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The Reverse Mass Balance Method for Distribution of Trunk Line Crude Oil Losses: Issues, Alternatives, and Recommendations

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Abstract:
In Nigeria, trunk lines are owned by few International Oil and Gas Companies and they are shared by independent producers, marginal field operation and some JV partners. Crude oil losses occur in these trunk lines due to use of wide range of non-compliant meters by the suppliers of crude to the trunk lines and leakages due to sabotage, aged pipeline and valve failures. These losses must be distributed among the suppliers of crude to the line (injectors). The Interim Methodology which apportioned 62% of the crude losses to measurement error and 38% to theft was promptly rejected by injectors and was replaced by the Reverse Mass balance methodology(RMBM). Less than two years of the RMBM's implementation, injectors are petitioning the DPR about unfair deductions by the trunk line owners. The aim of this research therefore is to highlight the issues with the RMBM and discuss alternatives. This study identified two alternatives to the RMBM, the use of Artificial Intelligence and Flow based models. This study found that flow based models account for both individual and group losses, unaccounted for in the RMBM, and allocates and corrects for leak volumes at the point of leak instead of at the terminal. This is a significant improvement from the RMBM, however, AI techniques, PSO and Genetic Algorithm, are purported to perform better for leak allocation.

Keywords: Reverse mass balance method, Proportionate rule, Artificial Intelligence application in the Oil and Gas Industry, Mathematical modeling of fluid flow in a pipeline, Leak detection

1. Introduction

Trunk line are pipeline that takes crude oil from flow stations to the terminal where the crude oil is sold. In Nigeria, the owners of trunk lines are few International Oil companies (IOCs). These trunk lines are shared by other independent producers and marginal field owners in Nigeria. And because of the wide range of non-compliant meters used by these independent producers and marginal field owners, a lot of measurement errors are being introduced into the trunk line. Another major feature of the trunk lines is that often times the trunk lines are sabotaged for theft and losses are incurred.

The issue here is how the owners of these trunk lines distributes these losses to their injectors. Initially, Interim Methodology was used where the crude loss in the trunk line was allocated in the following proportion – 62% to measurement error and 38% to theft. Measurement error was given a larger share of crude loss and the possible explanation is that the cumulative effect of measurement error is huge – loss/gain per unit time accumulated over the pumping period. This was the situation when the Department of Petroleum Resources (DPR) approved another methodology in 2017 called Reverse Mass Balance Methodology (RMBM).

2. The Reverse Mass Balance Methodology

The highlights of directives from DPR as contained in the letter DMR/CTO/COA/COM/v.2/154 of 21st March 2017 to Shell Petroleum Development Company (SPDC) on the adoption and implementation of the RMBM are as follows:

- The SPDC should replace the Interim Methodology (IM) of 62% to measurement error and 38% to theft with the RMBM.

- The RMBM should be applied to both the Bonny and Forcados Terminal Networks.

The RMBM methodology consists of three steps:

Step 1: Gross Volume is corrected for:
- Type of gross meter used
- Meter factors used (if required),
- Pressure and temperature (P&T) and BS&W uplift (if required).

Step 2: Theft Volume is determined by subtracting Focalized Terminal Receipts (FTR) from Corrected Injected Volume (CIV).

Step 3: Theft Volume Allocated to injectors to be proportional to shares of Corrected Injected Volume.

In situations where the difference between CIV and FTR is positive then excess crude is shared to only injectors without Lease Automatic Custody Transfer (LACT) units in proportion to their Corrected Net Production.

The RMBM took effect from January 2017, but less than two years of adoption and implementation of the approved RMBM, most of the stakeholders and JV partners, continued to complain about unfair crude deductions by the SPDC. Motivated by the complaints from stakeholders about unfair deductions by SPDC, the directives listed in Section 1 of the RMBM were appraised and the observations made during the appraisal of the adopted RMBM are as follows:
- The RMBM does not distinguish between measurement error and theft as listed in Directive A (see Directive D).
- Clearly the application of RMBM as outlined in Directive C is limited to LACT units that fall into categories described in Directive D.

