Software-Based Pipeline Leak Detection

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ABSTRACT

Pipeline leak detection has been a focus of numerous researches in industry. There are several methods based on expensive hardware. As an alternative, a less costly software based method is been proposed. This method makes use of the measured flows and pressures to infer through data reconciliation and bias detection methodologies whether a leak or a bias is present. In this report, the Generalized Likelihood Ratio (GLR) method proposed by Narasimhan and Mah (1987) is adapted to combine leak detection and instrument bias identification. The methodology is entirely implemented within a simulator.

INTRODUCTION

Over the years pipelines have been instrumental in the effective transportation and distribution of important commodities such as natural gas, petroleum products, liquid hydrocarbons and water. In most cases these commodities provide economic support for different countries, resulting in longer pipelines from one country to another. On a smaller scale, materials are also transported within the country, within a plant and within refineries. Most pipelines are buried underground and passed through commercial and residential areas. However, a major problem with safe pipeline operation is the development of cracks, rupture and leaks as a result of corrosion and pressure changes. The biggest challenge in the industry is to come up with a pipeline leak detection method that will accurately detect leaks in a timely fashion.

RESULTS OF LEAKAGE

The absence of a good leak detection method that monitors pipeline activity has numerous effects on the environment and human lives. Loss of product is the primary effect of pipeline leakage, resulting in loss of money and investment. In March 2006, about 267,000 gallons of oil was lost over a five day period before the leak was noticed in Prudhoe Bay complex, Alaska (Knickerbocker). The Environmental Protection Agency (EPA) held British Petroleum, BP responsible for failure to ensure adequate maintenance of their pipelines. The effect of the leak was felt around the world as it increased the price of oil. BP was later fined $20 million for the negligence. The most severe effect of pipeline leakage is the loss of lives. In November 2007, a gas explosion killed about two people, injured dozens and a left a total of 60 families displaced in Clarke County, Mississippi (News center). It was later investigated that a leak in the pipeline allowed gas to flow downhill causing an ignition. If there was an adequate leak detection scheme in place, the explosion would have been prevented or residents would have been evacuated.

METHODS OF LEAK DETECTION

Over the years, a lot of methods have been proposed and implemented to detect pipeline leaks and the possible location and magnitude of the leak, but have all fallen short in some way. Current leak detection methods can be classified into two forms; hardware and software. The hardware methods are based on instrumentations placed externally on the surface of the pipelines, while the software method uses different instruments to measure internal parameters of the fluid such as pressure, temperature, flow rates, etc.

Methods of leak detection selected for a pipeline depends on different factors which includes pipeline characteristics, product characteristics, instrumentation, communication capabilities and economic feasibility (Alaska Department of Environmental Conservation).Though pipeline systems vary in their physical characteristics and operational functions, it is however important that the selected leak detection scheme should include as many of the following leak detection utilities as possible:

- Accurate product release alarm
- Estimation of leak location and magnitude
- High sensitivity to product release
- Efficient field and control center support
- Minimum Software and configuration tuning
- Minimum impact from communication outages
- Accommodation for complex operating conditions, such as transients
- Configurability to complex pipeline networks
- Accurate imbalance calculations on flow meters

HARDWARE LEAK DETECTION METHODS

This report covers the most common forms of hardware leak detection methods currently used in the industry. They include: acoustic emission, fiber optic sensing and vapor sensing.

ACOUSTIC EMISSIONS

This method of leak detection uses acoustic emission technology that is based on the principle that escaping fluid gives off an acoustic signal as it flows though a leak in the pipe. Acoustic sensors are placed around the entire length of the pipeline to monitor the internal pipeline noise levels and possible leak locations. The data obtained during this measurement is used as a base line otherwise known as an "*acoustic map*" of the pipeline. In the event of a leak, there will be a low frequency acoustic signal that is given off and it is detected by the sensors and also analyzed by system processors. Any deviation from the acoustic map will trigger an alarm and an analysis on the line is carried out. The signal that is received will be stronger near the site of the leak and this makes it possible to locate the leak.

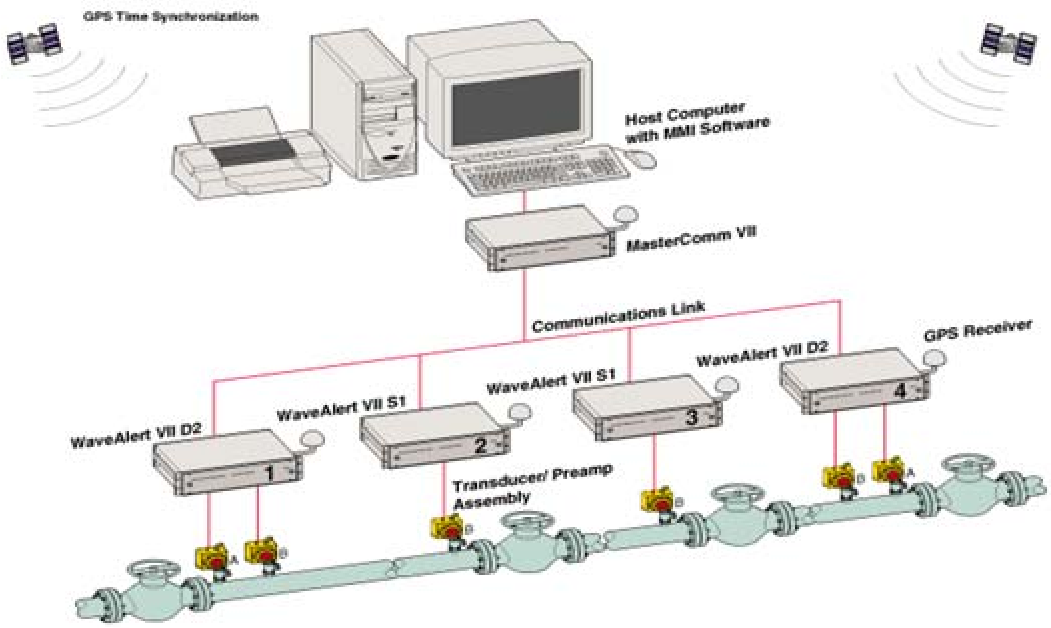


Figure 4. Acoustic Emission (www.wavealert.com)

FIBER OPTIC SENSING

The technology behind this method uses fiber optic sensing probes as the main instrument. The fiber optic sensing probes are placed into the soil in a manner in which they are in contact with the pipeline. In the case of a leak, the escaping hydrocarbons causes cooling of the area surrounding the leak according to the Joule Thompson effect; the sensing probes are used in analysis of this temperature change of the pipe. This cooled section of the pipe makes it possible to locate the leak.

