations:

$$\frac{dh}{dt} \approx c_{\mathrm{P}}\frac{dT}{dt} + V(1 - \alpha T)\frac{dP}{dt} \tag{67}$$

This approximation is designed to avoid the use of tables of enthalpy against pressure and temperature, which may introduce complexity and greater errors than the assumption of small changes in V.

11.2.3 Equations of Motion

Conservation of mass:

$$\frac{d\rho}{dt} + \rho\frac{\partial v}{\partial v} = 0 \tag{68}$$

Momentum:

$$\frac{dv}{dt} + \frac{1}{\rho}\frac{\partial P}{\partial x} + f_F \frac{v^2}{2D} + g \sin\theta = 0 \tag{69}$$

Conservation of energy:

$$\frac{dh}{dt} \approx c_P \frac{dT}{dt} + V(1 - \alpha T)\frac{dP}{dt} = \frac{1}{\rho}\frac{dP}{dt} - l_Q - f_F v \tag{70}$$

Treatment of heat flow per unit mass, l_Q:

One can use the steady state, assumed exponential temperature profile to estimate the heat flow per unit mass via a thermal conductivity k. Under steady state, and providing the line is not short, conservation of energy balances heat flow with dissipative losses:

$$l_Q = U(T - T_{ambient}) \tag{71}$$

where

$$U(x)\ (T_{ss}(x) - T_{ambient}) = -(f_F\ v)_{ss} \tag{72}$$

This assumption is again justified by the fact that these deviations are extremely slight compared with other uncertainties related to temperature measurement, fluid enthalpies, thermal transfer coefficients, and other elements of a full thermal model.

Furthermore it is justified because the absolute value of predicted temperature is not at issue—rather it is the variability of the temperature with respect to the boundary conditions that interest us.

The ambient temperature profile $T_{ambient}$ is estimated to at most a piecewise linear profile between end point ambient temperatures.

11.3 Calculation of Density

The calculation of density—or, equivalently, the computation of volumes at standard conditions—is central to a number of LD techniques that rely on the principle of conservation of mass. Therefore, for these kinds of LD methods the equations for density/standard volumes are important.

Liquids—The API RP 2540 presents a wide range of C_p and C_t tables for petroleum liquids that are used to produce tables for density and bulk modulus.

These same tables have been adopted as ISO 5024: *Petroleum liquids and liquefied petroleum gases—Measurement—Standard reference conditions*.

The ASTM D1250-80 is an extension of the API *MPMS*—it is particularly directed at mixtures of petroleum liquids.

Note that these tables for saturated liquids are for linearly compressible fluids. Therefore, any uncertainty will lie in the values of C_p *and* C_t (which are very accurate) as well as the inputs P and T.

The GPA Technical Paper TP-27 for LPG and NGL is included in the API *MPMS*, Chapter 11—*Physical Properties Data*—Section 2, Part 4—T*emperature Correction for the Volume of NGL and LPG*—Table 23E, Table 24E, Table 53E, Table 54E, Table 59E, and Table 60E

Note that the LPG and NGL tables are still linearly compressible. Note that C_t is substantially higher than for LVL—nevertheless, it is still linear.

Carbon dioxide pipelines are also treated using tables for CO_2 physical properties from the NIST *REFPROP* V.9.1 (2013).

Gases—The petroleum industry generally uses the AGA Report No. 8, *Compressibility Factor of Natural Gas and Related Hydrocarbon Gases* (1994).

This has also been adopted as ISO 12213, and GERG TM-5.

It is generally recommended to use these tabular RP 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 is often the case 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.

Nevertheless, widely used is the GERG-2008 equation of state model, also adopted as ISO 20765. The Benedict-Webb-Rubin-Starling (BWRS) equation of state (Starling, 1973) is popular in gas measurement systems and analysis.

The main difference is that AGA-8 is valid for the gas phase only, and cannot calculate phase equilibrium. GERG-2008 can calculate a complete phase envelope. For practical pipeline applications—except perhaps for CO_2 and for situations with more than “trace” impurities—this is not usually an issue.

A simplification of AGA-8 is the SGERG-88 (“gross method”) equation that leaves out two complex summation terms in the AGA-8 formula. For pure hydrocarbon components (industrial methane, for example) AGA-8 is accepted as extremely accurate. Therefore, it is suggested that it is not a substantial source of uncertainty. However, AGA-8 was not developed using gases produced from more recent shale gas wells and therefore for gas gathering systems in shale production environments other equations are sometimes appropriate.

The NIST provides accurate databases of the parameters that are used in these equations of state. The latest one is the *Reference Fluid Thermodynamic and Transport Properties Database* (*REFPROP*): Version 9.1. It replaces the NIST 12 and 14 databases. *REFPROP* has coefficients for AGA-8 and GERG-2008 plus many others (meaning, it is valid for liquid hydrocarbons, too), and it includes transport properties like viscosity. In this context, it is valuable as a source of highly accurate CO_2 and HVL data also.

11.4 Friction Factor

The full Colebrook-White formula is used for the Darcy-Weisbach friction factor f.

A correction factor is often used, in practice, as a multiplier on the pressure gradient term for practical purposes to improve performance (Modisette, 2003). In general, many modelers prefer to adjust a flow multiplier and specify a standard roughness rather than tune roughness. This is particularly beneficial with low flow modeling scenarios, as the roughness must be adjusted significantly to have small changes in the pressure gradient.

11.5 Parameters and Boundary Conditions

One must distinguish between boundary conditions (BCs) and parameters of the model, any of which may have an associated uncertainty and may require an estimate of variability.

Boundary conditions include items such as:

— inlet and outlet pressure and temperature;

— fluid type at the inlet (for example, during batch operations) and in the pipe.

Parameters include many items including:

— pipe diameter, thickness;

— ambient temperatures;

— pipe length, elevation.

In order to estimate the derivative of the pipeline state variables with respect to most boundary conditions, a transient simulation is generally needed. The impact of the change (i.e. the derivative) will tend to reduce with time.

11.6 Transient Treatment of Boundary Condition Uncertainties

Between each time-step in any leak detection algorithm—typically, each time a new set of data from telemetry is processed—an uncertain input will not only have a finite accuracy, but its value will also vary randomly around this unknown inaccuracy. For this reason the analysis of uncertainty in the boundary conditions of a pipeline is fundamentally a transient problem since even if the reference value is static, the random variable U will not be.

Since, except for few very special cases, the effect of a boundary condition change on the pipeline state is quite complicated, the only systematic procedure is to use mathematical simulation. With this approach the input boundary condition is sampled and used at each time-step, in a transient simulation lasting as long as the total time horizon of the uncertainty estimate. This is discussed in much more detail in Section 8: *Uncertainties Due to the Metric*.

The impact of each relevant boundary condition uncertainty is assessed in this way, and provided they are individually small they can be combined using the root-mean-square scaling described in 8.13.

11.7 Treatment of Numerical Uncertainty

11.7.1 General

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. 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 methods developed to evaluate it are based on a systematic grid refinement study where the solution is expected to asymptotically approximate the exact value, as the grid is refined, at a rate proportional to the discretization order of the solution. 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 usually estimated using the residual root mean square (RMS) between subsequent iterations of a variable over all the volumes of the domain.

11.7.2 Discretization Errors

Most CFD codes include discretization in space and in time. The standard procedure for bounding the discretization error in a simulation is illustrated in Figure 16:

— take the current simulation with a result that was found with a discretization N and double the number of points to $2N$;

— note the new result, and the absolute difference between the two results is an upper bound on the discretization error, assuming that N is large enough for convergence in the first place;

— this is done both for space (halving the spatial grid size) and in time (halving the time-step).

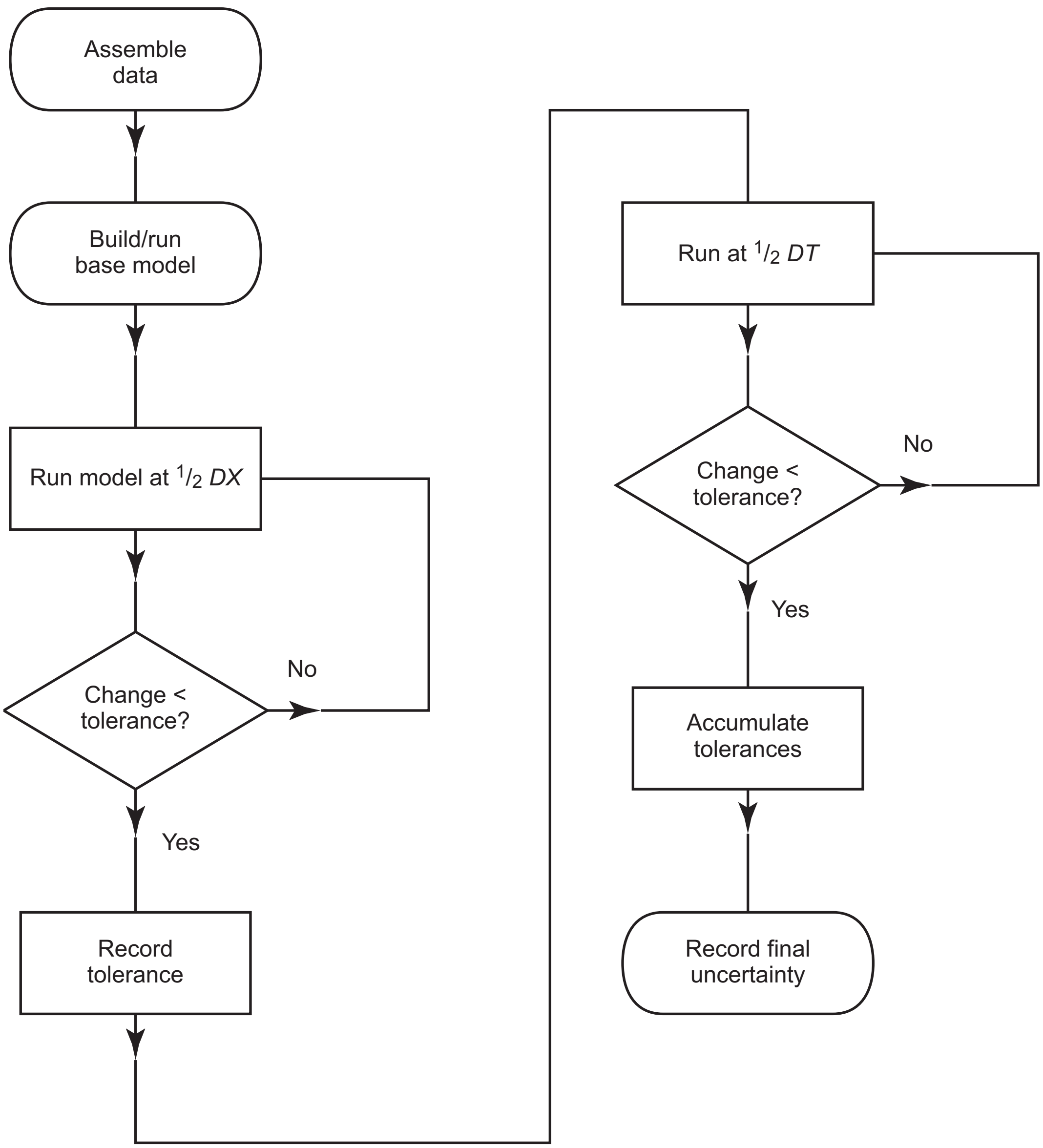


Figure 16—Flowchart for Numerical Uncertainty

The total (space and time) discretization is commonly found as the RMS of space and time errors.

11.7.3 Iteration Errors

Solvers for nonlinear equations commonly iterate upon a solution. Here, the error is usually pre-defined as the target tolerance for convergence of this iteration. Again, assuming that the number of iterations is large enough for convergence in the first place, this tolerance will be an upper bound on the iteration error.

11.8 Extrapolation to Networks

Multiple individual pipes each described by a model can be connected in a *simple* network so long as all boundary conditions are set at the external nodes of the network and there is no flow control at any nodes within the network. See, for example, Lurie (2008) for a detailed discussion of this principle.

Any general network that does include internal flow control and/or pumping or compression can be decomposed into several Simple networks if the flow devices have discharge pressure and/or flow measurement.

12 Definition of Leak Detection Techniques

12.1 General

This section defines the leak detection (LD) techniques covered by this document that are in practical use at present. Most of the pipeline leak detection methods are commonly termed computational pipeline monitoring (CPM) and they 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. This metric makes the decision regarding the declaration of a leak alarm.

An estimate of the *location* of a leak can also be made from the metric, using an additional algorithm independent of the LD technique. In addition, certain *filters* are often used to pre-process measurement data, and are occasionally used to post-process the metrics.

The reader is also referred to a review of these LD techniques presented by Geiger (2012), whose notation is followed closely here.

12.2 Summary

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;

— 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 complete pipeline state, the 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.

There are also two LDS methods 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.

Two location algorithms are in widespread use:

1) pressure gradient intersection;

2) pressure wave speed.

Leak location techniques are not within the scope of this document; nevertheless, a discussion of how the general uncertainty assessment procedure can be used for the evaluation of leak location uncertainty is included.

Three general classes of filters are considered in this document. Filtering techniques are not within the scope of this document; nevertheless, a discussion of how they affect the general uncertainty assessment procedure is provided.

1) Moving average.

2) High-pass filtering.

3) Outlier removal.

12.3 Metrics

12.3.1 Material Balance Method

The physical principle of the first two *imbalance methods* is the law of conservation of mass. For a single pipe, this reads:

$$\int_{\mathrm{t}-\Delta \mathrm{t}}^{\mathrm{t}} Q_{\mathrm{m,i}}^{(\mathrm{r})}\ dt_{\mathrm{i}}^{(\mathrm{r})} = \int_{\mathrm{t}-\Delta \mathrm{t}}^{\mathrm{t}} Q_{\mathrm{m,o}}^{(\mathrm{r})}\ dt_{\mathrm{o}}^{(\mathrm{r})} + \Delta l^{(\mathrm{r})}\ (\Delta t) \tag{73}$$

where

Q_{m} is the mass flow rate, in kg.s-1;

t is the time at which the balance is made, in s;

Δt is the balancing period, in s;

dt is the time interval at which readings are sampled, in s;

$\Delta l^{(r)}$ is the change in linepack, reference value, over the balancing period, in kg;

(r) superscript—reference (i.e. true, physical) value;

i subscript—inlet value;

o subscript—outlet value.

Here, the superscript (r) has been included to emphasize that this law holds with the actual physical reference values of all the variables. Also, it is emphasized that the change in linepack $\Delta l^{(r)}$ is a function of the time step,Δt. The unit of measurement of this equation is mass, kg.

In actual fact, measurements are used that are imprecise random variables and the change in linepack is only approximated. In this situation, write:

$$(Q_{\mathrm{m,i}}^{(\mathrm{r})} + Q_{\mathrm{m,i}}^{(\mathrm{a})} + Q_{\mathrm{m,i}}^{(\mathrm{p})})(1/f + S_i) = (Q_{\mathrm{m,o}}^{(\mathrm{r})} + Q_{\mathrm{m,o}}^{(\mathrm{a})} + Q_{\mathrm{m,o}}^{(\mathrm{p})})(1/f + S_{\mathrm{o}}) + (\Delta l^{(\mathrm{r})} + U(\Delta l)) + U \tag{74}$$

where

f frequency of balancing—$1/\Delta t$ (s^{-1});

S data—time skew, in s;

(a) superscript—average (i.e. mean) reading value;

(p) superscript—precision of the reading value;

U uncertainty, in kg.

Using the physical law of conservation of mass:

$$Q_{\mathrm{m,i}}^{(\mathrm{r})} S_{\mathrm{i}} + (Q_{\mathrm{m,i}}^{(\mathrm{a})} + Q_{\mathrm{m,i}}^{(\mathrm{p})})(1/f + S_i) = Q_{\mathrm{m,o}}^{(\mathrm{r})} + (Q_{\mathrm{m,o}}^{(\mathrm{a})} + Q_{\mathrm{m,o}}^{(\mathrm{p})})(1/f + S_{\mathrm{o}}) + U(\Delta l) + U \tag{75}$$

Re-arranging:

$$U = (Q_{\mathrm{m,i}}^{(\mathrm{r})} S_{\mathrm{i}} - Q_{\mathrm{m,o}}^{(\mathrm{r})} S_{\mathrm{o}}) + (Q_{\mathrm{m,i}}^{(\mathrm{a})} + Q_{\mathrm{m,i}}^{(\mathrm{p})})\Delta t_{\mathrm{i}} - (Q_{\mathrm{m,o}}^{(\mathrm{a})} + Q_{\mathrm{m,o}}^{(\mathrm{p})})\Delta t_{\mathrm{o}} + U(\Delta l) \tag{76}$$

To label the terms:

$$U = \text{time-skew effect} + \text{measurement uncertainty} + \text{linepack uncertainty} \tag{77}$$

It is useful to separate these into:

— uncertainties due to measurement: time-skew effect + measurement uncertainty;

— uncertainty due to calculation of the Leak detection metric: linepack uncertainty.

12.3.2 Volume Flow Imbalance

The volume flow imbalance estimates the inlet and outlet mass flow rates by their respective volumetric flow rates, multiplied by a *fixed* fluid density ρ. In this case:

$$Q_m^{(r)} \approx \rho_o Q_V^{(r)} \tag{78}$$

Here, Q_V a volume flow rate ($m^3.s^{-1}$). The metric that is used is:

$$M_1 \equiv Q_{V,i} - Q_{V,o} \tag{79}$$

Note that the linepack is not estimated and it is not part of the metric that is used.

12.3.3 Mass Flow Imbalance

Mass flow imbalance is the volume flow imbalance method, corrected to use *standard* (STP) volumes. It estimates the inlet and outlet mass flow rates using volumetric flow and then corrects to STP conditions. The metric that is used is:

$$M_2 \equiv \rho_i Q_{V,i} - \rho_o Q_{V,o} \tag{80}$$

Note that the Linepack is *not* estimated and it is not part of the metric that is used. Therefore, in this method, the physical linepack is a source of spurious uncertainty.

12.3.4 Model-compensated Mass Balance

Mass (or volume) flow imbalance is still the metric used in this technique. However, an estimate of the linepack *is also made*, usually by a RTTM.

12.3.5 Rate of Measurement Change

Either pressure or flow measurements can be used individually in order to monitor an unusual change. The metric in this case is typically the rate of change of the single measurement:

$$M_3 \equiv (P_{t+1} - P_t)/(\Delta t)$$

$$M_4 \equiv (Q_{v,t+1} - Q_{v,t})/(\Delta t) \tag{81}$$

Note that these pressure P (kPa) or rate measurements may be located anywhere along the pipeline. Therefore, unlike imbalance metrics that are unique for a given pipeline, the measurements require the location of the instrument to be specified. This method does not belong to the category of CPM according to API 1130 since only elementary computations are made.

12.3.6 Pipeline State

The pipeline state—for the present purposes—is a general list (or *vector*) of pressures, volume flow rates and temperatures sampled at a finite, discrete set of points on the pipeline. If the set of points is $x = (x_o, x_1, \ldots, x_n)$ then the state is generally:

$$S \equiv (Q_{V,o} \ldots Q_{V,n},\ P_o \ldots P_n,\ T_o \ldots T_n) \tag{82}$$

It is not always the case that a complete state is used. For example, several of the pressures, flow rates and temperatures may be missing at certain points. Then:

$$M_{5.1} \equiv S_t$$

$$M_{5.2} \equiv (S_{t+1} - S_t)/\Delta t \quad (83)$$

12.4 Comparisons

12.4.1 General

The simplest comparison is between any scalar metric and a fixed threshold ε:

$$M_i > \varepsilon \quad (84)$$

Similarly, two scalar metrics can be compared:

$$|M_i - M_j| > \varepsilon \quad (85)$$

It is quite common for the second metric not to be related to a leak detection algorithm at all. Instead, it can be a user-defined function that depends on the pipeline state and is designed to attempt to minimize false alarms. For example, it can be used to relax the threshold during periods of highly transient activity on the pipeline.

When the metric is a vector, then it is usual to use a weighted root-mean-square norm:

$$\|S\| \equiv \Sigma\, a_i\, S_i \quad (86)$$

Here the coefficients α_i are arbitrary scaling factors. Potential comparisons are then:

$$\|M_i\| > \varepsilon$$

$$\|M_i - M_j\| > \varepsilon$$

$$|\|M_i\| - M_j| > \varepsilon \quad (87)$$

The first (unusually) compares the magnitude of the state itself to a threshold. The second is most common, and compares one state against another state—for example, an expected state against a measured state. The third example compares the magnitude of a state metric against some other variable threshold M_j.

12.4.2 Student *t*-test

The student t-test is used to assess statistically whether two values are significantly different. It is most commonly used with the rate of pressure change metric M_3 but can in principle be used with any two metrics.

The readings $p(k)$ (usually, but not necessarily, pressures, kPa) are sampled discretely in time via SCADA or locally, and are treated over two different time windows. Each moving window contains a different fixed number of sample points at any one time: N_o, N_1.

This gives two estimates of the average measurement at any time, using the moving average estimator:

$$\hat{\mu}_o(k) = \hat{\mu}_o(k-1) + \frac{p(k) - p(k - N_o + 1)}{N_o}$$

$$\hat{\mu}_1(k) = \hat{\mu}_1(k-1) + \frac{p(k) - p(k - N_1 + 1)}{N_1} \tag{88}$$

If it is assumed that the original readings are normally distributed, then the moving average is also normal. To test whether these two are statistically different, use the statistic:

$$t = \frac{(\hat{\mu}_o(k) - \hat{\mu}_1(k))}{\frac{N_o - N_1}{N_o - 1} \times \frac{\sigma}{N_1}} \tag{89}$$

Here the variance σ is estimated using the sample variance of the time-series. This statistic has a Student-t distribution and can therefore be compared against standard tables to yield a level of confidence in a change.

Note how the threshold used in the comparison in this case is really the confidence level that is set to make the statistical decision.

12.4.3 Sequential Probability Ratio Test (SPRT)

The sequential probability ratio test is discussed in detail in 8.15.

In summary, this technique is not tied to a fixed threshold in order to sound an alarm. Rather, a statistical confidence interval is set.

12.4.4 Pattern Recognition

In machine learning, pattern recognition is the assignment of a label to a given input value or set of values. An example of pattern recognition is classification, which attempts to assign each input value to one of a given set of classes—in CPM these classes would be “leak” or “non-leak”.

In order to recognize the leak/non-leak classes as a function of arbitrary input values “training data” is needed. In CPM these are multiple known situations where a particular combination of readings and/or metrics occurs in combination with a leak, or a non-leak. These situations are often found from numerical simulations. In addition—particularly with non-leaks—operational situations where a previously unforeseen conjunction of readings and metrics occur that are visibly not leaks can be added to the training data.

These methods are generally most useful when a relatively large number of disparate potential indicators of a leak are incorporated. As an example, one might include all line imbalances, point pressures, temperature measurements and flow rates in a complex network into one single algorithm.

Scenario testing for location of a leak can also be accomplished using pattern recognition.

A *naive Bayes classifier* is a simple probabilistic classifier based on applying Bayes' theorem with strong (i.e. naive) independence assumptions among the inputs. The statistical independence of each potential leak indicator on a pipeline is physically dubious; nevertheless the assumption often works well in practice.

The first step is to develop the subsets of each independent indicator that correspond to each class C (i.e. leak or non-leak). Using an assumption of normality, it is possible to estimate the sample variance and mean of the distribution, so:

$$f(v_i|\mathrm{C}) \sim N(\mu_\mathrm{C}, \sigma_\mathrm{C}^2) \tag{90}$$

Use Bayes' formula to give:

$$P(\mathrm{C}|v) = P(\mathrm{C})\int f(v|\mathrm{C})\, dv \tag{91}$$

A *maximum entropy classifier,* also known as a multinomial logistic regression model, is a model that is used to predict the probabilities of the different possible outcomes given a set of independent variables, which may be real-valued, binary-valued, categorical-valued, etc. It does not assume statistical independence of the independent variables (or *features*) that serve as predictors.

It is most simply implemented as a multinomial expansion in the predictors:

$$f(v|\mathrm{C}) \approx \Sigma\, \beta_{i,\mathrm{C}}\, v_i \tag{92}$$

Here, there are two sets of coefficients β for the cases leak and non-leak. They are estimated by multivariate statistical regression from the training data. Then Bayes' formula is used as before to give $P(\mathrm{C}|v)$.

12.5 Location Algorithms

12.5.1 General

Once a leak is detected, a separate technique is typically applied in order to estimate the location of the loss. These techniques therefore all presuppose that there is some discrepancy in the pipeline state from steady state.

12.5.2 Pressure Gradient Intersection

For a simple horizontal pipeline of constant diameter D and cross-sectional area A, and with a constant friction factor f, the pressure profile is linear in normal steady flow. However, if there is a leak within the pipe then the pressure gradient upstream of the loss will increase, and downstream it will decrease. Conversely, if the pressure gradients at the inlet and the outlet of the pipe can be used, and where they intersect will be the location of the leak.

Furthermore (still assuming this simple pipeline) the change in the pressure gradients at the inlet and outlet provides an estimate of the mass flow rate of the leak.

12.5.3 Pressure Wave Speed

If a sudden leak occurs, of magnitude $Q_{\mathrm{m,leak}}$ at a location and time x_{leak}, t_{leak} then a pressure wave will form, traveling with speed a and of magnitude:

$$\Delta P = -\frac{1}{A}\, a\, Q_{\mathrm{m,leak}} \tag{93}$$

A pressure transducer will detect this change in pressure at time:

$$t = t_{\mathrm{leak}} + \frac{x_{\mathrm{leak}} - x}{a} \tag{94}$$

If two pressure transducers are used and their time of arrival are measured, then:

$$x_{\mathrm{leak}} = 0.5((x_2 - x_1) + a(t_2 - t_1)) \tag{95}$$

Furthermore (still assuming this linear pipeline) the change in the pressure measurement provides an estimate of the mass flow rate of the leak.

12.5.4 State Discrepancy

Most generally, the state of the pipeline can be used in an inverse problem in order to see what combination of leak magnitude $Q_{\mathrm{m,leak}}$ at a location and time x_{leak}, t_{leak} best match the current measurements.

In a *scenario-testing* algorithm, multiple discrete values of $Q_{\mathrm{m,leak}}$ and x_{leak} are examined and the best match against the measured pipeline state is reported. Multiple parallel simulations can perform this directly, or it can be accomplished from training data and a pattern recognition algorithm.

An alternative is to use a simulator with an automatic tuning algorithm, and to tune the values of $Q_{\mathrm{m,leak}}$ and $x_{\mathrm{leak}}$by *optimization* to find the best match against the measured pipeline state.

12.6 Filtering

Already discussed is the *moving average* where either an input measurement, or a metric, or both are averaged over a time-window of N samples:

$$\hat{\mu}(k) = \hat{\mu}(k-1) + \frac{p(k) - p(k-N+1)}{N} \tag{96}$$

This is also a special form of low-pass filter, since short-lived (i.e. high frequency) variations in the reading will be attenuated.

High-pass filtering can also be applied in order to remove long-term low-frequency variations. This is less usual.

Finally, with *outlier removal* all readings that lie beyond a certain number of standard deviations from the mean are dropped from the input data.

13 Rate of False Alarms and Measurement Uncertainties

13.1 General

This section provides commentary on three issues that can mislead and cause serious errors in the assessment of uncertainty, particularly in trying to estimate rates of false alarms. This document does not cover another major issue in assessing uncertainty, which is to maintain levels of certainty/accuracy in measurement; rigorous maintenance practices are needed that are not always followed. An instrument that is 0.25 % accurate may only be 0.6 % accurate when maintenance procedures are not ideal.

The first issue is that, whereas the mean and variance (bias and precision) of an uncertainty distribution is *generically* defined in probability theory, the probability of confidence of an estimate (or rate of failures of an estimate) depends upon a *precise* knowledge of the form of uncertainty distribution. Generally, this means that it is not possible to translate a bias and precision of an LDS into a *precise* rate of false alarms.

The second issue is that meters, sensors and instruments that provide the raw inputs to CPM methods are typically idealized to have *constant*, *normally-distributed* uncertainty distributions. In practice, this is *rarely* true and so although in order to make progress the API *MPMS* uses these approximations it is worth remembering that they may lead to substantial errors. The *actual* distribution of real world measurements are more long-tailed, or fat-tailed, meaning that beyond the nominal accuracy errors of any size are similarly likely.

Thirdly, readings from a SCADA system are *generally assumed* to have *independent, identically distributed* (IID) uncertainties. In practice, readings from a SCADA system are highly correlated and are more nearly multiple recordings of a single observation than they are independent observations.

13.2 Rate of False Alarms

13.2.1 General

The fundamental output of the entire procedure for the uncertainty in leak detection is an estimate of the bias and precision of the uncertainty in the CPM metric.

The rate of false alarms would—*in the simplest case*, meaning operations are consistent with the time period associated with the threshold tuning, the metric is compared against a fixed threshold—be the area under the “tail” of the uncertainty distribution of the metric greater than this threshold; and would represent the true determination of the tradeoff with false alarms and sensitivity. Conversely, a threshold could be found as a confidence interval, guaranteeing a P percent probability of an alarm being reliable.

This approach is used very often with *classical, standard probability density functions* (PDF) like the Gaussian, chi-squared, student’s or gamma distributions. Tables and formulae are available for the tail areas and confidence intervals for these known, analytic distributions.

The difficulty with the LDS is that most of the components of the total uncertainty do not have known, or even fixed, PDFs. For example, the linefill in the pipe is a complex nonlinear function of the inlet and outlet pressures, flows and temperatures. Worse still, it is not a predictable constant function of these uncertain inputs but depends on operational conditions and all the engineering factors. therefore, even if the measurement uncertainty PDFs are *assumed* to be *normal Guassian* according to the API *MPMS* (2013) there is little hope of predicting the resulting metric PDF *perfectly*.

For this reason, the procedure regards the issue of predicting the area under the tail of the uncertainty PDF as *impractical*. Therefore, the prediction of the rate of false alarms *is not generally possible*.

Nevertheless, a number of investigators (see Carpenter, Nicholas, and Henrie, 2003 and their references) seek to explore four main topics to *substantiate a possibility of prediction*.

— A qualitative, probabilistic relationship between sensitivity to real leaks, as well as creation of leak alarms or false positives when no leak is present.

— Software-based test methods coupled with recorded real world pipeline data to provide complete probabilistic performance mapping and evaluation of false alarm rates for pipeline leak detection systems.

— Similar testing approaches, applied to an existing leak detection system using actual pipeline data for periods of at least several months.

— Combining both the theoretical and field-tested performance measures to improve the measures of the rate of false positives.

13.2.2 Types of PDF Tails

It is instructive to consider how bad the issue of non-Gaussian distributions of total uncertainty can be. The tail of the Gaussian distribution is one of the more predictable, since there is only one parameter (sigma, the standard deviation) that dominates the "spread" from the mean, and one standard deviation from the mean contains a relatively large 68.2 % of the entire PDF. This makes the tails of the distribution relatively small.

So-called *fat-tailed* distributions (Rolski et al. 1999) have the property that the probability in the tail has an inverse power law:

$$Pr(X > x) \sim x^{-a} \text{ as } x \to \infty, \text{ for some } a > 0 \tag{97}$$

This is a special case of the *heavy-tailed* distributions, with:

$$\lim_{n \to \infty} e^{\lambda x} Pr(X > x) = \infty \text{ for all } \lambda > 0 \tag{98}$$

If the PDF of the LDS metric happens to be fat, then far more false alarms would actually occur at multiple-sigma thresholds, than for a normal distribution. In the normal distribution events that deviate from the mean by six or more standard deviations ("6-sigma events") are extremely rare, and are for example the ultimate standard in quality control theory. On the other hand, many fat-tailed distributions actually have "infinite sigma" (more technically, the variance does not exist).

Thus when data naturally arise from a fat-tailed distribution, force-fitting the normal distribution model of uncertainty—and an estimate of the corresponding sigma based necessarily on a finite sample size—severely understates the true degree of predictive difficulty.

This is often commented upon in economics and finance. Many econometric models, particularly the Black-Scholes model of option pricing, are based on a normal distribution. If the distribution is actually a fat-tailed one, then the model will underprice options that are far out of the money, since a 5- or 7-sigma event is much more likely than the normal distribution would predict.

The worst-case situation (where a variance is still defined) is where α = 1 and then:

$$Pr(X > k\sigma) \sim k^{-2} \text{ as } k \to \infty \tag{99}$$

In fact, this is a hard lower bound on the tail area of any distribution, and is known as *Chebyshev's theorem*. It is always true, but unfortunately is not of much practical use in LDS applications. As an order-of-magnitude discussion, suppose that the LDS were asked to provide no more than 5 % false alarms then k would be about 400, i.e. it would be necessary to work to 400-sigma precisions. To detect 1 % of total flow leaks, for example, metering systems with accuracies in the 0.0025 % range would have to be specified.

