Underlying the performance of real-time software-based pipeline leak-detection systems

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Introduction

Computational pipeline monitoring consist of pipeline leak detection which is an essential element of a pipeline-management system design. Computational pipeline monitoring is important in enhancing operational performance. It enables more-reliable pipeline operation, and contributes towards adequate safety for the public and environment. Its importance is increasing due to an ageing pipeline infrastructure. There is a continuing need to develop reliable pipeline-integrity-management systems to enhance safety and minimize leakage into the environment.

There are many techniques that may be used for detecting leaks. The software-based spectrum of different techniques includes volume-balance and pressure-point analyses. These methods cannot estimate leak location and are not suitable for pipelines with operational changes. What operating companies need are cost-effective leak-detection systems with a high degree of sensitivity to detect small leaks and estimate location, and not generate false alarms.

The objective of this review is to analyse the underlying approach of two software methods to detect leaks and estimate location. One is based on a real-time simulation method, and the other is based on a real-time statistical-analysis method. While just about any leak-detection system can detect pinhole leaks if provided with precise data, in practice these data contain uncertainties complicated by random errors. The problem stems from the fact that if the leak-detection-system sensitivity is set to alert on detecting of very small leaks, then the very presence of these data uncertainties will cause alarm declarations when in fact there is no leak.

False alarm is a common problem during pipeline operational changes, which results in reduced efficiency and lack of confidence placed in the leak-detection system. This lack of confidence results in all alarms being ignored, or the leak-detection system being switched off. The aim of this paper is to discuss the underlying factors influencing the performance of leak-detection systems. No particular reference is made to commercial products in this review, except where specifically mentioned.

Existing pipeline infrastructure

Pipeline construction world-wide totals around 1.6 million km, of which 60% are over 20 years old. Reference 6 reports on the international pipeline construction which started since 1948 (Fig.1). Reference 3 reports that only 10-20% of the pipelines are pigged regularly. Internal inspection using intelligent pigs is a critical part of an effective pipeline integrity-management programme, which can also provide valuable information about the pipeline. Better operational and maintenance planning reduces the risk of incidents.

Reference 2 presents information on the development of the European Gas Pipeline Incident Data Group (EGIG), and the main contributing causes of failure. Fig.2 shows the probability of failure of a corroded pipe. Reference 7 highlights the fact that "corrosion is becoming an increasing threat to the integrity of pipelines world-wide." Increase in demands for energy, ageing pipeline infrastructure, and the need to maximize the value of pipeline assets, are placing greater demand on pipelines and their operating reliability. The challenge faced by pipeline operators is ensuring the continued integrity of both ageing and new pipeline assets through improved operations and business processes in an environment of increasing commercial pressures.

Leak detectability importance and limits

Computational pipeline monitoring consist of pipeline leak detection which is an essential element of a pipeline-management system design, and is important in enhancing operational performance. Fig.3 shows a pipeline leak-detection system: the total release from a pipeline is dependent on the response of the line leak-detection/shutdown system and the closure time of the valves. Since the rate of outflow from a hole decreases as the pipeline depressurizes, the total mass released will be dominated by the early outflow. The mass of release during failure of a pipeline depends on the hole size, line pressure, shutdown time, and the inventory between the valves on either side of the leak.

The time required to detect a leak is an important attribute for a pipeline leak-detection system and pipeline risk assessment. Pipeline leak-detection systems exhibit variations due to common and special causes. In principle, for a leak to be detectable from a particular measured quantity at a certain moment in time, the leak must cause that quantity to change by more than the uncertainties in the measurement data and software application method at that time. As the leak size increases, both the detection time and location error decreases exponentially. Fig.4 shows the relationship between the pipeline pressure and flow before and after a leak develops in a pipeline. Before a leak, and during a steady-state pipeline operation, the inlet flow Qin equals the outlet flow Qout, whilst during a leak Qin does not equal Qout. The detection time is the time necessary to gain confidence in the leak being a true leak.