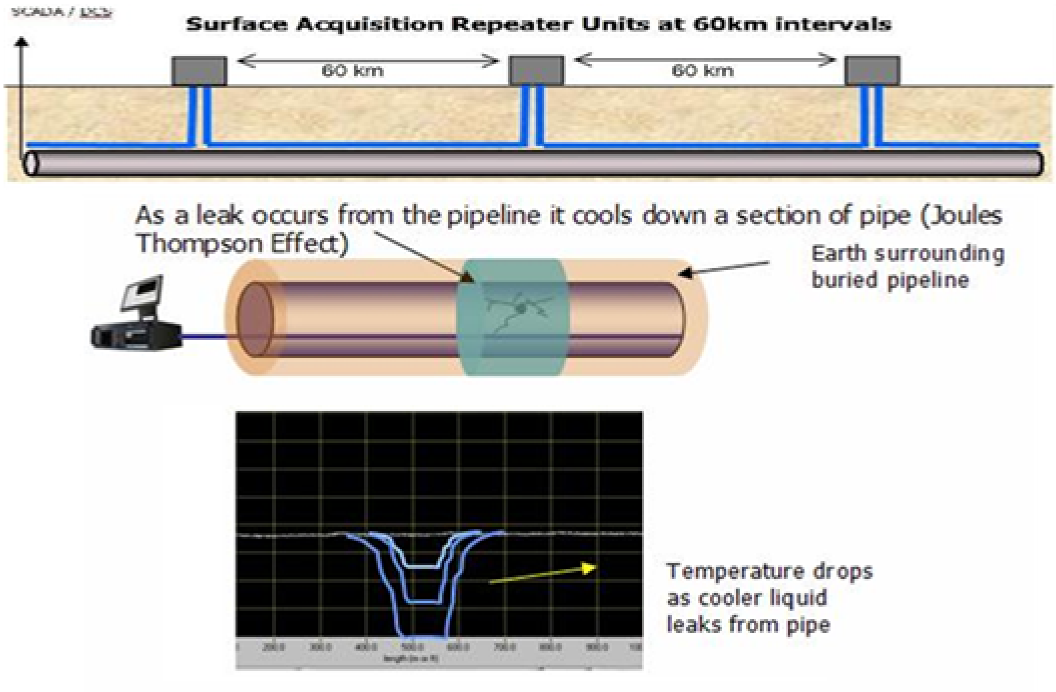


Figure 5. Fiber Optic Sensing Leak Detection

VAPOR SENSOR METHOD

In this method, a vapor sensing tube that is highly permeable to the material being transported is laid along the entire length of the pipeline. In the presence of a leak, some of the material diffuses into the tube and is collected for analyses in the lab. A test gas is pumped into the tube so as to mark the end of the pipeline segment being analyzed. In the presence of a leak, the size of the leak is proportional to the magnitude of the leak.

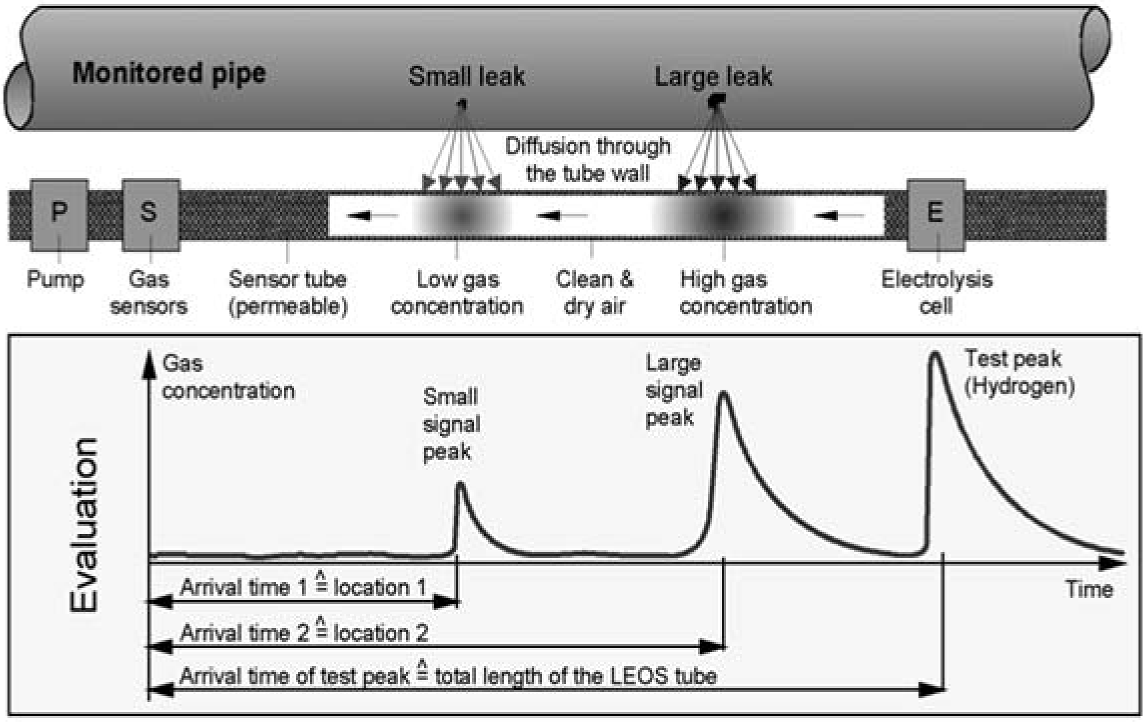


Figure 6. Vapor Sensing Leak Detection Method

ADVANTAGES OF HARDWARE LEAK DETECTION METHOD

Hardware methods generally have good sensitivity to leak because most of them have instrumentation along all the entire length of the pipeline and they are able to detect both large and small leaks at a fast rate. The location of the leak can also be estimated through the instrumentation on the placed surface of the pipeline and this helps save time and material loss in the event of a leak.

DISVANTAGES OF HARDWARE LEAK DETECTION METHOD

As stated above, the advantages of the hardware method is attributed to the instrumentation. Consequently, this high level of instrumentation also contributes to the disadvantages associated with this method. The installation and maintenance cost are also relatively high. Also, there is a high complexity of installation as most of the hardware methods require a lot of below surface activities in order to correctly place the instruments along the pipelines. For these reasons, the hardware methods are commonly used on pipelines travelling through high risk areas where there is a high possibility of loss of life in the case of a leak.

SOFTWARE LEAK DETECTION METHODS

Unlike the hardware method, the software leak detection method uses instrumentation to measure different internal parameters of the pipeline. The more parameters that are used for a particular software method, the more accurate the results will be. The most common forms of software leak detection include: balancing systems, pressure analysis and real time transient method (RTTM).

BALANCING SYSTEMS

The principle behind this method is the principle of mass conservation

$$\dot{M}_I(t) - \dot{M}_O(t) = \frac{dM_L}{dt}$$ **Equation 1**

Where: $\dot{M}_I$ = inlet mass flow rate

M_O = outlet mass flow rate

M_L = line pack

It is assumed that when there is no leak mass is conserved and the mass stored in the line for a pipeline of length L changes over time because of changes in the density ϱ and cross sectional area A as seen in the equation below:

$$\frac{dM_L}{dt} = \frac{d}{dt}\int_0^L \rho(x)A(x)dx = \int_0^L \frac{d}{dt}\langle \rho(x)A(x)\rangle dx$$ **Equation 2**

There are 3 forms of balance systems and they can be identified through the description of the line pack M_L. they include: volume balance, compensated mass balance, and model compensated mass balance.

Volume balance

Volume balance uses a bulk modulus of elasticity K along with an average temperature T_L and pressure P_L over the entire length of the pipe. When there is no leak in the pipeline, the average temperature and average pressure makes it possible to calculate the line pack: $M_L = M_L(P_L, T_L)$. An average density ϱ_L of the fluid along the pipeline is also involved: VL = M_L / ϱ_L. The estimated imbalance R that is estimated allows the elimination of the line pack equation:

$$R(t) \equiv \dot{V}_I(t) - \dot{V}_0(t) - \frac{dV_L}{dt}$$ **Equation 3**

Compensated mass balance

This balance approach is more rigorous that the volume balance. The estimated imbalance is:

$$R(t) \equiv \dot{M}_I(t) - \dot{M}_0(t) - \frac{dM_L}{dt}$$ **Equation 4**

By dividing the pipeline into segments, the p, T, ϱ will be assumed to be the uniform results in the line fill calculation as well as the uniform segment density $\varrho_{i.}$ The line pack equation will be as follows:

$$M_L = \int_0^L \rho(x)A(x)dx \approx \sum_1^n \rho_i A_i$$ **Equation 5**

Model compensated mass balance

This is the most rigorous form of balancing systems as it uses the real time transient models (RTTM) method to evaluate leaks. The RTTM uses the computational power of modern computers makes it possible to compute density ϱ(x,t) along the pipeline. It gives the most accurate result because it uses more variables to correctly determine the line fill M_L.