3. The Reverse Mass Balance Methodology Explained

In figure 1, flow stations 1- 5   are the points of injection into the trunk line and X_1 is the point of sabotage; SPDC would deduct percentage loss from all injectors including from flow stations 1 – 4, not minding that their crudes came into the blend after the sabotage had occurred on the line
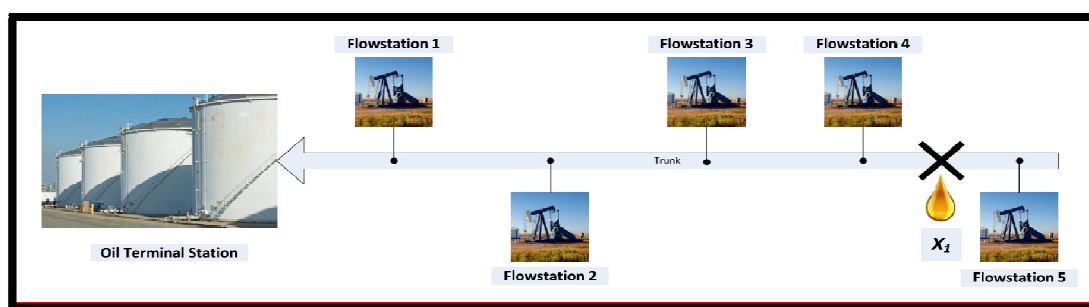

Figure 1: Trunk Line Showing Contributing Flow Stations at Different Custody Transfer Points

The RMBM is based on the net loss or gain of crude on the trunk lines where the accurate measurement of injected crude cannot be determined accurately for each injector as specified in Directives C and D. However it can be argued that on trunk lines where the accurate measurement of injected crude can be determined for fully compliant LACT meters and the accurate measurement of crude cannot be determined for other non-compliant meters the application of the RMBM using Step 3 in Directive C is arbitrary and may disproportionately compensate some injectors at the expense of others.

Consider an injector with fully compliant LACT meters pumping crude at a 100 km distance from the Bonny Terminal. Suppose the line is sabotaged 20 km from the LACT unit (i.e. 80 km from the Bonny Terminal) and substantial loss of crude is incurred. Assume injectors pumping crude at distances less than 80 km from Bonny Terminal all belong to categories specified in Directive C, Step 3 (i.e. they do not have LACT units) and Directive D (i.e. they operate LACT units with non-compliant meters). Apparently crude loss or gain will be difficult to apportion at the Bonny Terminal since there are two or more sources of indeterminate loss or gain:
- Firstly, at the point of sabotage (a definite but indeterminate loss accruable to the fully compliant LACT unit only),
- Secondly, at non-complaint pumps in LACT units less than 80 km from the Bonny Terminal (where there may be indeterminate loss or gain accruable to all non-compliant meters).

If there is a net loss after applying Step 2 in Directive C then the fully complaint LACT unit is included in crude loss and theft computations as specified by Directive D. Since loss to theft is indeterminate, then any computed loss cannot be assigned to the injector with the fully complaint LACT unit and cannot be distributed proportionately since loss (or gain) is also indeterminate for other injectors using non-complaint meters. If there is a net gain after applying Step 2 in Directive C then the fully complaint LACT unit is not included in crude loss and theft computations as specified in Step 3 of Directive C. The proportional distribution of gain to other injectors of non-compliant LACT units on the trunk line is based on untenable assumptions and arbitrary for the reasons that loss (from the fully complaint LACT unit) is indeterminate and therefore gain (from injectors with non-compliant meters) cannot also be accurately determined. Injectors with Water Cut Meters on the NCTL were not included in the RMBM. If these injectors share the same trunk line with fully compliant LACT units, then the arguments in Observation C above also apply. Losses from sections on the trunk that can only be assigned to fully compliant LACT units will be shared proportionately with LACT units using WCM using the replaced Interim Methodology. The IM is applied even though non-compliant LACT units are not affected by sabotaged sections on the trunk. They are penalized for injecting crude with non-compliant meters and not defective meters.While the use of the VCF

is based on international best practices it propagates the errors inherent in the proportionate distribution rule on the allocation of net loss (or gain) of crude at the Bonny and Forcados Terminals as expounded in Section 3 of Directive C and presented in Observation C above

4. Mathematical Explanation of the Reverse Mass Balance Methodology

To prove that the total crude oil loss in the trunk line can be reduced to independent measurement errors which are indeterminate let us assume that:

M_i be meter reading of mass of crude injected into trunk at flow station i in unit time

X_i is actual mass of crude injected into trunk for meter reading Mi from flow station i in unit time