The set of conditions that conspire to mask the presence of a leak is a complex combination of the uncertainties, including measurement instrumentation data, SCADA system characteristics, the mathematical model, numerical errors, and changing pipeline-operating conditions. Leak-detection thresholds are a strong function of these and the time allowed to detect a leak. The longer the detection time, the smaller the leak that can be detected due to the long period required for a system to recognize hydraulic changes generated by this small leak. Choice of threshold values is a compromise between

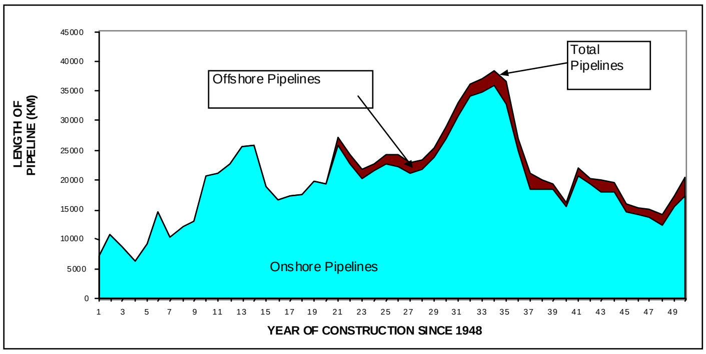


Fig.1. Total length of pipeline construction.

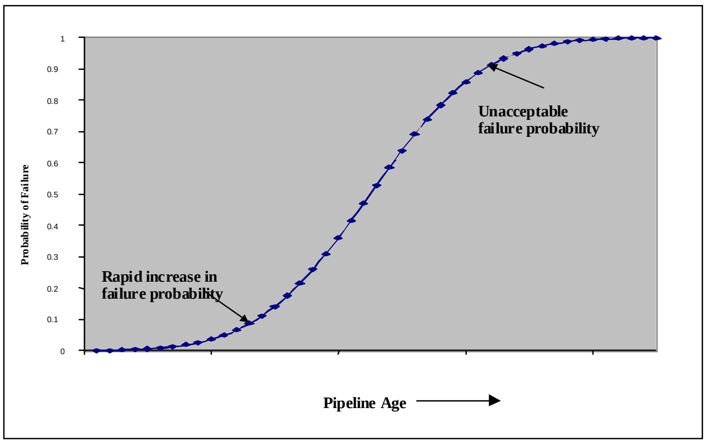
detection time, false alarms, and acceptable risk.

Reference 9 highlights the fact that "many companies offer leak-detection software packages, the majority of which employ some form of statistical analysis and claim their ability both to detect and locate the leak. The track record of the success of these systems on complicated multi-product pipelines has not, however, been clear cut." This paper reviews the underlying factors influencing the performance of real-time leak-detection systems that capitalize on information technologies to manage pipeline-integrity, and improve risk management and productivity.

Leak analysis and measurement

There are many techniques that may be used for detecting leaks, not just those associated with real-time software-based methods. Leak analysis would be relatively easy if the pipeline operated totally in a steady state, but pipelines frequently do not operate in steady state. The flow rate at inlet may often be different from the delivered flow rate during pipeline operational changes, such as the starting of an additional pump, pipeline packing and unpacking, opening a valve, or pigging the pipeline. It

Fig.2. Probability of failure of a corroding pipe.