Advantages & Disadvantages of the Balancing System

It is very simple to implement because it is based solely on the principle of mass conservation. Due to this, there is little or no requirement of extra instrumentation, making the method very cost effective.

Although it does not require a lot of instruments, its accuracy is highly dependent on the precision of the instruments in use. In order words, instrument biases could cause large errors in leak detection. False alarms are also prevalent in this scheme, as any little deviation from the baseline flow conditions is registered as a leak. To reduce false alarms, a threshold value is set. However, small leaks happen to go undetected if its magnitude is below the prespecified threshold.

PRESSURE ANALYSIS

When a leak suddenly occurs in a pipeline, there is a sudden change in pressure and flow (at both ends of the pipeline) that accompanies it. This software method uses the changes in pressure to evaluate leaks. The most common forms of the pressure analysis method includes: rarefaction wave monitoring, reflected wave or timing methods and the gradient intersection method.

Rarefaction wave monitoring

When there is a leak and the fluid flowing in the pipeline breaches the pipeline wall, there is a sudden drop in pressure at the location of the leak followed by rapid line depressurization a few milliseconds later. The low pressure expansion wave that is formed travels at the speed of sound through the fluid away from the leak in both directions. The leak should be seen at opposite ends of the line simultaneously and this gives the leak location.

Reflected wave or timing method

The changes in flow conditions always produce pressure transients. When there is a leak, the pressure transients created at any location of the pipeline propagates though out the system until a steady state is reached. Reflected waves are always produced when there is an abrupt change in geometric or hydraulic properties. The characteristics of the reflected waves are dependent on the cross sectional area and wave speed of the pipeline. Also, the magnitude of the reflected wave depends on the magnitude of the flow.

Gradient intersection method

This method was derived by integrating the volume balance method and the pressure deviation method. The supervisory control and data acquisition (SCADA) values are used to derive a theoretical hydraulic profile that is compared to the actual physical hydraulic profile. Any deviation from the hydraulic baseline indicates a leak and its position can also be detected.

Advantages & Disadvantages of the Pressure Analysis Method

This method can give the location of the leak by analyzing any deviations from the baseline. However, gradient intersection is dependent on instrument sensitivity in order to accurately report leaks and locations. Smaller leaks tend to be ignored if they do not show a significant deviation from the set baseline and this is unacceptable in the industry. This method is not able to provide an estimate of the leak magnitude.

REAL TIME TRANSIENT MODELING (RTTM)

The most sensitive and accurate software leak detection method is the real time transient modeling (RTTM). RTTM involves a simulation of pipeline internal conditions by using advanced fluid mechanics and hydraulic modeling. It combines the conservation of momentum calculations, conservation of energy calculations, continuity equation and numerous flow equations. The RTTM approach is able to predict the size and location of leaks by comparing the measured data for a segment of pipeline with the predicted modeled conditions. The pressure-flow profile of the pipeline is calculated based on the measurements of the pipeline inlet and outlet. The two profiles are later overlapped and the location of the leak can be identified as the point of intersections.

Advantages & Disadvantages of the RTTM

RTTM takes into account the configuration of the pipe as well as the product characteristics because of the number of parameters it can work with. It also detects leaks at a fast rate because it carries out continuous analysis of the pipeline conditions. However, because of the vast parameters that make up the RTTM, it is a very complex way of leak detection. In addition to the complexity, it is very expensive to set up as it requires many instruments, controller training and maintenance. Additionally, errors in instrument calibration could raise false alarms.

GENERALIZED LIKELIHOOD RATIO (GLR)

The generalized likelihood ratio (GLR) is a statistical method modeled after the flow conditions in the pipeline. The GLR is able to derive a mathematical model that describes effects of leaks on the flow process and it can be used to detect, locate and estimate leaks occurring in networks of pipelines (Narasimhan and Mukherjee). This method was adapted by Narashimhan and Mah for identifying biases and process leaks in steady state processes. The model based method provides a general framework for identifying any type of fault that can be modeled. The strengths of the GLR is in its capability of producing an estimate of the magnitude of the fault in the pipeline, and distinguishing between leaks and biases; putting it a step above the common leak detection schemes in use.

GLR METHOD FOR GROSS ERROR IDENTIFICATION

This report evaluates the accuracy of the generalized likelihood ratio in identifying gross errors. In order to use this approach, a mathematical model that describes the effects of a leak and / or bias on the process is needed. The biases include both measurement bias and process leaks in steady state processes.

THEORY

The model of the generalized likelihood ratio used was the same as that used as Narasimhan and Mah (1987).

PROCEDURE

For a given pipeline configuration and covariance matrix of errors Q, the measured values are simulated within ±5% error in the steady state true values using the RANDBETWEEN function in excel. Biases were introduced in a measurement by picking a random number outside the given range of measured values. If a leak is being simulated, it is looked at as an extra outflow and the new mass balance of the network is computed. Measured values are subsequently introduced as earlier stated. Different runs are performed for each type of bias introduced, and a different set of measurements is generated in each run.

Methods proposed by Rosenberg (1985) were used to evaluate the performance of the generalized likelihood ratio in each simulation trial.

The overall power of the method in identifying gross errors is given by:

$$overall\,power = \frac{number\;\;of\;\;gross\,errors\,correctly\,identified}{number\,of\;\;gross\,errors\,simulated}$$

RESULTS AND DISCUSSION

The generalized likelihood ratio as developed by Narasimhan was first tested on different pipeline configurations. A single gross error was simulated in each run and the GLR was used to identify the error and provide an estimate of its magnitude. In all simulations, the covariance matrix Q is taken to be an identity matrix and constraint matrix and gross error vectors were created as earlier stated. In the following simulations, the constraint matrix was created using only flow balances, and the flow rates. All streams are assumed to be measured. The shaded values in the tables presented correspond to runs in which the simulated bias was correctly identified.

The generalized likelihood ratio method was first applied to the simplest form of pipeline configurations, as seen in figure 7 below. It is found that the GLR method cannot be successfully used in gross error identification of a single pipeline. This is because no constraint matrix can be obtained for the pipeline as only one flow balance is possible for the system. Also, the resulting supremum or maximum likelihood for a bias would occur from the gross error vectors of both streams, with the estimated magnitude of the bias in one stream simply being the negative of the other. Due to this reason, flow measurements on the inlet and outlet of a single pipeline segment are insufficient for gross error detection. An example of this is given in the later sections of this report to further clarify on this issue.

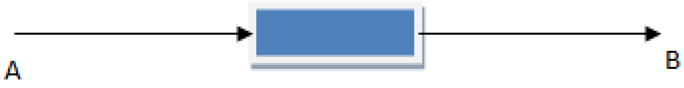


Figure .7

The next set of simulations was performed on the configuration shown in figure 8.