- If $\Delta x_i = 0$ there is no error at flow station i in unit time
- If $\Delta x_i > 0$ there is a net loss at flow station i in unit time
- If $\Delta x_i < 0$ there is a net gain at flow station i in unit time
- $\Delta x_i = x_i - m$ is error in meter reading at flow station i in unit time

L_i is total loss from flow station i over a pump period T_i

$M_i = \Sigma x_i T_i$ is Fiscalised mass at Oil terminal injected from flow station i over a pump period T_i

5. Assumption: No Measurement Error But There Is Theft at Two Locations
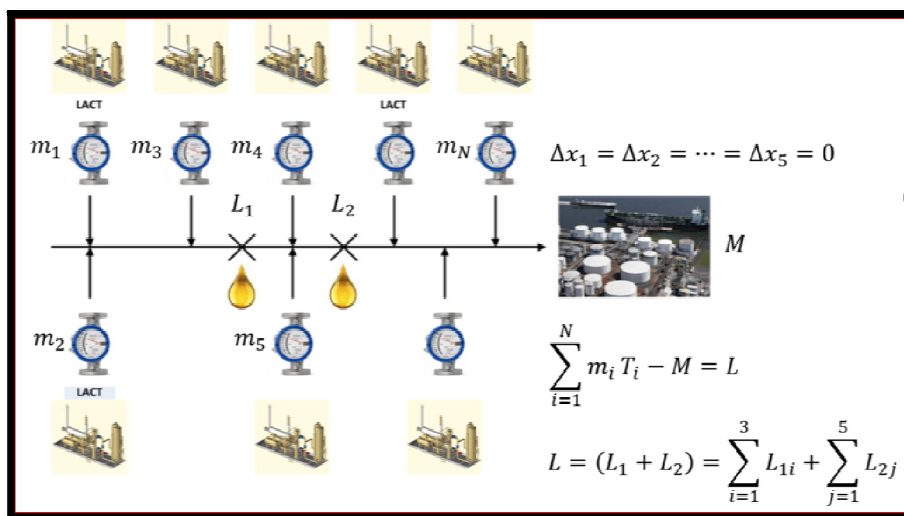

Figure 2: Trunk Line Showing Multiple Point of Sabotage or Failures

The missing fiscalized mass, ΔM at the oil terminal is the sum of two indeterminate values E(Error due to measurement) and L (loss due to sabotage), and since L = L_1 + L_2, it is easily shown in figure 2, that the total crude oil loss in the trunk line can be reduced to independent measurement errors which are indeterminate.
Also,

$$\sum_{i}^{N} m_i T_i - M = \sum_{i=1}^{3} L_{1i} + \sum_{j=1}^{5} L_{2j} \qquad\qquad (1.0)$$

$$\left(\sum_{i=1}^{3} m_i T_i - L_{1i} - L_{2i}\right) + \left(\sum_{i=4}^{5} m_i T_i - L_{2i}\right) + \sum_{i=6}^{N} m_i T_i = M \qquad\qquad (2.0)$$

The RMBM will fail in all scenarios where there are multiple points of failures in between any arbitrary selection of flow stations. Applying the proportionate rule for distribution of losses will be inequitable since the missing fiscalized mass at the terminal(ΔM) is a net value with unknown independent errors, the application of Proportionate rule of Reverse Mass Balance Methodology (RMBM) is inequitable. Even when it is assumed that flow station with LACT units are without errors, proportional rule for distribution of loss to injectors without LACT units is still inequitable because for some injectors the errors (Δ_{xi}) is greater than zero while other injectors the errors (Δ_{xi}) is less than zero.

In competitive upstream sector of crude oil supply chain, inequitable distribution of loss will adversely affect crude producers and may drive them out of business.Operation in oil and gas industry in Nigeria is marred by petitions from concerned companies and there will be an increase in the unit cost of Production as most companies recede from facility sharing.

The aim of this research therefore is to highlight the issues the operators are facing with Reverse Mass Balance Methodology and discuss the alternatives – Artificial Intelligence and Mathematical Modelling of Flow and Leaks in a pipeline. We shall be discussing crude oil losses andexisting methodology for distribution of losses, artificial intelligence theory and optimization technique and the theories behind mathematical modelling of flow and leak detection in a pipeline.

6. Crude Oil Losses during Transportation

The volume of crude oil loss during transportation is the difference between the volume of crude oil at off-take (say flow station) and the volume of crude at the delivery end (terminal). Losses occur due to leakages, thermal and pressure losses, density difference, emulsion, evaporative (flash), and shrinkage. Leakages could be in form of ruptures due to aged pipeline, failure of valves or in form of sabotage for theft. Other factors influencing line loss are measurement errors due to inaccurate tank dip measurement, use of non-compliant meters, use of invalid meter factor, and water content of the crude and wax deposit in the line. Line losses are expressed in percentages of delivered dry tones.