Estimating α or deciding whether a PDF is heavy-tailed from a data sample is an area of open and active research. There are no practical ways of using the relatively small samples available to us either from field data or simulations in order to analyze the metric PDF itself. The reference list provides some useful introductions to current thinking in this area.

— Rolski, Schmidli, Schmidt, and Teugels (1999) derive and apply multiple statistical inference measures from the parameter α with a particular emphasis on reliability measures (i.e. confidence intervals).

— Foss, Konstantopolous, and Zachary (2007) view the reliability issue from the perspective of random walks (i.e. repeating regular processes, like a CPM).

— Willekens, E. (1986) explores the exponential transform as a means of estimating the parameter.

— Falk, Hüsler, and Reiss (2010); also Alves, de Haan, and Neves (2006) investigate the extreme case where.

— Crovella and Taqqu (1999) provide a numerical scheme for estimating the parameter providing there are many data points available (which is in practice rarely the α case with leak detection).

Finally, perhaps the worst issue with the potential for mistaking the nature of the PDF of uncertainties in the Metric of the CPM lies not so much with the actual shape of the PDF, but rather that there may well exist multiple PDFs corresponding to different operational scenarios, engineering factors, or ranges of readings at the meters and instruments. It is reflected in the fact that the procedure purposely restricts the uncertainty assessment only to the scenarios and meter uncertainties used in the sensitivity runs. Extrapolating to other scenarios or engineering factors can be very dangerous.

13.2.3 Rate of Misses vs Rate of False Alarms

The API 1130 refers both to the rate of false alarms—in other words, false positives—and the rate of misses. It observes that in general the two measures are inversely proportional; when the rate of misses is low (perhaps by setting a low threshold of uncertainty in an LDS to catch as many *true* alarms as possible) then the rate of *false* alarms will correspondingly be higher.

However, the rate of misses is generally a much more difficult quantity to assess. The uncertainty PDF shown in Figure 4 and the bias of the LDS estimated by the procedure are for a pipeline that is operating normally. Therefore, the tail of the metric PDF represents *normal* situations that cause *false* alarms.

Misses can be caused generally by two factors: (a) operational failures, including operational changes, or inconsistencies in the physical data, bad assumptions, etc.; and (b) situations where the LDS is operating normally, but the leak is too small or sudden to be caught at the thresholds/levels of uncertainty that were used. The first factor is addressed in the procedure document as an issue of MTBF and MTTF—any of the components of the LDS can be assigned a failure rate and the compound system failure rate can be calculated as described in Section 7 on uncertainties in measurement. Note that in practice this is normally the largest source of misses in any case.

It is conceptually possible to explore the second of these issues, misses as an engineering factor. With this approach, leaks are introduced to the procedure as explicit hydraulically modeled features, with a given position and a given rate. Both the position and the rate might have a value for B and the rate might have a precision P as well. The resulting bias in the metric due to this factor alone might then represent the minimum threshold for any detection of this given leak. Note that the uncertainty in the metric depends on position and rate—there is unlikely to be a single value for every potential leak on the line. This makes this procedure lengthy as well as perhaps only qualitative at best.

13.2.4 General Features of False Alarm Rate

In light of all the irregularities and with all the warnings given, there are nevertheless certain features of the rate of false alarms that are *purely probabilistic* (i.e. independent of the PDF of the uncertainty in the metric), and many others that are *approximately or qualitatively* useful in situations where the *PDF of the uncertainty in the metric is approximately normal.*

Most of the inputs to the CPM system are likely to be normally distributed, at least near to normal operational/tested conditions. Any linear transformation of these multiple normally distributed variables would also be normal. The reason that the CPM metric is not normal is that pipeline hydraulics are highly nonlinear. Nevertheless, in situations where there are only small changes in the operational conditions, the pipeline hydraulics might be *almost* linear and therefore the CPM metric might be *almost* normal. For example, this approximation might hold for nearly or quasi-steady-state situations with small leaks and very high certainties in the measurements. Most transient situations would break these assumptions altogether and make the approximation poor.

Using multiple averaging periods—this observation is made by Carpenter, Nicholas, and Henrie (2003) but is also the basis of the Student t-test method described in Section 12. Most CPM methods do not rely on the instantaneous value of the metric, but rather a time-averaged value. It is true of *any* random variable that the variance of an average of N samples is inversely proportional to N. The systematic bias, on the other hand, remains the same; it does not affect the global average.

The first consequence is that instead of simply using one moving averaged metric for threshold alarming, it is useful to consider the difference between two of them. Using notation in Section 12, write:

$$\Delta(k) = \hat{\mu}_o(k) - \hat{\mu}_1(k) \tag{100}$$

Where the two averages are taken over different sample periods: N_o, N_1.

This new metric has zero bias. Practically, N_1 is set to a large fixed value so that $\hat{\mu}_1$ represents a long-term average of readings. In that case, the precision of $\Delta(k)$ varies inversely as the square root of N_o. The zero theoretical bias fact alone can be used constructively to improve the uncertainty in actual alarming. The scaling of the precision also has the profound consequence that uncertainty *only has to be estimated for one averaging period*. Any other averaging period will have the same systematic bias and a standard deviation that decays as the square root of N. Similarly, all minimum time to detection formulae are also self-similar, with the minimum time to detection scaling as the square root of estimated uncertainty precision.

Again, these two statements are true with *any* PDF of the metric. Note however that the student t-test described in Section 8 only applies when the PDF is normal. *With that assumption*, Equation (42) of Section 8 yields a statistic t that can be used with tables of the student distribution to estimate the probability of a false alarm.

It can also be used to estimate the converse—that is, the probability of a true alarm. Equally, the appropriate threshold to use for either a desired rate of false or true alarms can be read from inverse-student t tables.

Carpenter, Nicholas, and Henrie (2003) use a very similar method, based however on the additional assumption that the estimate of σ is perfect—perhaps, by using a very long-term averaging period for its estimator. In that case, the distributions are Gaussian and not student.

In summary, these approaches are an attempt to: (a) improve alarming by comparing multiple indicators in a combined metric that is bias-free; and (b) extrapolating the estimated σ to be not only a standard deviation of the metric, but also the basis of some PDF that allows a rate of false alarms to be predicted. Whether σ is estimated from a sample (student test) the entire population (normal test) or by simulation/modeling using the procedure in this document, there still has to be some *a priori* assumption as to the nature of the PDF.

Using multiple scenario analyses—another observation made by Carpenter, Nicholas, and Henrie is that if multiple transient operational scenarios are possible on a given pipeline (batch changes, pump operations, rate changes, etc.), then they can be combined to give a single estimate of performance over all operational time on this pipeline. Supposing that transient scenario j with an LDS bias Bj and precision Pj occurs with a relative frequency f_j; $\Sigma f_j = 1$:

$$B_{total} = \frac{1}{N} \Sigma f_j B_j$$

$$P_{total} = \sqrt{\frac{1}{N} \Sigma f_j^2 P_j^2} \tag{101}$$

A corresponding compound rate of false alarms could then be made with the assumptions discussed.

Off-line testing of CPM systems—the API 1130 specifies a methodology for testing on-line LDS, including CPM systems. It is equally possible to use these methods with an "artificial" LDS offline. In essence, this is what the entire procedure described in this document aims to do.

Earlier work, including Carpenter, Nicholas, and Henrie (2003) as well as others, have followed these strategies:

— Software-based test methods coupled with recorded real world pipeline data to provide complete *probabilistic performance mapping*. This corresponds to running the reference model using both idealized test scenarios as well as SCADA recorded scenarios in order to estimate the metric bias and precision. Non-parametric statistics can be used (for example, using histograms of the data) that reduce the need to assume Normality of the data, if sufficient simulations are performed. Recall that this approach is risky when "complete performance mapping" is attempted. The Gaussian distribution approach is predicated on small deviations from steady state and the reference condition. Transient behavior and/or different engineering factors may lead to entirely different distributions and precisions.

— Similar testing approaches, applied to an existing leak detection system using actual pipeline data for extended periods. This approach simply substitutes software reference models by the actual, running pipeline. The same remarks related to attempting to extrapolate to different transient behaviors and/or different engineering factors may lead to entirely different distributions and precisions.

— Combining both the theoretical and field-tested performance measures. The most modern forms of this are covered in Section 12 under the pattern recognition techniques. Both the Bayes and maximum entropy classifiers are systematic procedures for continually "learning" which situations are true or false alarms. The database used for preparing these classifiers can either be populated from off-line simulations or from actual field performance.

— Dynamic alarming—learning the operational conditions under which false alarms tend to be generated as well as the appropriate wider tolerances/thresholds to use.

— Systematic availability and reliability surveys of the components of the LDS—including instrumentation, measurement, telemetry and IT. This addresses the major factor in assessing rates of false alarms and misses due to system failure as opposed to physical uncertainty.

Hybrid observation/estimation techniques—As an example observation of the performance of a CPM leak detection system on a specific asset provides the definitive measure of the performance of the system. A performance estimation technique such as API 1149 must be used to estimate the performance that can be expected if the operation or configuration of the asset is to be changed. An API 1149 analysis might also be used to determine if the observational performance is expected or if the observed performance indicates a problem with the system. As always, sound engineering practice and experience must be used when deciding whether a difference in the estimated and observed performance of a system should be attributed to inaccuracies inherent to the estimation procedure or if additional investigation is warranted.

A special case of using the two techniques together is to use observed performance to "tune", or reverse engineer, the inputs to the estimation technique to cause it to calculate the observed performance. There are many pitfalls to this practice that should be considered.

— The number of independent observations must at least exceed the number of inputs to the estimation procedure to provide a unique solution. Recorded SCADA data is highly correlated and so SCADA scans cannot be considered independent observations.

— If the leak detection technique whose performance is being estimated involves non-linear equations further analysis must be performed to guarantee the uniqueness of the solution.

— All of the engineering factors that could influence the performance of the leak detection system must be identified and considered in the estimation.

Without great care, such an exercise can produce inputs to the estimation procedure that will match the observations used to tune the system but will not produce correct results when used to estimate the performance of the system with new operations or configurations.

13.3 Uncertainties in Metering

13.3.1 General

The section on uncertainty due to measurement in the procedure describes how uncertainties in the readings of meters, instruments, and sensors are generally assumed to be Gaussian. This is despite the fact that it is generally accepted that these uncertainties are only approximately Gaussian, and only under at least these situations:

1) The readings are close to the value at which the meter was calibrated. Large excursions from this mean value are unlikely to have a Gaussian distribution.

2) A related issue—while the meter is functioning correctly and in normal scenarios, most errors will be Gaussian. However, there are generally far more completely extraneous outliers in measurement that would be expected from a Gaussian distribution.

3) Each reading has an error unrelated to the error of the previous readings—i.e. they are statistically independent. This is known to be untrue particularly when reading values change rapidly.

In other words, a practical measurement system will have an uncertainty rather greater than the “classical” one based on normal statistics. The non-classical behavior will generally void any traditional predictions of performance (including this document) and will need to be included as a failure in a failure rate estimate for the device.

13.3.2 Known Non-Gaussian Devices

Certain sensors—notably pressure transducers—are actually known to have a lognormal response. Nevertheless, under assumption (1) this is practically estimated using a locally normal distribution near the average reading. These sensors are a classic example of the difficulty with this approach. If the pressure reading is significantly different from its mean value, then its error will vary as a lognormal curve, which decays far more slowly than the theoretical normal PDF.

13.3.3 Outliers

This is discussed under rate of false alarms also, but it is known that practical meters may be locally Gaussian near their mean readings, but have much fatter tails to their PDFs. Therefore, it is to be expected that 4-, 5-, and 6-sigma bad readings will still occur, despite their being regarded as nearly impossible using normal theory.

This factor compounds the difficulty of estimating rate of false alarms.

13.3.4 Linearity

It is also known that the accuracy and precision of a meter is not constant, but rather depends on the reading value itself. This is shown in Figure 17 (ISA, 2003).

This linearity effect is often quantified as an additional variance to add to the single-point precision of the meter. However, more importantly it is simply not possible to have a Gaussian error distribution that has a variable standard deviation that depends on the parameter x.

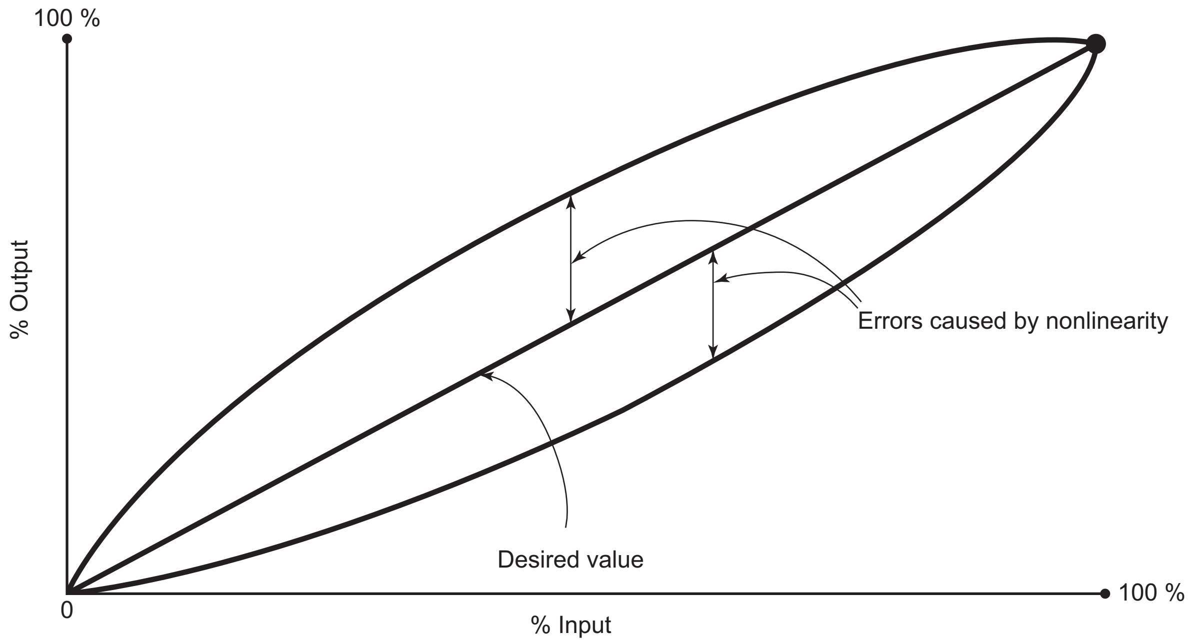


Figure 17—Nonlinearity of Instrumentation

13.3.5 Auto-correlation of Readings

The third assumption of independence of the readings is not true of data collected by pipeline SCADA systems. These systems typically record data at a fixed interval from measurements that are continuously attached to the system. To be truly independent a pressure transducer, for example, would need to be disconnected from the pipeline, depressurized, reconnected to the pipeline, and re-pressurized between each SCADA poll cycle. Since this is not done, recording a measurement of an unchanging process variable multiple times provides no additional statistical information about the process. When the measured process variable does change, additional information is available but if the change is slight the new reading is still not completely independent. The degree to which each measurement provides useful statistical information is reflected by the auto-correlation of the measurement. This auto-correlation between readings of a given meter is practically estimated using autoregressive analysis of the data. Almost invariably, when this is done, there is a non-zero autocorrelation coefficient in the stream of readings.

14 Case Study: Using Manufacturer Specifications and Meter Proving Reports

14.1 General

One of the first steps in the procedure is to assess the bias and precision of the meters and the instruments used for the LDS. There is often some confusion in this process and engineering judgment is usually required. This note discusses how these parameters can be derived from two common sources:

— meter or instrument proving reports; and

— manufacturer ratings or specification sheets.

Even these two routinely used sources of information are often inconsistent, and it is important to be careful with the specifications that are cited. Data and methodology presented in the remainder of this section are due to Van Reet (2014).

14.2 Example Flow Meter

An example meter proving run, executed using the standard API procedures in the *MPMS* (2013) standards, Chapter 4: *Proving Systems,* is shown in Figure 18.

METER PROVING REPORT BY PIPE PROVER

Date	Ambient Temp	Report No.
10/30/2015 09:40:11	60	

Previous Report			
Flow Rate	Factor	Date	Non-Reset Totalizer
500	1.0006	10/10/2012 09:48:56	1565094

System

Location	Meter	FMP Number	Code Ref No

Prover Data

Base Volume at 60deg. F and '0' psi.	Size O.D.	Wall	Calibration Date	Flow Rate	Non Reset Totalizer
4.58455	8	0.322	5/5/11 0:00	510	1815703

Meter Data

Serial No	Pulses/bbl.	Temp Comp.	Manufacturer	Size	Model
	8400	No	SMITH	4	F4-S6

Run Data

Run No.	Sel.	Temperature		Pressure		Total Pulses Gross
		Prover	Meter	Prover	Meter	
1	☒	70.2	70.2	150	150	38494
2	☒	70.2	70.2	150	150	38499
3	☒	70.2	70.2	150	150	38500
4	☒	70.2	70.2	150	150	38501
5	☒	70.2	70.2	150	150	38498
Average		70.2	70.2	150	150	38498.4

CTS	Correction for Temperature on Steel
CPS	Correction for Pressure on Steel
CTL	Correction for Temperature on Liquid - Table 8 or Table 24
CPL	Correction for Pressure on Liquid
CTPL	Correction for combined Temperature and Pressure on Liquid

Liquid Data

Grade	Obsv Gravity	Obsv Temp	Api Gravity	Vapor Pressure	Oper. Pressure
West Texas Intr	41.8	69	41		150

Field Calculations

CTS 1.00019 X CPS 1.00011 X CTLp 0.99481 X CPLp 1.00086 X Prover Vol 4.58455 = Corr. Prover Vol 4.566030

Avg. Pulses 38498.4 / Pulses/bbl. 8400 = Gross Meter Vol 4.583140 X CTLm 0.99481 X CPLm 1.00086 = Corr Meter Vol 4.563300

Corr. Prover Vol 4.566030 / Corr. Meter Vol 4.563300 = Meter Factor 1.0006 X CPL at Mtr Cond 1.0009 = Composite Factor 1.0015

Remarks

Figure 18—Example Meter Proving Run Data

In summary:

— five successful proving runs were executed and the data recorded;

— the tests were executed at a flow rate of 510 BBL/Hr;

— a light crude oil with API gravity of 41.8 was used.

A background assumption that is made is that the proving equipment has zero test-retest error. The "Maximum Run Repeatability Deviation" is not a specification—it is rather a quality control threshold to help identify a bad run.

Note two main points about the value of proving reports such as this one in practice.

1) Five runs—even if the tests *were* representative, independent and identically distributed (IID) samples—yield very little confidence in the estimates of bias and precision. This is compounded by difficulties in the test equipment and the test procedure itself.

2) The runs are known not to be IID samples—they are in fact highly auto-correlated and are taken over a very brief period of time. Furthermore, they are not nearly a representative sample of operational situations where rates, temperatures and fluids will all change.

To issue one: the results of the five runs apparently show: (a) a sample mean estimate of the bias as 0.0006 of the flow rate, or about 0.3 BBL/Hr.; and (b) a sample variance estimate for one-sigma of precision as 0.02 %, or about 0.01 BBL/Hr. However, in order to be 95 % certain of these estimates of bias and precision, the tables of confidence in the Gaussian and chi-squared distributions show that 4.8 and 4.5 times these values should be used, respectively.

Sources of covariance (i.e. non independence of proving runs) are often subtle or hidden. For example, 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. Likewise, pressure measurements from the same pressure transmitter on the prover are used to determine the correction for the effect of pressure on the prover steel and the correction for the effect of pressure on the liquid passing through the prover during a meter proving.

Note that this single meter prove run corresponds to sample points on just one of the curves shown in Figure 5.

Issue number two is far more serious. This proving report by itself provides little useful information for estimating the uncertainty of the meter. These runs will be highly correlated and the results do not represent the performance of the meter over longer time spans that include multiple starts and stops of the pipeline. To estimate the required parameters from proving reports requires analysis of many proving reports over a reasonable time scale. A year is a reasonable amount of time for most situations. The data for this same meter over a twelve-month interval is provided in Table 12.

Note again that at face value the biases at each proving run are small compared with flow rate—the worst case, on 6/26/2013, represents a 0.31 % mean error. Equally, the precisions are extremely small compared with the counts—the worst case, on 6/6/2013, represents a 0.034 % mean precision.

Referring to Figure 5, each run represents sample points on one of the individual bell curves. Two approaches are reasonable.

— The first approach simply treats all the data as a single, large group of data.

— The second approach works instead with the difference of meter factors between proving runs. This is a smaller data set—only 17 changes of meter factor were made over the 12 months. However, this approach reflects the

Table 12—Data from Multiple Proving Runs

Date	Meter Factor	Δ from Previous	Total Pulses					Std. Dev.
			Run 1	Run 2	Run 3	Run 4	Run 5	
10/30/2012	1.0015		38494	38499	38500	38501	38498	5.92
11/28/2012	1.0002	-0.00130	38529	38531	38520	38521	38525	10.55
12/13/2012	0.9996	-0.00060	38543	38543	38541	38542	38545	3.25
12/27/2012	0.9994	-0.00020	38547	38546	38546	38540	38539	8.28
1/4/2013	0.9986	-0.00080	38570	38571	38575	38566	38576	8.85
1/24/2013	1.0001	0.00150	38518	38524	38526	38520	38518	7.96
2/5/2013	1.0001	0.00000	38528	38527	38524	38528	38532	6.27
2/26/2013	1.0002	0.00010	38503	38507	38510	38517	38508	11.28
3/13/2013	1.0007	0.00050	38500	38510	38499	38493	38500	13.38
3/25/2013	1.0008	0.00010	38494	38498	38505	38503	38507	11.66
4/30/2013	1.0015	0.00070	38483	38481	38479	38484	38479	5.00
5/15/2013	1.0004	-0.00110	38526	38518	38530	38518	38525	11.55
6/6/2013	1.0028	0.00240	38431	38444	38443	38435	38432	13.42
6/26/2013	1.0031	0.00030	38428	38424	38423	38425	38429	5.67
7/30/2013	1.0026	-0.00050	38440	38446	38440	38437	38439	7.36
8/8/2013	1.003	0.00040	38434	38429	38429	38431	38436	6.82
8/29/2013	1.0025	-0.00050	38454	38451	38444	38455	38452	9.47
9/5/2013	1.0028	0.00030	38435	38433	38433	38438	38435	4.49

fact that at any given time the latest meter factor was being applied to the meter in operations. Therefore, the worst measured data errors were of the order of the recalibration at the next meter proving.

Results of these two methods are as follows:

Method 1:	Global Mean	1.001105556
	Global St. Dev.	0.001378621
Method 2:	Mean D_Factor	1.000076704
	D_Factor St. Dev.	0.000916445

Method 1, as expected, yields mean biases much higher since it assumes that the "raw" meter readings are used—i.e. the meter is never proved. Nevertheless, the estimated precisions are comparable reflecting the fact that application of a meter factor has little impact on repeatability. Referring to Figure 6, the standard deviation of the biases is 0.14 %. To a 95 % certainty (remembering 18 x 5 = 90 samples were taken), the mean lies between the global mean ±0.14 % x 1.762 = 0.11 % ±0.247 %. Unlike the situation in Figure 6, the mean bias is not zero but rather 0.11 %.

It is recommended, however, to use Method 2. Referring to Figure 6, the standard deviation of the biases is 0.09 %. To a 95 % certainty (remembering 17 samples were taken), the mean lies between ±0.09 % x 2.692 = ±0.242 %—this is the figure to be used for "B". The mean bias estimate (at 0.008 %) can be zero, to 95 % confidence.

The mean of the standard deviations of each proving run "P" is a small 0.01 %

14.3 Example Pressure Transducer

Calibrations of pressure instruments are generally performed more rarely than flow meters, perhaps only annually, making the development of empirical statistics more difficult. It is therefore generally more practical to work from manufacturer specifications.

For example, the accuracy of a Rosemount 3051 pressure transmitter is 0.15 % span. For a 0 to 1500 psi span, the accuracy would be 2.25 psi. The stability is 0.125 % of upper reference limit (URL) over 5 years = 1.875 psi. Total accuracy would therefore be 4.125 psi.

No precision data is available. This is typical for pressure transducers, for example. The implication is that the accuracy—in the sense of mean precision, see Figure 6—is being quoted as a given number of standard deviations of confidence already. Unfortunately, this number of standard deviations is itself rarely specified. For this application, it is assumed that this already represents a 95 % confidence in the bias. Therefore:

— the spread of biases "B" on Figure 6 is ±4.125 psi;

— the mean precision "P" is zero

14.4 Example Temperature Transducer

Calibrations are again generally performed more rarely than flow meters, so it is more practical to work from manufacturer specifications.

Also as an example, the accuracy of a Class B Resistance Temperature Detector is 0.3 + 005 x T °C. The accuracy of a typical temperature transmitter is 0.1 + 0.02 % of span. Stability is 0.1 % of T or 0.1 °C (whichever is more). At a nominal 44 °C, this results in a cumulative accuracy of 0.72 °C or 1.64 %.

No precision data is made available as is typical. The implication is that the accuracy—in the sense of mean precision, see Figure 6—is being quoted as a given number of standard deviations of confidence already. For this application, it is assumed that this already represents a 95 % confidence in the bias. Therefore:

— the spread of biases "B" on Figure 6 is ±0.72 °C or 1.30 °F;

— the mean precision "P" is zero.

15 Case Study: Worked Example Uncertainty Assessment

15.1 General

In this worked example, the aim is to follow the overall process flowchart in Figure A.1.

15.2 Assemble Data

15.2.1 Reference Model Data

1a. Pipeline and fluid data—critical inputs are:

— the pipeline configuration;

— units of measurement;

— source/sink configuration—in this example, there is just one inlet and one outlet;

— elevation survey;

— pipe data;

— operating state;

— fluid data (including viscosities).

Some other optional inputs may include:

— heat transfer data (this problem does include a simple thermal model);

— environmental data;

— equipment data;

— equipment curves.

The pipeline is a single straight line carrying crude oil, with elevation changes of up to 300 ft.

The pipe is divided into three sections, whose only difference is in the wall thickness:

— pipe O.D. = 10.75 in.;

— Section 1, 5.7546 mi long – wall thickness = 0.188 in.;

— Section 2, 2.5327 mi long – wall thickness = 0.219 in.;

— Section 3, 8.3785 mi long – wall thickness = 0.188 in.;

— total dry volume = 9182 BBL.

A uniform heat transfer coefficient of 0.3 BTU/°F ft^2 H is used. This figure is tuned slightly to match the nominal conditions of the flowing pipeline.

These configuration data are all held fixed in this analysis (i.e. they are not varied during the runs in order to assess their impact on the uncertainty of the LDS).

The baseline operating conditions on the line, once running, are:

— inlet pressure 700 PSIA;

— inlet temperature 111 °F;

— flow rate1657STBPH.

The pipeline properties (heat transfer coefficient, roughness factor, etc.) are tuned to give a nominal outlet pressure of 120 PSI and outlet temperature of 90 °F. In practice, the precise matching is not critical.

The elevation profile of the pipeline is shown in Figure 19.

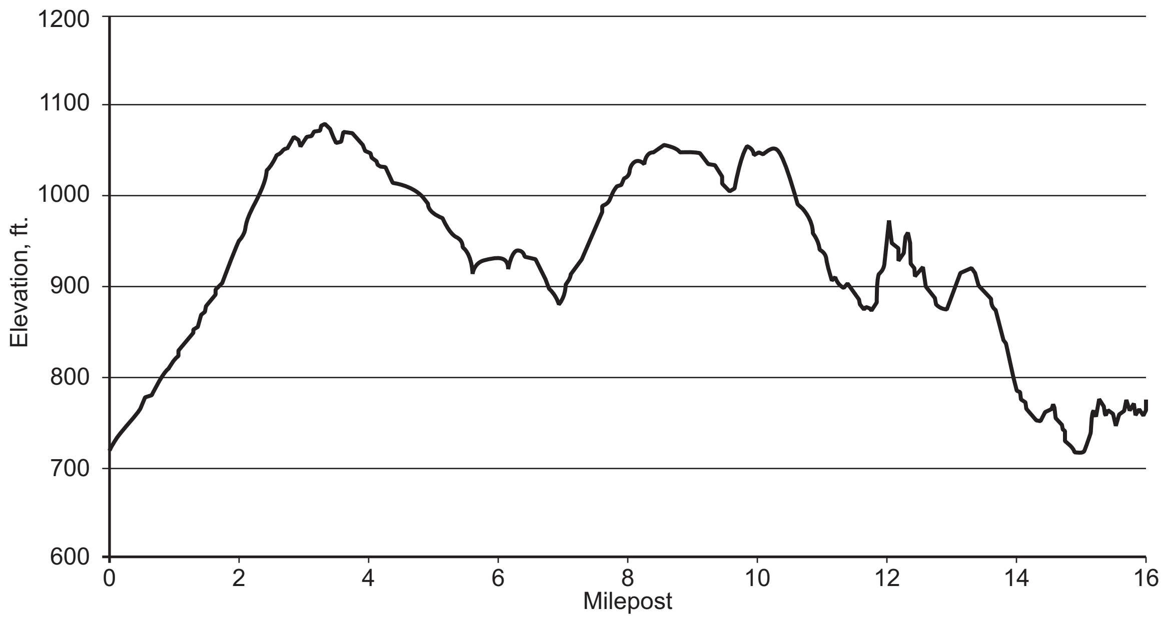


Figure 19—Example Problem Elevation Profile

Measurements are made at both ends of the pipeline, for pressure, flow rate and temperature. These measurements are made once every 15 s.

Pressure and temperature are used within the simulation to predict line-pack and in-situ densities and viscosities.

The fluid is a 23.8098 deg API (specific gravity of 0.9111) crude.

Viscosity is input as a table, shown in Figure 20.

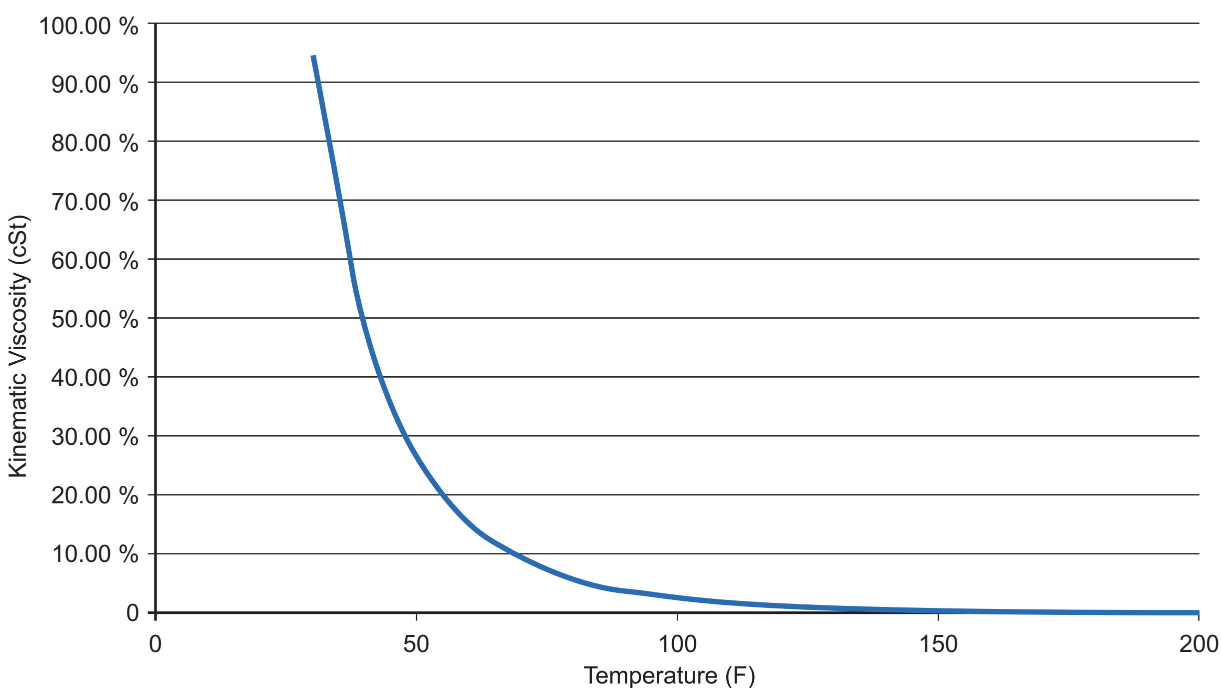


Figure 20—Example Problem Viscosity vs Temperature

1.b Operational scenarios—two scenarios are run.

— No. 1 Steady state.

— No. 2 Transient scenario, defined from recorded SCADA values for inlet and outlet pressure, temperature and flow rate.