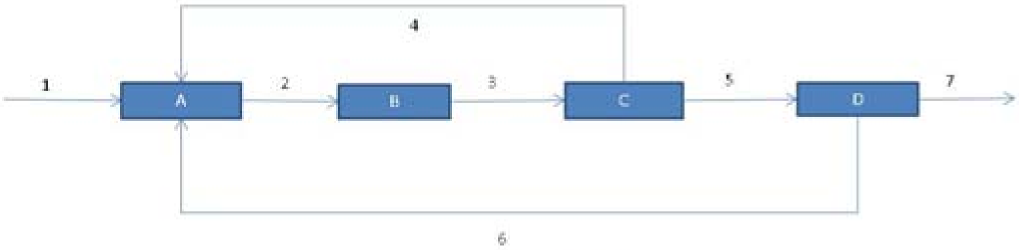


Figure .8

In the first set of runs, random biases were introduced in sensor 1 and the results are summarized in table 1. As previously stated, the shaded values represent runs in which the bias was correctly identified in sensor 1, and the resulting AVTI was 0.4. This value may seem high but this is due to the fact that only 10 runs were performed. As more runs are introduced, the AVTI would reduce as the next set of simulations shows. It can be seen that the GLR method gives a very good estimate of the bias, which is very useful in risk analysis.

	Bias in Sensor1									
Run Number	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10
Magnitude of gross error simulated	-50	-35	35	-33	32	-60	45	-55	40	-50
Est. Magnitude of Gross Error	-58	34	-50	-35	49	-63	47	66	48	-41

Table .1

Biases of varying magnitudes were alternated between sensors 1 and 2 to further estimate the power of the method. The AVTI reduced to 0.08, confirming the earlier hypothesis, thought this is still insufficient in drawing an accurate conclusion of the method. The estimated values of the bias also remained within a reasonable range of the true value. The results for these simulations are summarized in tables 2a and 2b.

	Bias in Sensor1 and 2											
Run Number	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12
Magnitude of gross error simulated	50	-50	78	-100	-60	-90	-34	67	78	80	-133	77
Est. Magnitude of Gross Error	51	-34	75	-106	-50	104	-54	-68	70	79	-150	74
Sensor with bias simulated	1	2	1	2	1	2	1	2	1	2	1	2

Table .2a

	Bias in Sensor1 and 2											
Run Number	2.13	2.14	2.15	2.16	2.17	2.18	2.19	2.20	2.21	2.22	2.23	2.24
Magnitude of gross error simulated	-76	47	-102	-78	123	-101	68	-67	72	91	43	-44
Est. Magnitude of Gross Error	-72	-43	-111	-90	127	-92	73	-52	71	93	36	-45
Sensor with bias simulated	1	2	1	2	1	2	1	2	1	2	1	2

Table .2b

The next set of simulations involved introducing a bias in sensor with the possibility of leaks to the network. The leaks were treated as extra streams from pipe A and B, though no actual leaks were simulated. In other words, the general gross error vector set F contains 9 vectors instead of 7 vectors as in the previous simulations. The same random numbers as in the first vector were used.

The results are presented in table 3 below. It can be seen that the AVTI of the method increased drastically. Therefore as suggested by Narasimhan and Mah (1987), if a possibility of many different errors exist, additional constraints or measurements are required for better performance.

	Bias in Sensor1									
Run Number	3.1	3.2	3.3	3.4	3.5	3.6	3.7	3.8	3.9	3.10
Magnitude of gross error simulated	-50	-35	35	-33	32	-60	45	-55	40	-50
Est. Magnitude of Gross Error	-53	45	-50	-33	48	-54	54	62	43	-55

Table .3

An actual leak of magnitude 50 was then introduced to the aforementioned system. The location of the leak was alternated between pipes B and C. The results are presented in table 4. Runs in which negative values of leaks were estimated can be disregarded and classified as a product of unsteady state behavior, as specified in the formulation of the method. The AVTI increased from the previous simulation to a value of 0.2, but additional constraints are still required for optimal performance as the estimated magnitude of the leak differed largely from the simulated value.

	Leak in Pipe B and C									
Run Number	4.1	4.2	4.3	4.4	4.5	4.6	4.7	4.8	4.9	4.10
Magnitude of gross error simulated	50	50	50	50	50	50	50	50	50	50
Est. Magnitude of Gross Error	37	70	-29	76	88	-38	72	79	76	34
Simulated Pipe with Leak	B	C	B	C	B	C	B	C	B	C

Table .4

The GLR method was further tested on the previous system by inducing 2 biases in the system at the same time; a leak in pipe B and a bias in sensor 1. The results are presented in table 5

	Leak in Pipe B and C									
Run Number	5.1	5.2	5.3	5.4	5.5	5.6	5.7	5.8	5.9	5.10
Simulated location of Leak	Pipe B	Pipe C	Pipe B	Pipe C	Pipe B	Pipe C	Pipe B	Pipe C	Pipe B	Pipe C
Bias with Sensor simulated	1	1	1	1	1	1	1	1	1	1
Magnitude of Leak simulated	50	50	50	50	50	50	50	50	50	50
Magnitude of Sensor Bias simulated	50	-100	-127	-50	77	122	-68	37	-61	-52
Est. Magnitude of Leak	*	*	*	54	114	*	*	87	*	*
Est. Magnitude of Bias	98.5	-76	-83			141	75		98	31

Table .5

The results show that the GLR method as earlier specified cannot be applied to systems with multiple gross errors, as only one error can be identified at a time. The shaded values represent correctly identified gross errors. For example in run 5.1, a leak in pipe B and bias in sensor 1 was introduced in the system however only the bias was successfully identified with its estimated value equal to 98.5, a 50% difference from the simulated value . In run 5.2, 5.7, 5.9 and 5.10, neither the simulated bias nor the leak were successfully identified. Consequently, the AVTI increased drastically. Narasimhan and Mah (1987) suggested as a serial compensation strategy for multiple gross error identification. In this case, if a gross error is identified, its estimated magnitude is used to compensate for the gross error, and this is carried out until no more gross errors are identified. This strategy is preferred to the more common combinatorial approach as the computational requirements are significantly less. Due to time constraints, we would not be analyzing this strategy in this paper, but would be making the assumption that we are dealing with well-maintained systems where only one gross error occurs at a time.

The next configuration used in simulations is shown in figure 9. The same procedure for generating the numbers as in the previous network was used, and the GLR method was subsequently used for identification of process leaks and sensor biases.

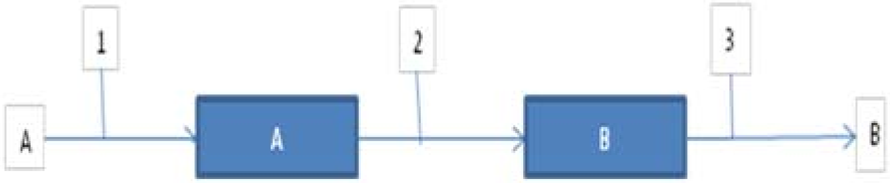


Figure .9

A bias in sensor 1 of varying magnitude was introduced to the system and the results are given in table 6. It can be seen that the AVTI for this case is zero as the location of the bias was correctly identified in all ten runs. This is due to the simplicity of the system in question. As there are only 3 measurements, the likelihood that the maximum test statistic would be successfully determined is a lot higher than in the previous network. The average difference between the estimated and simulated bias was 3 units, which indicates a very good performance of the GLR with this system.