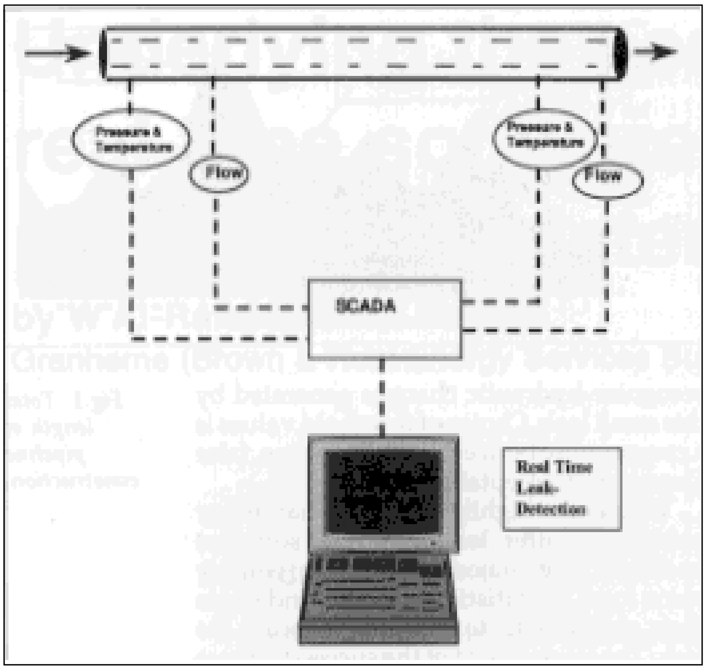


Fig. 3. Pipeline leak-detection system.

takes longer to detect a leak during transient conditions than if the pipeline is operating in a steady state.

Transient measurements are more difficult to make. If the software, for example, is not presented with data from which it can deduce the reason for the apparent change, then in practice the leak-detection system can incorrectly signal a leak alarm. In a transient environment, the pressure signature due to the leak is still there, but it is masked by the pressure noise due to the transients.

Real-time simulation models are driven by SCADA information, which can, in principle, compensate for changes in inlet flow. Compensation is achieved by accounting for the packing or unpacking of the pipeline due to its average increase or decrease in pressure respectively. Uncertainties imposed particularly on the real-time simulation models can be detrimental to constructing a mathematical representation of the behaviour of the flowing fluid. There are practical limits as to how well the real-time simulation models can perform this function. The presence of pipeline-system variance, complicated by random errors, will tend to increase complexity and reduce robustness of real-time leak-detection systems.

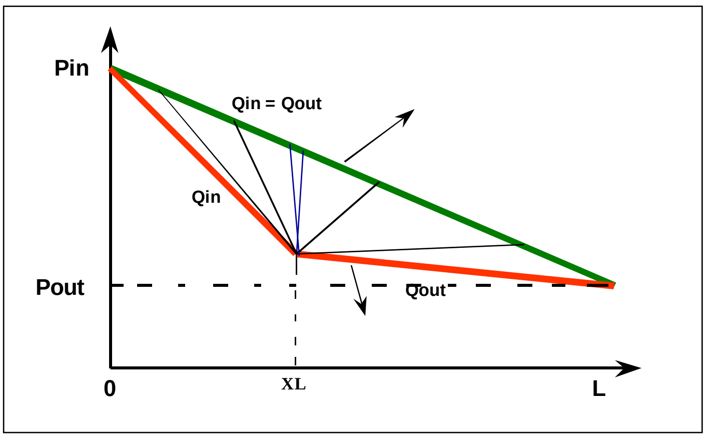


Fig. 4. Pipeline response to a leak.

System variation

The concept of systems thinking and statistical process control was introduced by Dr W. Edwards Deming [5]. This concept is one of the fundamental components of total quality management, largely based upon the philosophy of Deming, the American guru who introduced the concept of total quality to Japan in the 1950s. His work is the foundation-stone of Japanese world industrial dominance. The key, according to Deming, is that management must constantly strive for systems that are in statistical control and work constantly to reduce the variances within systems.

Statistical process control provides a framework within which improvements can be measured by examining the variations in output from a process. It separates those that are inherent (common-cause variations) from those that are external to the process (special-cause variations). It is essential to understand the basic statistical concepts due to two types of causes needed to interpret variations [8]:

- common causes - those causes that are inherently part of the process over time, i.e. SCADA information uncertainties, instrument drift, turbulence, density variation, and pipeline operational changes that affect all outcomes of the process.

- special causes - those causes that are not part of the process all the time, but arise because of specific circumstances, i.e. a failed instrument or occurrence of a leak.

A process is defined as a set of causes and conditions that repeatedly come together to transform inputs into outcomes. A process with only common causes (in a state of statistical control) is called a stable process. A stable process implies only that the variation is predictable within statistically-established limits. Processes whose outcomes are affected by both common causes and special causes are unstable processes. An unstable process does not necessarily mean one with large variations. It means that the magnitude of the variation from one time period to the next is unpredictable.