The steady state scenario corresponds to the baseline conditions:

— inlet pressure 700 PSIA;

— inlet temperature 111 °F;

— flow rate 1657 STBPH.

The pipeline properties (heat transfer coefficient, roughness factor, etc.) are tuned to give a nominal outlet pressure of 120 PSI and outlet temperature of 90 °F.

The transient scenario corresponds to a startup situation, with inlet flow abruptly changing from zero to about 1500 STBPH (spiking at 1900 STBPH) over a short period of time. With similar charts for pressure and temperature data, the SCADA recorded inlet flow rate is shown in Figure 21.

This represents about 5500 SCADA scans at 15 s intervals, or about 23 hrs. of recorded data. The scenario begins with a period (up to about scan # 480) of zero flow, and then an abrupt startup with a few seconds of overshoot.

Actual, recorded outlet meter data is also recorded, so it is possible to see how a basic mass balance CPM system would have performed. The instantaneous standard volume imbalance, at STP, is shown in Figure 22.

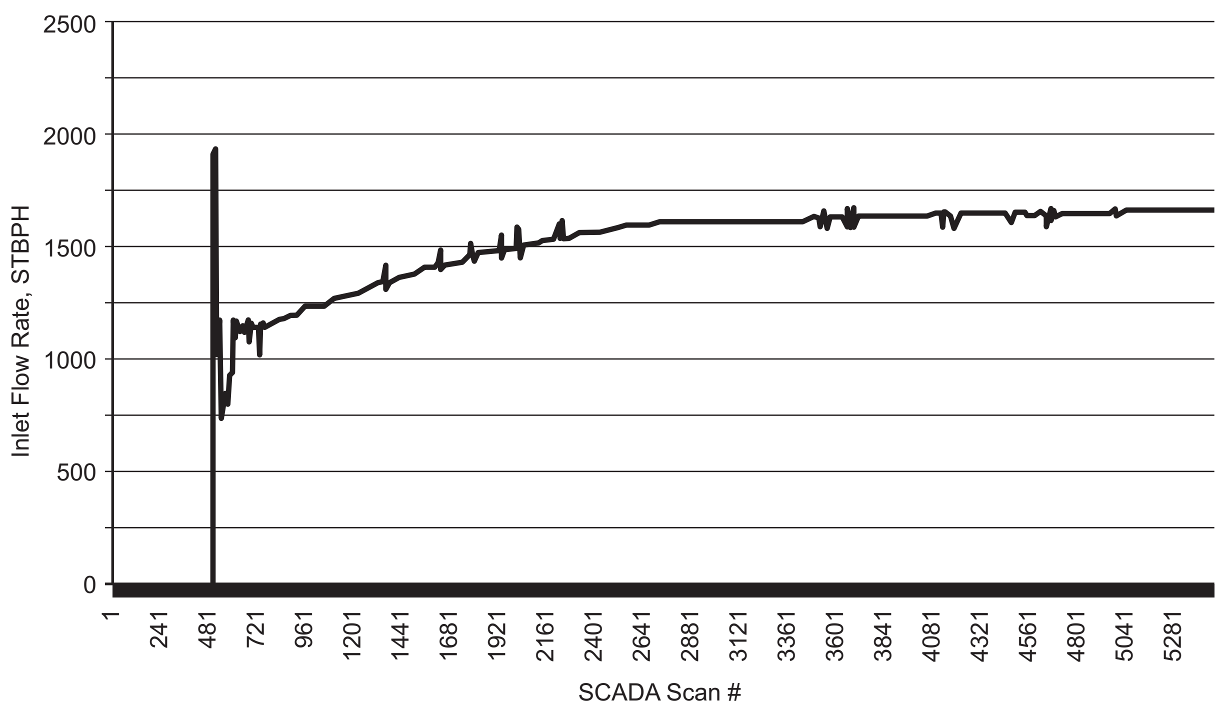


Figure 21—Example Problem Transient Scenario

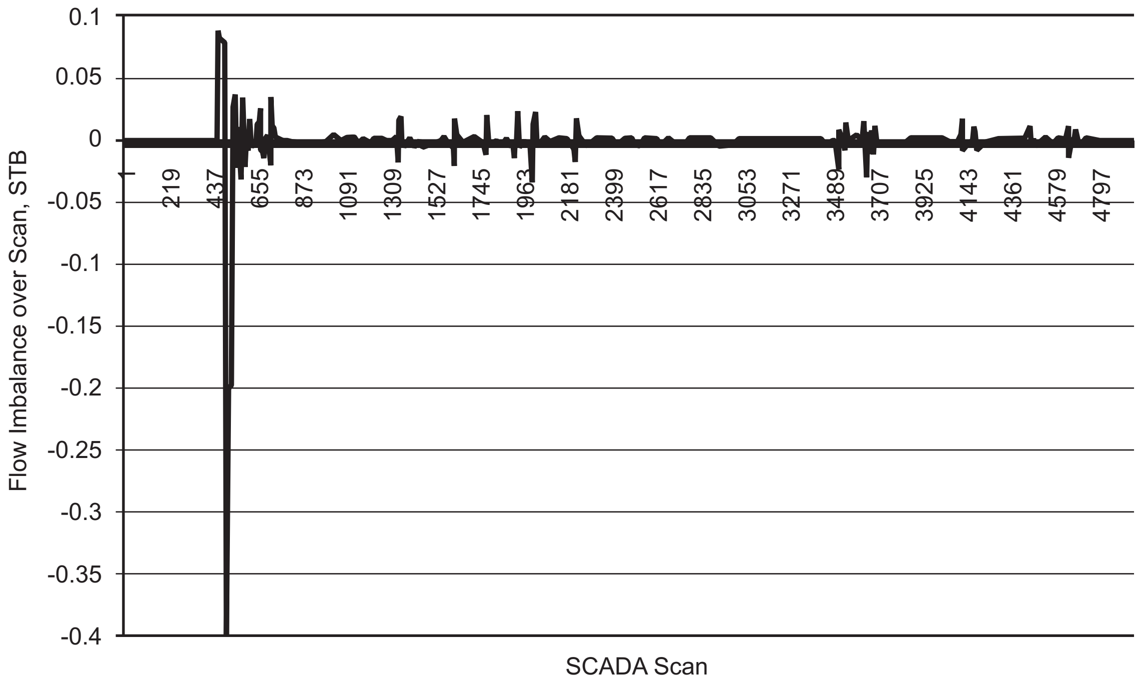


Figure 22—Example Problem Instantaneous Imbalance

This illustration makes it very clear how the CPM Metric has its maximum uncertainty over a relatively short period of time. The same chart expanded around just before the startup (scan # 450, 112 minutes into the scenario) and 50 minutes later, and also expressed as a % of reference (1657 STBPH) flow rate, is shown in Figure 23.

The maximum imbalance is +17 % and the minimum is −55 %. Note that this is rather less than the original API 1149 (1993) estimate of 278 % described in 15.5.

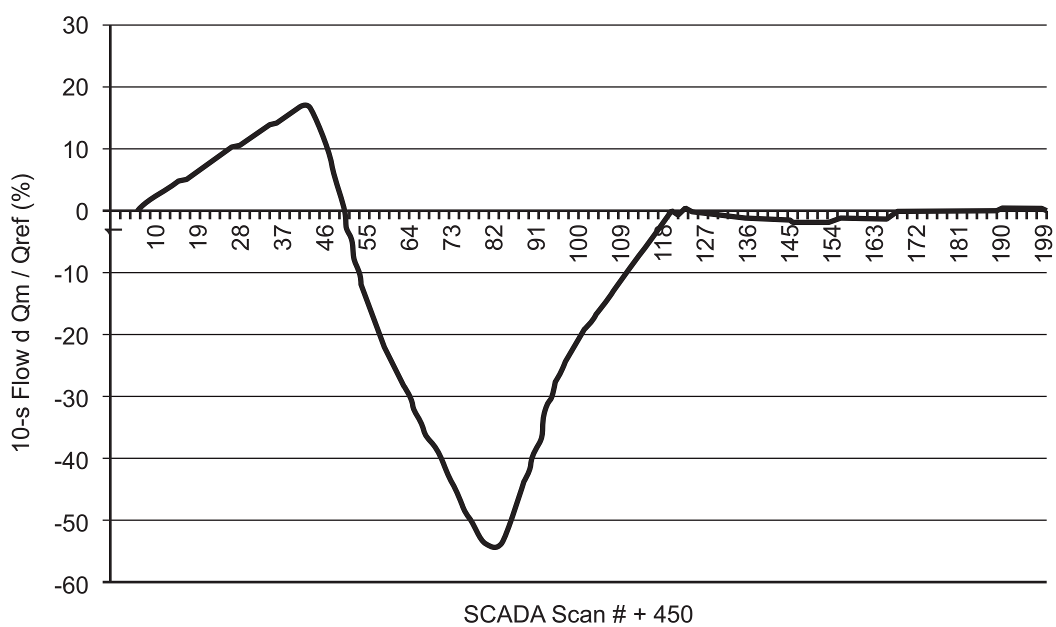


Figure 23—Example Problem 10-s Percent Imbalance

15.2.2 Measurement Model

2.a Instrument Precision and Bias—The measurement uncertainties are taken to be similar to the meters and sensors described in the Case Study (values for “B), listed in Table 13.

Table 13—Example Problem Instrument Bias and Precision

Measurement	Bias ± “B”
Flow In	0.24 %
Flow Out	0.24 %
Pressure In	4.125 psi
Pressure Out	4.125 psi
Temperature In	1.30 °F
Temperature Out	1.30 °F

The Flow Meters both have estimated precisions “P” of 0.01 %. Pressure and temperature have zero assessed precisions.

There is a collection period of 5 seconds. It is assumed that any data-time skew is systematic—i.e. that a given reading *always* leads or lags another by a fixed amount. This assumption would in general have to be checked. In this situation, the skews are uniformly distributed, and a one-sigma for their potential variance is $\Delta^2/12 \cong 2$. Using a value of “B” of three standard deviations gives $B \cong 3\sqrt{2} = 4.243$ s. It is assumed that the value of “P” is negligible—consistent with the systematic lead or lag assumption.

15.2.3 Engineering Factors

Two Engineering Factors are considered:

1) **SCADA—**As an example, the SCADA parameters (defined in Table 4) are assessed to be as listed in Table 14.

Table 14—Example Problem SCADA Uncertainties

Scan Period	5	(s)	Frequency of Data Collection (mean)
TSM	0.01	(s)	Data-time skew (bias)
TSS	0.0001	(s)	Data-time skew (sigma)
TCF	0.0022	(s)	Front-end processing latency
Resolution	0.002314815	(32-bit)	All measurements, numerical rounding error
Scale Factor	0		All measurements, error in any scaling
Noise	0.001157407	(32-bit)	All measurements, random noise
Noise Bias	0		All measurements, added bias

Applying the equations in 7.2, these figures imply adding these additional biases and precisions:

Applied to all balancing periods:

Bias Time-Data Skew	0.0122	(s)
Variance T-Data Skew	2.083433333	(s)

Applied to all instrument uncertainties:

Added Bias	0	
Added Variance	5.58163E-07	(s)

2) **Availability**—As an example, the LDS subsystem MTBFs are listed in Table 15.

— The weakest link MTBF is 1.00E+04 Hrs.

— The cumulative system MTBF is 1.65E+03 Hrs.

Table 15—Example Problem Input Subsystem MTBF

Location	**Property**	**Nominal MTBF** (hrs)
SUPPLY	P	2.00E+05
SUPPLY	Q	1.00E+04
SUPPLY	T	1.00E+05
DELIVERY	P	2.00E+05
DELIVERY	Q	1.00E+04
DELIVERY	T	1.00E+05
	SCADA	3.40E+04
	IT / CPM	1.40E+06

The Robustness of the system might then be quoted as an MTBF of 1.65E+03 Hrs. The availability is then calculated in Table 16.

Table 16—Example Problem Availability Calculation

Balancing Period (min)	**Scan/Hr**	**MTBF of Total System** (hrs)	**Probability of Failure/Period** (%)	**Probability of Availability/Period** (%)
1	60.00	1.65E+03	3.33E-04	99.9996667
5	12.00	1.65E+03	1.67E-03	99.9983333
10	6.00	1.65E+03	3.33E-03	99.9966667
30	2.00	1.65E+03	1.00E-02	99.9900000
360	0.17	1.65E+03	1.20E-01	99.8800000
720	0.08	1.65E+03	2.40E-01	99.7600000

15.2.4 CPM System

The overall LDS technology used is summarized as follows:

4.a CPM method: API 1130 # 2a: Simple mass balance, volumes corrected to STP by P, T instrument

4.b Metric(s): St. Vol. Diff, Qs(SUPPPLY) – Qs(DELIVERY)

4.c Balancing period:

1-min

5-min

10-min

30-min

6-hrs

12-hrs

15.3 Scenario 1: Steady-State

15.3.1 General

The reference state for the steady state scenario is at the nominal conditions, with the pipe roughness and heat transfer coefficients having been adjusted.

The steady state condition is a very special case for the material balance CPM method. In this special case, the RM line pack is unchanging. Therefore, *reference* mass over/short is always nil.

15.3.2 Varying Flow Rate, Pressure and Temperature, and Data Skew

Within the steady state scenario, vary the measurements and factors under consideration: flow rate, pressure and temperature, and data-time skew:

Loop B:1–2—Flow rate measurements:

There is no need to even run the RM in order to assess the result of changing the inlet mass flow rate at STP. The outlet mass flow rate will be precisely the same, in steady state. Therefore, the table of uncertainties are as shown in Table 17.

Table 17—Uncertainties

	Inlet Rate (STBPH)	RM Outlet Rate (STBPH)
Run # 1	1657 + 0.24 %	1657 + 0.24 %

	Outlet Rate (STBPH)	RM Inlet Rate (STBPH)
Run # 2	1657 + 0.24 %	1657 + 0.24 %

Mean Error (% of reference) 0.24 %.

Loop B:3–4—Pressure measurements:

It is assumed that the inlet and outlet pressure measurements are used to perform the conversion from in-situ barrels of volume to stock-tank barrels. If this conversion is in fact performed in the meter, and the corresponding error already accounted for, then varying pressure will have no impact on the reference RM material balance.

However, with this assumption, the model is run with the flow rate measured in-situ (at 1677.25 BPH in-situ) to see the impact of a small pressure change. Running the model is perhaps optional since the variation in stock-tank barrels will probably be very close to c_p times the small change in pressure. This table now looks like Table 18.

Table 18—Pressure Values

	Inlet Pressure (psi)	**Inlet, and Outlet Rate** (BPH)	**% Balance Error**
Baseline	700	1677.245	0.00000
Run # 3	700 + 4.125	1677.096	−0.00889%

	Outlet Pressure (psi)	**Inlet, and Outlet Rate** (BPH)	**% Balance Error**
Baseline	700	1677.245	0.00000
Run # 4	700 + 4.125	1677.096	−0.00889 %

Loop B:5–6—Temperature measurements:

It is assumed that the inlet and outlet temperature measurements are used to perform the conversion from in-situ barrels of volume to stock-tank barrels. If this conversion is in fact performed in the meter, and the corresponding error already accounted for, then this will have no impact on the reference RM material balance.

However, assuming this, the model is run with the flow rate measured in-situ (at 1677.25 BPH in-situ) to see the impact of a small temperature change. The variation in stock-tank barrels will again probably be very close to c_T times the small change in temperature. This table looks like Table 19.

Table 19—Temperature Values

	Inlet Temperature (°F)	**Inlet, and Outlet Rate** (BPH)	**% Balance Error**
Baseline	111	1677.245	0.00000
Run # 5	111 + 1.30	1678.874	0.09713 %

	Outlet Temperature (°F)	**Inlet, and Outlet Rate** (BPH)	**% Balance Error**
Baseline	111	1677.245	0.00000
Run # 6	111 + 1.30	1678.874	0.09713 %

Loop B:7–8—Data-time skew:

For the steady state situation, the effects of time translation are nil. They do, however, have a large impact on transient scenarios.

15.3.3 Metric Analysis

Now, accumulate CPM metrics from the runs:

Another special feature of steady state is that, since all imbalances are constant, it makes no difference to the resulting biases B if instantaneous or time-averaged values are used. The 1-min, 5-min, 10-min, 30-min, 6-hrs, and 12-hrs balancing periods all have the same resulting values, for B.

However, the effect of taking moving averages is—purely statistically—to improve the precision P. Note that this is not the same as with the original 1993 API 1149 where this time-dependent uncertainty corresponds to a physical/hydraulics uncertainty, and note also that since the P for the meters is only 0.01 % this impact is small.

The completed Table 2 summary then looks like Table 20.

The corresponding Table 2 precision P table looks like Table 21 (only the flow meters have a precision).

The potential biases (the potential range/spread of B) can be represented graphically in a Tornado diagram, Figure 24, which represents Table 20.

Table 20—Example Problem, Steady State RM Runs for Bias

Inputs						Imbalance ±B as % of Q_{ref}
QIN	PIN	TIN	QOUT	POUT	TOUT	
1657	700	111	1657	120	90	0.00
1657 + 0.24 %	Ref	Ref	Ref	Ref	Ref	0.24 %
Ref	700 + 4.125	Ref	Ref	Ref	Ref	0.00889 %
Ref	Ref	111 + 1.30	Ref	Ref	Ref	0.09713 %
Ref	Ref	Ref	1657 + 0.24 %	Ref	Ref	0.24 %
Ref	Ref	Ref	Ref	700 + 4.125	Ref	0.00889 %
Ref	Ref	Ref	Ref	Ref	111 + 1.30	0.09713 %
					Total RMS "B"	**0.366 %**

Table 21—Example Problem, Steady State RM Runs for Precision

Inputs						Imbalance ± P as % of Q_{ref}
QIN	PIN	TIN	QOUT	POUT	TOUT	
1657	700	111	1657	120	90	0.00
1657 + 0.01 %	Ref	Ref	Ref	Ref	Ref	0.01 %
Ref	Ref	Ref	1657 + 0.01 %	Ref	Ref	0.01 %
					Total RMS "P"	**0.014 %**

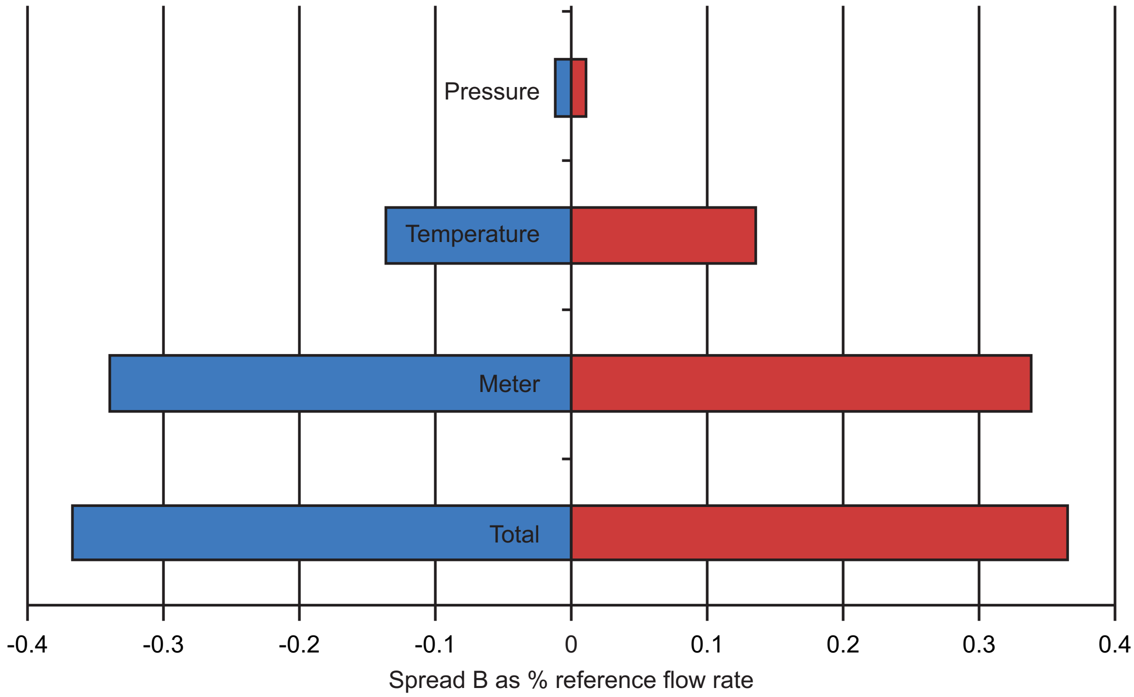


Figure 24—Example Problem Steady State Tornado Diagram

Note that in general the meter uncertainties in a steady state analysis are an order of magnitude larger than the other uncertainty factors.

Finally, for the precision curve use the formula for the moving average:

$$Var\left(\frac{1}{N}\Sigma_{i=1}^{N} X_1\right) = N \times \frac{1}{N^2} Var(X) \approx \frac{P^2}{N} \tag{102}$$

15.3.4 Alarm Analysis

This effect is so small that this curve is included for completeness only. Table 22 shows the extra precision effect, above the 0.366 % bias "B", in percent of nominal flow rate multiplied by 10^6.

Table 22—Example Problem Steady State Alarm Analysis

Balancing Period	N	Additional P effect, % x 10^6 of Q_{ref}
1-min	4	8.54E-02
5-min	20	3.42E-03
10-min	40	8.54E-04
30-min	120	9.49E-05
6-hrs	1440	6.59E-07
12-hrs	2880	1.65E-07

15.4 Scenario 2: Transient Startup

15.4.1 General

Now, analyze the second scenario: startup transient:

A RM run is performed at zero uncertainty conditions, which yields reference values for all the pipeline state variables, and in particular the over/short imbalance, as a function of time.

It is important to be explicit about how this scenario is set up. For this example, the model is driven by SCADA upstream pressure and flow rate (not upstream and downstream flow, for example). This choice might be similar to a design situation where only an idealized model with nominal inlet pressures and an artificial inlet flow rate ramp schedule might be used.

The overall uncertainty method is open to any choice of driving boundary conditions, *provided that they are stated clearly.*

The results of the simulation match the measured outlet conditions well. In fact, with this scenario and boundary condition setup, they match to within numerical precision at balancing periods above one minute (1-min).

The reference condition CPM Imbalances, in standard barrels, can be summarized in Table 23 (% of Q_{ref}).

Table 23—Example Problem Maximum Transient Imbalances

Balancing Period	Seconds	Max Imbalance ±% Q_{ref}
1-min	60	7.7686
5-min	300	3.4742
10-min	600	2.4567
30-min	1800	1.4183
6-hrs	21,600	0.4094
12-hrs	43,200	0.2895

15.4.2 Loop B: Varying Flow Rate, Pressure and Temperature, Data Skew

Within the transient scenario, vary the measurements and factors under consideration: Flow Rate, Pressure and Temperature, and Data-Time Skew.

The same RM is now run in Loop B (Table 2, Figure 12) varying all the control parameters: upstream and downstream flow rate, pressure and temperature.

The Data-Time Skew effect is also modeled. In this scenario, where both boundary conditions are upstream, the skew is not applied to the input boundary condition schedule. Rather, it is applied to the calculation of the imbalance. With the skew set to B = 4.243 s, the modified imbalance is:

$$\Delta Q_{\text{m,B}}(t) = Q_{\text{in}}(t) - Q_{\text{out}}(t+B) \qquad (103)$$

The imbalances are then compared with the reference imbalances, from the baseline RM run, and summarized in Figure 25.

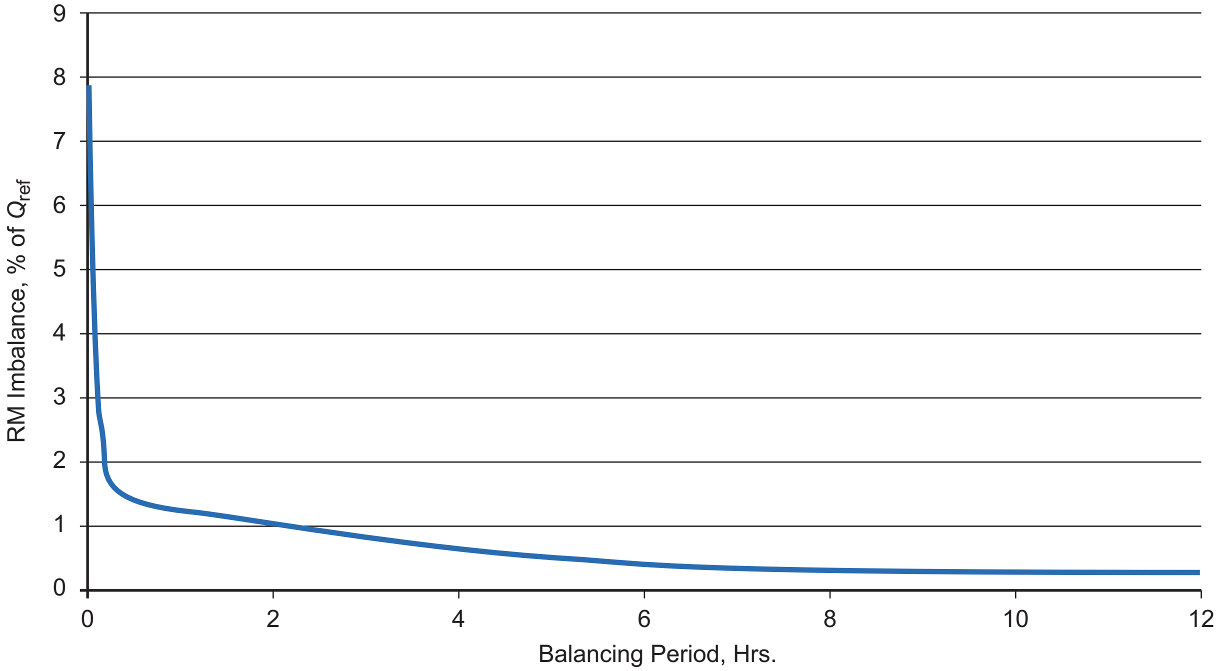


Figure 25—Example Problem Maximum Transient Imbalances

This produces a number of time-series charts, showing the incremental impact of each uncertainty factor on the STP imbalance, above the reference imbalance. As an example, the chart in Figure 26 summarizes the impact on the 1-min averaged imbalance. Again, for clarity, the focus is on 50 minutes around the startup.

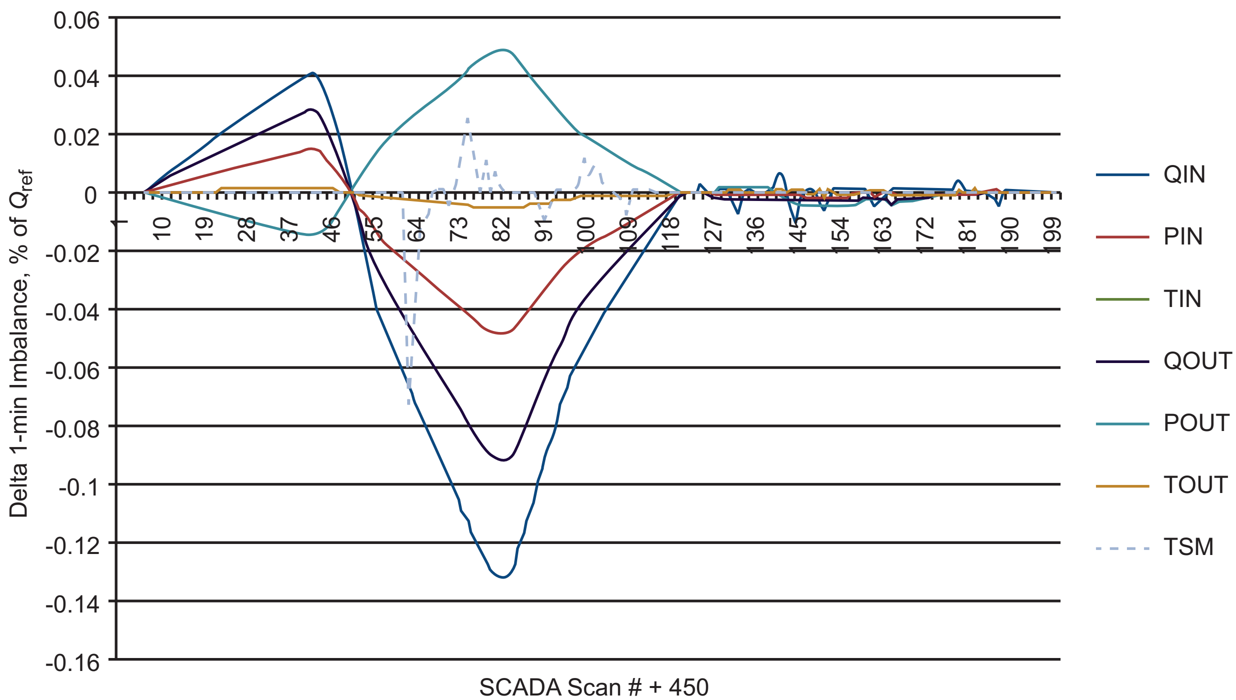


Figure 26—Example Problem Transient Contributions to Uncertainty

15.4.3 Metric Analysis

Now, accumulate CPM metrics from the runs.

Again picking the 1-min imbalance period for focus, the Table 7summary then becomes Table 24.

Table 24—Example Problem, Transient RM Runs for Bias

Inputs							Incremental ±B
QIN	PIN	TIN	QOUT	POUT	TOUT	TSS	
Ref	Ref	Ref	Ref	Ref	Ref	Ref	7.76 %
Ref + 0.24 %	Ref	Ref	Ref	Ref	Ref	Ref	0.24 %
Ref	Ref + 4.125	Ref	Ref	Ref	Ref	Ref	0.00891 %
Ref	Ref	Ref + 1.30	Ref	Ref	Ref	Ref	0.09755 %
Ref	Ref	Ref	Ref + 0.24 %	Ref	Ref	Ref	0.17 %
Ref	Ref	Ref	Ref	Ref + 4.125	Ref	Ref	0.00887 %
Ref	Ref	Ref	Ref	Ref	Ref + 1.30	Ref	0.09713 %
Ref	Ref	Ref	Ref	Ref	Ref	Ref + 2.423	0.078 %
						Total RMS. “B”	**7.78 %**

In short, the measurement uncertainty contributions are extremely close to the steady state case. However, the underlying physical uncertainty due to the CPM method (row 1) completely dominates. This is reflected in the tornado diagram in Figure 27.

Note that the assessed 7.78 % uncertainty is rather less than the original API 1149 (1993) estimate of 46.42 % (see 15.5).

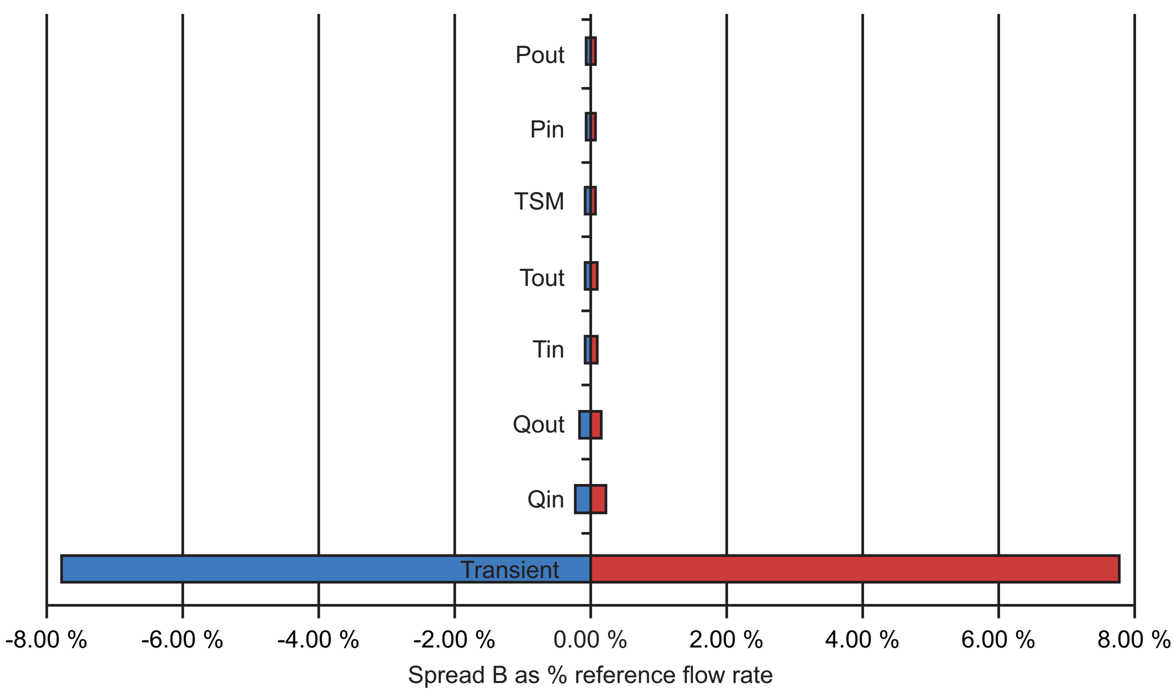


Figure 27—Example Problem Transient Tornado Diagram

15.4.4 Conclusions and Alarm Analysis

This concludes the transient scenario.