	Bias in Sensor 1															
Run Number	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12	1.13	1.14	1.15	1.16
Magnitude of gross error simulated	-60	50	100	-70	-72	76	-100	57	-77	62	88	92	-55	47	-190	102
Est. Magnitude of Gross Error	-50	45	118	-58	-70	62	-96	57	-81	65	102	86	-43	35	-190	112
Sensor with bias	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1

Table .6

A leak in pipe A was then introduced to the system and the new steady state balance calculated. Though the AVTI for the system stayed at zero, the average difference between the estimated and simulated values was a value of 14.5 units, which is larger than in the first case. One observation with this system is that the supremum of the test statistic was obtained in both stream 1 and the leak stream A. the difference between the two is that the resulting estimate of the gross leak for using the supremum for stream 1 gives a negative value, rendering it a product of unsteady state behavior. This shows how the GLR can differentiate between leaks and other biases in the system. A summary of the results is given in table 7.

Bias in Sensor 1												
Run Number	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12
Magnitude of gross error simulated	50	50	50	50	50	50	50	50	50	50	50	50
Est. Magnitude of Gross Error	27	65	58	66	64	58	58	59	53	43	74	29.5
Pipe with Leak	A	A	A	A	A	A	A	A	A	A	A	A

Table .7

The GLR method was also applied to the network in figure 10 below.

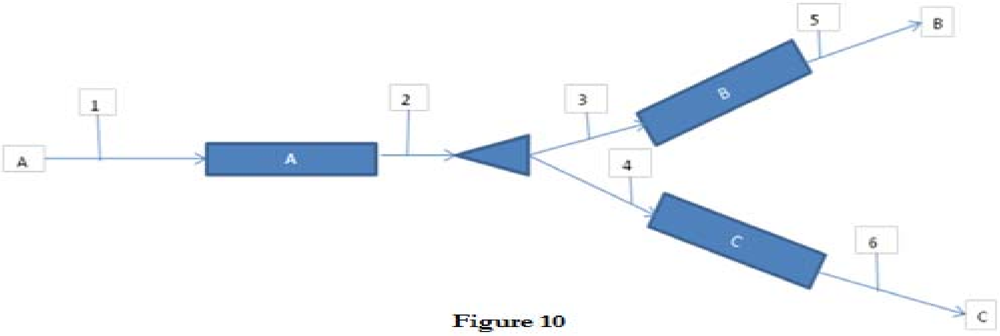


Figure 10

Biases with random magnitudes were introduced in sensor 3 in the first set of simulations, and their values estimated. As in the previous case, the AVTI for the system was zero indicating that the flow balance is sufficient in estimating biases in the system. The results are summarized in the table 8 below:

Bias in Sensor 3												
Run Number	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10	1.11	1.12
Magnitude of gross error simulated	-50	50	-38	32	66	-61	82	58	-88	-97	62	76
Est. Magnitude of Gross Error	-47	43	-45	34	63	-67	91	65	-81	-109	75	70
Simulated sensor Bias	3	3	3	3	3	3	3	3	3	3	3	3

Table .8

Possibilities of leaks were introduced in all three pipes, with a leak of varying magnitude in pipe B simulated. The flow balance for the system was recalculated to include the leaks and the generalized likelihood ratio method subsequently applied. The leak was correctly identified in all ten runs and the estimated magnitudes were reasonably close to the simulated values in all the runs. The results are presented in table 9 below.

Leak in Pipe B												
Run Number	2.1	2.2	2.3	2.4	2.5	2.6	2.7	2.8	2.9	2.10	2.11	2.12
Magnitude of gross error simulated	100	90	91	89	80	95	77	89	80	87	88	76
Est. Magnitude of Gross Error	80	86	92	81	72	83	71	101	100	77	84	76
Simulated leak in Pipe	B	B	B	B	B	B	B	B	B	B	B	B

Table .9

The last set of simulations was performed on the gas gathering system taken from Bagajewicz and Cabrera (1987), shown in figure 11. The flow rates of the streams were provided in the paper and the measured values were randomly generated within ±12% error in the true values.

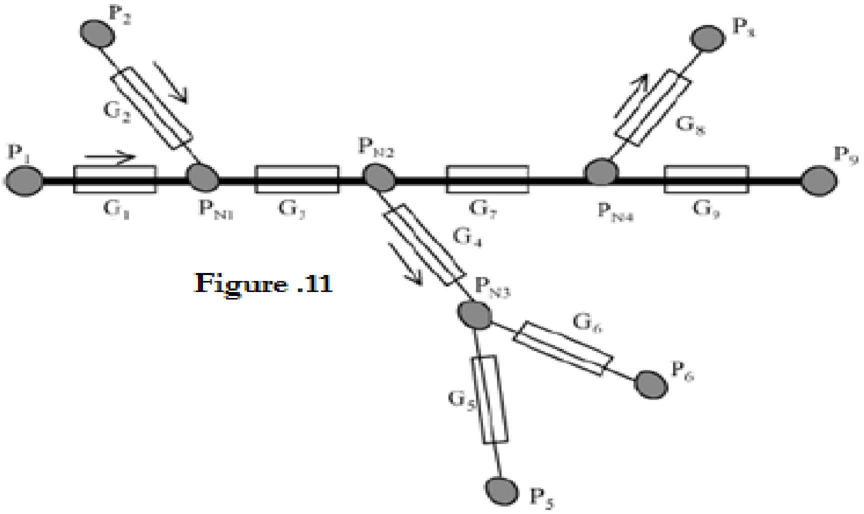


Figure .11

Leak possibilities were introduced in four of the streams, and a sensor bias was induced in sensor 7. The results are presented in table 10. It is immediately noticed that the bias was not correctly identified in any of the runs, as none of the estimated values are shaded. This is due to the similarity in gross error vectors and constraint values of most of the streams. Therefore, the flow balance constraint alone is not sufficient for this system.

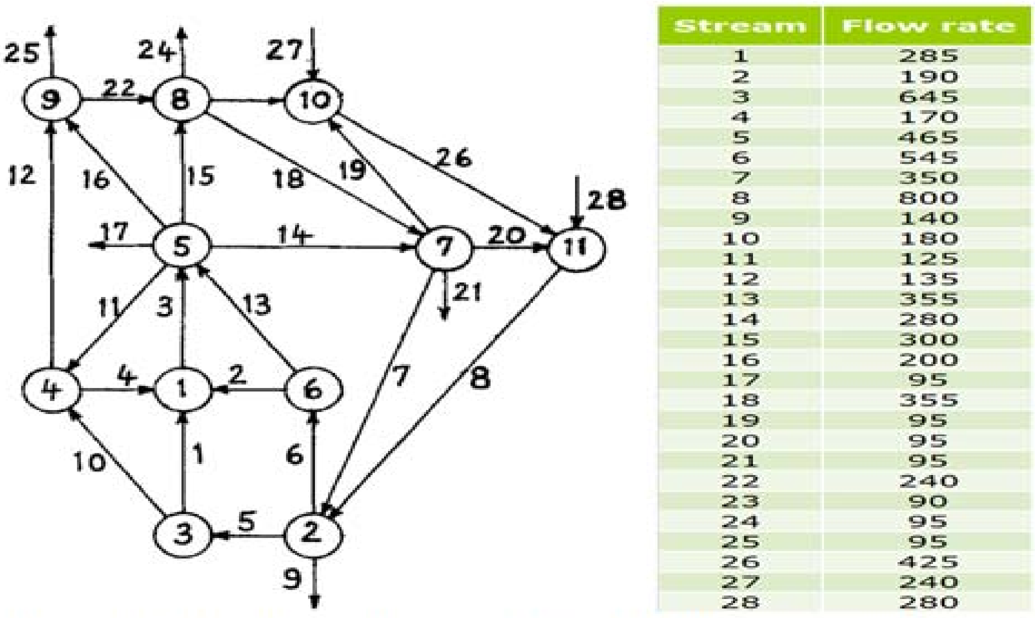
	Bias in Sensor 7									
Run Number	1.1	1.2	1.3	1.4	1.5	1.6	1.7	1.8	1.9	1.10
Magnitude of gross error simulated	12.47	-7.23	-12.19	19.57	-5.33	8.68	-13.41	-13.81	40.67	14.94
Est. Magnitude of Gross Error	-6.27	6.42	0.35	-12.61	3.19	-0.94	7.38	6.65	-21.95	-9.54
Sensor with Bias	7	7	7	7	7	7	7	7	7	7

Table .10

Pressure measurements are included in the aforementioned network and the leak detection strategy is implemented solely in a simulator. This methodology is evaluated and discussed further in subsequent sections of the report.