The impact of measurement errors is such that one cm dip tank error will generate a volume loss or gain of 4 to 36 kl depending on the size of the tank (Srivastava M. 2013). The temperature of one-degree error will generate in crude volume of 0.08 to 0.1%. Density variation of 0.001 will result in crude weight variation of 0.1%. Water content has direct impact on line loss or gain (Srivastava M. 2013). In North America 0.30% is expected to be deducted from all crude oil received from transportation at the point of off-take and retained by the receiver to cover losses due to pipeline evaporative and shrinkage factors (Srivastava M. 2013),

In 2013, Srivastava, proffered control measures to reduce line losses which include the following
- Uniformity in measurement
- Automatic sampler to be installed to ensure error free measurement.
- Necessary Piping modifications to be carried out routinely.
- Mechanical mixer to be installed at all testing points.
- Close supervision which requires laboratory testing to ensure proper equipment calibration.

Srivastava (2013) discussed in details all the pipeline losses but did not discuss how to determine the volume losses in the pipeline transportation.

In a paper comparing the proportional distribution of losswith stratified methods in Krisna field, Hermawan and Kristanto (2019) enumerated the crude oil line losses to include emulsion, evaporative, shrinkage, leakages, sabotage and errors due to measurement. The paper however focused on emulsion, flash and shrinkage losses. Measurement errors and leakages including theft were not included in their study. These crude oil losses were categorized into individual and group losses. Emulsion and evaporative losses were considered as individual losses. Losses from emulsion is caused by the presence of based sediments and water (BS&W) and also when the temperature of crude oil is higher than the bubble point temperature, the light components of the crude will be released from the oil causing the evaporative losses (Hermawan and Kristanto, 2019).

The paper suggested that crude oil temperature must be maintained lower than its bubble point to minimize the evaporative losses. The paper further used empirical equation and Antoine equation to calculate emulsion correction factor (ECF) and flash correction factor (FCF) respectively(Hermawan and Kristanto, 2019). Group losses occur when crude oil of different densities is mixed. The viscosity of oil and GOR were left out in the calculation ofgroup loss because of the mixing phenomena in the storage tank, the study used mixed crude oil from 7 different shippers and chose equation of API 12.3 for the calculation of shrinkage losses. The shrinkage correction from the proportional method almost the same with all shipper which was 0.20% while that of stratified methodology was between 0.05 and 0.31%. Their study recommended stratified methodology for the sharing of crude oil losses(Hermawan and Kristanto, 2019).

The use of simulation-based leak detection systems is gaining popularity and some companies' market software modules for that specific purpose. Two different detection methods currently in use: are neural network-based decision making and the calculations based on flow models. Implementing a particular leak detection system requires studies of how accurately various types of leaks can be detected by the desired method when fed by signals from temperature, pressure and flow meter sensors. The desired leak detection accuracy has an impact on the chosen system's costs and complexity(Lam Hong Lee et al, 2013).

The incidence of oil and gas pipeline leaks and failures are now rampant hence caused loss of life, properties and irreversible damages to the environment(Lam Hong Lee et al, 2013). This is because there has not been a full-proof method of inspection on the oil and gas pipelines condition (Lam Hong Lee et al, 2013). It was difficult for the existing failure prediction system to detect the onset of corrosion and other defects which caused unplanned shut downs and disruption of energy supply(Lam Hong Lee et al, 2013).The installation of a long ranged ultrasonic transducers (LRUTs) which will provide an inspection platform that monitors on continuous basis the critical pipeline sections was suggested. Real time data are acquired and processed to make informed decision on the condition of oil and gas pipeline in order to provide timely sufficient information for the operators to plan and organize shut down before it occurs (Lam Hong Lee et al, 2013).

7. Artificial Intelligence in the Oil and Gas Industry

Artificial Intelligence can optimize and automate data rich processes to mitigate business risks. It has capability to increase efficiency. It is the cost effectiveness that is making the technology increasingly attractive and speedy in its adoption across the sectors of oil and gas industry (Robert Tian, et al 2016). Successfully application of Artificial Intelligence in Petroleum Industry started in early 1990s initially from solving simple task tomore complex optimization and modelling problem involving hybrid systems (Popa et al., 2012). H. Rahmanifard et al.,(2018)in their paper,'Application of Artificial Intelligent Techniques in the petroleum industry' gave detailed literature on the type of artificial intelligent algorithms and their areas of application in petroleum industry.