Longer averaging periods yield a chart showing total uncertainty as a function of time, first including the reference imbalance in Table 25.

Table 25—Example Problem Transient Alarm Analysis, with RM Imbalance

Balancing Period	Seconds	Max Imbalance ±% Q_{ref}
1-min	60	7.776 %
5-min	300	3.487 %
10-min	600	2.475 %
30-min	1800	1.449 %
6-hrs	21600	0.504 %
12-hrs	43200	0.413 %

Secondly, excluding the reference imbalance in Table 26:

Table 26—Example Problem Transient Alarm Analysis, Without RM Imbalance

Balancing Period	Seconds	Max Imbalance ±% Q_{ref}
1-min	60	0.334 %
5-min	300	0.303 %
10-min	600	0.298 %
30-min	1800	0.296 %
6-hrs	21600	0.294 %
12-hrs	43200	0.294 %

Table 25 and Table 26 can be presented graphically in Figure 28.

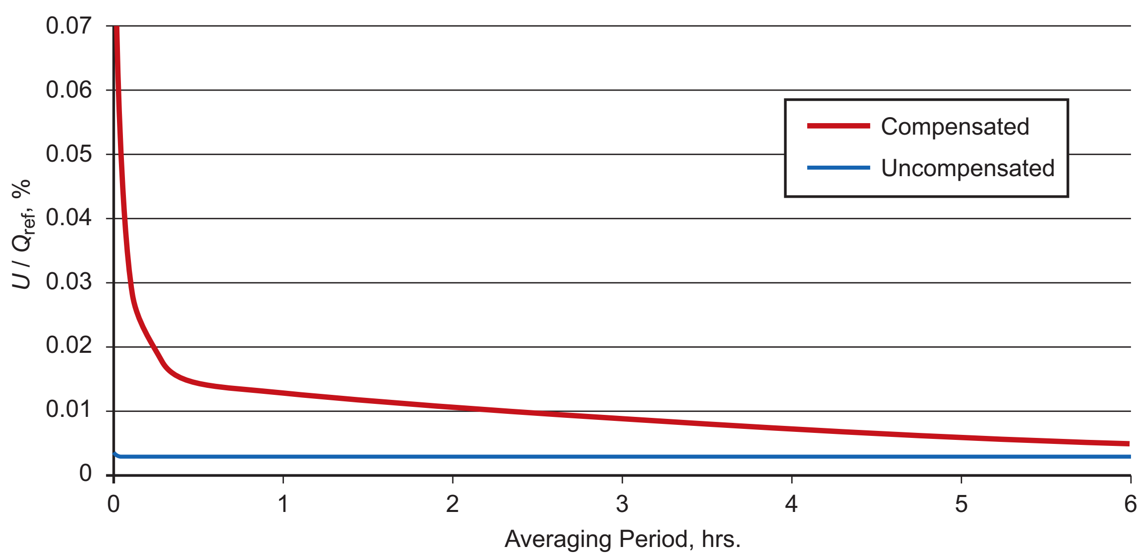


Figure 28—Example Problem Transient Alarm Analysis

It might be expected, as reflected in the graph, that a CPM like RTTM that takes account of the line pack—and therefore the Reference Imbalance—would eliminate the reference line pack uncertainty and follow the blue line. An uncompensated method like a basic mass balance would follow the red line.

15.5 (Original, 1993) API 1149 Estimates

This section is a remark, to illustrate how the original API 1149 procedure might be used to perform the same assessment. Note that data-time skew cannot be analyzed by the original procedure.

In order to use the original API 1149 (1993) procedure, it is assumed that the "accuracy" of the instrumentation, in the API 1149 sense, corresponds to "B".

Chapter 5 (of the original 1993 API 1149) defines the estimates for steady state flow. The first component of the uncertainty is due to metering [Equation (5.3) in standard barrels volume per hour time]:

$$dQ_{\mathrm{m}} = Q_{\mathrm{ref}}\sqrt{k_{\mathrm{in}}^2 + k_{\mathrm{out}}^2} = 1657 \times \sqrt{2} \times 0.24\ \% = 5.624\ \mathrm{STBPH}$$

Step 2: The next step is to calculate the rate of line fill change with respect to pressure [Equation (5.9)]. The coefficients a are taken from the database in Table 5.9 of API 1149 (1993) for crude oil. The appropriate parameters for the table are:

Deg API = 23.8 (use the row for 19.96 – 24.69); D/e = 57.2 – 49.1 (use the row for 75)

Coefficients $\{a\}$ = {6.209E+00, −3.141E-04, 7.984E-03, −8.531E-07, 1.179E-05}

P = 685.3 PSIG; T = 111 °F.

From the expansion 5.9, $\partial I/\partial P$ = 6.960E-06 PSI-1 so (Step 3) volumetric line fill uncertainty due to pressure = 6.960E-06 x 4.125 x 9182 = 0.2636 BBL.

Step 4: For the rate of line fill change with respect to temperature [Equation (5.10]). The coefficients b are taken from the database in Table 5.9 of API 1149 (1993) for crude oil. The appropriate parameters for the table are:

Deg API = 23.8 (use the row for 19.96 – 24.69); D/e = 57.2 – 49.1 (use the row for 75)

Coefficients $\{b\}$ = {3.730E-01, −7.366E-06, 1.331E-04, −2.361E-08,−1.430E-07}

P = 685.3 PSIG; T = 111 deg.F.

From the expansion 5.10, $\partial I/\partial T$ = 3.792E-04 F^{-1} so (*Step 5*) volumetric line fill uncertainty due to temperature = 3.792E-04 x 1.3 x 9182 = 4.526 BBL

There is no *Step 6* since there is only one line. Combining these with Equation (5.8) (*Step 7*):

$$dV_s = \sqrt{2(0.2636^2 + 4.525^2)} = 6.410\ \mathrm{BBL}$$

The sensitivity against time is found from Equation (5.6) and is shown in Table 27 and Figure 29 (*Steps 8 to 9*).

The ten-second (10 s) threshold (which is used for comparison) is similarly found to be 139.27 %.

Transient Scenario—the transient scenario that is considered involves a cold start from standstill to full flow rate.

Table 27—Example Problem, Original 1993 API 1149 Estimates

Minimum Detection Time	Ql/Q_{ref} %
1-min	23.21
5-min	4.65
10-min	2.35
30-min	0.84
6-hrs	0.35
12-hrs	0.34

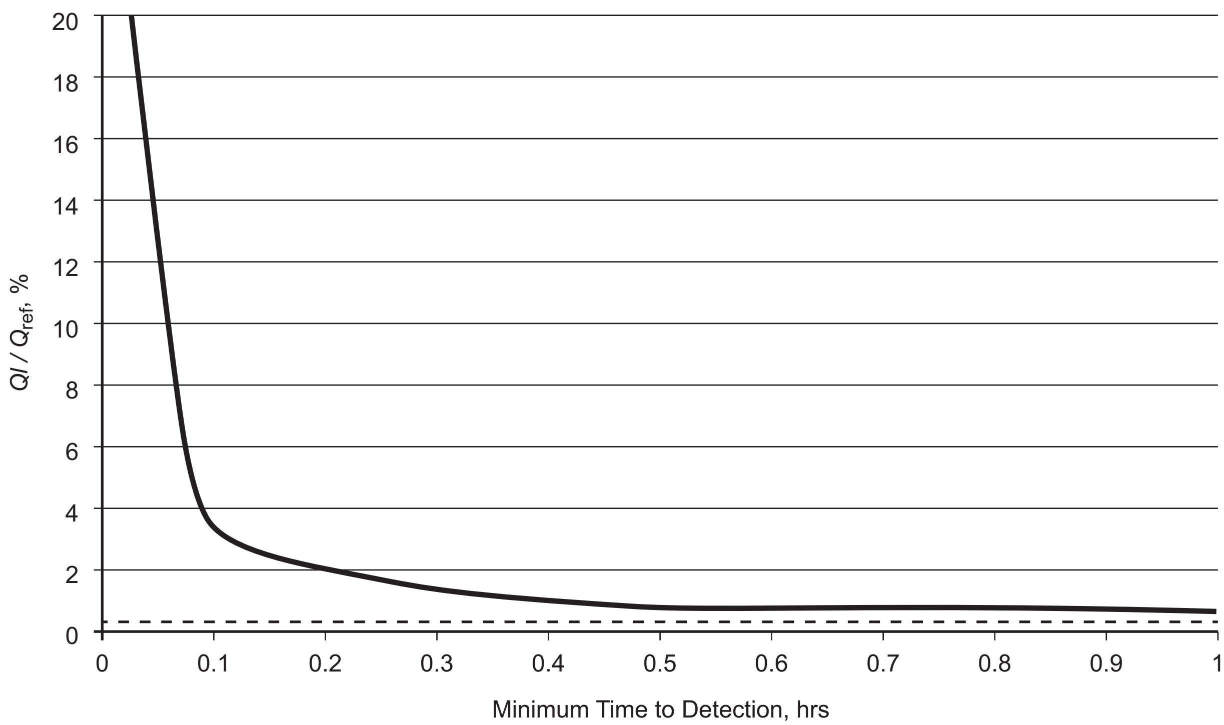


Figure 29—Example Problem, Original 1993 API 1149 Estimates

In this situation, the value of *TSV* [Equation (9.1)] is 1 (i.e. 100 %).

The Reynolds number of this pipeline, at nominal conditions, is 1.879 [Equation (8.15)].

This means that the tables in Chapter 9, for R = 2 can be used, with reasonable accuracy.

Figure 9.3 in Chapter 9 (of the 1993 API 1149) shows the impact of using only the endpoint pressures, and also the impact of using an RTTM, on the transient percent uncertainty:

$$dV_t/Q_{ref} = 1 \text{ (no pressure correction) and } dV_t/Q_{ref} = 0 \text{ (RTTM)}$$

Therefore, with an RTTM the sensitivities against time in Table 7 are unchanged in this transient scenario. However, without any line pack compensation the line pack error is broadly speaking doubled, yielding this revised table (Table 28).

The 10 s transient threshold (compare with Figure 23) is similarly found to be 278.53 %.

Table 28—Example Problem, Original 1993 API 1149 Estimates with Transient Correction

Minimum Detection Time	Ql/Q_{ref} %
1-min	46.42
5-min	9.29
10-min	4.65
30-min	1.58
6-hrs	0.36
12-hrs	0.35

Annex A
(informative)

Technical Report Summary

This document is a revision of industry standard procedures for the assessment of uncertainties in software-based leak detection systems.

Software-based leak detection systems (LDS), often 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.

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

This revision of API 1149 (1993) 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 were not thoroughly addressed in the original revision. In brief summary, these include:

— the need to cover the complete range of CPM methods in current, practical use;

— the need to extend the assessment to Highly Volatile Liquids (HVL) and natural gases;

— alignment of the definitions and approach to uncertainty with those used systematically in instrument and measurement engineering;

— recognition of the nonlinear and strongly time-dependent nature of certain engineering factors;

— inclusion, in detail, of a number of engineering factors that occur regularly in pipeline operations;

— inclusion of the major telemetry (SCADA) uncertainties in measurement

A section of this document provides 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 some of these alarms occur due to a complete failure in the overall leak detection system—which in turn would be outside of a normal statistical probability. This procedure provides an estimated bias and standard deviation for uncertainty in the leak detection alarm. Another section addresses the difficulty of estimating false alarm probability, or rate.

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 the CPM metric that can be observed even when no leak is present, and therefore represents a limit on the minimum size leak possible to detect with the given CPM system. The approach measures *uncertainty* in terms of a *systematic bias* and a *precision*. The bias can be thought of as a constant error in the CPM metric over time scales of interest to leak observation. Bias can in theory be eliminated by calibration, but over longer time scales the bias in a CPM system may not be truly constant. The precision is a continually varying error that cannot be eliminated even in theory. To improve CPM performance beyond the precision limit requires changes to the measurement system or the CPM system itself.

The overall process to calculate the leak detection potential can be summarized in the flowchart shown in Figure A.1 (Salmatanis, 2014), which also provides a cross-reference to the procedure used in the original 1993 API 1149.

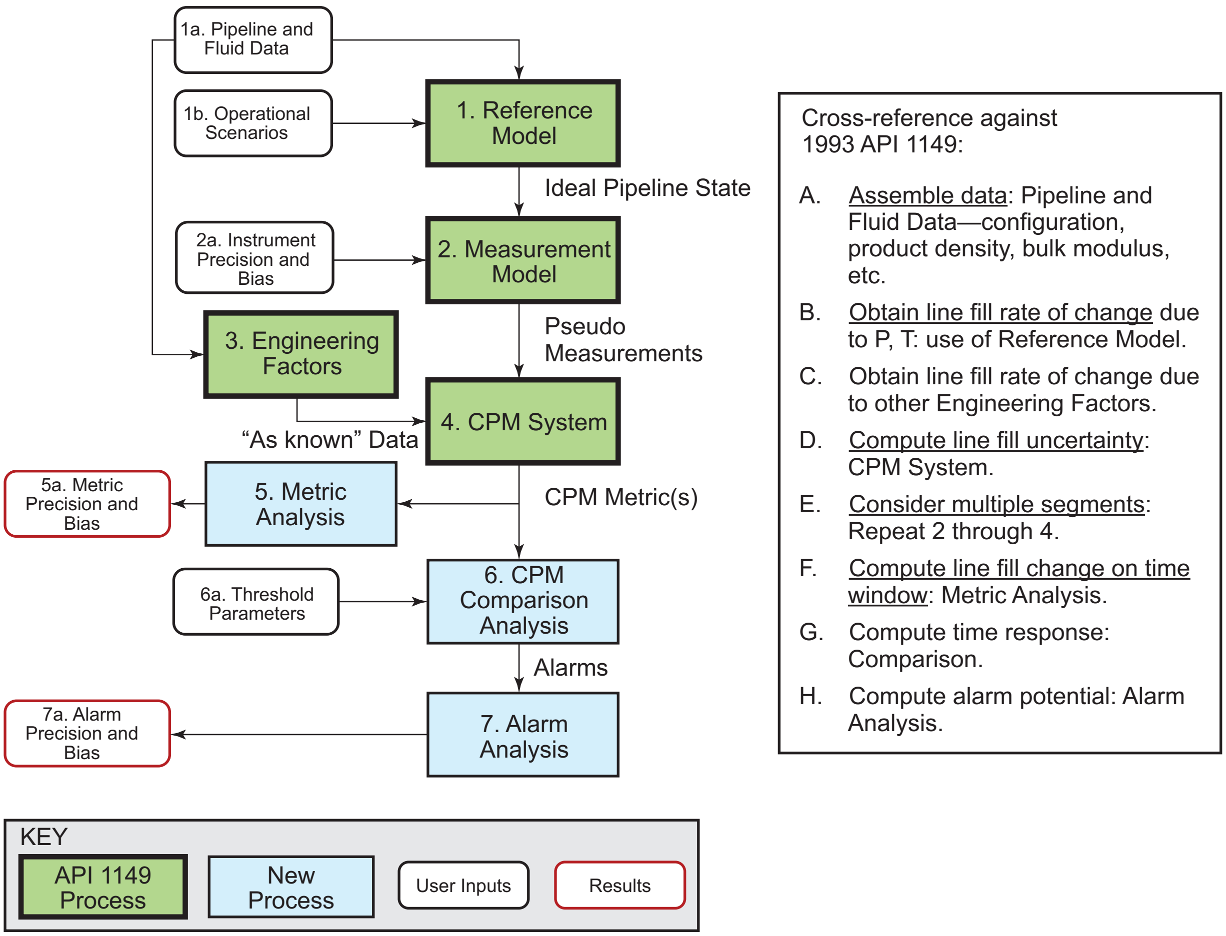


Figure A.1—Process Summary

1) A pseudo pipeline is built using the *reference model* (RM), and typically (though not necessarily) this will be a mathematical hydraulic transient simulator of the pipeline. This model can be as complex or as simple as appropriate to the level of accuracy desired for the final assessment. The RM takes account of—apart from other items—the configuration of the pipeline, any engineering factors that affect the LDS performance, and any transient scenarios on the pipeline.

2) The next step is to analyze the inputs to the LDS by using a systematic procedure defined by the *measurement model*. this requires statistics of the bias and precision for each of the meters and instruments used by the LD technique, as defined by the 2013 API *MPMS*. It also takes into account the most important SCADA system uncertainties. This generates a set of pseudo measurements with known uncertainty properties for input to the CPM system. In parallel the configuration data used in the reference model are perturbed by errors specified by the user to account for the fact that this data is not known with certainty.

3) Any number of *Engineering factors* can be considered while running the RM in order to assess their effects on the physical pipeline state, and therefore on the LDS.

4) The *CPM system* is run using the measurement and configuration data that includes introduced errors with known statistical properties and computes its CPM metric. The CPM metric will indicate some level of leak due

to the introduced errors, even when there is none. The CPM system can be configured to simulate any number of operational *scenarios*—including perhaps steady state, shut-in, startup, shutdown, or batch changes.

5) The CPM system is run repeatedly, using a perturbed set of potential inputs and engineering factors. Each time that it is run, a new perturbed metric is produced and metric statistics are developed. This statistical *metric analysis* determines the statistical properties of the false indication and this is presented to the user as the primary result of the process.

6) The metric is potentially *compared* in several ways against a threshold. The threshold may be a constant value, dynamic (varying with time), and/or a calculated function of the pipeline state, and/or an array of values against which individual pipeline state variables are compared. This final comparison represents the total uncertainty in the leak detection system itself, and quantifies how small and how quickly a leak can be detected, given all the other factors.

7) This final comparison is used to describe the total uncertainty in the alarms of the leak detection system as a whole. The detectable leak size will be expressed as a function of response time.

The entire process can be repeated to analyze other operating scenarios, physical configuration changes, and/or CPM system types.

The reader who does not require complete details of the algorithms and the procedure can follow this document selectively.

— Annex A is generally sufficient to understand, at a managerial level, the intent, mission and approach to the problem.

— The Introduction provides the basic scope, objectives, and approach to the procedure.

— The engineering summary (approximately five pages) provides sufficient detail for an experienced engineer to be able to understand the approach.

— The subsequent sections provide the details for an experienced engineer to complete a detailed analysis including any of the engineering factors in scope.

— Section 10 provides mathematical and statistical details for completeness.

Annex B
(informative)

Worked Examples

B.1 Summary

This annex is a set of Worked Examples that use the algorithms developed to assess uncertainty in CPM techniques. Operators on the project team contributed these specific test cases.

This revision of API 1149 (1993) was undertaken, in part, to allow the analysis of engineering uncertainty factors that prove, in practice, to have a significant effect on LDS uncertainty but were not thoroughly addressed in the original revision. The test cases were selected in order to include several of these, notably:

— SCADA and Telemetry;

— system availability and robustness;

— the impact of fluid properties;

— severe transient effects;

— basic pipe networks;

— LVL and HVL products;

— natural gas;

— batch products operations.

These examples supplement the Case Study: Worked Example Uncertainty Assessment in Section 15, which provides more step-by-step directions in completing the procedure.

B.2 Introduction

These examples include a basic LDS Uncertainty Assessment, covering the same essential components.

1) A robustness/availability calculation. This is covered in 7.2.3. This is notably the minimum level of uncertainty that can be expected from a LDS.

2) A SCADA and telemetry calculation. This is also covered in Section 7. It is important to do this first, since a result of this calculation is the additional bias and precision to apply to all instruments, and also the bias and precision to apply to any balancing periods.

3) A scenario in steady state, using the RM, designed to isolate just the impact of measurement on the LDS uncertainty.

4) Typical and perhaps also worst-case, transient scenarios. These either may be driven from recorded SCADA measurements, or may be idealized step-change style predictive scenarios.

The Case Study: Worked Example Uncertainty Assessment in Section 15 describes the steps that are taken in more detail. These worked examples are much more abbreviated in their presentation.

B.3 Robustness/Availability Calculation

B.3.1 General

All the examples include the same robustness/availability calculation, which is based upon synthetic representative input data. The typical report is presented in Figure B.1, and it includes: table of input system MTBF; system MTBF; and availability.

B.3.2 Table of Input System MTBF

The first step is to identify the main components in the LDS system and to list them in column 1 of the table. For information, only column 2 shows the purpose of the component. Column 3 reports the rated or nominal MTBF; and column 4 any revisions to this nominal MTBF due to practical testing, field experience, etc. The result is a column of minimum value, “as-used” MTBF.

B.3.3 System MTBF

Both approaches to total system MTBF are shown.

— Weakest link MTBF assumes that the system has no redundancy and as soon as one component fails, the entire LDS fails. This value is the minimum MTBF in the system.

— Cumulative MTBF is essentially the cumulative mean of the means to expected failure. This value is the harmonic average of the MTBF in the system.

Either of these values may be used, with the weakest link MTBF being substantially more conservative.

B.3.4 Availability

Using the equations in Section 7, according to different LDS calculation frequencies, a basic chart showing availability (%) and probability of failure (%) is drawn as in the lower-right of Figure B.1.

B.4 SCADA and Telemetry Uncertainties

B.4.1 General

All the examples include the same SCADA uncertainty calculation, which is based upon synthetic representative input data. The typical report is presented in Figure B.2, and it includes: Table of input system parameters; resulting processing parameters; and tornado diagram.

B.4.2 Table of Input System Parameters

Figure B.2 lists all the possible SCADA system uncertainties, and these are representative values based on a 32-bit digital SCADA and telemetry setup.

B.4.3 Results: Processing Parameters

Using the equations in Section 7, these result in a cumulative set of:

1) additional bias and variance to apply to time-data skew in averaging/balancing calculations; and

2) additional bias and variance to apply to all measurements.

1 **Input Component MTBF** (Hrs.)

Location	*Property*	*Rated / Nominal*	*Measured Value*	*Min. Value*
SUPPLY	P	2.00E+05		2.00E+05
SUPPLY	Q	1.00E+04		1.00E+04
SUPPLY	T	1.00E+05	5.00E+04	5.00E+04
DELIV-1	P	2.00E+05		2.00E+05
DELIV-1	Q	1.00E+04	5.00E+03	5.00E+03
DELIV-1	T	1.00E+05		1.00E+05
DELIV-2	P	2.00E+05		2.00E+05
DELIV-2	Q	1.00E+04		1.00E+04
DELIV-2	T	1.00E+05		1.00E+05
DELIV-3	P	2.00E+05		2.00E+05
DELIV-3	Q	1.00E+04		1.00E+04
DELIV-3	T	1.00E+05		1.00E+05
DELIV-4	P	2.00E+05		2.00E+05
DELIV-4	Q	1.00E+04		1.00E+04
DELIV-4	T	1.00E+05		1.00E+05
	SCADA	3.40E+04	2.38E+04	2.38E+04
	IT / CPM	1.40E+06		1.40E+06

2	**Weakest link**	1.00E+04	5.00E+03 (Hrs.)
	Cumulative MTBF	1.65E+03	1.37E+03 (Hrs.)

3

Balancing Period (Min.)	**Scan / Hr.**	**MTBF of total system (Hrs.)**	**Probability of Failure / Period (%)**	**Probability of Availability / Period (%)**
1	60.00	1.37E+03	3.33E-04	99.9996667
5	12.00	1.37E+03	1.67E-03	99.9983333
10	6.00	1.37E+03	3.33E-03	99.9966667
30	2.00	1.37E+03	1.00E-02	99.9900000
360	0.17	1.37E+03	1.20E-01	99.8800000
720	0.08	1.37E+03	2.40E-01	99.7600000

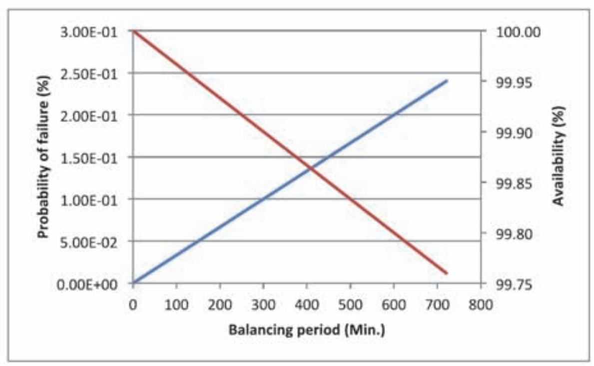


Figure B.1—Robustness/Availability

B.4.4 Tornado Diagram

To visualize the relative impact on total uncertainty, the total contribution to final uncertainty of each component is shown in a tornado diagram as shown in Figure B.2.

B.5 Data Set 1—Pump Startup

B.5.1 General

This data set corresponds to the Case Study: Worked Example Uncertainty Assessment in Section 15. Please refer to the main text for a detailed step-by-step discussion.

1 Input Data — See Table 2 of the document for definitions

Scan Period	5 (s)	Frequency of data collection (mean)
TSM	0.01 (s)	Data-time skew (bias)
TSS	0.0001 (s)	Data-time skew (sigma)
TCF	0.0022 (s)	Front-end processing latency
Resolution	0.002314815 (32-bit)	All measurements, numerical rounding error
Scale Factor	0	All measurements, error in any scaling
Noise	0.001157407 (32-bit)	All measurements, random noise
Noise Bias	0	All measurements, added bias

2 Processing Parameters — See Section 7.1 for equations

Applied to all balancing periods	Bias Time-Data Skew	0.0122 (s)
	Variance T-Data Skew	2.08343333 (s)
Applied to all instrument uncertainties	Added Bias	0
	Added Variance	5.5816E-07

3 Tornado Diagram

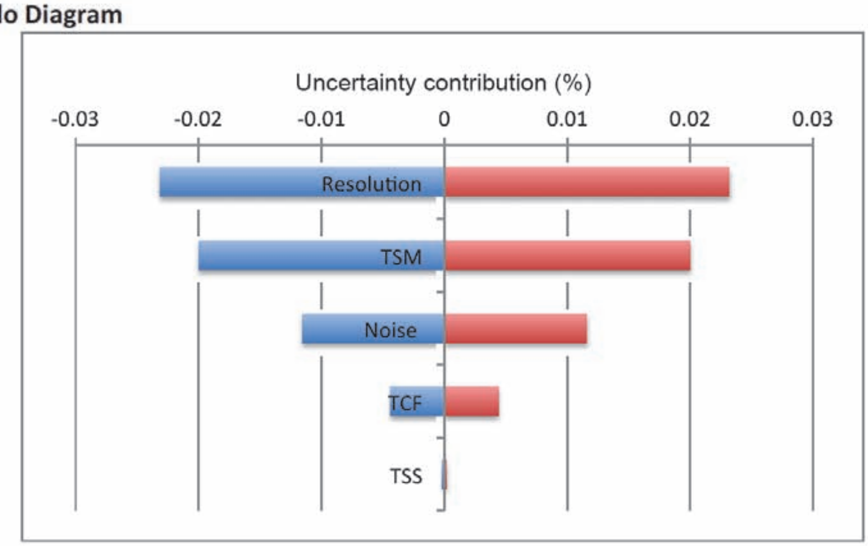


Figure B.2—SCADA Uncertainties

B.5.2 General Flowchart

This flowchart (see Figure B.3) is the same for all examples, and is not repeated for every data set.

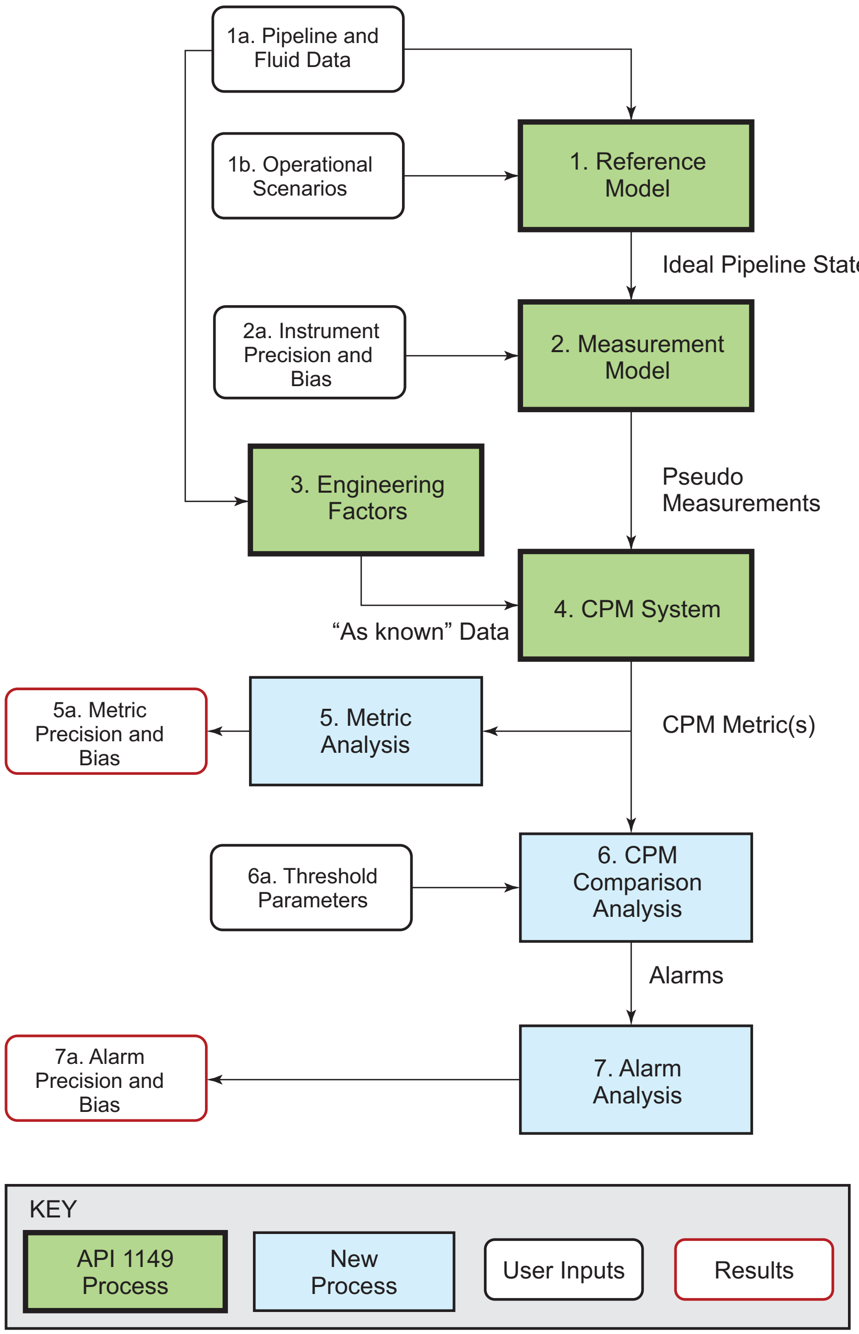


Figure B.3—General Flowchart

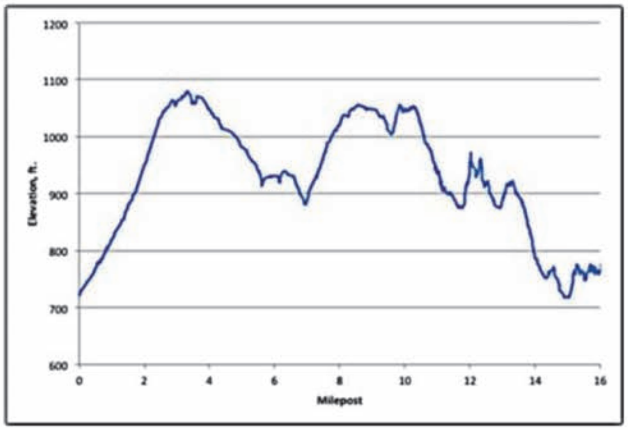
B.5.3 Other Inputs

Figure B.4 shows the pipeline description, as input to the Reference Model, as well as the transient scenarios to be considered.