GLR Excel Macro

The generalized likelihood ratio method for detecting biases in a pipe network has been shown to work for simple systems using a few simulation trials. However, to completely understand the limits of the GLR method, a more complex network must be studied with a larger number of test iterations. A complex network of nodes and pipes was chosen from Narasimhan and Mah (1987) with flow rates chosen arbitrarily to satisfy the material balances present, see Figure 12 below:

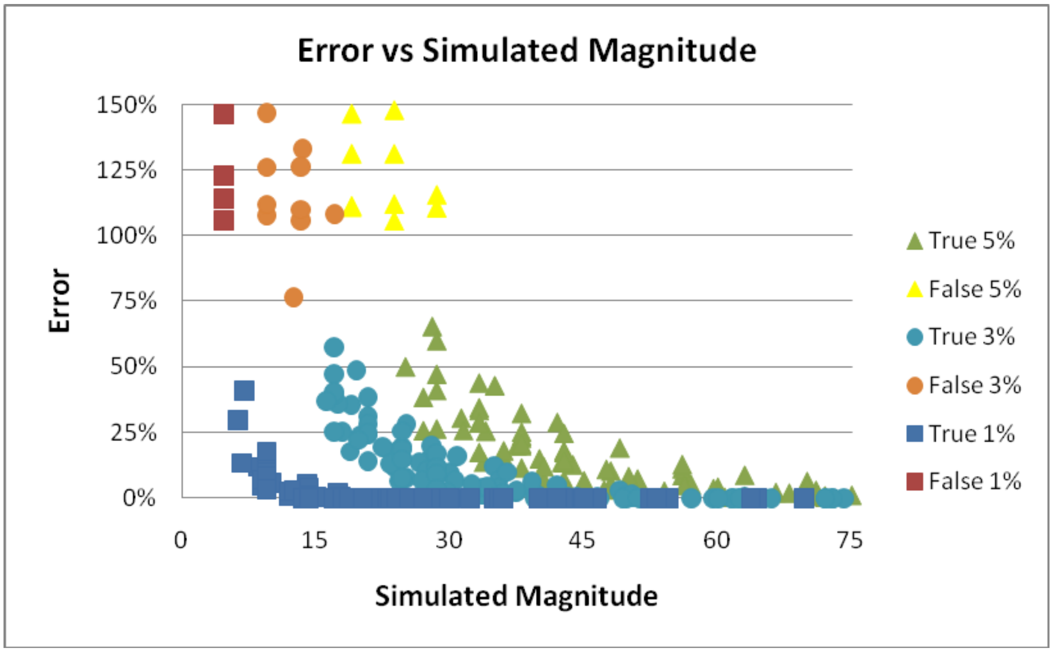


Stream	Flow rate
1	285
2	190
3	645
4	170
5	465
6	545
7	350
8	800
9	140
10	180
11	125
12	135
13	355
14	280
15	300
16	200
17	95
18	355
19	95
20	95
21	95
22	240
23	90
24	95
25	95
26	425
27	240
28	280

Figure 12: Complex pipeline network with the flow rate in each pipe.

To get a large number of program iterations, a macro was written in excel to implement the GLR method a specified number of times for any pipeline network given inputs of stream flow rates, the number of nodes, the constraint matrix, the magnitude of the random instrument error, and a simulated bias. The simulated bias can be of any magnitude and in any stream. The program then calculates the maximum test statistic and tells the user the stream that has a bias, the magnitude of the bias, and the overall power. The program ran the GLR method 15,000 times for biases of different magnitudes in different streams. The overall power and the error in the estimated magnitude of the bias are then plotted against the simulated bias magnitude.

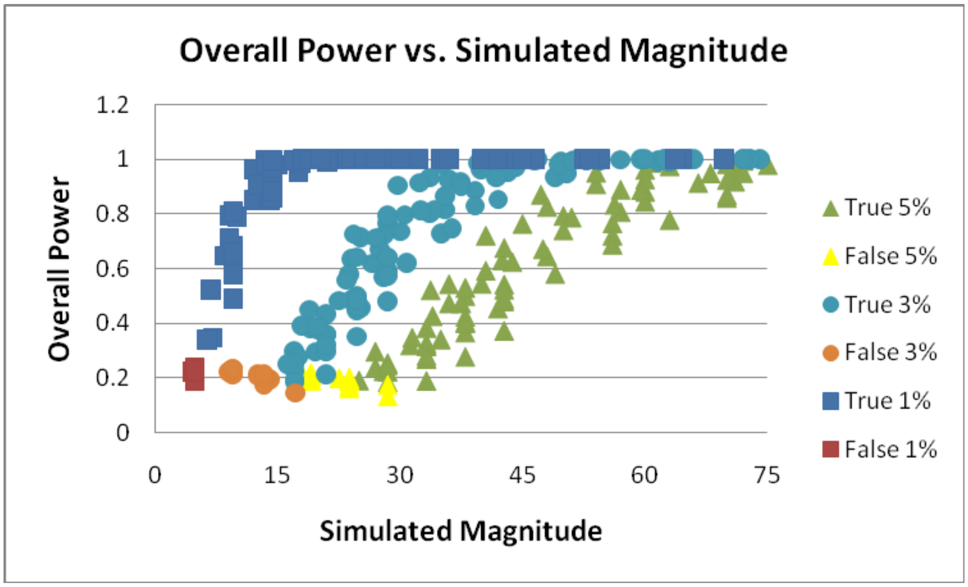
The error verse the simulated magnitude is plotted for meter variances of 1%, 3%, and 5%, Graph 1.



Graph 1. Error vs. Simulated Magnitude

As the magnitude of the simulated bias increases the accuracy of the GLR method increases. However, as the magnitude of the bias decreases the error increases and eventually reaches a point where the GLR method will no longer identify the correct location of the bias. This is because a small bias is hidden by the random variance of the flow meters. More accurate flow meters with a lower meter variance are able to correctly identify smaller biases.

Another test of the generalized likelihood ratio's usefulness is the overall power. The overall power verse the simulated magnitude is plotted for meter variances of 1%, 3%, and 5%, graph 2.



Graph 2. Overall Power vs. Simulated Magnitude

As the magnitude of the simulated bias increases the overall power of the system approaches a value of one. As the simulated magnitude of the bias decreases the overall power decreases until the GLR method is no longer able to correctly identify the simulated bias. As with the error above, more accurate flow meters improve the overall power of small biases.

The generalized likelihood ratio method is able to correctly identify biases if they are of sufficient size. In order to identify smaller biases more accurate instruments, with less variation, are required.