Reference 8 points out that, if a process was exactly stable and if we knew the details of its underlying (fixed) statistical distribution, we could then work in terms of probability limits. Even if the process was exactly stable and if the normal distribution was appropriate, we would still never know the value of its mean, and even if we did, we would never know the value of its standard deviation; we could only estimate these from the data. Deming points out, that in practice, exactly-stable processes never exist. That is, real processes are never entirely free of special causes, thus the information to create optimum systems is unknown and unknowable.

Deming uses the term "unknowable"; again and again he asks, "how would you know?", challenging the assumptions of people as to what they believe is certain. Predicting with certainty the previous state of a complex pipeline system would be impossible. Complex engineering systems do not respond in a linear fashion to changes in their inputs, and non-linear changes make even simple systems impossible to predict.

The changing of knowledge from absolute to statistical and from fixed to changing is the reason why Deming emphasized that the most important knowledge needed to improve a system is unknown and unknowable. Bringing the process into statistical control is the key to widening the application of one's knowledge about it via the scientific method.

The scientific method

Deming stated that "using the scientific method we learn what is unknown but knowable faster". Because the most important information is not only unknown, but unknowable, in the face of variation and uncertainty, processes can only be improved, never optimized. The path to improvement is via constantly gaining new knowledge using the scientific method.

The scientific method is the path toward what is unknown but knowable. Because it is much more effective at discovering new knowledge, using the scientific method facilitates real-time pipeline leak-detection system learning. Statistical methods monitor and detect changes by determining whether the patterns of variations that are observed when operating a complex pipeline system are indicative of a trend or a random variation that is similar to what has been observed in the past.

System observation

Deming stated that "by observing the operation of the system, built-in flaws can be detected and isolated". By statistically observing a complex pipeline system while it is in operation, we can, by using the scientific method, detect and isolate the built-in-flaws. By using a series of measurements during steady-state pipeline operation, we can perform analysis for state of statistical control to detect and isolate the built-in-flaws. For example, gradual instrument drift and increase in the pressure drop due to an increase in the pipeline friction factor can be incorporated in the observed system behaviour during steady-state pipeline operation.

Once observed, the flaws can be isolated, which will reduce the variability and lower the pipeline system entropy. Once a complex pipeline system is in statistical control, designed experiments can reveal the leverage points for removing some of the common causes of variation, and hence maximize the real-time leak detection system's robustness and performance.

Complexity

Deming also stated that "complexity can be reduced and entropy lowered by removing the built-in flaws". Reducing complexity is the key to improving grade (quality). Complexity is associated with higher degrees of randomness, disorder, and unpredictability, and leads to greater variation in outputs. Complexity is a cause of problems and a product of complicated interactions, and is both a cause and an effect of variation.

The disorder arises because we do not know which state a complex pipeline system is in during operational changes. The special behaviour of the flowing fluid which is associated with finite speed is the wave speed, the speed at which information travels through the pipeline. Disorder is then essentially the same as ignorance. The concept of entropy as defined in reference 4 is as follows: "the quantity of disorder is measured in terms of entropy. One way of defining entropy is in terms of the number of states, or degrees of freedom, that are possible in a system in a given situation".

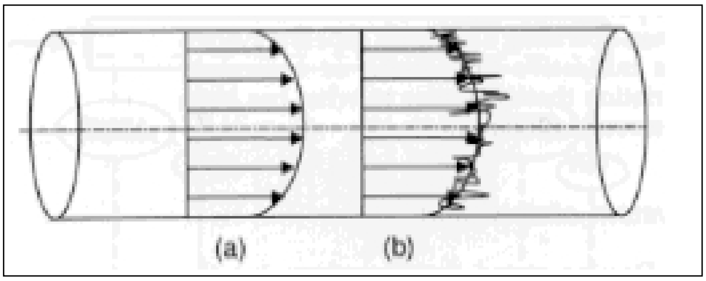


Fig.5. Turbulent flow in a pipe.

Comparison of two leak-detection software methods

Real-time simulation methods

The real-time simulation methods solve partial differential equations by numerical solution. This technique requires flow, pressure, and temperature measurements at the inlet and outlet of a pipeline segment (and additional pressure/temperature measurements at intermediate points). This method presents a picture of current pipeline flow conditions using the SCADA smoothed information. It composes a discrete set of measurement data at preselected locations, and sampled at discrete times which typically occur over a number of minutes 'SCADA scan'.