1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File:	TNETConfig.txt	(File)
Input Data Set:	TestData\Line106	(Folder)



Pipeline Configuration Data:	TNETConfig.csv	(Sketched Above)
Units of Measurement (US Oilfield)	FieldUnits.csv	
Source/Sink Config	TNETbatch.csv	
Elevation Survey	elevProfile.txt	
Heat Transfer Data	HeatXferData.txt	(Not used)
Equipment Curves	EquipCurve.txt	(Not used)
Equipment Data	EquipData.csv	(Not used)
Pipe Data	pipeLibrary.txt	(Not used)
Operating State	TNETscenario.csv	
Fluid Data	FluidData.txt	(Not used)
Viscosity Data	VisCurve.txt	
Environmental Data	Environment.txt	(Not used)

See pipeCube Input Reference Manual v2014-04-05

1.b Operational Scenarios (Input)

No. 1	Steady State	*No changes at all to the measurements sketched above*	
No. 2	Transient Scenario		
	Scenario Data Set:	TNETScenario.csv	(CSV File)
		Describes an abrupt pump startup situation	

Figure B.4—Reference Model

Figure B.5 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	*Spread "B"*		*Precision "P"*	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	4.125		0	(PSI)
Pressure Out	4.125		0	(PSI)
Temperature In	1.3		0	(F)
Temperature Out	1.3		0	(F)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods	Bias Time-Data Skew	0.032	(s)
	Variance T-Data Skew	2.08343333	(s)
Applied to all instrument uncertainties	Added Bias	0	
	Added Variance	5.5816E-07	

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF	5.00E+03	(Hrs.)
Cumulative MTBF	1.37E+03	(Hrs.)
24-Hr. Availability	99.76	%

4. CPM System

4.a CPM Method:

API 1130 # 2a Simple mass balance, volumes corrected to STP by P, T instrument

4.b Metric(s):

No. 1 St. Vol. Diff SUPPLY-JCT Qs(SUPPLY) - Qs(JCT)

4.c Balancing Period:

60	1-min	(Seconds)
300	5-min	(Seconds)
600	10-min	(Seconds)
1800	30-min	(Seconds)
21600	6-hrs	(Seconds)
43200	12-hrs	(Seconds)

Figure B.5—Other Uncertainties

B.5.4 Steady-State Analysis

Given that the metering and instrumentation uncertainties are the same for all examples, steady-state results as shown in Figure B.6 are practically the same for all examples, and therefore are not repeated for every dataset. The corresponding tornado diagram is shown in Figure B.7.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.8.

Steady State **Metric No. 1** Qs(SUPPLY) - Qs(JCT)

1 Summary of Runs:

Bias

				Inputs			*Ideal CPM Metrics, using RM ideal state / Pseudo Measurements*
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.10%
	TOTAL						0.366%

Precision

				Inputs			
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	TOTAL						0.014%

Figure B.6—Summary of Steady State Runs

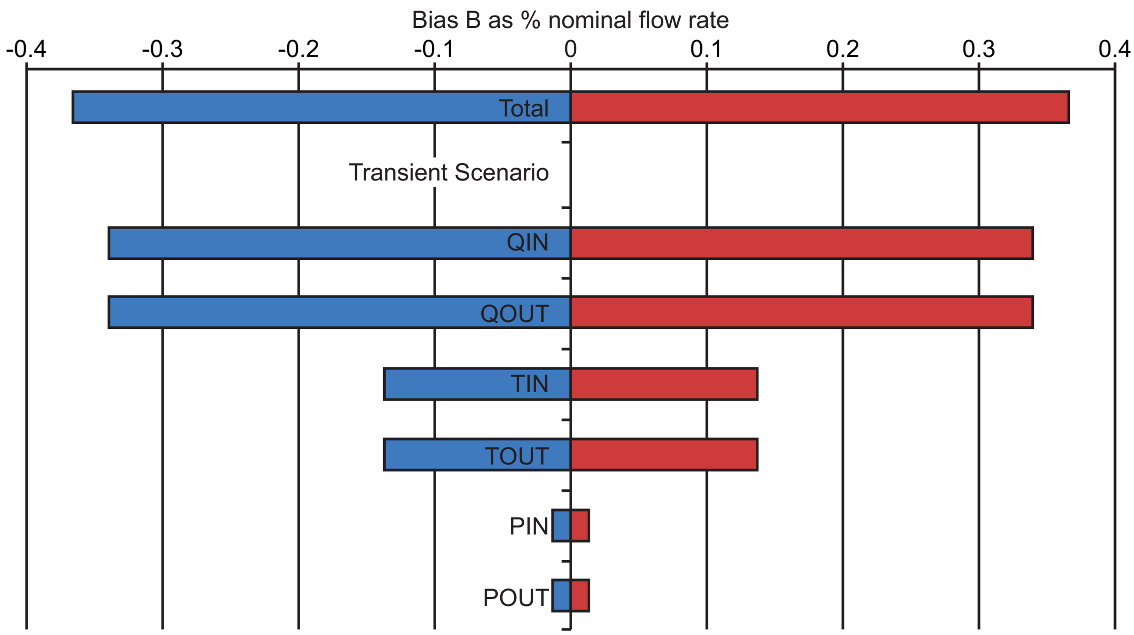


Figure B.7—Tornado Diagram, Steady State

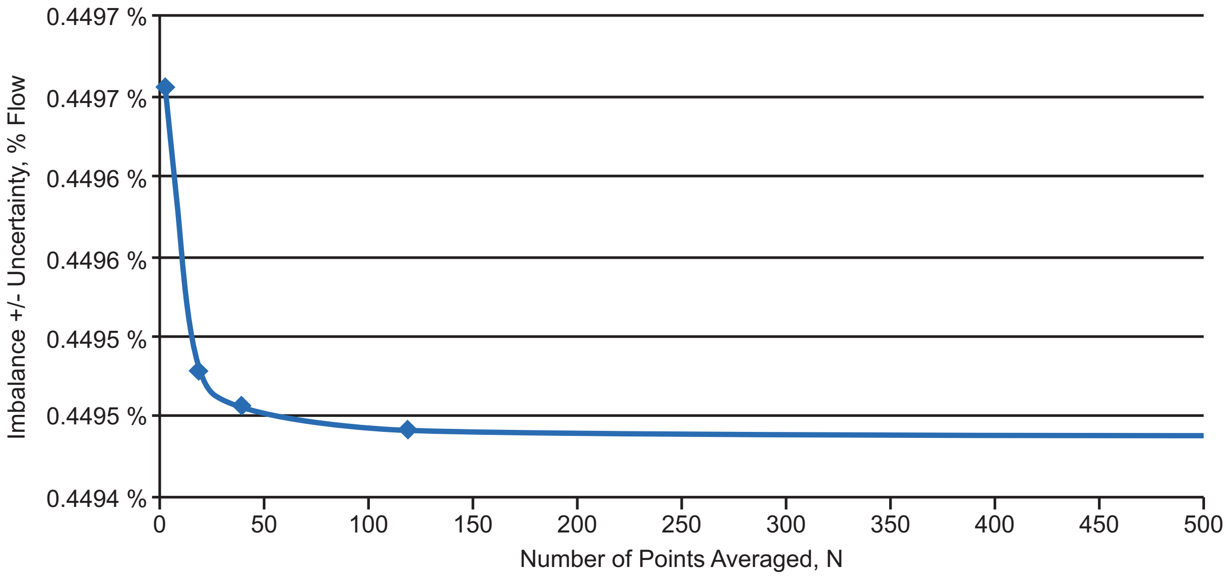


Figure B.8—Steady State, Impact of Balancing Period

B.5.5 Transient Analysis

The transient analysis is quite different. Instead of having a constant imbalance (as in the steady-state case) the imbalance varies markedly with time as shown in Figure B.9. The corresponding table of maximum uncertainties is shown in Figure B.10, and the resulting tornado diagram in Figure B.11.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.12.

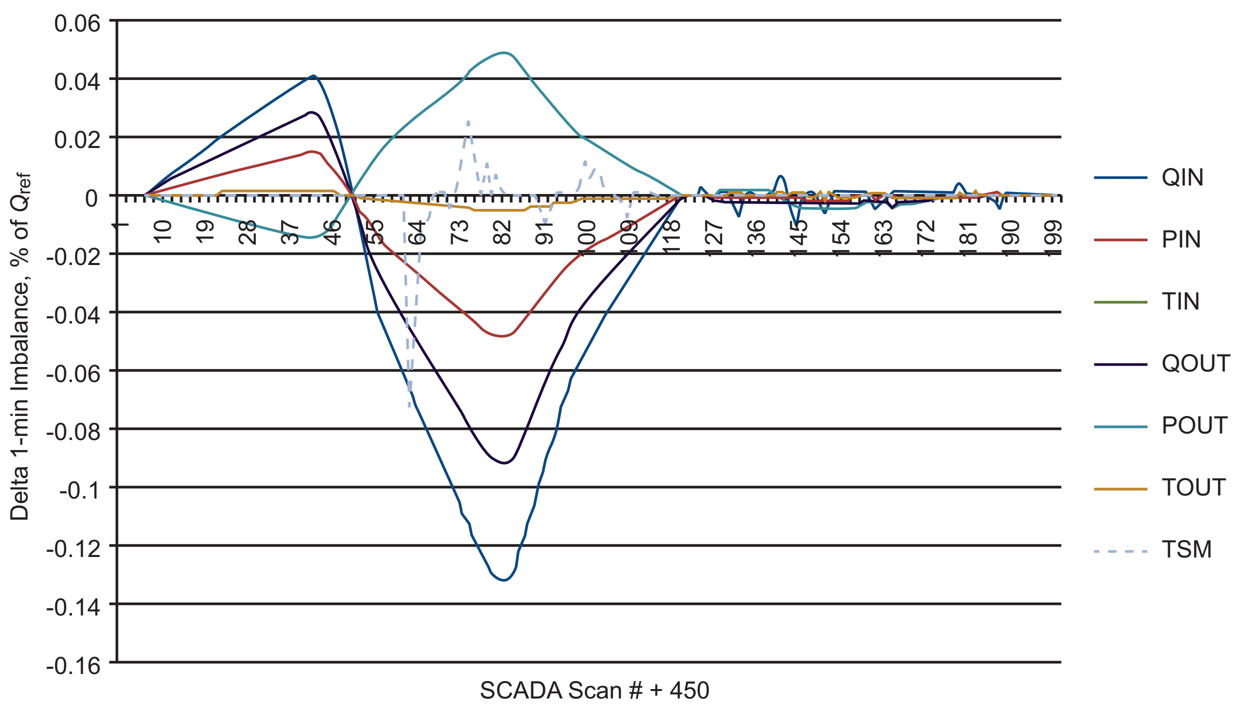


Figure B.9—RM Ideal (Reference) State Results

2 Summary of Runs:

				Inputs			*Ideal CPM Metrics, using RM ideal state / Pseudo Measurements*
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Re,	7.76%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.10%
	TOTAL						7.769%

				Inputs			
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	TOTAL						0.014%

Figure B.10—Summary of Transient Runs

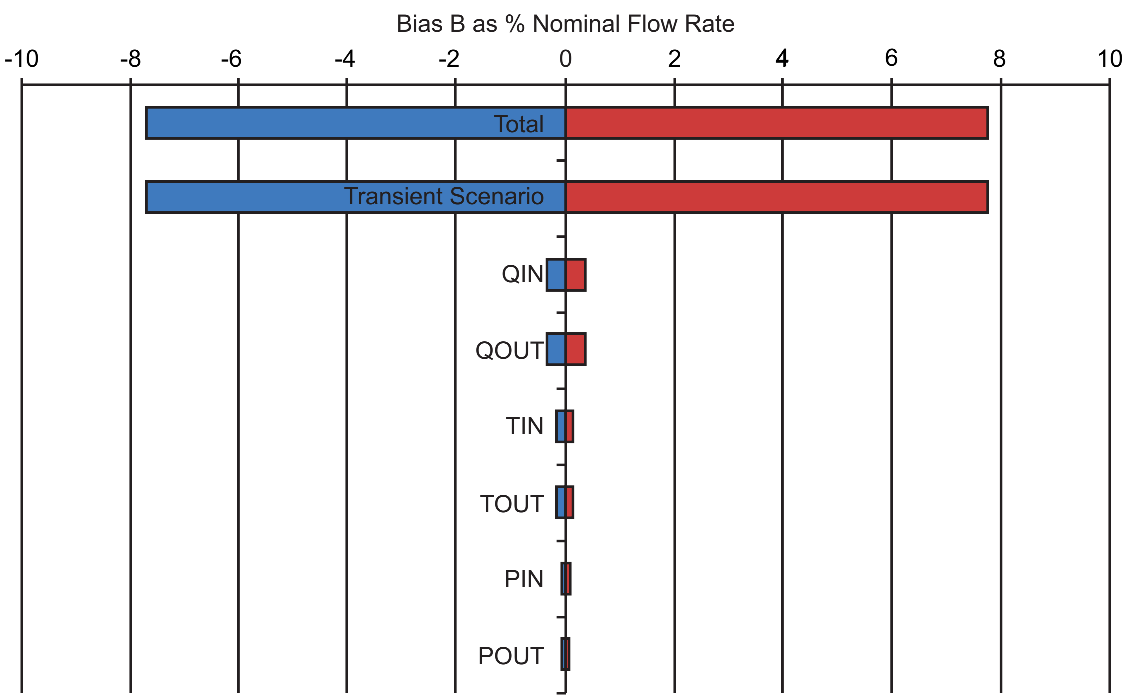


Figure B.11—Tornado Diagram, Transient

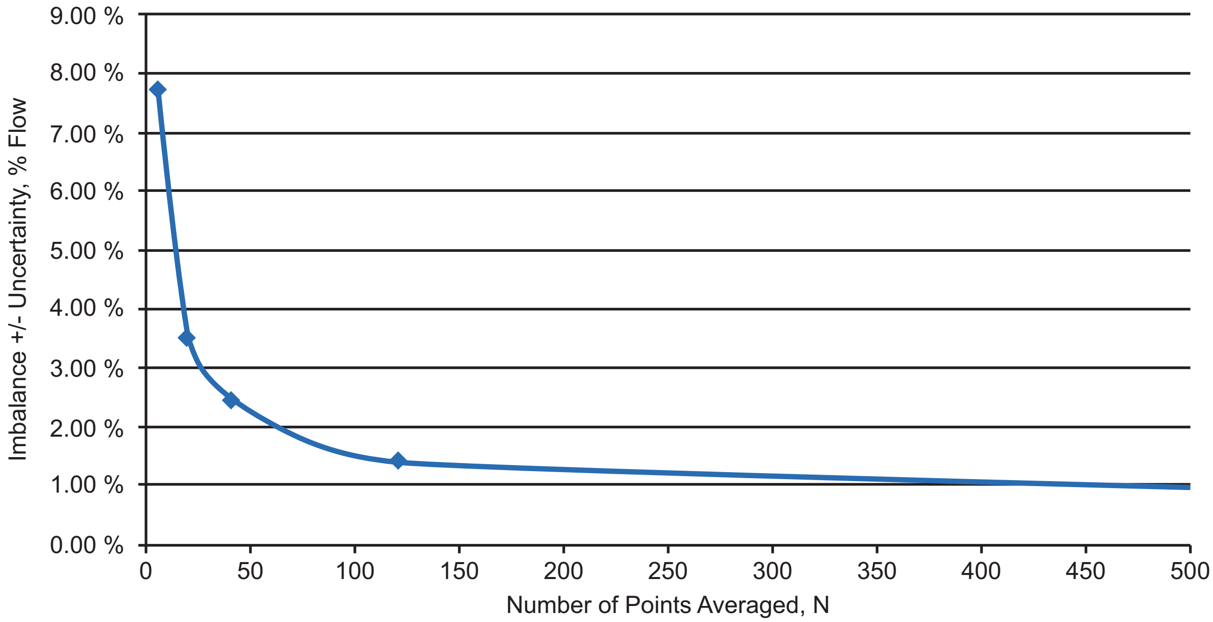


Figure B.12—Transient, Impact of Balancing Period

B.5.6 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.13 also includes SCADA effects.

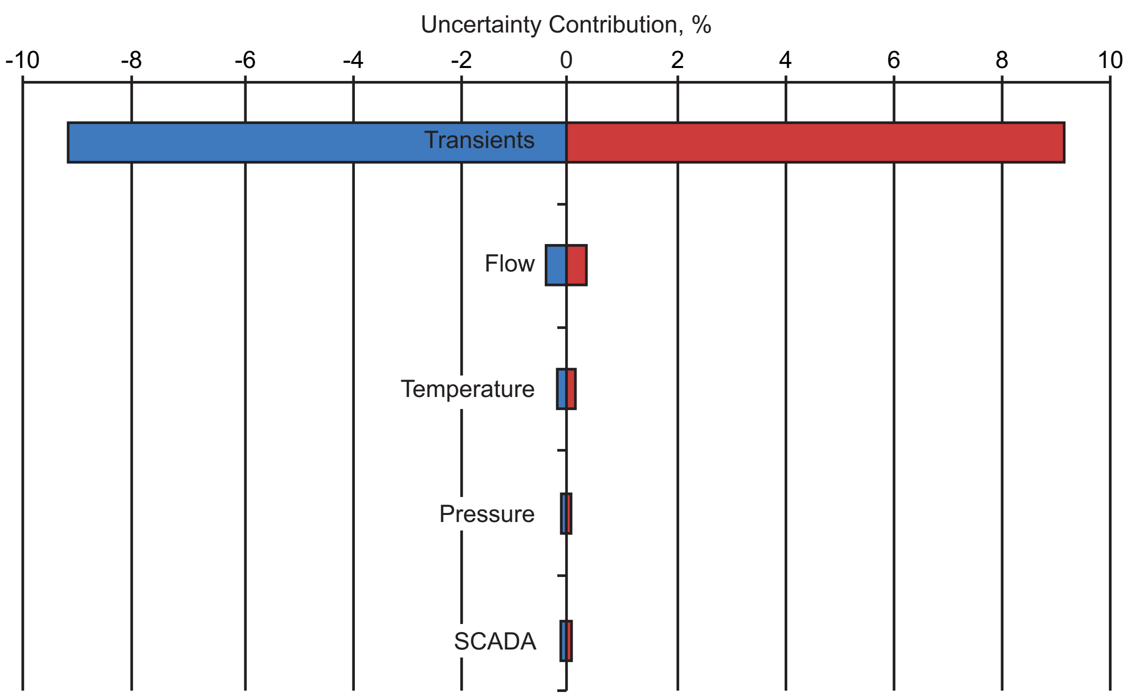


Figure B.13—Overall Relative Uncertainties

B.6 Data Set 2—Pump Startup

B.6.1 General

This data set is similar to the first one, except that the fluid in the line is more viscous and does not vary with temperature. In addition, the precise startup scenario is slightly different. It shows the impact of fluid properties and of using recorded SCADA on ultimate uncertainty.

B.6.2 Transient Analysis

While the steady-state analysis is the same, the transient analysis is quite different. The imbalance varies markedly with time as shown in Figure B.14. The corresponding table of maximum uncertainties is shown in Figure B.15, and the resulting tornado diagram in Figure B.16.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.17.

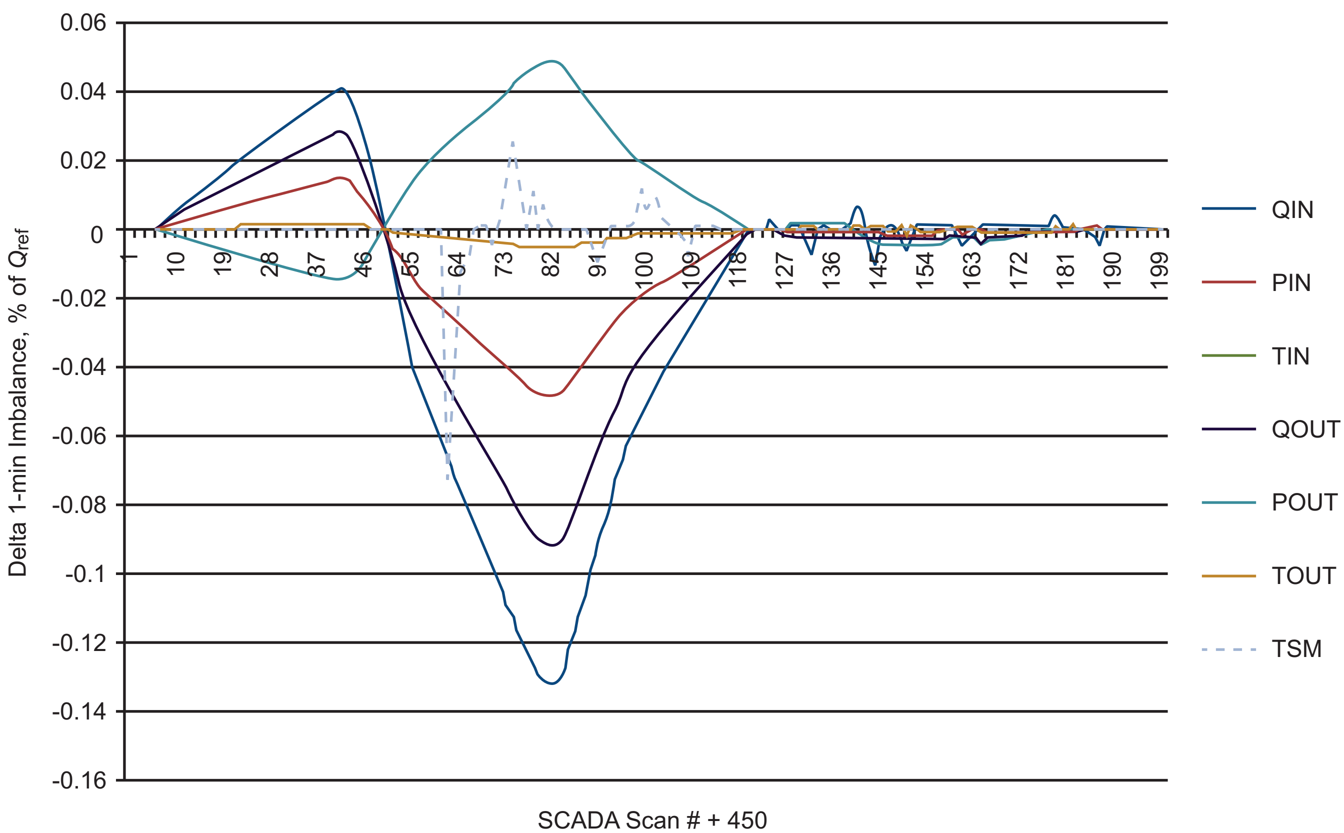


Figure B.14—RM Ideal (Reference) State Results

2 Summary of Runs:

							Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
				Inputs			
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	6.29%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.10%
	TOTAL						6.301%

				Inputs			
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	TOTAL						0.014%

Figure B.15—Summary of Transient Runs

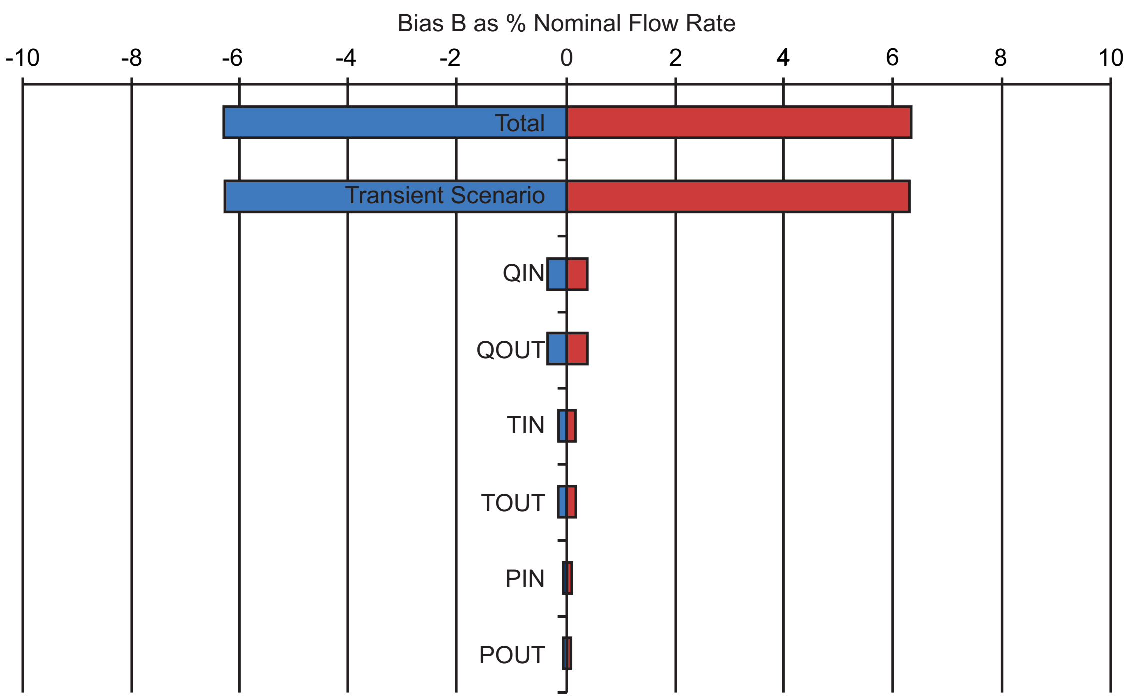


Figure B.16—Tornado Diagram, Transient

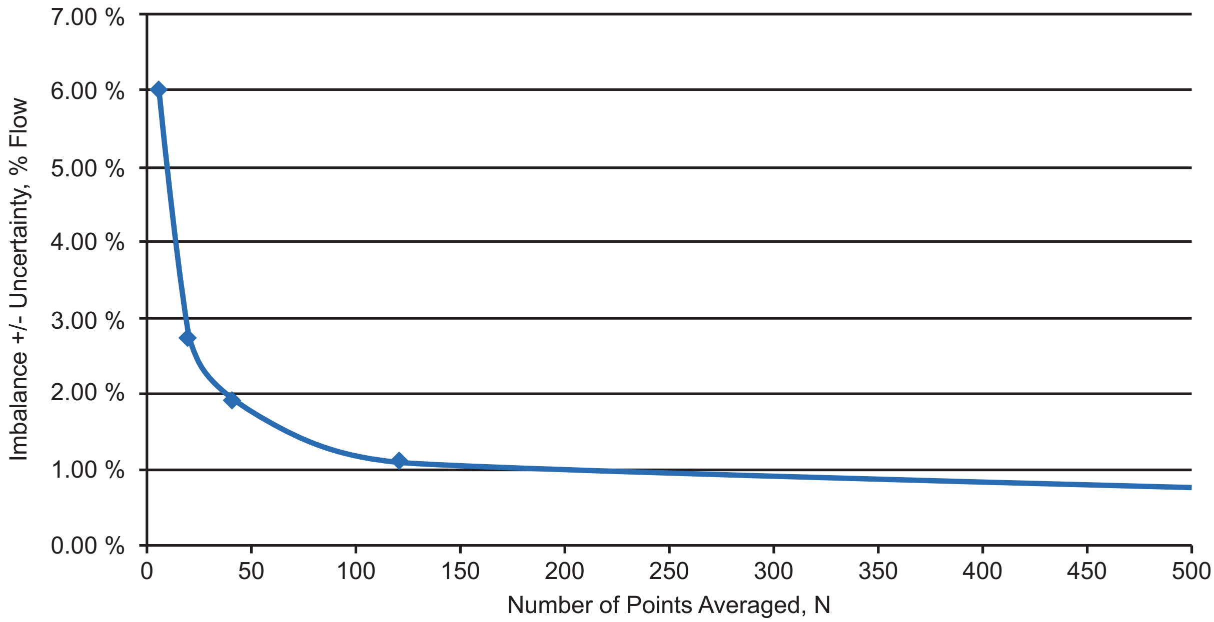


Figure B.17—Transient, Impact of Balancing Period

B.6.3 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.18 also includes SCADA effects.

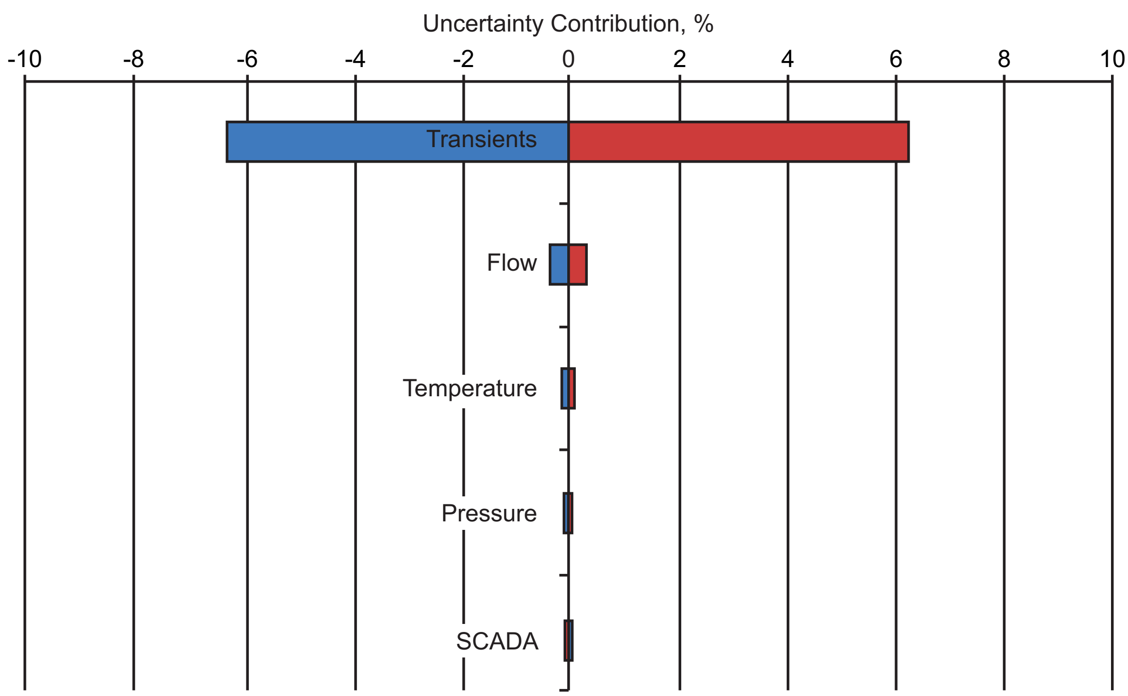


Figure B.18—Overall Relative Uncertainties

B.7 Data Set 3—Crude Oil

B.7.1 General

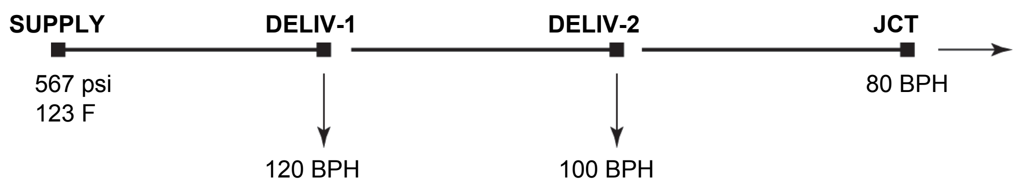
This data set corresponds to the simplest straight line, single-phase LVL pipeline. It illustrates the use of an idealized, predictive scenario in the analysis—supply and delivery flow rates and pressures are changed according to a hypothetical timetable as shown in Figure B.19.

1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File:	TNETConfig.txt	(File)
Input Data Set	Test Data/Line 105	(Folder)

Line-105



Pipeline Configuration Data:	TNETConfig.csv	(Sketched Above)
Units of Measurement (US Oilfield)	FieldUnits.csv	
Source/Sink Config	TNETbatch.csv	
Elevation Survey	elevProfile.txt	
Heat Transfer Data	HeatXferData.txt	(Not used)
Equipment Curves	EquipCurve.txt	(Not used)
Equipment Data	EquipData.csv	(Not used)
Pipe Data	pipeLibrary.txt	(Not used)
Operating State	TNETscenario.csv	
Fluid data	FluidData.txt	(Not used)
Viscosity Data	VisCurve.txt	(Not used)
Environmental Data	Environment.txt	(Not used)

See pipeCube Input Reference Manual v2014-04-05

1.b Operational Scenarios (Input)

No. 1	Steady State	No changes at all to the measurements sketch	
No. 2	Transient Scenario		
	Scenario Data Set:	TNETScenario.csv	(CSV File)

Time (Min)	*Location*	*Property*	*Value*	
Ref	SUPPLY	P	567	(psig)
Ref	DELIV-1	Q	120	(BPH)
Ref	DELIV-2	Q	100	(BPH)
Ref	JCT	Q	80	(BPH)
10	SUPPLY	P	585	(psig)
60	SUPPLY	P	140	(psig)
120	DELIV-2	Q	120	(BPH)
720	JCT	Q	100	(BPH)

Figure B.19—Reference Model

B.7.2 Inputs

Figure B.20 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	*Spread "B"*		*Precision "P"*	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	4.125		0	(PSI)
Pressure Out	4.125		0	(PSI)
Temperature In	1.3		0	(F)
Temperature Out	1.3		0	(F)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods — Bias Time-Data Skew 0.032 (s); Variance T-Data Skew 2.08343333 (s)

Applied to all instrument uncertainties — Added Bias 0; Added Variance 5.5816E-07

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF 5.00E+03 (Hrs.)
Cumulative MTBF 1.37E+03 (Hrs.)