SIMULATION PROCEDURE

Motivating Example

The generalized likelihood ratio for bias detection was implemented and evaluated using only simulations in Simsci Esscor's PRO/II. Pressure measurements were introduced along with the flow measurements not to only identify and estimate the leak, but also to provide an estimate of its location. As earlier mentioned, flow meters alone are insufficient for error location as different number of scenarios may arise. Take the case of the simple pipeline seen in figure 13, with the flow in and out only assumed to be measured.

Figure 13

Three possible scenarios could arise as seen in the table 11.

	Sensor 1	Leak	Sensor 2
Case 1	0.4	0	0
Case 2	0	0.4	0
Case 3	0	0	-0.4

Table 11

Firstly a bias of 0.4 may be present in the first sensor, or a leak of 0.4 may be present in the pipeline and lastly, a bias of -0.4 may be present in the second sensor. With flow measurements only, these three scenarios cannot be differentiated, therefore, pressure measurements have to be introduced for analysis of the pipeline.

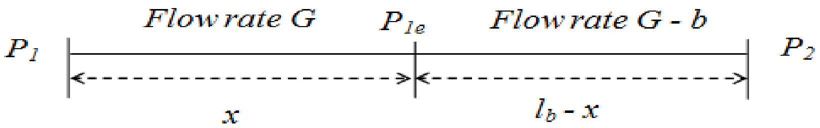
Problem Formulation

Energy balance without leak is as follows:

$$P_1 - P_2 = f(G) \qquad \textbf{Equation 24}$$

Where: P_1 and P_2 = inlet and outlet pressures respectively

G= flow rate



In the presence of leak of magnitude b and location x from the head of the branch, the energy balance becomes:

$$P_1 - P_2 = (P_1 - P_{1e}) + (P_{1e} - P_2) \qquad \textbf{Equation 25}$$

The pressure drop becomes:

$$P_1 - P_2 = f(G, b, l_b) \qquad \textbf{Equation 26}$$

Where: $b = leak\ magnitude$
$x = leak\ location$

In the case where no gross error is present, the following data reconciliation problem is solved:

$$Min\sum_i (\tilde{G}_i - G_i)^2 * S_{G_i}^{-1} + (\tilde{P}_i - P_i)^2 * S_{P_i}^{-1}$$ **Equation 27**

$$where\ \ \tilde{G}_i = variable\ flow, \tilde{P}_i = variable\ pressure,$$
$$S_{G_i}^{-1} = variance\ of\ flow measurement, S_{P_i}^{-1} = variance\ of\ pressure measurement$$

Where Equation 27 is subject to the following constraints:

$$G_{i,in} - G_{i,out} = 0$$ **Equation 28**

So, $$P_{i,in} - P_{i,out} = f(G)$$ **Equation 29**

In the case of an error of magnitude b and location x, the model becomes:

$$Min\sum_i (\tilde{G}_i - G_i)^2 * S_{G_i}^{-1} + (\tilde{P}_i - P_i)^2 * S_{P_i}^{-1}$$ **Equation 27**

Where Equation 30 is subject to:

$$G_{i,in} - G_{i,out} - b = 0$$ **Equation 31**

So, $$P_{i,in} - P_{i,out} = f(G, b, l_b, x)$$ **Equation 32**

Leak detection procedure is as follows:

1. Hypothesize leak in every branch and solve data reconciliation problem
2. Obtain GLR test statistic for each branch $obj_{no\_leak} – obj_{with\_leak\_k}$
3. Determine the maximum test statistic $obj_{no\_leak} - obj_{with\_leak\_k}$
4. We compare the max test statistic with the chosen threshold value: Max{obj_{no_leak} – $obj_{with\_leak\_k}$}> threshold value: leak is identified and located in the branch corresponding to the maximum test statistic

The pipeline network and measurements taken from Bagajewicz et al was used in our simulations. Figure 14 is a depiction of the same pipeline network in the simulator. A leak is being simulated in pipe 1 and the calculator is used to solve the data reconciliation problem, while the optimizer minimizes the result from the calculator by varying the parameters where measurements are assumed to be taken. This corresponds in this case to all inlet and outlet streams.

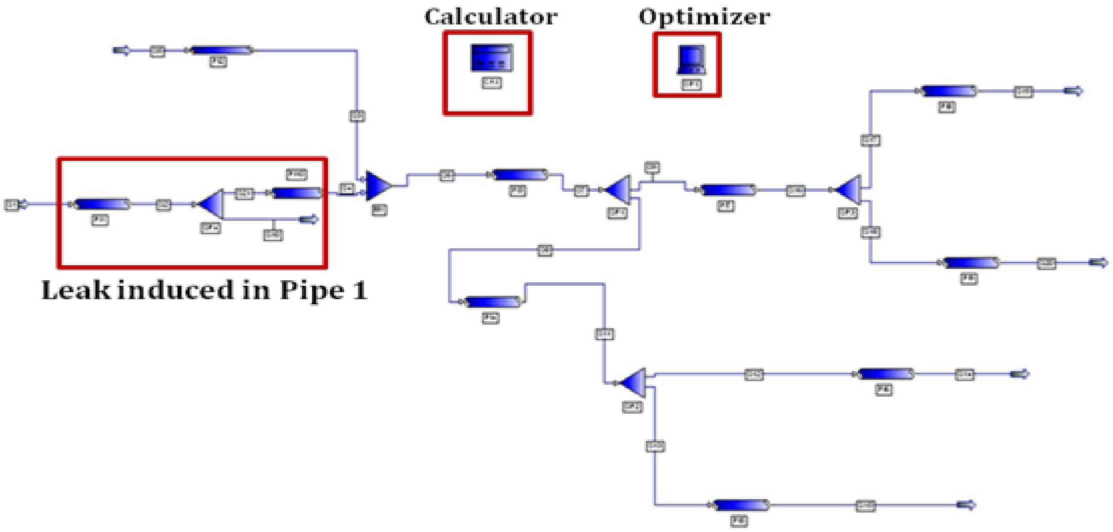
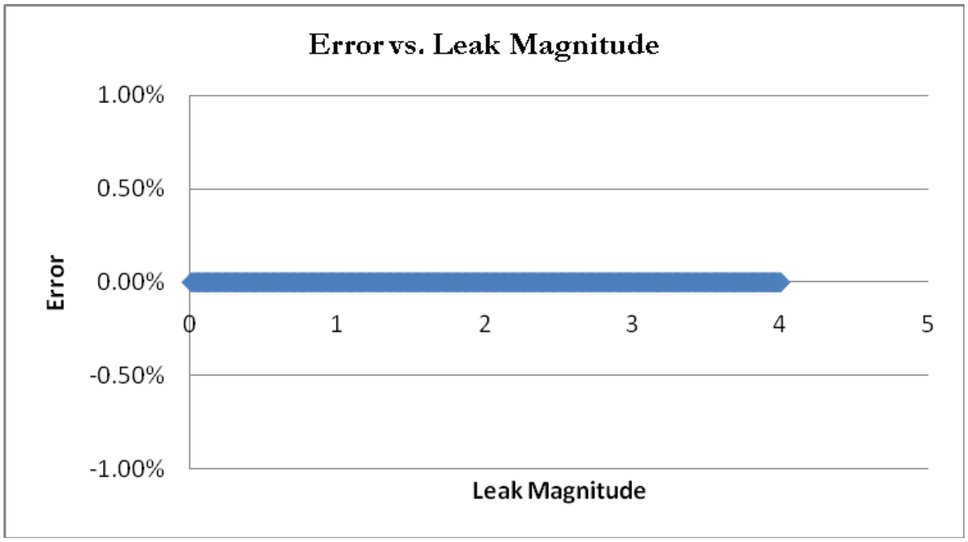


Figure 14.