Artificial Intelligence is seen as a tool that would assist oil and gas companies make accurate decision that would bring down their unit cost of production and increase their profit margin. In a few more years Artificial Intelligence

powered industrial internet of things (IOT) comprising of more than a trillion sensors will generate and share data that would dramatically change the way oil and gas industry operate(syncedreview.com, 2018)

Artificial intelligence has found application in various aspect of the oil and gas business and has been deployed in different countries. In Prudhoe Bay oil production, Alaska, a series of neural network model was developed to optimize the facilities against ambient temperature swings, compressor failures, or planned maintenance. A state-of-the-art algorithms-based optimization tool was developed to determine the rates of gas discharge and pressure at each separation facility. This helped to maximize oil rate at a given ambient temperature in the field and this was achieved by building a representative model of the gas transit pipeline system(Mohaghegh et al., 2008).

In Romania oil field, in order to ease the pipeline transportation of viscous crude, a blend of two or more different crude oil were used and with application of a new algorithm based on discrete time neural network, the oil blend properties evolution was found. This was an illustration of effective modeling approach of crude oil blend using neural network system (International Multidiscipline Scientific Geo-conference - SGEM). In western Canada, optimum operation of a pipeline system was achieved by the use of neural network to predict the demands of a pipeline system in the city of Regina, resulting in an increased performance and reduction in the energy consumption of the pumping station (N.Lertpalangsunt et al, 1995). In order to provide the industry with a friendlier reliable and cost-effective technique for handling of pipeline leakage, artificial neural network was integrated with OLGA simulator and was able to locate 90% of the induced leaks to a distance that is less than 10m away from the actual leak location (Afebu, 2015).

The two most promising Artificial Intelligence techniques for determining the leak volume from a pipeline is the Particle Swarm Optimization (PSO) and the Genetic Algorithm (GA) methods. The PSO is based on natural pattern of bird flocking or schooling of fish. It starts with the generation of random population and using fitness function value to evaluate and update population and then search with random techniques. Particles Swarm Optimization technique considers unique position of particles vector in the search space and motion velocities of the particles. The Particles Swarm Optimization method therefore produces random particles' positions and velocities. Each particle updates its position and velocities iteratively until satisfactory solutions are obtained. Particles best experience (Pbest) and the others' best experience (gbest) are combined in Particles Swarm Optimization method to update the particles' position in each iteration (H. Rahmanifard et al 2018).

Genetic Algorithm applies 'population' of solution also known as 'parents' to generate 'offspring population' of solution. This is said to be similar to natural evolution in which the new generation appears 'smarter'. The Algorithm deploys mathematical operators like crossover and mutation which is same as natural mating/ breading and genetic mutation, each generation evaluates solution against objective function and repeat the process for other generations until objective function is met. The resultant solution in the current population is termed 'algorithms solution' to the problem posed. Genetic Algorithm is also very attractive to the oil and gas industry because of its ability to search very large spaces and multiple data for optimal solutions (Holland ,1975).

Artificial Intelligence approach therefore is expected to be an improve methodology for leak detection and calculation using object oriented modelling. The flow of crude in a pipeline can be modelled and leak volume determined with Crude Received Optimizer (CRO) using PSO as follows:

If $\{V: \sum_{j=1}^{N} a_j\}$ $represent\ the\ crude\ pumped\ from\ a\ flow\ station\ where\ V\ is\ the\ pumped\ volume,\ \ and\ \sum_{j=1}^{N} a_j = 100\ represents\ the\ assay\ and\ j\ represents\ the\ hydrocarbons\ in\ the\ assay\ (eg\ j = 1\ represents\ Alkenes)$

Given that $\{V^{recv} \sum_{j=1}^{N} a_j^{recv}\} represents\ the\ crude\ volume\ received\ at\ the\ terminal$

and $\{V^{pump} \sum_{j=1}^{N} a_j^{pump}\}$ $represents\ the\ crude\ volume\ pumped\ from\ \iota^{th}\ injector$

where $\iota = 1., 2, \ldots\ldots M$

Particle Swarm Optimization (PSO) would track a near Optimum $\{V^* \sum_{j=1}^{N} a_j^*\}$ such that $|V^{recv} - V^*| \cong 0$