24-Hr. Availability 99.76%

4. CPM System

4.a CPM Method:
API 1130 # 2a Simple mass balance, volumes corrected to STP by P,T instrument

4.b Metric(s): No. 1 St. Vol. Diff SUPPLY-JCT Qs(SUPPLY) – Qs(JCT)

4.c Balancing Period:

60	1-min	(Seconds)
300	5-min	(Seconds)
600	10-min	(Seconds)
1800	30-min	(Seconds)
21600	6-hrs	(Seconds)
43200	12-hrs	(Seconds)

Figure B.20—Other Uncertainties

B.7.3 Transient Analysis

The total imbalance varies with time as shown in Figure B.21. The corresponding table of maximum uncertainties is shown in Figure B.22, and the resulting tornado diagram in Figure B.23.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.24.

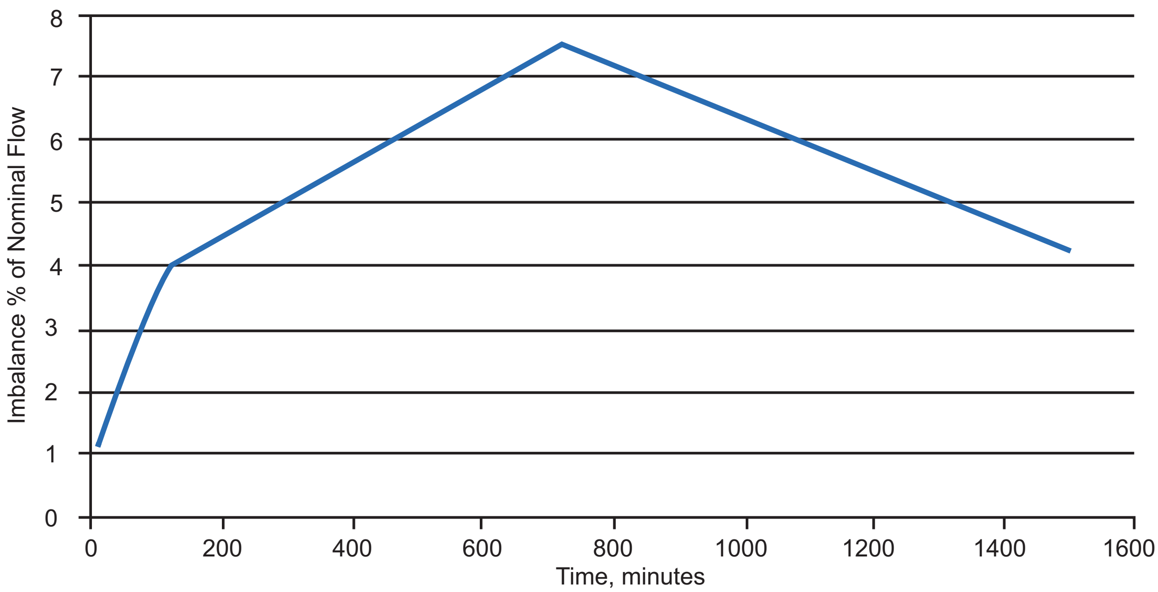


Figure B.21—RM Ideal (Reference) State Results

2	Summary of Runs:						
							Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
			Inputs				
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	7.51%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.10%
	Total						7.519%
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	Total						0.014%

Figure B.22—Summary of Transient Runs

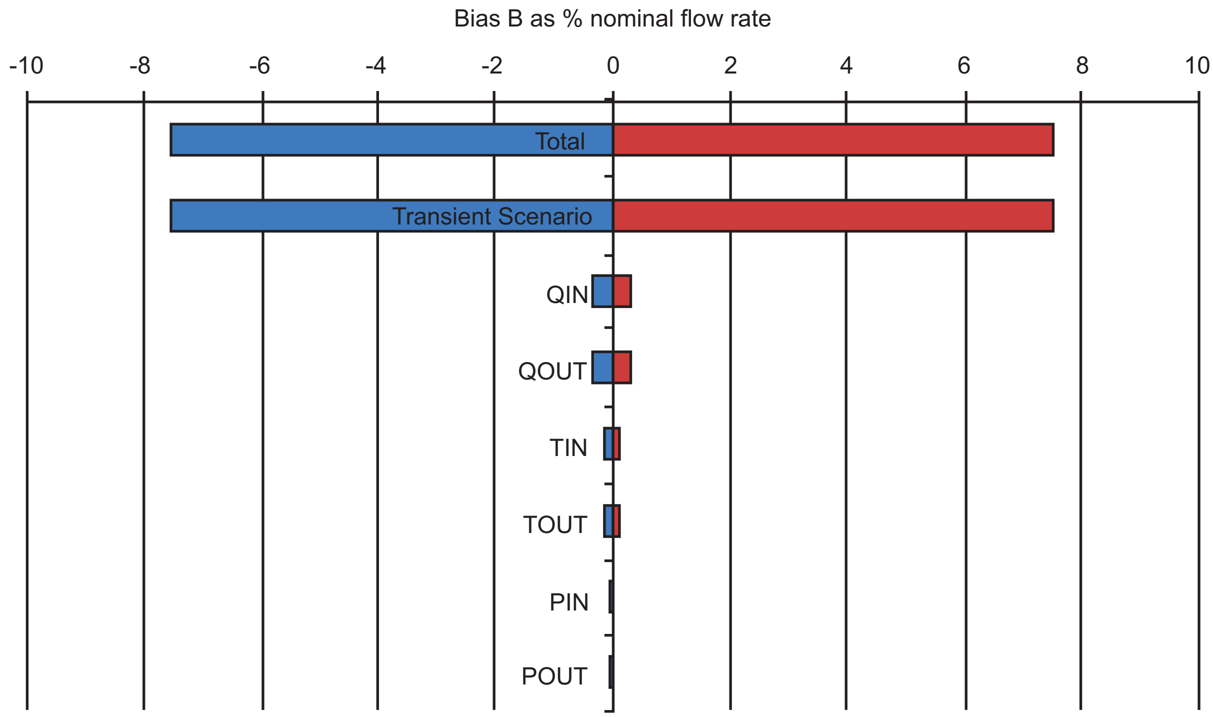


Figure B.23—Tornado Diagram, Transient

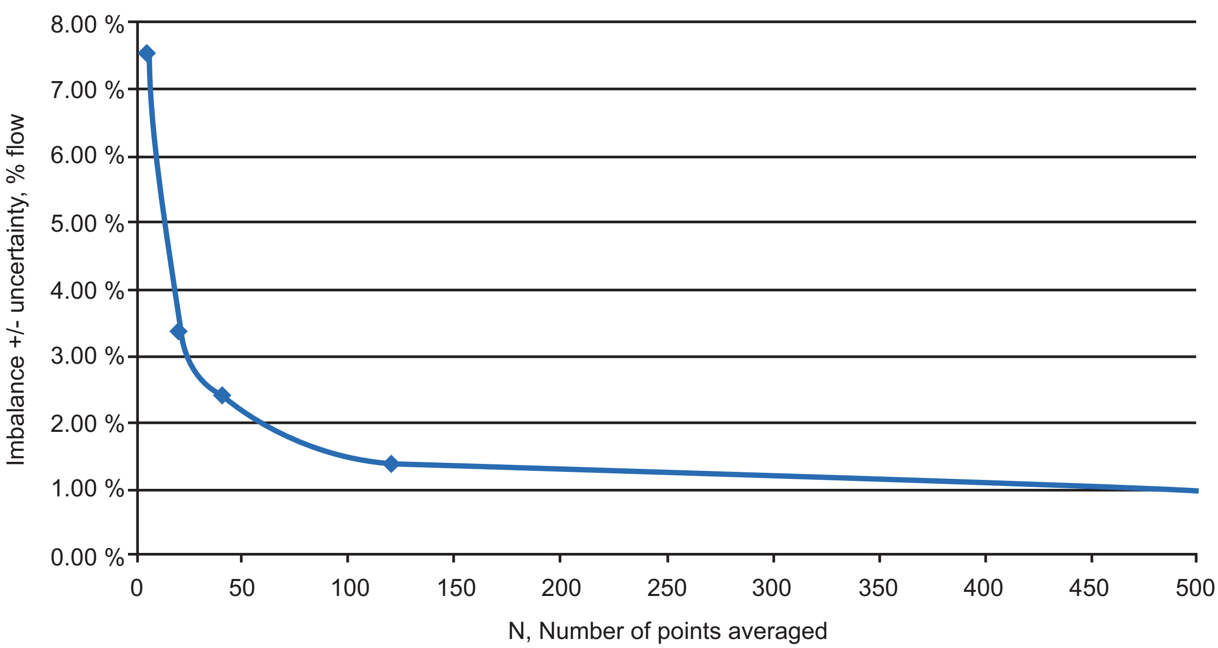


Figure B.24—Transient, Impact of Balancing Period

B.7.4 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.25 also includes SCADA effects.

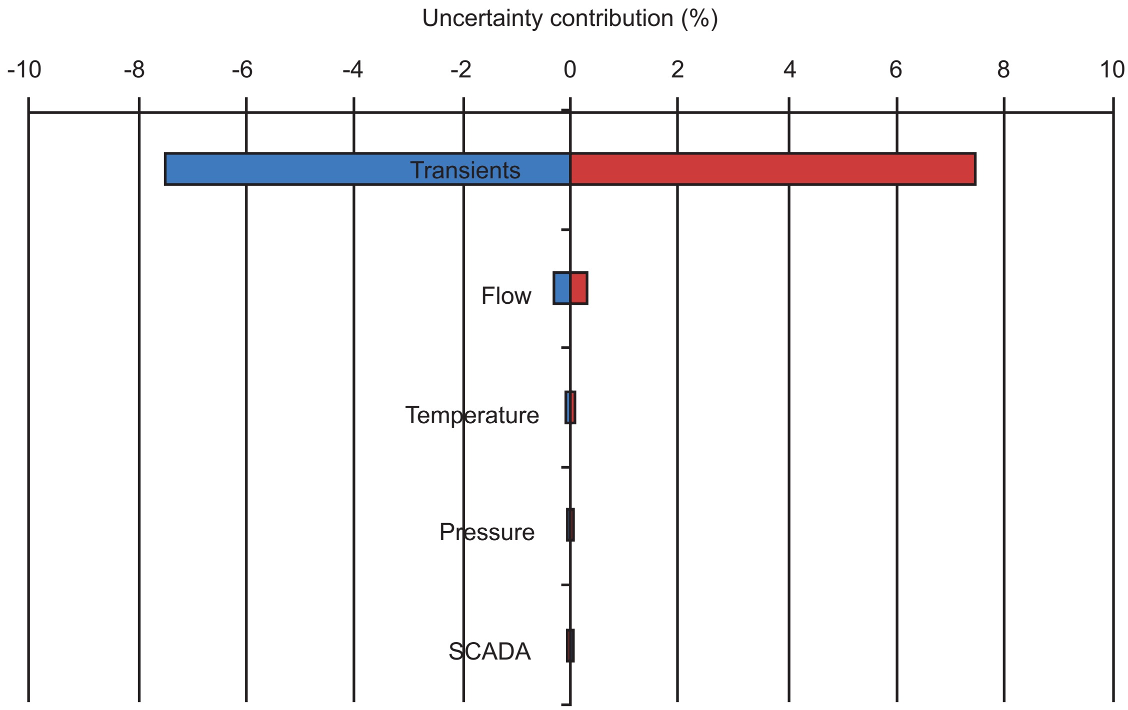


Figure B.25—Overall Relative Uncertainties

B.8 Data Set 4—Crude Oil Network

B.8.1 General

This data set corresponds to a basic branched network, single-phase LVL pipeline. It illustrates the use of an idealized, predictive scenario in the analysis—supply and delivery flow rates and pressures are changed according to a hypothetical timetable as shown in the Figure B.26.

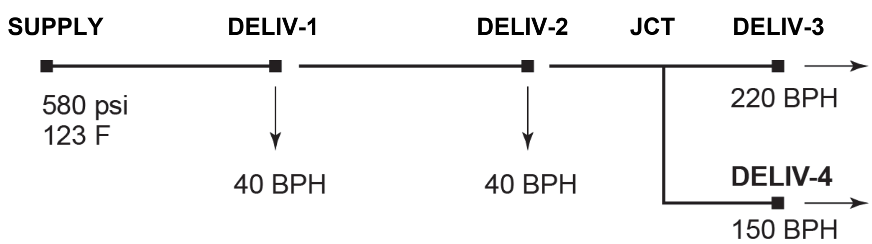
1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File: TNETConfig.txt (File)
Input Data Set TestData\Line104 (Folder)

150 BPH

Line-104



Pipeline Configuration Data:	TNETConfig.csv	(Sketched Above)
Units of Measurement (US Oilfield)	FieldUnits.csv	
Source/Sink Config	TNETbatch.csv	
Elevation Survey	elevProfile.txt	
Heat Transfer Data	HeatXferData.txt	(Not used)
Equipment Curves	EquipCurve.txt	(Not used)
Equipment Data	EquipData.csv	(Not used)
Pipe Data	pipeLibrary.txt	(Not used)
Operating State	TNETscenario.csv	
Fluid data	FluidData.txt	(Not used)
Viscosity Data	VisCurve.txt	(Not used)
Environmental Data	Environment.txt	(Not used)

See pipeCube Input Reference Manual v2014-04-05

1.b Operational Scenarios (Input)

No. 1 Steady State — No changes at all to the measurements sketch
No. 2 Transient Scenario
Scenario Data Set: TNETScenario.csv (CSV File)

Time (Min)	*Location*	*Property*	*Value*	
Ref	SUPPLY	P	580	(psig)
Ref	DELIV-1	Q	40	(BPH)
Ref	DELIV-2	Q	40	(BPH)
Ref	DELIV-3	Q	220	(BPH)
Ref	DELIV-4	Q	150	(BPH)
10	SUPPLY	P	585	(psig)
60	SUPPLY	P	602	(psig)
120	DELIV-2	Q	60	(BPH)
720	DELIV-3	Q	240	(BPH)

Figure B.26—Reference Model

B.8.2 Inputs

Figure B.27 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	*Spread "B"*		*Precision "P"*	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	4.125		0	(PSI)
Pressure Out	4.125		0	(PSI)
Temperature In	1.3		0	(F)
Temperature Out	1.3		0	(F)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods	Bias Time-Data Skew	0.032 (s)
	Variance T-Data Skew	2.08343333 (s)
Applied to all instrument uncertainties	Added Bias	0
	Added Variance	5.5816E-07

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF 5.00E+03 (Hrs.)
Cumulative MTBF 1.37E+03 (Hrs.)

24-Hr. Availability 99.76%

4. CPM System

4.a CPM Method:
API 1130 # 2a Simple mass balance, volumes corrected to STP by P,T instrument

4.b Metric(s): *No. 1* St. Vol. Diff SUPPLY-JCT Qs(SUPPLY) – Qs(JCT)

4.c Balancing Period:

60	1-min	(Seconds)
300	5-min	(Seconds)
600	10-min	(Seconds)
1800	30-min	(Seconds)
21600	6-hrs	(Seconds)
43200	12-hrs	(Seconds)

Figure B.27—Other Uncertainties

B.8.3 Transient Analysis

The total imbalance varies with time as shown in Figure B.28. The corresponding table of maximum uncertainties is shown in Figure B.29, and the resulting tornado diagram in Figure B.30.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.31.

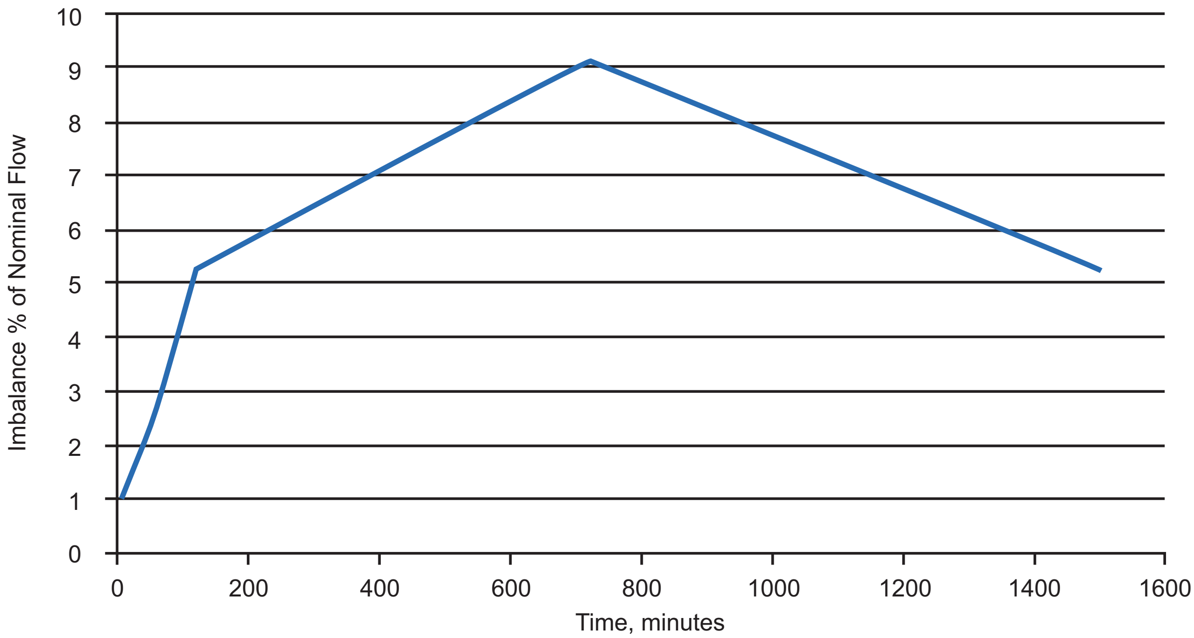


Figure B.28—RM Ideal (Reference) State Results

2 Summary of Runs:

			Inputs				Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	9.15%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.10%
	Total						9.153%
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%

Figure B.29—Summary of Transient Runs

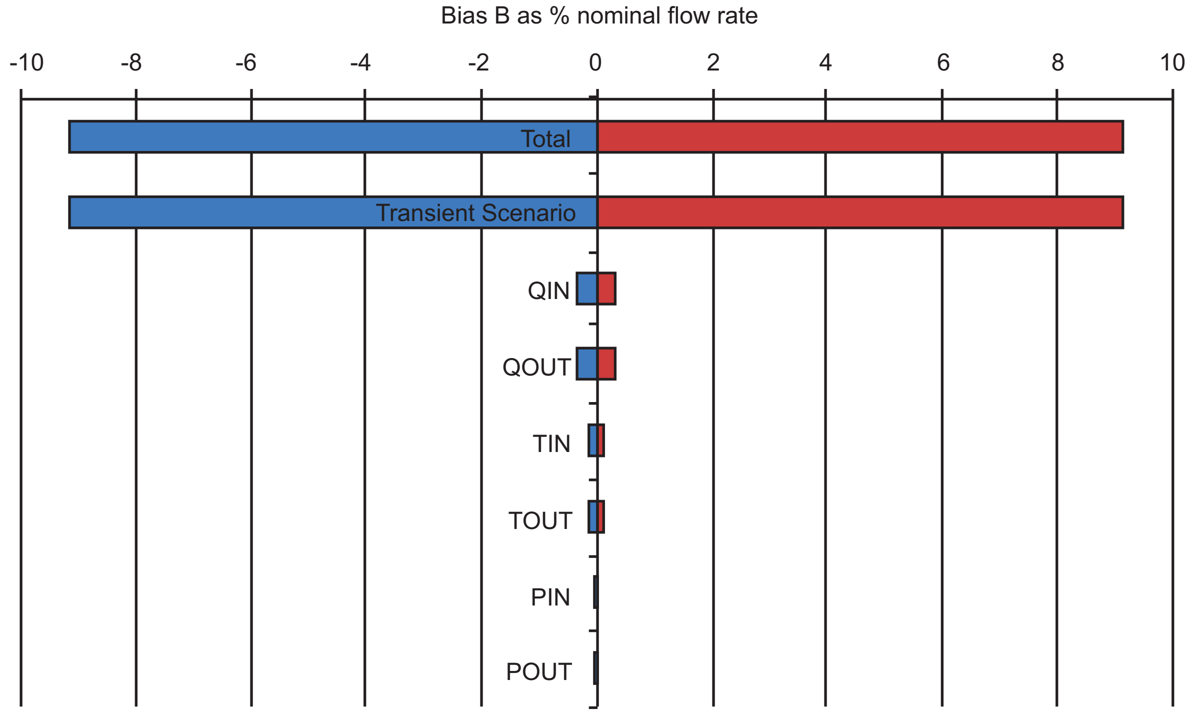


Figure B.30—Tornado Diagram, Transient

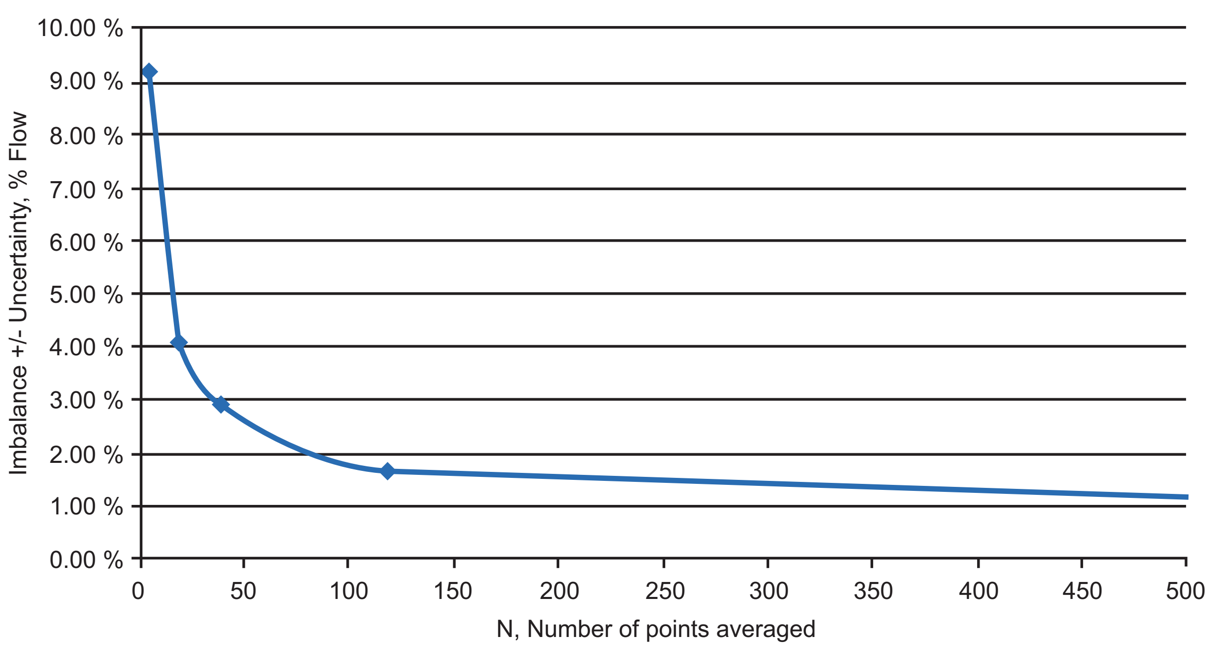


Figure B.31—Transient, Impact of Balancing Period

B.8.4 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.32 also includes SCADA effects.

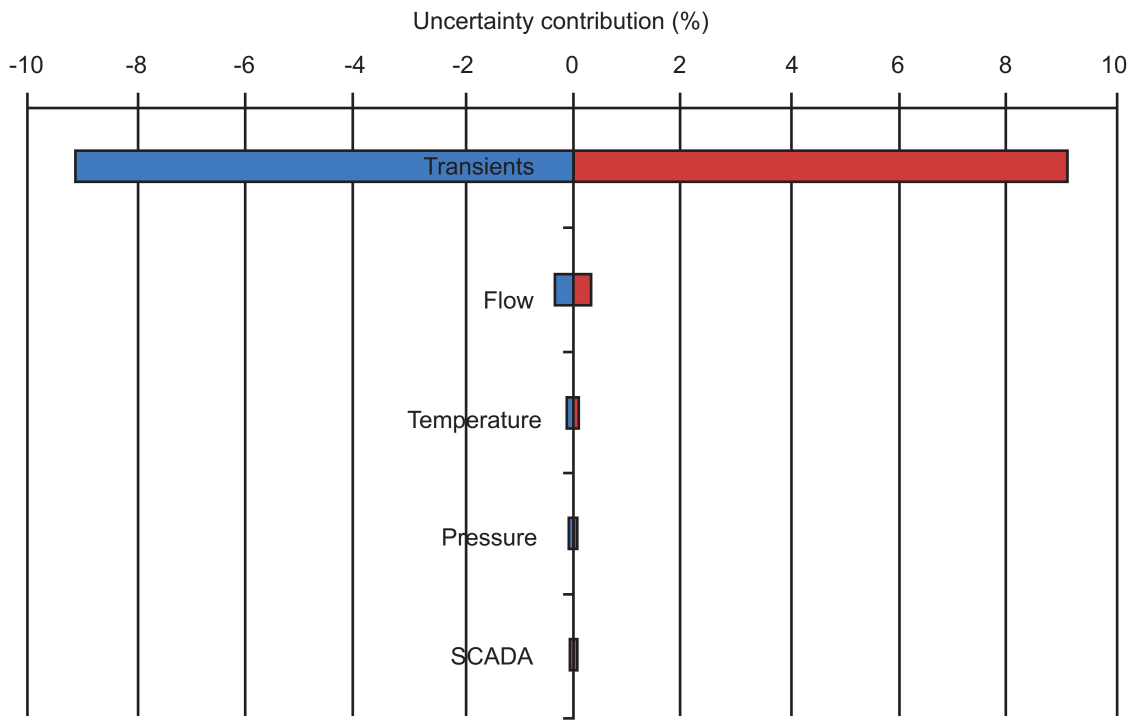


Figure B.32—Overall Relative Uncertainties

B.9 Data Set 5—Batch NGL Pipeline

B.9.1 General

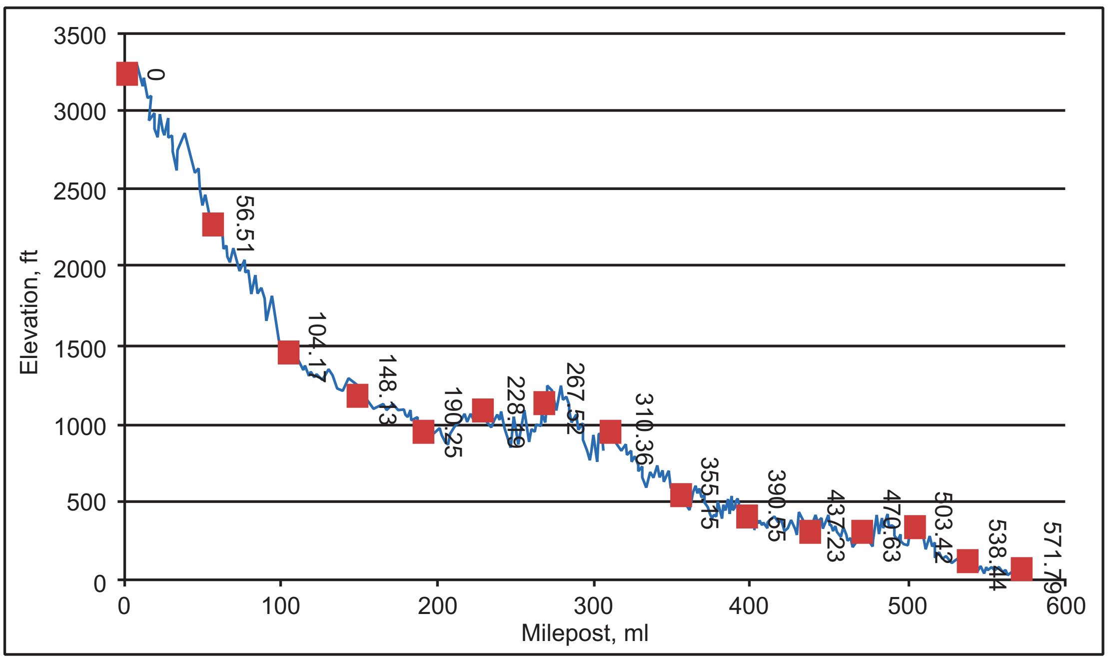
This data set corresponds to an HVL products pipeline. The scenario used is a typical batch schedule, pumped at a constant rate along a single line. Propane, Butane, E/P Mix and RGP are modeled in the system. Their physical properties (Viscosity, Density, Bulk Modulus, Heat Capacity, Thermal Expansion, etc.) are input as curves, similar to the viscosity curve in Figure 20 for the first Worked Example. These properties have an important impact on the pipeline state since they vary significantly with pressure.

The pipeline configuration data and the batch schedule description are given in Figure B.33a and Figure B.33b.

1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File:	TNETConfig.txt	(File)
Input Data Set:	TestData\Line104	(Folder)



Single, straight pipe with uniform diameter—stations # 1 through15 shown with mileposts

Pipeline configuration data:	TNETConfig.csv	(Sketched above)
Units of measurement (U.S. oilfield)	FieldUnits.csv	(U.S. Oilfield)
Source/sink config	TNETbatch.csv	(See below)
Elevation survey	elevProfile.txt	
Heat transfer data	HeatXferData txt	(Not used)
Equipment curves	EquipCurve txt	(Not used)
Equipment data	EquipData csv	(Not used)
Pipe data	pipeLibrary.txt	(Not used)
Operating state	TNETscenario.csv	(See below)
Fluid data	FluidData.txt	(See next tab)
Vicosity data	VisCurve.txt	(Not used)
Environmental data	Environment txt	(Not used)

See pipeCube Input Reference Manual v2014-04-05

Figure B.33a—Reference Model

1.b Operational Scenarios (Input)

No. 1	Steady State	No changes at all to the measurement sketched above – line full with just E/P Mix	
No. 2	Transient Scenario	Batch movement down line at a constant 1300 BPH rate	
	Scenario Data Set:	TNETScenario.csv	(CSV File)
	Batch Data Set:	TNETbatch.csv	(CSV File)

Fluid Type	*Volume MBBL*	*Density Lb/ft3*
EP Mix	54.438	25.58
RGP	19.006	32.671
Butane	10.007	36.386
EP Mix	60.003	25.58
Propane	0.15	31.9
RGP	18.526	32.671
Propane	12.144	31.9
EP Mix	33.726	25.58
EP Mix	72.733	25.58
Propane	0.144	31.9
RGP	18.155	32.671
Propane	0.22	31.9
EP Mix	97.259	25.58
Propane	0.289	31.9
RGP	18.271	32.671
Propane	11.684	31.9
EP Mix	70.139	25.58
Propane	0.167	31.9
RGP	18.443	32.671
Butane	6.804	36.386
EP Mix	11.882	25.58
RGP	46.263	32.671
EP Mix	50.006	25.58

Initial Fill
Batch Queue

Constant Rate	1300 (BPH)
Total Volume	630459 (BBL)
Time at Rate	485 (Hr)
Time at Rate	20(Day)

Figure B.33b—Reference Model

B.9.2 Inputs

Figure B.34 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	Spread “B”		Precision “P”	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	4.125		0	(PSI)
Pressure Out	4.125		0	(PSI)
Temperature In	1.3		0	(F)
Temperature Out	1.3		0	(F)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods — Bias Time-Data Skew 0.032 (s); Variance T-Data Skew 2.08343333 (s)

Applied to all instrument uncertainties — Added Bias 0; Added Variance 5.5816E-07

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF 5.00E+03 (Hrs.)
Cumulative MTBF 1.37E+03 (Hrs.)

24-Hr. Availability 99.76%

4. CPM System

4.a CPM Method:
API 1130 # 2a Simple mass balance, volumes corrected to STP by P,T instrument

4.b Metric(s): No. 1 St. Vol. Diff SUPPLY-JCT Qs(SUPPLY) – Qs(JCT)

4.c Balancing Period:

60	1-min	(Seconds)
300	5-min	(Seconds)
600	10-min	(Seconds)
1800	30-min	(Seconds)
21600	6-hrs	(Seconds)
43200	12-hrs	(Seconds)
	24-hrs	(Seconds)

Figure B.34—Other Uncertainties

B.9.3 Transient Analysis

The total imbalance varies with the batch schedule as shown in Figure B.35. The corresponding table of maximum uncertainties is shown in Figure B.36, and the resulting tornado diagram in Figure B.37.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.38.