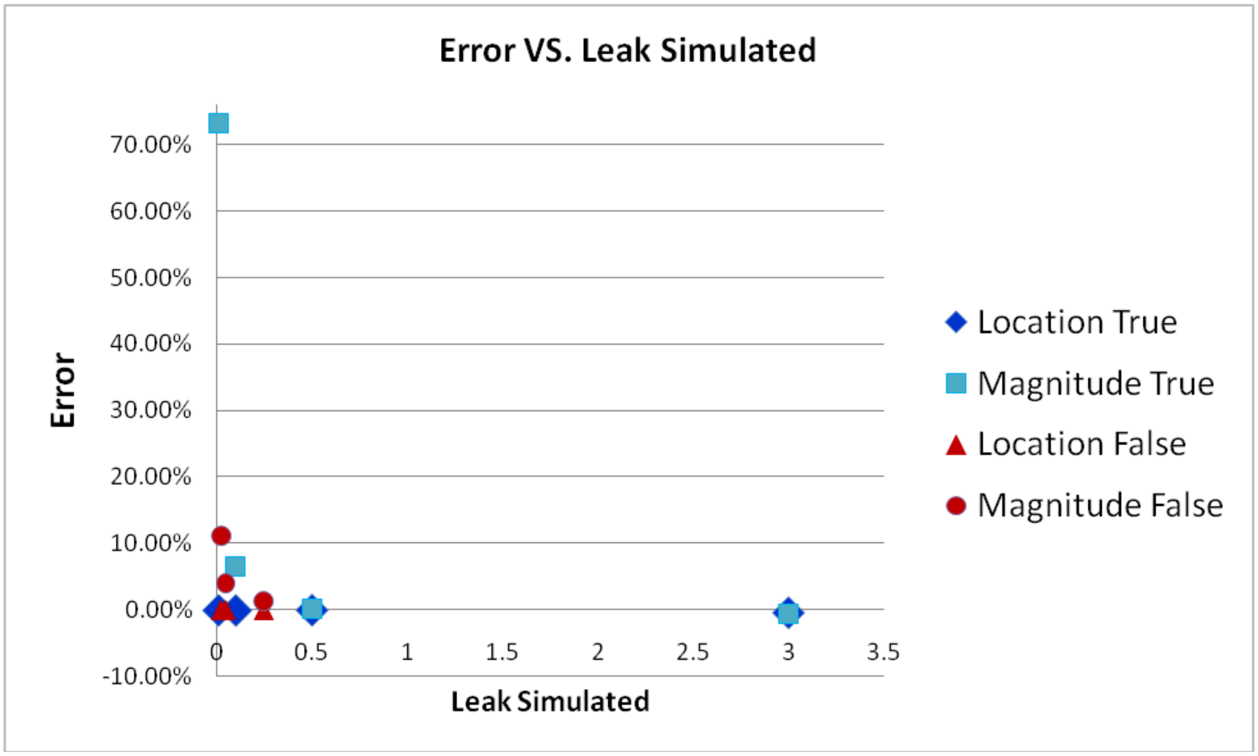
The procedure was tested first under perfect measurement conditions, meaning no random variance or noise in the pipeline sensors, graph 3.



Graph 3. Error vs. Leak Magnitude

A leak of varying size was introduced into the system to test the theory behind the procedure. As expected, the procedure is able to correctly identify both the location and magnitude of the leak for even very small leaks. This case is highly unlikely as meter variance or noise is always present in measurements.

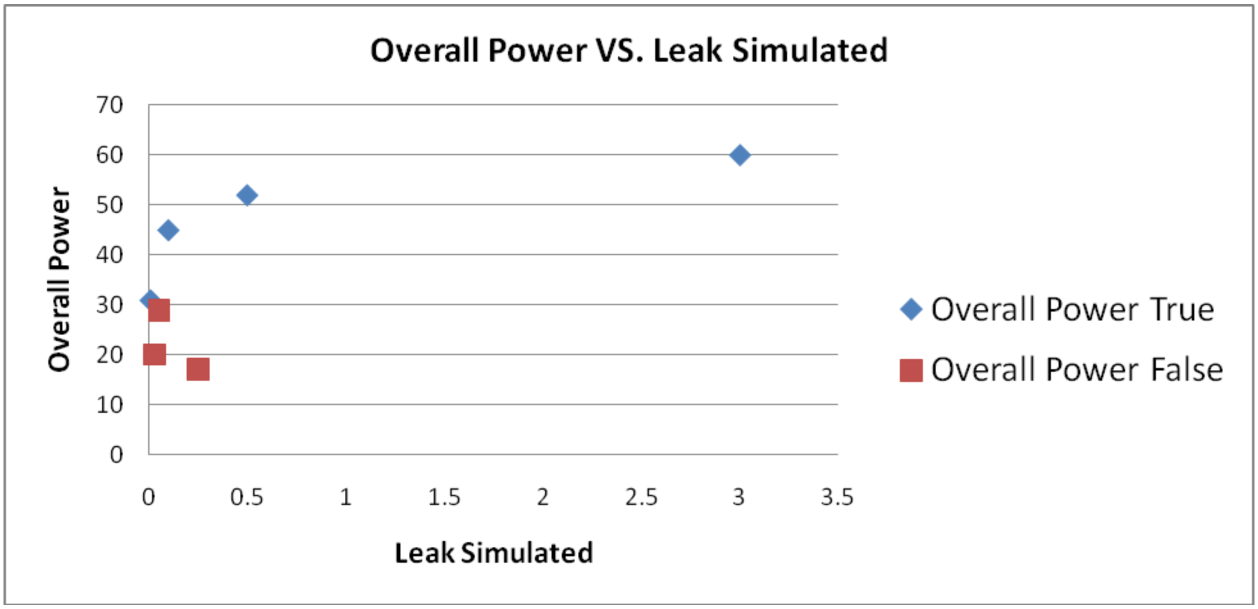
To further test the ability of the procedure to correctly identify both the magnitude and location of a leak, a random variable generator was introduced into the system in the form of a code in calculator. The random variable generator caused the measured variables in the system to vary by 2.5%. The error in both the location and magnitude of the leak is plotted verse the true size of the leak simulated as seen in graph 4.



Graph 4. Error vs. Leak Simulated

There is an apparent trend of decreasing error in the calculated magnitude with increasing leak size. This trend is the same as was found in the GLR method, however, there is insufficient data to conclude this trend is accurate. The error in the leak location is always small with no apparent trend.

The overall power is also found and plotted verse the magnitude of the simulated leak, graph 5.



Graph 5. Overall Power vs. Leak Simulated

As the magnitude of the simulated leak increases the overall power increases, which is also what happened with the earlier mentioned GLR method. However, there is insufficient data to conclude this trend is accurate. More case studies need to be run to correctly evaluate the simulation procedure.

The procedure is a viable method since it is able to always identify the size and location of a leak when there are perfect measurements available. It also shows similar trends when compared to the GLR method used by Narasimhan and Mah, in that larger leaks are more accurately identified in both location and magnitude.

CLOSING REMARKS AND CONCLUSION

The generalized likelihood ratio method provides an outline for identification of all gross errors that can be modeled in a pipeline network. It is especially useful as it can differentiate between sensor biases and leaks, which is an essential tool for risk assessment in pipeline networks. The simulations in this paper showed that with the proper constraints, the GLR method can successfully detect and locate gross errors in various pipeline systems

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