The equations, which the dynamic model solves, are derived from two basic equations: the equation of momentum and the equation of mass. Dynamic-simulation methods provide invaluable information during the front-end engineering design of a complex pipeline system and determine how to optimize the engineering design and efficiently operate a pipeline [1]. Dynamic simulations provide reduction of costs of new pipeline designs and the ability to study complex pipeline systems under conditions beyond their normal performance limit.

Theory

The dynamic model solves conservation equations for mass and momentum for the velocity and pressure.

Conservation of momentum:

$$\frac{DV}{Dt} + \frac{1}{\rho}\frac{\partial p}{\partial x} = -g\sin\alpha - \frac{2f}{d}V|V| \qquad (1)$$

Conservation of mass:

$$\frac{Dp}{Dt} + c^2\rho\frac{\partial V}{\partial x} = 0 \qquad (2)$$

where: $\frac{D}{Dt} = \frac{\partial}{\partial t} + V\frac{\partial}{\partial x}$

p = pressure in the pipeline
V = fluid velocity along the pipeline
ρ = fluid density
c = wavespeed
t = time
f = friction factor
g = acceleration due to gravity
α = inclination of the pipe to the horizontal

These equations can be solved using either the finite-element or finite-difference method. Using the method of characteristics [10] reduces the two partial differential equations to two ordinary differential equations valid along certain 'characteristic' lines in the xt plane, where x denote the axial direction of the pipeline and t represent time.

The method of characteristics is the natural numerical procedure for hyperbolic systems in two independent variables. For fluid velocities, which are much smaller than the wavespeed (as is generally the case in most transient problems in pipelines), the characteristic lines are defined by:

$$\frac{dx}{dt} = \mp c$$

The lines x - ct = constant and x + ct = constant are called the characteristics. These equations hold for each pipeline segment and allow the pressure and flowrate to be calculated using the finite-difference numerical solution procedure at various time steps from knowledge of pressures and flowrates at the start of computations. Since the wavespeed is constant for a particular pipe, the above equation defines straight lines in the xt plane and the integration scheme to step forward in time.

The numerical method performs a number of iterations at each time step to predict pipeline operational changes. Many such time steps must be sequentially executed to cover the desired transient time period and additional equations may need to be solved, namely conservation of energy and equation of state. The presence of pipeline entropy and variance preclude the ability to accurately couple the SCADA information with a real-time simulation method during transient conditions.

Turbulence

Solving the Navier-Stokes equations, if possible, yields instantaneous values of velocity and pressure. In turbulent flow, velocity and pressure fluctuate widely about mean values. If the velocity at each point in the cross section was measured with a pitot-static tube, the resultant distribution would be that of Fig.5a. If a more-sensitive instrument is used, a distribution such as that in Fig.5b would result. The instantaneous velocity at any point oscillates randomly about a mean value.

In the central region of the pipeline, a fully-developed turbulent flow exists. Near the wall, a laminar sublayer forms within which Newton's law of viscosity describes the flow. Between the two is the buffer zone within which both laminar and turbulent effects are considered important. Fig.6 shows the result of using a sensitive instrument to measure velocity at a point in a pipe at which turbulent flow exists. Two velocities can be identified: the mean velocity, which is the average or mean value, and the instantaneous velocity, which fluctuates randomly about the mean.

The instantaneous velocity can be time-smoothed to obtain the mean velocity. That is, if the instantaneous velocity is averaged over a finite time interval the mean value results. This process results in a similar equation to the Navier-Stokes equations, except that the time-smoothed velocities replace the instantaneous velocities. Moreover, these equations of motion have the time-smoothed pressure. This results in the appearance of a new term, referred to as the turbulent momentum flux called Reynolds stresses. This necessitates the need to simplify the equations using semi-empirical relationships to relate the Reynolds stresses to a strain rate in the fluid, in order to provide a true representation of the flowing conditions in the pipeline when employing accurate real-time simulation models.