And for each $|a_j^{recv} - a_j^*| < \varepsilon$ smallest error ε

Particle swarm Optimization Algorithm will be deployed to find $V^* = \sum_{j=1}^{M} V_i^*$ (where V_i^* is actual volume received for the $\iota^{th}\ injector$)in the following steps:

Step 1: Initialize the PSO parameters and $\{V^{pump} \sum_{j=1}^{N} a_j^{pump}\}$ for each injector

Step 2: Generate a population of solutions or particles

Step 3: Move each solution or particle in the search space using the following equations

$$v_{ij}(n+1) = v_{ij}(n) + C_1 r_{1ij}\left(P_{best,i} - x_{ij}(n)\right) + C_2 r_{2ij}\left(g_{best,i} - x_{ij}(n)\right)$$
$$x_{ij}(n+1) = x_{ij}(n) + v_{ij}(n+1)$$

Step 4: Evaluate the fitness of each particle

Step 5 Update P_{best} and g_{best}

Step 6: if error is less than ε terminate otherwise go to step 3

8. Mathematical Flow Modelling of Fluid in a Pipeline

The gathering lines (GLs) or injectors supply a trunk line with the fluid it delivers to the terminal. Therefore, both the flow in the GLs and the trunk line should be studied to fully understand the system. In a GL, the fluid properties (for example, density and viscosity) are assumed to be constant throughout the length of the pipe. A gathering line has an entry and exit pressure and the pressure along the pipeline decrease at a constant rate between its point of entry and exit. Different gathering lines supply the trunk line with crude of different properties at various points along the trunk line. Therefore, the properties of the comingled crude changes from one custody transfer point (CTP) to another custody

transfer point. The trunk line operator generally provide the injector operators with a specifications about flow rates and pressure at CTPs and injectors supply crude to the trunk line at these specification to prevent backflow into the GL. The pressure profile and fluid properties in the trunk line is generally more complex than that in a GL. The volume losses experienced in a GL are individual (due to flash and emulsion) and leak losses, while that for a trunk line are group (mainly shrinkage) and leak losses. Leak losses are easily accounted for in GLs because of the pressure and flow meters at important junctions (entry and exit). However, it is more difficult to account for leaks in the trunk line, especially if the leak occur upstream of other GLs. This study will mathematically model flows in the GLs and in the trunk line, and will account for both individual, group and leak losses.

9. System of Equations for Modeling One-Dimensional Flow in Pipes
The mathematical modeling consists of the equations as follows:

1. Continuity equation

$$\frac{\partial \rho S}{\partial t} + \frac{\partial \rho v S}{\partial x} = 0 \tag{3.0}$$

2. Momentum equation

$$\rho\left(\frac{\partial v}{\partial t} + v\frac{\partial v}{\partial x}\right) = -\frac{\partial \rho}{\partial x} - \frac{4}{d}\tau w - \rho g \sin\alpha(x) \tag{4.0}$$

3. Equation of mechanical Energy balance

$$\frac{\partial}{\partial t}\left(\frac{\alpha k v^2}{2}\right) + v.\frac{\partial}{\partial x}\left(\frac{\alpha k v^2}{2} + P(\rho) + gz\right) = vg.\iota \tag{5.0}$$

4. Equations for frictional factor:

     a) Laminar Flow:

$$\lambda = \frac{64}{Re} \tag{6.0}$$

     b) Turbulent flow:

$$\frac{1}{\sqrt{f}} = -2 * \log\left(\frac{\varepsilon}{3.7D} + \frac{2.51}{Re\sqrt{f}}\right) \tag{7.0}$$

5. Relationship between change in pressure and flow rate:

     a) Laminar Flow:

$$Q = \frac{\pi \Delta p r_0^4}{8\mu L} \tag{8.0}$$

     b) Turbulent Flow:

$$P_1 - P_2 = \frac{f \,.\, L \,.\, sg \,.\, Q^2}{D^5} \tag{9.0}$$

6. Head and Exit Losses:

$$h_f = \left(\sum_1^n C_i + \frac{fL}{D}\right) x \frac{v^2}{2g} \tag{10.0}$$

10. Modelling a Slightly Compressible Fluid
There are processes which require that account is taken of even a small variation in fluid density, for example at custody transfer point in the trunk line with crude oil of different densities. For this model the fluid density depends on pressure as follows:

$$\rho(p) = \rho_0[1 + \beta(p - p_0)] \tag{11.0}$$

Where β (1/Pa) is the compressibility factor; ρ_0 the fluid density at normal pressure p_0. The compressibility factor is the inverse of the elastic modulus K (Pa).