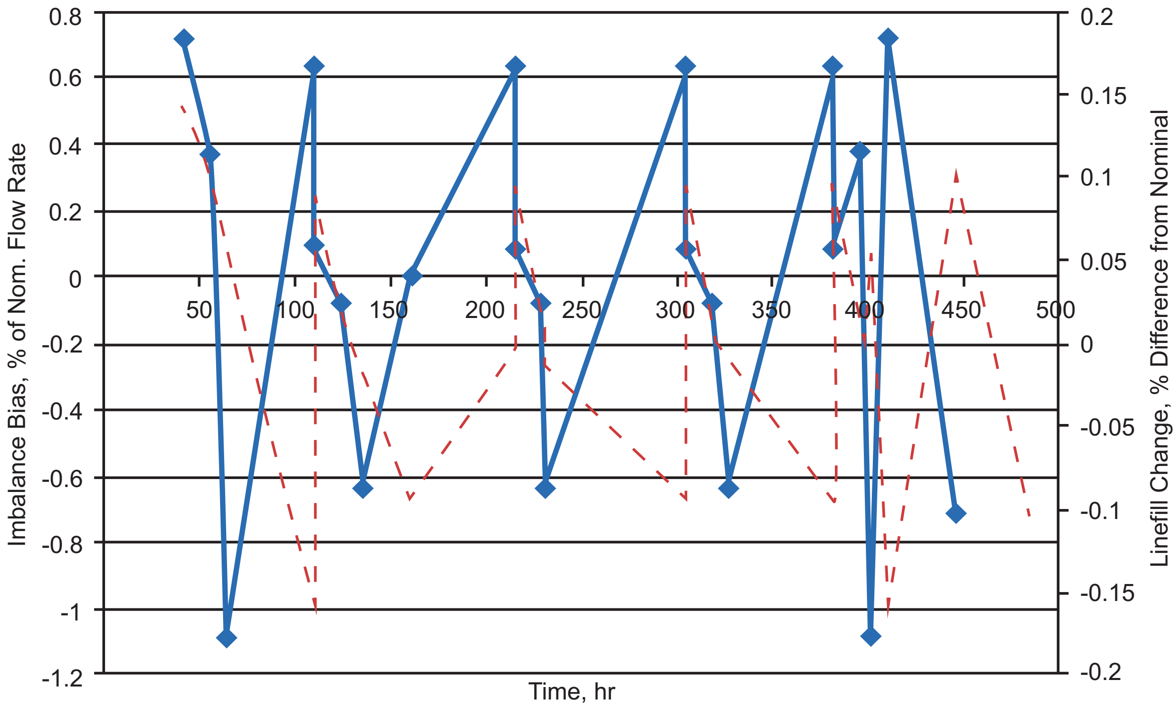


Figure B.35—RM Ideal (Reference) State Results

2	**Summary of Runs:**						Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
			Inputs				
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	1.08%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.21%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.21%
Total							1.170%
							Imbalance Precision (% of Qref)
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
Total							0.014%

Figure B.36—Summary of Transient Runs

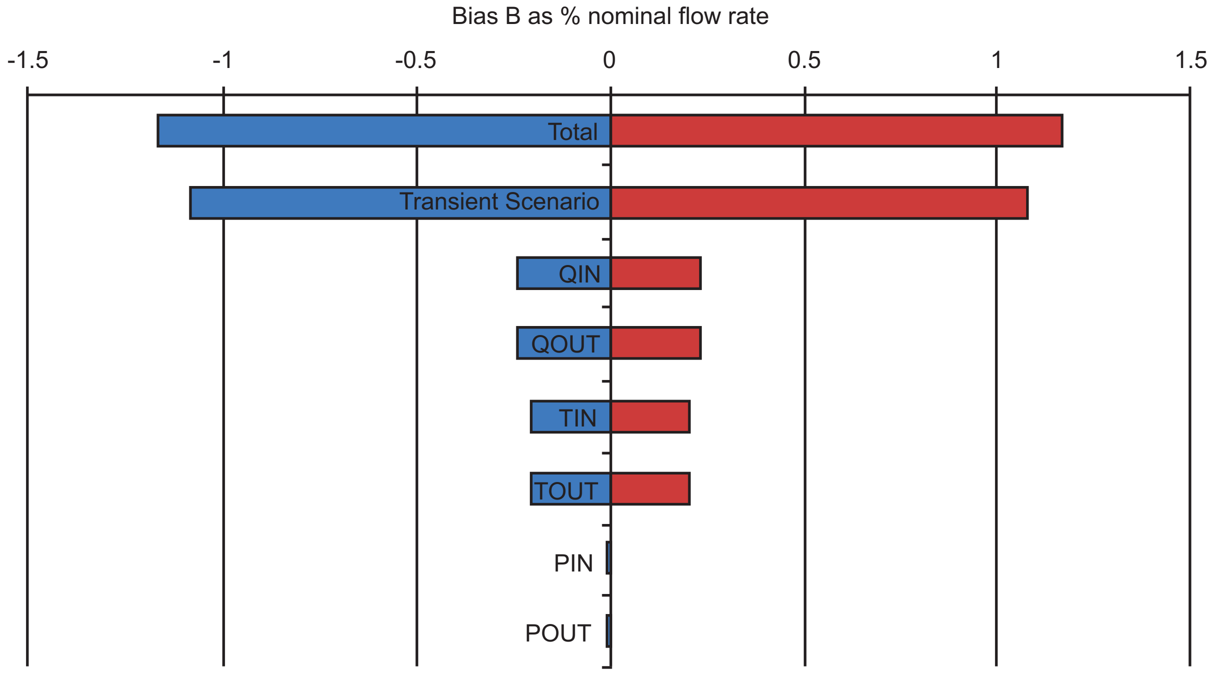


Figure B.37—Tornado Diagram, Transient

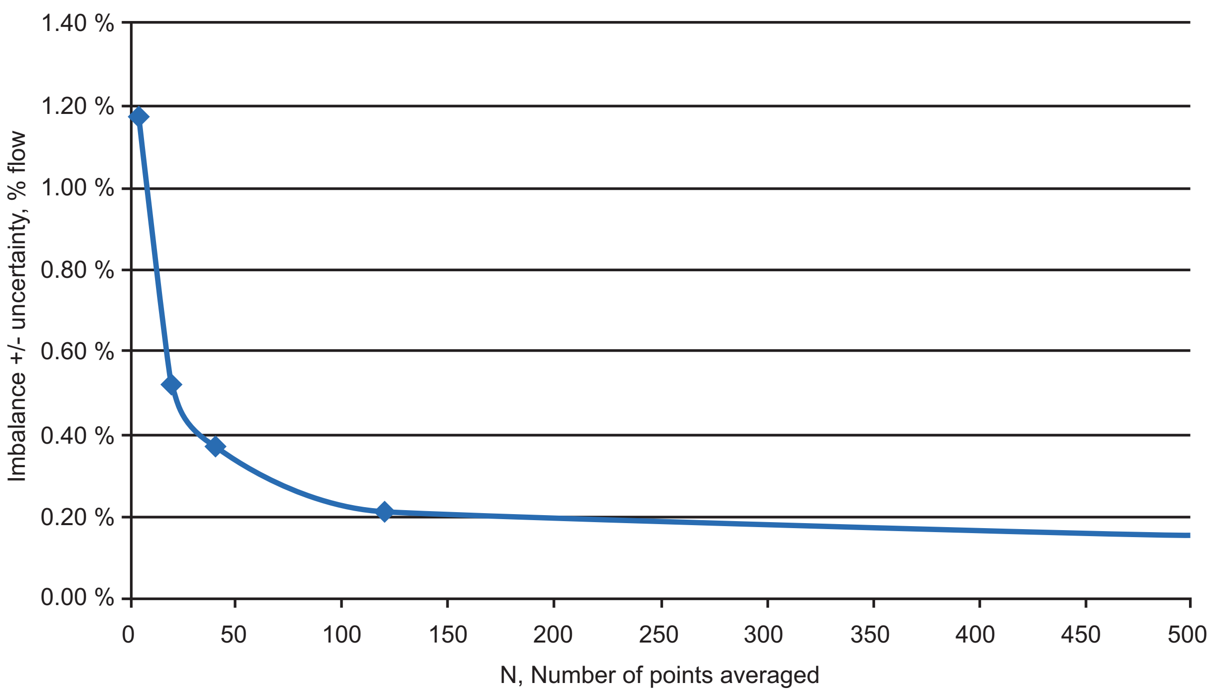


Figure B.38—Transient, Impact of Balancing Period

B.9.4 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.39 also includes SCADA effects.

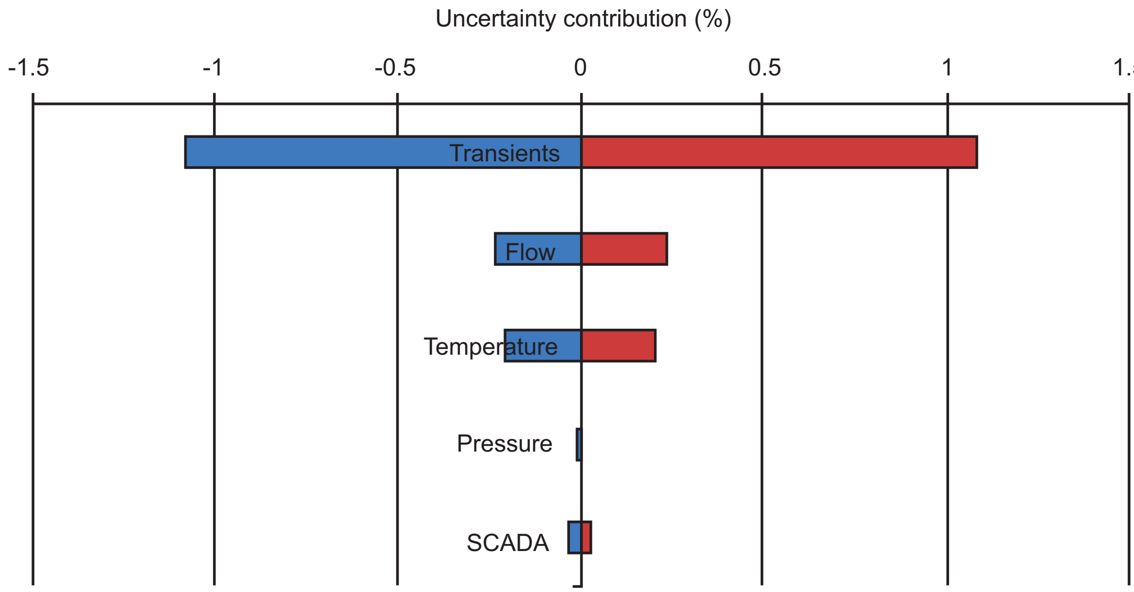


Figure B.39—Overall Relative Uncertainties

B.10 Data Set 6—Gas Pipeline Network

B.10.1 General

This data set corresponds to a gas pipeline with a very basic network layout—three branches and tees—described in Figure B.40, Figure B.41 and Figure B.42. The fluid being transported is industrial methane. The transient scenario is a basic delivery flow rate change by dropping delivery pressure. Note the relatively higher significance of temperature uncertainty in this example.

1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File:		TNETConfig.txt(File)
Input Data Set		TestData/Line 105 (Folder)
Pipeline Configuration Data:	TNETConfig.csv	(See Next Tab)
Units of Measurement (US Oilfield)	FieldUnits.csv	(U.S. Oilfield)
Source/Sink Config	TNETbatch.csv	(Not used)
Elevation Survey	elevProfile.txt	
Heat Transfer Data	HeatXferData.txt	(Not used)
Equipment Curves	EquipCurve.txt	(Not used)
Equipment Data	EquipData.csv	(Not used)
Pipe Data	pipeLibrary.txt	(Not used)
Operating State	TNETscenario.csv	(See below)
Fluid data	FluidData.txt	(Industrial Methane)
Viscosity Data	VisCurve.txt	(Industrial Methane)
Environmental Data	Environment.txt	(Not used)

See pipeCube Input Reference Manual v2014-04-05

1.b Operational Scenarios (Input)

No. 1	Steady State	No changes at all to the measurements	
No. 2	Transient Scenario	Abrupt delivery change at Node 22 to -400.074 **mmscfd**	
	Scenario Data Set:	TNETScenario.csv	(CSV File)

Figure B.40—Reference Model

Nodes						**“+” Ext. Flow is supply to the PL** **“-” Ext. Flow is a delivery**
Node #	*Pressure*	*Ext. Flow (mmscfd)*	*Elevation (ft)*	*X Coordinate*	*Y Coordinate*	
0	1097	353	0	1488890	11689610	**Inlet**
1	1074	0	0	1438973	11601084	
2	1075	0	0	1437610	11601450	
3	1091	302	212	1420712	11679042	
4	1095	151	210	1408035	11676630	
5	1068	101	200	1440599	11600436	
6	1019	302	218	1496656	11575270	
7	1069	603.5	320	1435498	11602527	
8	1357	0	40	1968345	11184300	
9	1346	0	40	1968562	11184135	
10	1259	0	0	20191120	11145995	
11	926	0	0	2202654	10930851	
12	1031	0	214	1483891	11582745	
13	1189	0	0	1846476	11290710	
14	959	-100	0	2182912	10988268	
15	1062	-75	0	2118006	11092345	
16	1530	0	55	1873249	11264276	
17	1090	0	180	1433980	11678540	
18	1150	-300	55	1873249	11264221	
19	1100	-100	0	2104713	11116972	
20	1091	0	220	1417565	11679060	
21	1070	-325	0	2115857	11101096	
22	920	-400.074	0	2229650	10900505	Terminal Delivery – Steady State is –412 mmscfd
23	1503	0	0	1596515	11518860	
24	1601	0	220	1503584	11571436	
25	1010	0	220	1503584	11571546	
26	957	-100	0	2174419	11004735	
27	1037	0	212	1477401	11585293	
28	1168	0	0	2079362	11145302	
29	892	-400	0	2231085	10931341	
30	1214	0	0	1827123	11308259	
31	1234	0	0	2035944	11147613	
32	1309	0	80	1755853	11376165	
33	1150	0	0	2089376	11139918	
34	1197	0	0	1839902	11296305	

Figure B.41—Reference Model (continued)

Sections								
Name	Diameter (in)	Length (mi)	From-Node Name	To-Node Name	Wall Thickness (in.)	Temp F (deg. F)	From-Node Pressure (psig)	To-Node Pressure (psig)
Pi-1	40.644	10.94	Node 0	Node 17	0.678	96.2	1097	1090
Pi-2	19.5	1.96	Node 4	Node 20	0.25	99.15	1095	1091
Pi-3	40.942	15.35	Node 17	Node 7	0.529	93.33	1090	1069
Pi-4	40.942	0.48	Node 7	Node 2	0.529	103.79	1069	1075
Pi-5	40.942	0.27	Node 2	Node 1	0.529	104.13	1075	1074
Pi-6	40.644	25.88	Node 24	Node 23	0.678	115.27	1601	1503
Pi-7	40.644	43.19	Node 23	Node 32	0.678	103.73	1503	1309
Pi-8	40.644	3.31	Node 30	Node 34	0.678	90.62	1214	1197
Pi-9	34.97	11.8	Node 14	Node 11	0.515	82.48	959	926
Pi-10	34.97	0.6	Node 20	Node 3	0.515	97.93	1091	1091
Pi-11	40.942	0.33	Node 1	Node 5	0.529	103.73	1074	1068
Pi-12	40.942	7.63	Node 5	Node 27	0.529	101.79	1068	1037
Pi-13	34.97	8.23	Node 11	Node 22	0.515	80.61	926	920
Pi-14	23.25	5.69	Node 11	Node 29	0.375	80.26	926	892
Pi-15	23.25	4.11	Node 14	Node 26	0.375	82.73	959	957
Pi-16	40.644	20.18	Node 32	Node 30	0.678	93.96	1309	1214
Pi-17	40.644	1.65	Node 34	Node 13	0.678	89.89	1197	1189
Pi-18	34.75	25.16	Node16	Node 8	0.625	113.7	1530	1357
Pi-19	40.644	7.14	Node 13	Node 18	0.678	88.5	1189	1150
Pi-20	40.942	6.05	Node 33	Node 19	0.529	94.58	1150	1100
Pi-21	40.942	2.19	Node 28	Node 33	0.529	96.47	1168	1150
Pi-22	40.942	1.84	Node 21	Node 15	0.529	91.2	1070	1062
Pi-23	34.97	25.13	Node 15	Node 14	0.515	87.19	1062	959
Pi-24	40.942	3.99	Node 19	Node 21	0.529	92.34	1100	1070
Pi-25	40.942	3.38	Node 10	Node 31	0.529	101.52	1259	1234
Pi-26	40.942	12.01	Node 9	Node 10	0.529	104.9	1346	1259
Pi-27	40.942	8.38	Node 31	Node 28	0.529	98.85	1234	1168
Pi-28	40.942	2.81	Node 12	Node 6	0.529	99.5	1031	1019
Pi-29	40.942	1.34	Node 27	Node 12	0.529	100.22	1037	1031
Pi-30	34.97	2.54	Node 3	Node 17	0.515	98.62	1091	1090
Pi-31	40.942	1.53	Node 6	Node 25	0.529	102.19	1019	1010

Figure B.42—Reference Model (continued)

Figure B.43 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	*Spread "B"*		*Precision "P"*	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	4.125		0	(PSI)
Pressure Out	4.125		0	(PSI)
Temperature In	1.3		0	(F)
Temperature Out	1.3		0	(F)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods — Bias Time-Data Skew 0.032 (s); Variance T-Data Skew 2.08343333 (s)

Applied to all instrument uncertainties — Added Bias 0; Added Variance 5.5816E-07

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF 5.00E+03 (Hrs.)
Cumulative MTBF 1.37E+03 (Hrs.)

24-Hr. Availability 99.76%

4. CPM System

4.a CPM Method:
API 1130 # 2a Simple mass balance, volumes corrected to STP by P,T instrument

4.b Metric(s): *No. 1* St. Vol. Diff NODE22-NOIQs(21) – Qs(0)

4.c Balancing Period:

	1-min	(Seconds)
60	5-min	(Seconds)
300	10-min	(Seconds)
600	30-min	(Seconds)
1800	6-hrs	(Seconds)
21600	12-hrs	(Seconds)
43200	24-hrs	(Seconds)

Figure B.43—Other Uncertainties

B.10.2 Transient Analysis

The total imbalance decays with time as shown in Figure B.44. The corresponding table of maximum uncertainties is shown in Figure B.45, and the resulting tornado diagram in Figure B.46.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.47.

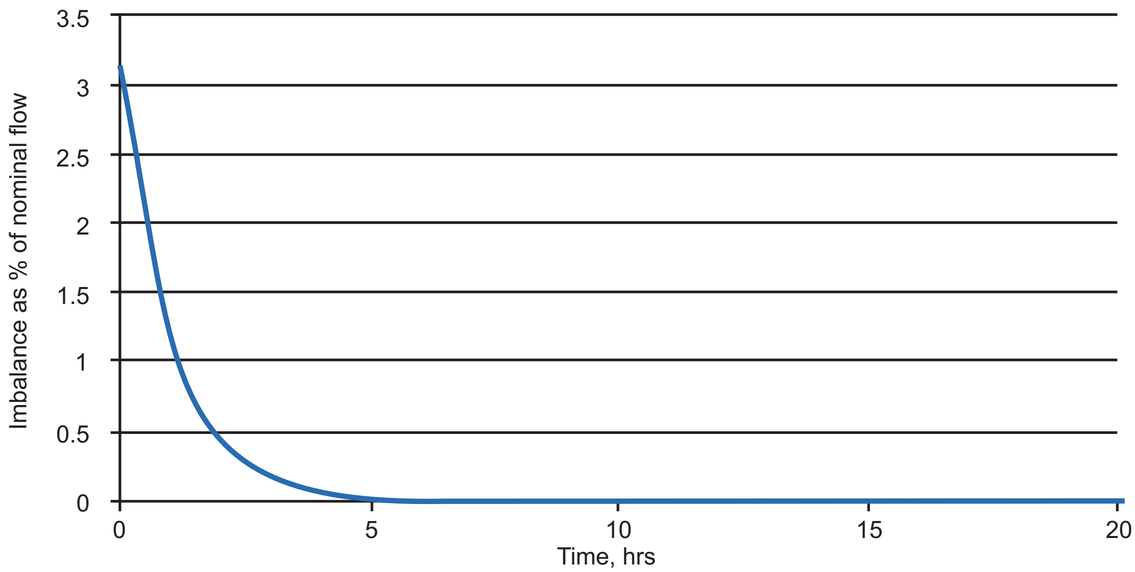


Figure B.44—RM Ideal (Reference) State Results

2 Summary of Runs:

			Inputs				Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	3.08%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 4.125	Ref	Ref	Ref	Ref	-0.04%
3	Ref	Ref	Ref + 1.30	Ref	Ref	Ref	0.31%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 4.125	Ref	0.04%
6	Ref	Ref	Ref	Ref	Ref	Ref + 1.30	-0.31%
Total							3.130%
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
Total							0.014%

Figure B.45—Summary of Transient Runs

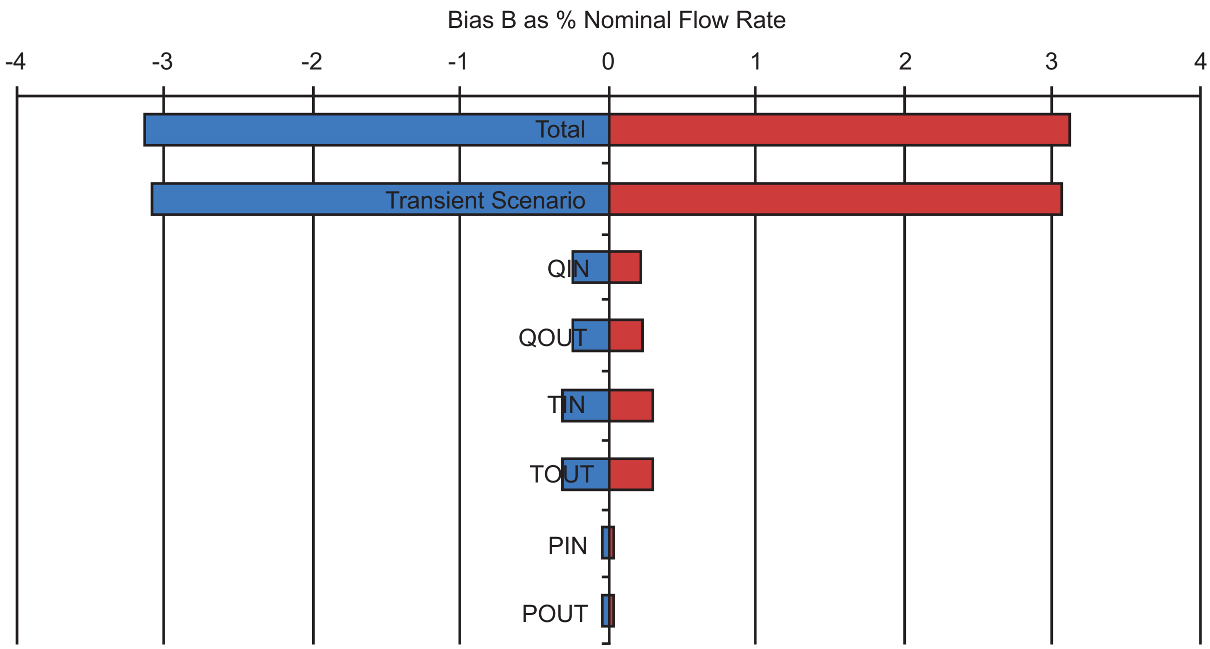


Figure B.46—Tornado Diagram, Transient

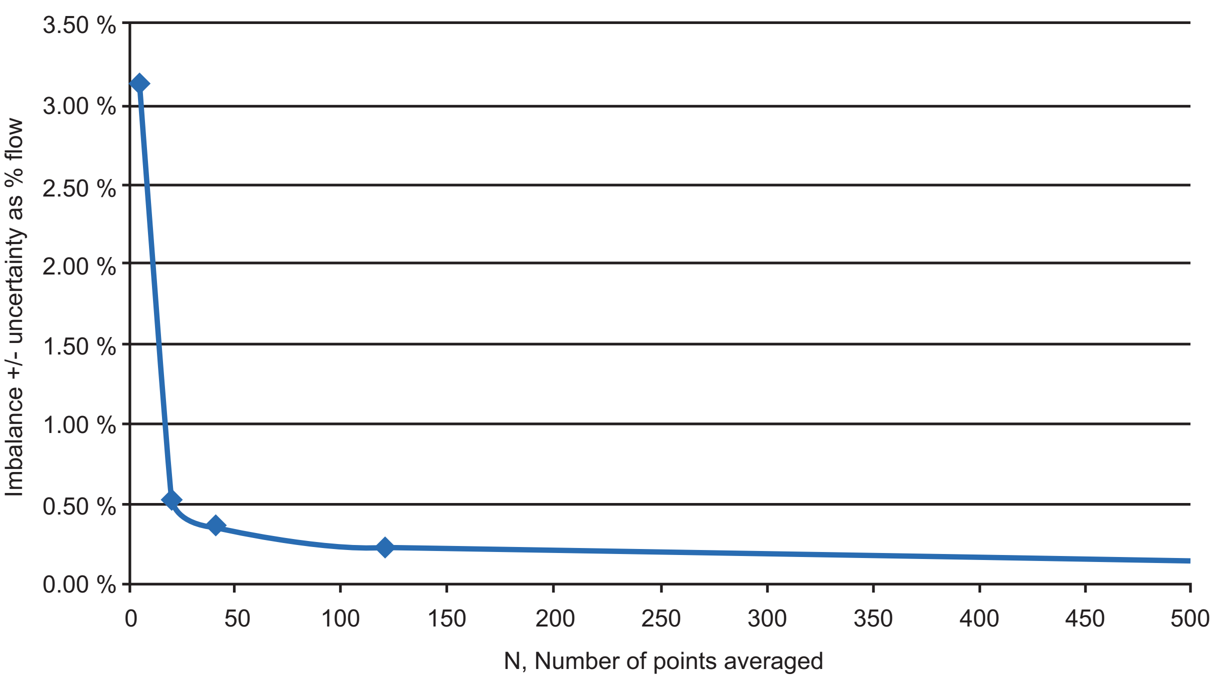


Figure B.47—Transient, Impact of Balancing Period

B.10.3 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.48 also includes SCADA effects.

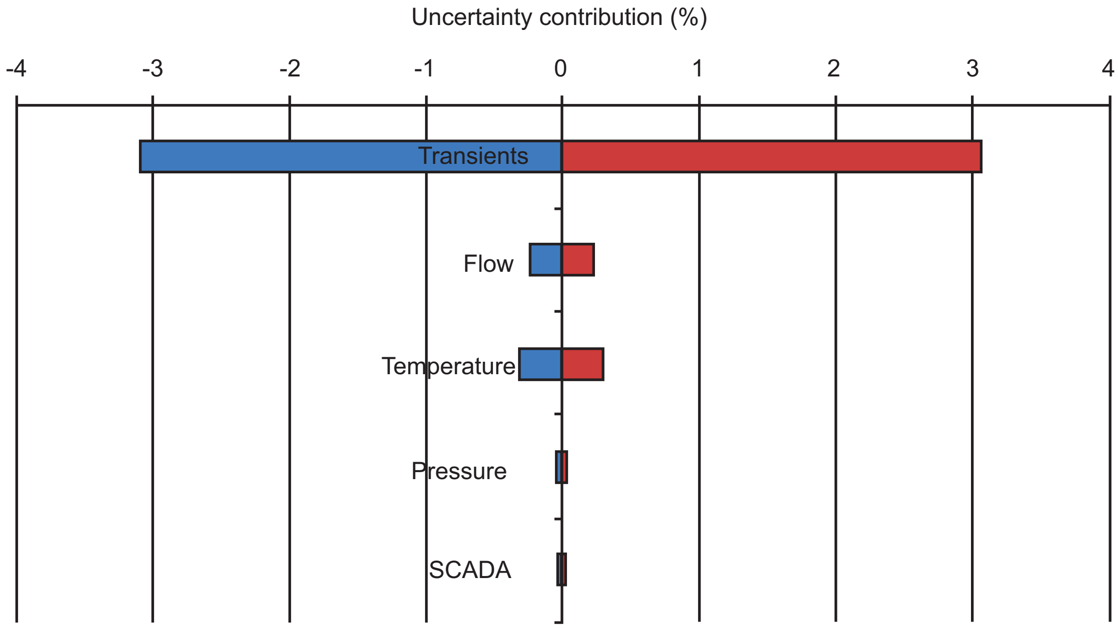


Figure B.48—Overall Relative Uncertainties

B.11 Data Set 7—Pump Startup, Extreme Elevation Change

B.11.1 General

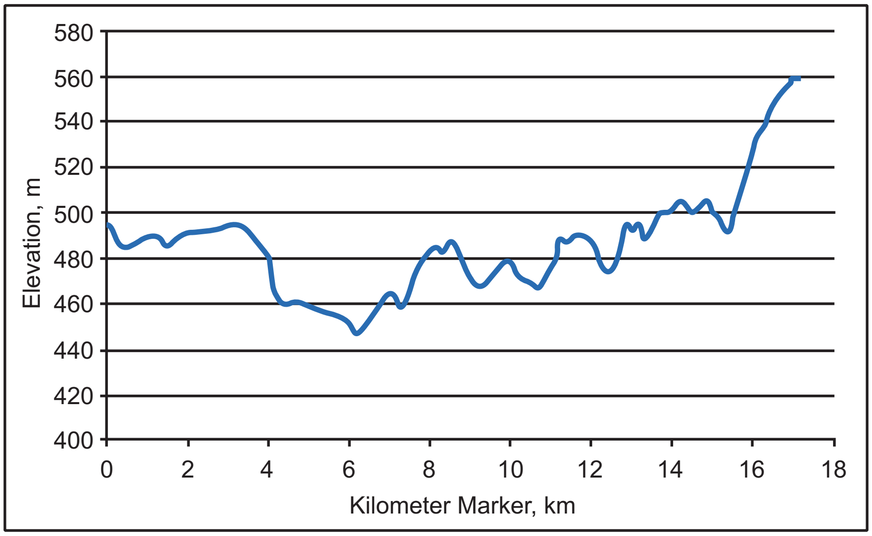
This data set (Figure B.49) corresponds to a crude pipeline in a pump startup scenario, similar to Data Set 1. However, the line has extreme elevation changes, and is known to exhibit slack-line flow (SLF).

A scenario where the pump provides even 5 % less pressure leads to SLF. This situation is excluded from the procedure, as described in Section 4, since any RM will be unacceptably inaccurate in that situation. This data set is oilfield metric.

1. Reference Model

1.a Pipeline and Fluid Data (Input)

Model Control File:	TNETConfig.txt	(File)
Input Data Set:	TestData\Line104	(Folder)



Single, straight pipe with uniform diameter (O.D. 323.85, W.T. 5.207 mm)

Pipeline configuration data:	TNETConfig.csv	(Sketched Above)
Units of measurement (U.S. oilfield)	FieldUnits.csv	(Canadian Metric)
Source/sink config	TNETbatch.csv	(Not used)
Elevation survey	elevProfile.txt	
Heat transfer data	HeatXferData.txt	
Equipment curves	EquipCurve.txt	(Not used)
Equipment data	EquipData.csv	(Not used)
Pipe data	pipeLibrary.txt	(Not used)
Operating state	TNETscenario.csv	(See below)
Fluid data	FluidData.txt	832.0 kg/m^3 crude
Vicosity data	VisCurve.txt	2.9 cSt fixed
Environmental data	Environment txt	10 C fixed

See pipeCube Input Reference Manual v2014-04-05

1.b Operational Scenarios (Input)

No. 1	Steady State	No changes at all to a 412 sm^3/hr flow, 1640 kPa inlet pressure state
No. 2	Transient Scenario	Abrupt startup from zero flow according to measured SCADA schedule
	Scenario Data Set	TNETscenario.csv (CSV File)

Figure B.49—Reference Model

B.11.2 Inputs

Figure B.50 includes the other uncertainties that are present in the analysis, particularly the instrument biases and precisions. It also specifies the CPM method that is being used.

2. Measurement Model

Instrument Precision and Bias (Input)

Measurement	*Spread "B"*		*Precision "P"*	
Flow In	0.24%		0.01%	(Percent)
Flow Out	0.24%		0.01%	(Percent)
Pressure In	28.44		0	(kPa)
Pressure Out	28.44		0	(kPa)
Temperature In	0.72		0	(C)
Temperature Out	0.72		0	(C)

3. Engineering Factors

No. 1 See SCADA Tab for input SCADA parameters

Applied to all balancing periods	Bias Time-Data Skew	0.032 (s)
	Variance T-Data Skew	2.08343333 (s)
Applied to all instrument uncertainties	Added Bias	0
	Added Variance	5.5816E-07

No. 2 See Availability Tab for sub-system MTBF parameters

Weakest link MTBF	5.00E+03 (Hrs.)
Cumulative MTBF	1.37E+03 (Hrs.)
24-Hr. Availability	99.76%

4. CPM System

4.a CPM Method: API 1130 # 2a Simple mass balance, volumes corrected to STP by P, T instrument

4.b Metric(s): *No. 1* St. Vol. Diff NODE22-NOIQs(21) – Qs(0)

4.c Balancing Period:		
60	1-min	(Seconds)
300	5-min	(Seconds)
600	10-min	(Seconds)
1800	30-min	(Seconds)
21600	6-hrs	(Seconds)
43200	12-hrs	(Seconds)

Figure B.50—Other Uncertainties

B.11.3 Transient Analysis

The total imbalance varies with time as shown in Figure B.51. The corresponding table of maximum uncertainties is shown in Figure B.52, and the resulting tornado diagram in Figure B.53.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.54.