Repeating a measurement several times can reduce, but not eliminate, errors. By making some determination of the magnitude of these uncertainties, the real-time simulation models must then couple measurements of pressure and flow at inlet and pressure and flow at outlet through obeying the fundamental laws of fluid mechanics. Real-time simulation models will have an unavoidable tendency to create false alarms during pipeline operational changes when attempting to obey the fundamental laws of fluid dynamics.

This aspect makes real-time simulation model-type software more complex in order to interpret and filter the incoming SCADA information, by considering all of the measurement data and at the same time to find the best set of values which are hydraulically consistent. Dynamic checks on variations in pressure and flow at the inlet and outlet are necessary. These checks are difficult, if not impossible, to carry out accurately when using a real-time simulation model during 'pipeline operational changes'. Therefore, threshold levels must be increased to prevent false alarms at a time when the leak-detection system is needed most.

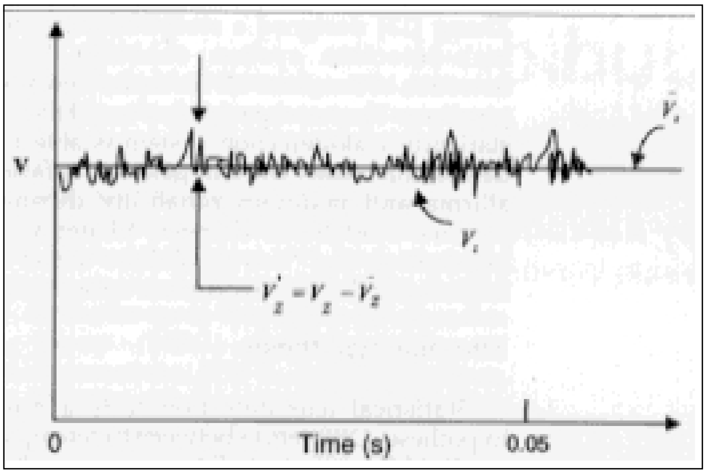


Fig.6. Velocity at a point in a turbulent flow.

Statistical leak-detection-based methods

Statistical software methods do not use numerical solution procedures to calculate flow or pressure in a pipeline, but detect changes in the relationship between flow and pressure using measured data at the inlet and outlet and test a null hypothesis. This technique requires flow, temperature, and pressure measurements at the inlet and outlet of a pipeline (and, ideally, additional pressure/temperature measurements at intermediate points). The method itself produces no numerical errors and detection is based on relative changes in the 'mean value' and pattern recognition whilst accepting errors as normal discrepancy.

The statistical leak-detection-based method is able to monitor a complex pipeline system continuously; it learns about continual changes in the pipeline. "This on-line learning capability is useful as pipeline operation always changes and instrument drift could occur over a long time period"[12]. Instrument drifts can be accounted for by tuning measurements available during steady-state pipeline operations and no leak alarm period, thus allowing easier operation.

A statistical leak-detection system would, in principle, have a low false-alarm rate, provide simplicity, and improve grade. Zhang [13] designed a statistical pipeline leak-detection system enabling leak detection of less than 1% on liquid and gas pipelines.

The test data demonstrated that a statistical leak-detection system is able to detect small leaks without generating false alarms and maintain reliability during pipeline operational changes. Zhang also highlighted that "it is possible to detect a leak smaller than the instrument errors"[13].

The null hypothesis

Statistical leak-detection tests a null hypothesis. Differences between two sample means of measured data are normally distributed around the mean difference in the population of a raw SCADA scans. Most differences will be close to the true difference, and a few will be significantly different. In order to determine whether a difference found represents a true difference (a leak developed) or a chance difference (data scatter), tests of significance are applied to the SCADA scans.

Statistically, the mass entering and leaving the pipeline must be balanced by the inventory variation inside the pipeline. The test of significance determines whether or not there is a significant difference between the means of the inlet flow and pressure, and outlet flow and pressure. Tests of significance are based upon an estimate of standard error and test a null hypothesis.