For fluid of different specific gravity mixing, the relationship can be expressed as volume fraction:

$$sg_{mix} = \frac{sg_1 x_1 + sg_2 x_2 + \cdots + sg_n x_n}{\sum_{i=1}^{n} x_i} \qquad (12.0)$$

The viscosity of the mixing fluid is given by:

$$In\mu_{mix} = \sum_{i=1}^{N} x_i In\mu_i + \sum_{i=1}^{N}\sum_{i=1}^{N} x_i x_j d_{ij} \qquad (13.0)$$

Where $x_i x_j d_{ij}$ are the binary interaction parameters.

11. Modelling Emulsion Losses in the Gathering Line
To calculate the emulsion losses the following equations apply:

$$\gamma_1 = a_1 x_1 + b_1 \qquad (14a)$$

$$\gamma_2 = a_2 x_2 + b_2 \qquad (14b)$$

$$\chi_2 = \frac{(Y_2 - b_2)}{a_2} \qquad (14c)$$

$$ECF_i = X_1 - X_2 \qquad (14d)$$

Where:
X_1 = Measured BS&W
X_2 = % Volume of additional water
Y_2 = Calculated SG
Y_1 = Measured SG
a_1, b_1, a_2, b_2 = Constants

12. Modelling Shrinkage Losses in the Trunk Line
To calculate the shrinkage losses in at the respect comingling points the following equations apply:

$$\xi_{ji} = \frac{\chi_i \frac{1}{sg_i}}{\sum_{j=1}^{n} \chi_i \frac{1}{sg_i}} \qquad (15)$$

$$\xi_{ji} = \xi_{1i} + \xi_{2i} + \cdots + \xi_{ni} \qquad (16)$$

$$v_{ji} = v_{1i} + v_{2i} + \cdots + v_{ni} \qquad (17)$$

$$SCF_i = \frac{\xi_{ji}}{v_i} \qquad (18)$$

$$v_{ni} = \frac{\frac{\chi_{ni}}{sg_i}}{\sum_{j=1}^{n} \frac{\chi_n}{sg_n}} \cdot v_{sh} \qquad (19)$$

The total shrinkage loss, v_{sh}, is the difference in expected and actual volume between the meter reading at the custody transfer point and the next meter reading when there is no leak in the pipeline; SCF_i is the shrinkage factor, and v_{ni} is the shrinkage volume allocated to a particular injector.

13. Mathematical Modelling of Leaks in a Circular Pipe
Leaks occurs in a pipeline due to fatigue from operating the pipe, natural disasters, and sabotage. Leaks are common occurrence in pipeline operations and it is important to accurately calculate the volume of leaks for accurate crude accounting.
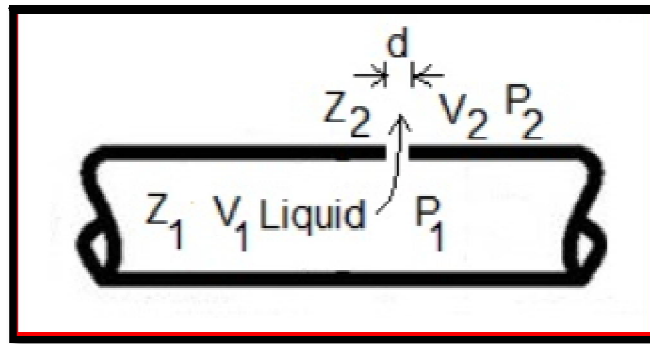
Figure 3: Schematic of a Leak in a Pipe

In Figure 3, a fluid flows in a pipe with velocity, V_1, and pressure, P_1, and it becomes ruptured. Let the diameter of the rupture be d and the pressure outside the pipeline be P_2. The velocity at which the fluid flow through the rupture can be obtained solving the Bernoulli equation:

$$0 = Z_2 - Z_1 + \frac{P_2 - P_1}{\rho g} + \frac{V_2^2 - V_1^2}{2g} \qquad (20)$$

V2 >> V1 as pipe diameter is far bigger than the hole, and we assume that, elevation, $Z_2 = Z_1$

Therefore:

$$V_2 = \sqrt{\frac{2(P_1 - P_2)}{\rho}} \qquad (21)$$

$$Q = CAV_2 = CA.\sqrt{\frac{2(P_1 - P_2)}{\rho}} \qquad (22)$$

Where C is the coefficient of discharge and A is the area of the leak with diameter, d.