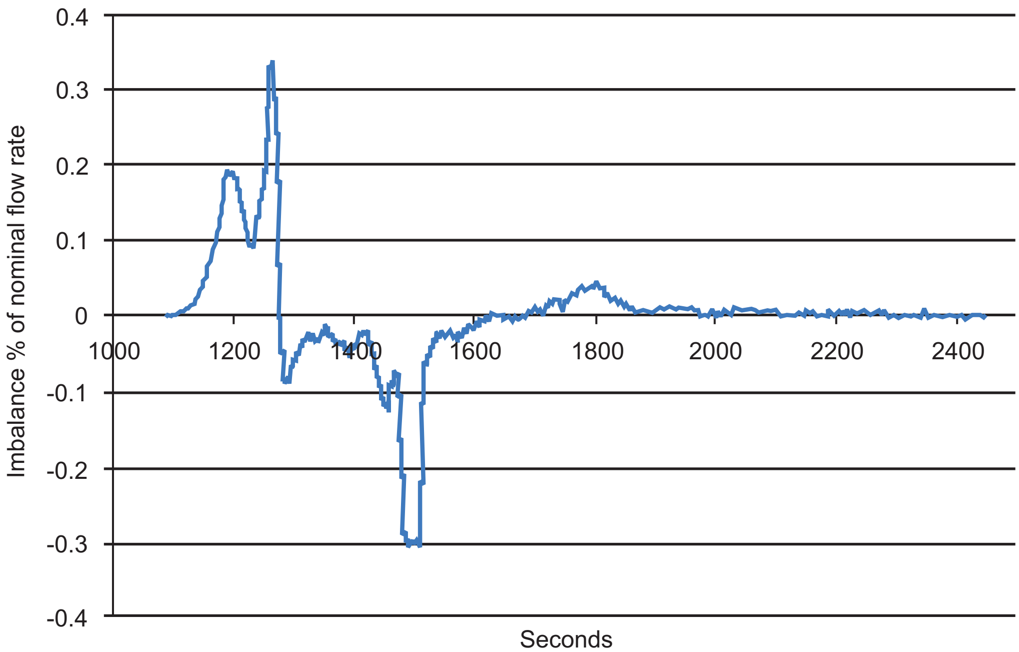


Figure B.51—RM Ideal (Reference) State Results

2 Summary of Runs:

			Inputs				Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	0.34%
1	Ref + 0.24%	Ref	Ref	Ref	Ref	Ref	0.24%
2	Ref	Ref + 28.44	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 0.72	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.24%	Ref	Ref	-0.24%
5	Ref	Ref	Ref	Ref	Ref + 28.44	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 0.72	-0.10%
	Total						0.499%
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	Total						0.014%

Figure B.52—Summary of Transient Runs

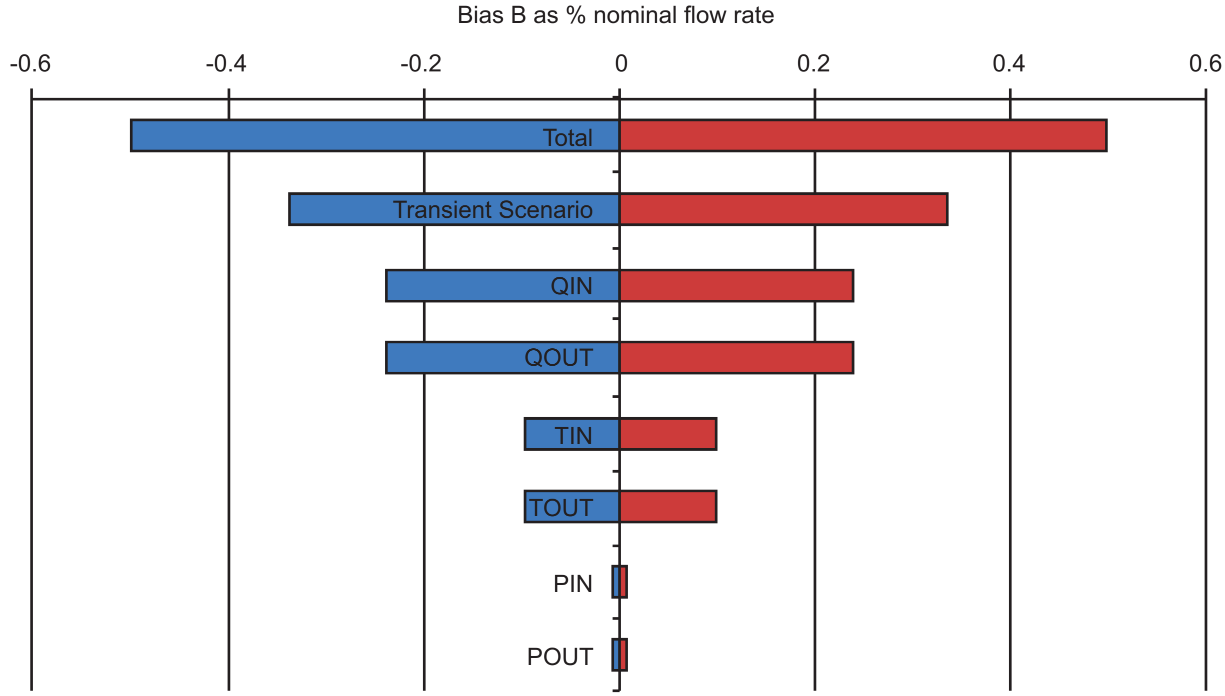


Figure B.53—Tornado Diagram, Transient

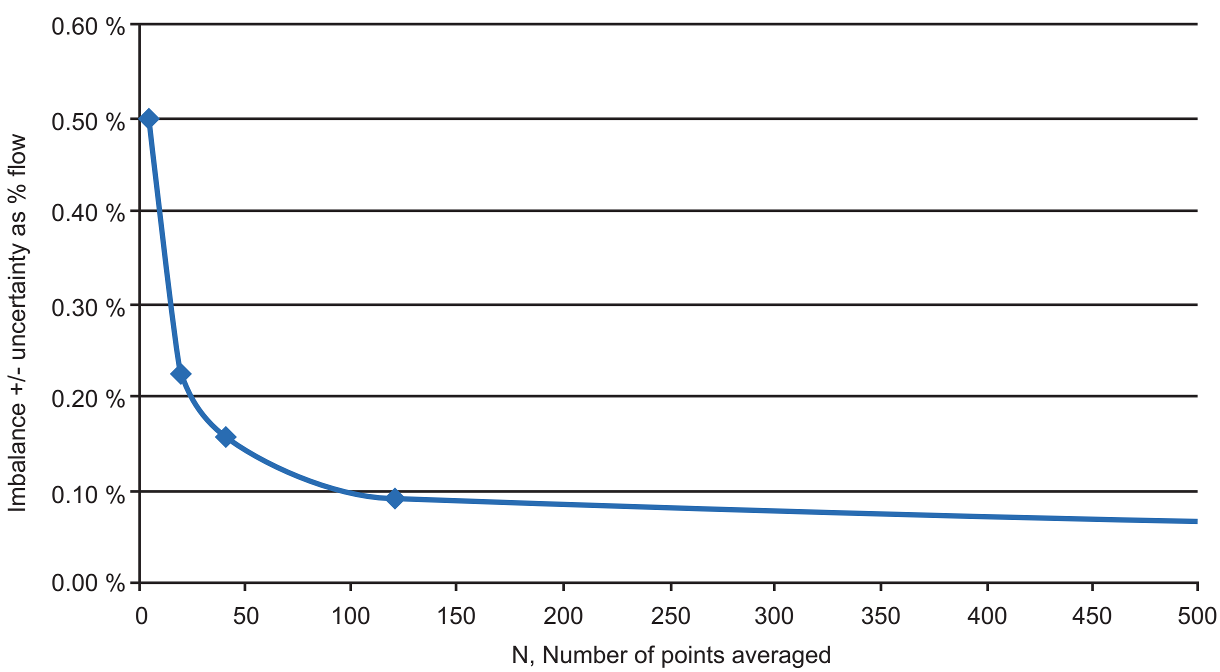


Figure B.54—Transient, Impact of Balancing Period

B.11.4 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.55 also includes SCADA effects.

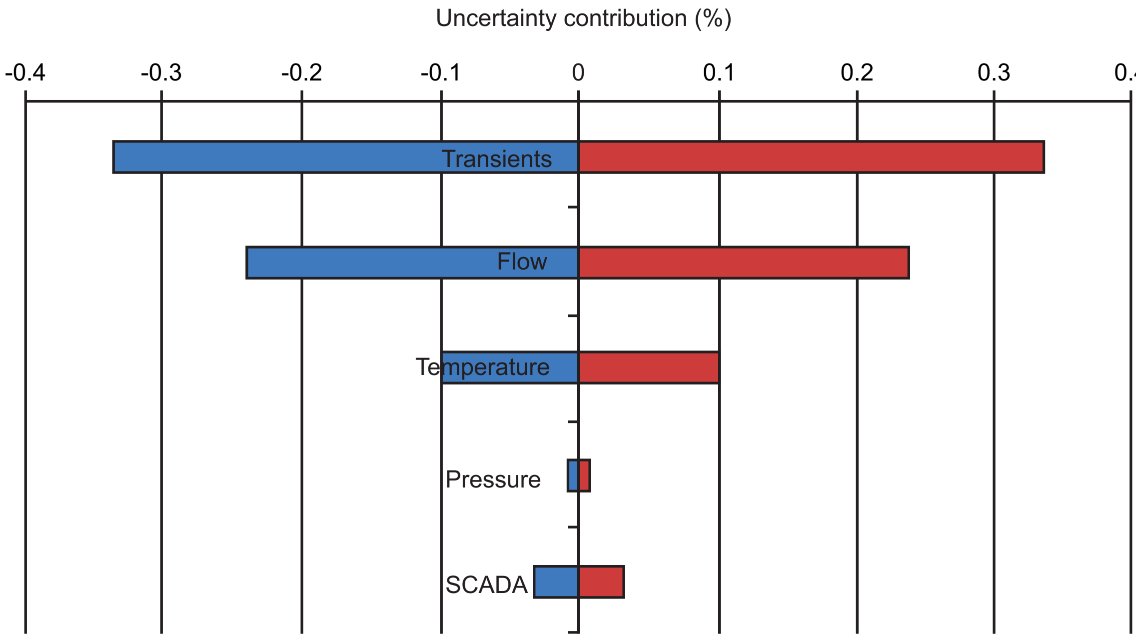


Figure B.55—Overall Relative Uncertainties

B.12 Data Set 8—Standstill, Extreme Elevation Change

B.12.1 General

This data set (Figure B.49) corresponds to the same crude pipeline as the last one in a standstill scenario. However, while in standstill a LDS based upon rate of linefill change is being used. This is a different situation to ordinary material balance, since the “transient” scenario is used to calculate percentage uncertainties in linefill, not in material imbalance. In the results, it is evident that at least in this example, the transients on the line are an order of magnitude smaller than flow, pressure and temperature measurements.

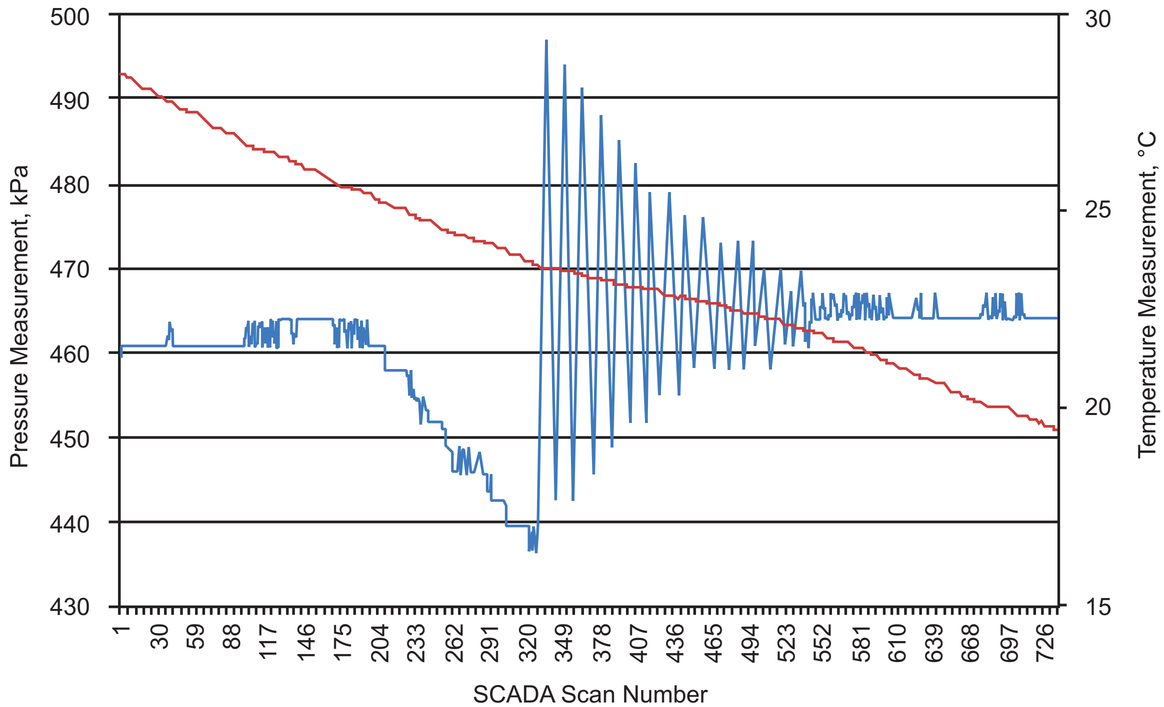
This analysis might be repeated excluding flow measurement uncertainty, if it is absolutely certain that there is no flow in or out of the line.

This data set is also oilfield metric.

B.12.2 Transient Analysis

The total linefill uncertainty varies with time as shown in Figure B.56. The corresponding table of maximum uncertainties is shown in Figure B.57, and the resulting tornado diagram in Figure B.58.

The impact of multiple averaging periods on the uncertainty is shown in Figure B.59.



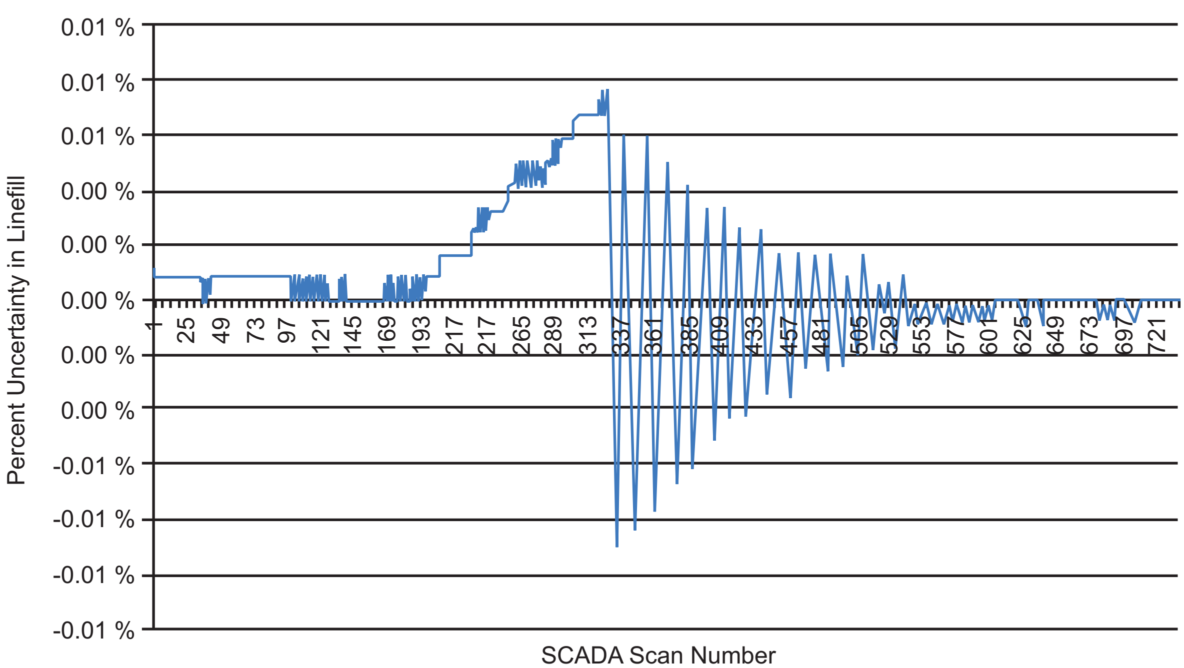


Figure B.56—RM Ideal (Reference) State Results

2	Summary of Runs:						
							Ideal CPM Metrics, using RM ideal state / Pseudo Measurements
				Inputs			
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Bias as % of Qref
0	Ref	Ref	Ref	Ref	Ref	Ref	0.0093%
1	Ref + 0.20%	Ref	Ref	Ref	Ref	Ref	0.20%
2	Ref	Ref + 28.44	Ref	Ref	Ref	Ref	-0.01%
3	Ref	Ref	Ref + 0.72	Ref	Ref	Ref	0.10%
4	Ref	Ref	Ref	Ref + 0.50%	Ref	Ref	-0.50%
5	Ref	Ref	Ref	Ref	Ref + 28.44	Ref	0.01%
6	Ref	Ref	Ref	Ref	Ref	Ref + 0.72	-0.10%
	Total						0.557%
Run #	QIN	PIN	TIN	QOUT	POUT	TOUT	Imbalance Precision (% of Qref)
0	Ref	Ref	Ref	Ref	Ref	Ref	0
1	Ref + 0.01%	Ref	Ref	Ref	Ref	Ref	0.01%
2	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
3	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
4	Ref	Ref	Ref	Ref + 0.01%	Ref	Ref	-0.01%
5	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
6	Ref	Ref	Ref	Ref	Ref	Ref	0.00%
	Total						0.014%

Figure B.57—Summary of Transient Runs

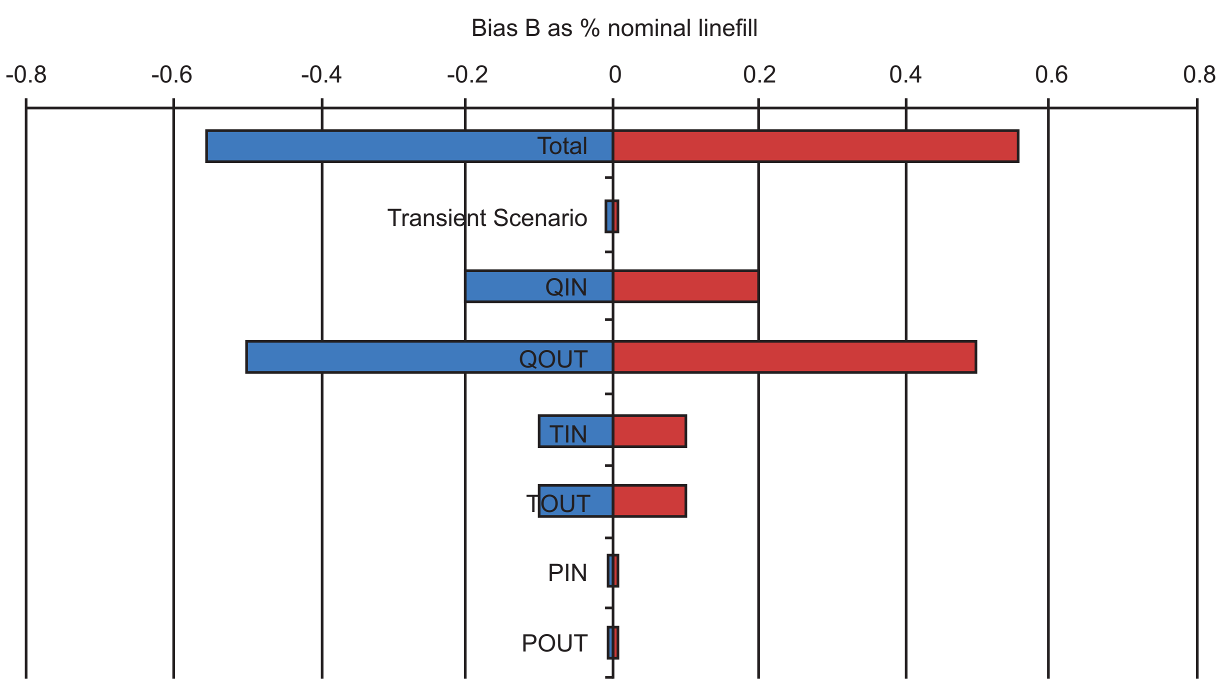


Figure B.58—Tornado Diagram, Transient

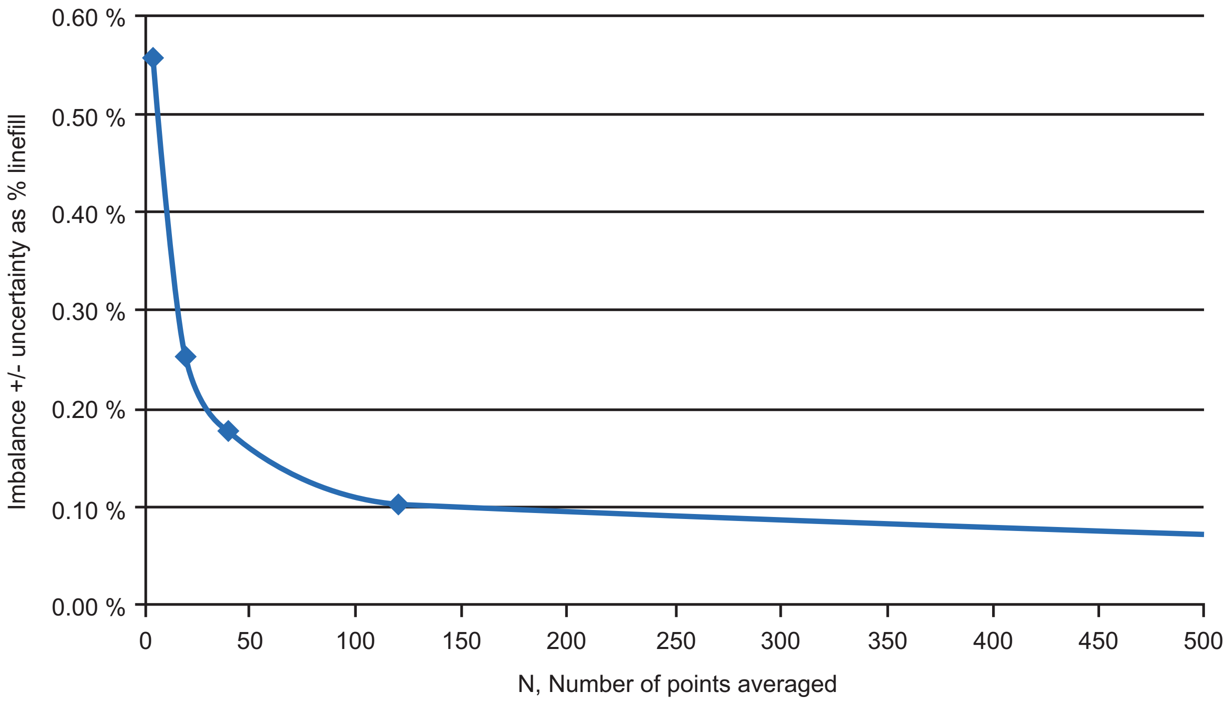


Figure B.59—Transient, Impact of Balancing Period

B.12.3 Summary of Uncertainties

To summarize all the sources of uncertainty, the tornado diagram in Figure B.60 also includes SCADA effects.

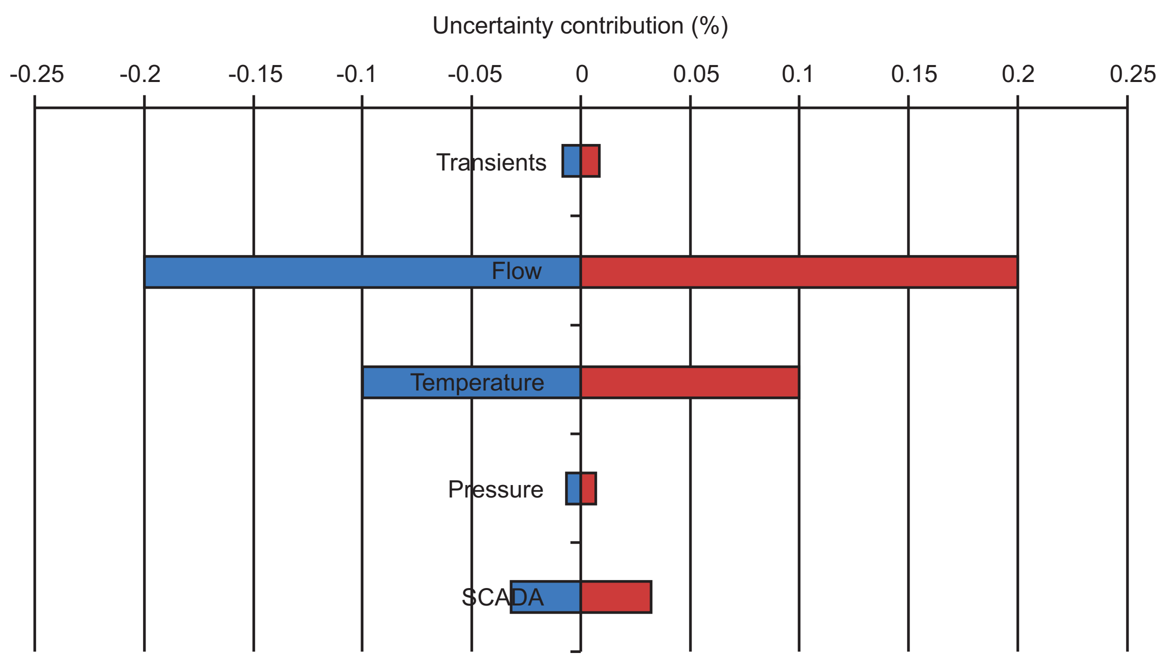


Figure B.60—Overall Relative Uncertainties

Acknowledgment

The case studies in Annex B are provided courtesy of the Pipeline Research Council International (PRCI).

Bibliography

[1] Bennett, W. R. (1948), "Spectra of Quantized Signals," *Bell System Technical Journa*l, Vol. 27, pp. 446–472, July 1948.

[2] Burger, E.D., Munk, W.R., Wahl, H.A. (1982) "Flow Increase in the Trans Alaska Pipeline Through Use of a Polymeric Drag-Reducing Additive," *Journal of Petroleum Technology*, February 1982.

[3] Colebrook, C.F. (1939), "Turbulent flow in pipes, with particular reference to the transition region between smooth and rough pipe laws," *Journal of the Institution of Civil Engineers* (London), February 1939.

[4] Cox, D. R. (2006), *Principles of Statistical Inference*, Cambridge New York: Cambridge University Press, ISBN 978-0-521-68567-2.

[5] Fazlollah M. Reza (1994), *An Introduction to Information Theory*, Dover Publications, Inc., New York.

[6] Geiger, G. (2006) "State-of-the-Art in Leak Detection and Localization". Pipeline Simulation Interest Group Paper 0301, New Orleans, LA.

[7] Geiger, G. (2012), "Principles of Leak Detection", Internal Report Revision April 9, 2012, Westphalia Energy Institute.

[8] Knuth, Donald (1997), *The Art of Computer Programming: Fundamental Algorithms*, Volume 1 (3rd ed.). Reading, Massachusetts, Addison-Wesley, ISBN 0-201-89683-4.

[9] Lurie, Mikhail V. (2008), *Modeling of Oil Product and Gas Pipeline Transportation*. Wiley-VCH; ISBN-10: 3527408339.

[10] Modisette, J.P. (2003), "Automatic Tuning of Pipeline Models," Pipeline Simulation Interest Group Paper 0406, Palm Springs, CA.

[11] Nicholas, R. E. (1995), "Simulation of Slack Line Flow—a Tutorial," Pipeline Simulation Interest Group Paper 9505, Albuquerque, NM.

[12] NIST (2013) [1], *Reference Fluid Thermodynamic and Transport Properties Database (REFPROP)* V.9.1.

[13] Starling, Kenneth E. (1973), *Fluid Properties for Light Petroleum Systems*, Gulf Publishing Company, p. 270, ISBN 978-0872012936.

[14] Wylie, E.B., Streeter, V. and Bedford, K.W. (2010), *Fluid Mechanics* (9th ed.), Tata McGraw—Hill Education.

[15] ASME (2004) PTC (Performance Test Code)19.5 [2], *Flow Measurement*.

[16] ASME (2001) MFC-3M, *Measurement of Fluid Flow in Pipes*.

[17] ASME (2009) *V&V* 20-2009, *Standard for Verification and Validation in Computational Fluid Dynamics and Heat Transfer*.

1 National Institute of Standards and Technology, 100 Bureau Drive, Stop 3460, Gaithersburg, Maryland 20899, www.nist.gov.
2 ASME International, 2 Park Avenue, New York, New York 10016-5990, www.asme.org.

[18] API (2013) Recommended Practice 2540, *Temperature Compensation in Liquid Measurement*. Taken from API *MPMS* Chapters 10 and 11.

[19] API (2013) *Manual of Petroleum Measurement Standards* (*MPMS*).

[20] "GPA Technical Paper (TP) 27 for LPG and NGL" [3], taken from the *Manual of Petroleum Measurement Standards*, *Chapter 11—Physical Properties Data—Section 2, Part 4—Temperature Correction for the Volume of NGL and LPG*—Tables 23E, 24E, 53E, 54E, 59E, and 60E.

[21] AGA (1994) Report No. 8 [4], "Compressibility Factor of Natural Gas and Related Hydrocarbon Gases", AGA XQ9212.

[22] ISO 11631 [5], *Specification of flow meter performance*.

[23] ISO 3171, *Sampling standards*.

[24] ISO 5168, *Evaluation of uncertainties*.

[25] ISO 20765, *The GERG-2008 equation of state model*.

[26] GERG (2008), *Wide-Range Equation of State for Natural Gases*.

[27] ISA (2003) [6], *Automation, Systems, and Instrumentation Dictionary*, 4th Edition.

[28] Carpenter, Nicholas, and Henrie (2003), "Accurately Representing Leak Detection Capability and Determining Risk" Paper 05A1; Pipeline Simulation Interest Group (PSIG) Annual Meeting New Orleans, Louisiana, 26 October to 28 October 2005.

[29] Rolski, Schmidli, Schmidt, Teugels (1999), *Stochastic Processes for Insurance and Finance*.

[30] Foss, Konstantopolous, Zachary (2007), "Discrete and continuous time modulated random walks with heavy-tailed increments", *Journal of Theoretical Probability*, 20, No.3, 581–612.

[31] Willekens, E. (1986), "Subexponentiality on the real line." Technical Report, U. Leuven.

[32] Falk, M., Hüsler, J. & Reiss, R. (2010), *Laws of Small Numbers: Extremes and Rare Events*, Springer. p. 80. ISBN 978-3-0348-0008-2.

[33] Alves, M.I.F., de Haan, L. & Neves, C. (2006), *Statistical inference for heavy and super-heavy tailed distributions*.

[34] Crovella, M. E.; Taqqu, M. S. (1999), "Estimating the Heavy Tail Index from Scaling Properties", *Methodology and Computing in Applied Probability,* 1: 55.

[35] Van Reet, J. D. (2014), *Personal Communication.*

3 Gas Processors Association, 6526 E. 60th Street, Tulsa, Oklahoma 74145, www.gasprocessors.com.

4 American Gas Association, 400 N. Capitol Street, NW, Suite 450, Washington, DC 20001, www.aga.org.

5 International Organization for Standardization, 1, ch. de la Voie-Creuse, Case postale 56, CH-1211, Geneva 20, Switzerland, www.iso.org.

6 The Instrumentation, Systems, and Automation Society, 67 Alexander Drive, Research Triangle Park, North Carolina, 22709, www.isa.org.

[36] Salmatanis, N. (2014), *Personal Communication.*

[37] Lewis, E. E. (1995), *Introduction to Reliability Engineering*, ISBN 978-0471018339.

[38] ISO 5024: *Petroleum liquids and liquefied petroleum gases—Measurement—Standard reference conditions.*

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