The null hypothesis says that there is no true difference in the SCADA sample (leak-free) and that any difference found in the SCADA samples is the result of sampling error (uncertainty). Since there is no way to know for certain whether a decision made is correct, it is necessary to estimate the probability of being wrong. Hence, when the null hypothesis is rejected, it can be concluded that a leak exists.

The test has been set up as:

Null hypothesis Ho: $\mu 1$ equals $\mu 1$
Alternative hypothesis H1: $\mu 1$ does not equal $\mu 2$

The probability of being correct is referred to as the significance level, or probability level, of the test of significance. If the decision is made to reject the null hypothesis, the means are concluded to be significantly different or too different to be the result of uncertainty. If the null hypothesis is not rejected, the means are deemed to be not significantly different. The level of significance, or probability level, selected determines how large the difference between the means must be in order to be declared significantly different. The most commonly used probability level is the 0.05 level.

The probability level selected determines the probability of committing a Type I error, that is, of rejecting a null hypothesis that is really true and hence generating a false alarm. Thus with a probability level of 0.05, there is a 5% probability of making a Type I error. As the probability of committing a Type I error decreases by using a smaller probability level, say 0.01 instead of 0.05, then the probability of committing a Type II error, i.e. not rejecting a null hypothesis when it should have been rejected, increases, and hence the leak is not detected. The consequences of making a Type II error, i.e. not detecting a leak, are serious. Hence by considering the relative seriousness of committing a Type II error versus a Type I error, a probability value can be established during the statistical parameter tuning.

Shell has developed and tested a statistical leak-detection system following several years of research, which is licensed to REL Instrumentation Ltd and trademarked as ATMOS pipe. Zhang and Di Mauro [12] developed a statistical software leak-detection algorithm that is based on probability calculations of mass conservation and hypothesis testing at regular sample intervals. The mean value of the flow difference in a pipeline between inlet and outlet, together with inventory variation, remains unchanged unless a leak develops or an instrument error occurs. Deviation is detected by a test method termed the 'sequential probability test'.

The statistical system, incorporating pattern recognition, has now been tested by Shell on a number of its operating pipelines. During 1997 it was commissioned on Shell's North Western Ethylene Pipeline [11] in the UK. In March, 1998, Shell performed a site acceptance test during which ATMOS pipe detected a 0.38m3/minute (16% of throughput) leak in 15 minutes, with an accurate leak size and location estimates [12]. Leak detection in ethylene pipelines operating at a range of pressures is highly challenging for evaluating a leak-detection system performance. Field tests and real-time applications have demonstrated that the reliability of ATMOS pipe is founded on the principle of quality management.

Conclusions

Computational pipeline monitoring is an essential element of a pipeline-management system design and is important in enhancing operational performance and risk management. There is a continuing need to develop reliable pipeline integrity-management systems to enhance safety and minimize leakage into the environment. The performance of real-time pipeline leak detection is influenced by common causes that introduce uncertainties. These uncertainties are complicated by random errors.

Real-time simulation methods are more dependent on the absolute accuracy of the smoothed SCADA information and need to perform additional tests to establish the plausibility of the data from a range of possible hydraulic values. The presence of pipeline entropy and variance preclude the ability to accurately correlate the SCADA information with the real-time simulation method during pipeline operational changes. If ignored, they can be detrimental to calculating a mathematical representation of the transient flowing conditions.

Real-time simulation models will have an unavoidable tendency to create false alarms during pipeline operational changes when attempting to obey the fundamental laws of fluid dynamics. The presence of pipeline entropy precludes the ability to accurately couple the SCADA information with a real-time simulation method during transient conditions. Consequently, threshold levels must be increased to prevent false alarms during pipeline operational changes at a time when the leak-detection system is needed most.

Reducing complexity is an important lever in any attempt to improve the quality of real-time pipeline leak-detection systems. The benefit of reducing complexity is that it is progressively easier to identify leaks. Statistical leak-detection methods reduce complexity and observe the reality itself. Pipeline operational learning capability is a key to reduce false alarms without impairing reliability during pipeline operational changes. Statistical leak-detection systems provide operators with the value of Deming's philosophy of total quality management through improved pipeline operations in an environment of increasing commercial pressures.

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