14. Leak Detection, Location and Allocation

Using simulation-based leak detection systems is also becoming increasing popular, and some companies' market software modules for that specific purpose. There are two different detection methods currently in use: the neural network-based decision making and the calculations based on flow models.

Implementing a particular leak detection system requires studies of how accurately various types of leaks can be detected by the desired method when fed by signals from temperature, pressure and flow meter sensors. The desired leak detection accuracy has an impact on the chosen system's costs and complexity. The decision on the required accuracy to target is an important part of deciding which system to install. Note also that implementation phase has not always been completely successful in previous leak detection projects. It is very crucial to bring all stakeholders on board in the system planning, design and testing, and while developing standard operational procedures.

Leak detection and location in a pipeline using flow models has important application of pipeline real-time model. Two most important numerical methods for the performance of this function are:

- Deviation Analysis: Here leak can be detected when the measured values at the end of pipeline deviate from the computed values of pressure and flow rates
- Model Compensated Volume Balance: This method is achieved by comparing in real time the measurement generated by the flow balances (meters) with that generated by the model (packing rates). The packing rate is the inventory rate of change in the pipeline as computed by the model.

The Compensated Volume Balance method is mathematically described as follows:

$$FB = \sum_x F_x^{in} - \sum_x F_x^{out} \qquad (22.0)$$

Where F_x^{in} and F_x^{out} are measured flows in and out of the pipeline.

PK = F (P_1, P_2, T_1) (23.0)

VB = FB- PK   (24.0)

Where PK and VB are packing rate and volume balance respectively.

The volume balance equals to zero at no- leak conditions but when the leak occurs, the packing rate will sharply drop and flow balance goes up in response to the leak. This gives rise to positive value volume balance that signifies a leak. The leak location is realized by the modeling the pressure drops along the leg of the pipeline and matching the modeled with the measured pressure drop.

The leak volume is allocated at the point of rupture to the respective injectors with crude in the trunk line system up to that point with the following equation:

$$q_i = \frac{m_i}{\sum_{i=1}^{N} m_i} \, x \, q_{leak} \qquad (25.0)$$

15. Conclusions

The RMBM replaced the much less effective Interim Methodology (IM). However, operators are still unsatisfied and have continued to write petition about unfair deductions from trunk line operators for crude supplied. This petition

seems genuine as the current RMBM practices is unfair to injectors downstream of a leak. Leak volumes are deducted from injectors downstream of a leak even though theoretically their crude is not part of the leaked volume. The RMBM does not make any effort to identify the point of leak before the proportionate rule is applied and injectors' volume correct; instead, the proportionate rule is applied at the terminal. With the Proportionate rule, the loss is allocated as a percentage of an injector production to the total production in the trunk line. This method punishes high producers and subsidizes their losses at the expense of the revenues of the other injectors.

Furthermore, the RMBM in its present form does not take into account individual and group losses as crude for different injectors tend to have different properties, it corrects for only leak and meter factor. Applying artificial intelligence or fluid flow models are two methods that could identify and equitably allocate losses to each injector.

Mathematical modelling of the entire pipeline system identifies and corrects for individual losses in the GLs; identify and corrects for group losses in the trunk line; identify the point of leak and leak volume; and allocate and corrects for leak volume at the point of leak. The point of leak is calculated by deviation analysis, where the estimated pressure profile and flow rate in the trunk line is compared with the actual along the pipeline.

This is an improved method over the RMBM; however, the PSO or Genetic Algorithm does a better job in tracking fluid flow and identifying leak volumes when compared to the mathematical method for leak detection and allocation. This is because in a premeditated leak/ rupture where the crude oil is siphoned at unusual velocity, the mathematical modeling may not be able to calculate the loss volume when the velocity is not known.

Artificial neural networks provided a more powerful and sophisticated method for crude accounting along the pipeline system; but this method will require heavy investments and significant changes to how operations are currently run.

16. Recommendations
We recommend that:
- A case-study based approach should be used to investigate and quantify the improvements the flow-based modelling has over the RMBM.
- A case-study based approach to investigate the improvements PSO have over flow based leak models in leak volume calculation and allocation.

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