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A New Pressure-Based Modeling Approach for Early Leak Detection in Gas Processing Plants Using Machine Learning

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

Natural gas is composed mostly of methane, the simplest hydrocarbon molecule, with only one carbon atom. But most gas at the wellhead contains other hydrocarbon molecules known as Natural Gas Liquids (NGL). Heavier gaseous hydrocarbons such as propane (C_3H_8), normal butane (n-C_4H_{10}), isobutane (i- C_4H_{10}) and pentanes, may also be processed in gas plants and exported as Liquified Natural Gas (LNG). During operational services in gas plant from inlet to outlet piping, gas leaks tend to occur undetected at some points in the facility. Apart from loss of gas resources, leaks and venting at natural gas processing plants release other pollutants besides methane (e.g., benzene, hexane, hydrogen sulfide) that can threaten air quality and public health. Hence, the need for early detection of gas leaks by using appropriate Machine Learning (ML)

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models. Insight from existing general flow equations was used to develop a new modelling approach for Machine Learning, in a test case: Gas Plant JK – 52. Input gas pressure data is calibrated and evaluated for consistency in real-time. The data is then corrected for lag-time and used to compute tolerance. Indicated time of alarm is checked against events such as residual gas, supply, pumping, etc. Where alarm is eventless, leak is suspected and eventually confirmed, suggesting that action should be taken to mitigate against the leakage. Following the input of a split training dataset, different types of regressions were used for the machine learning before automating the system for real-time evaluation and detection. Linear regression provided a 39% test accuracy, which was considered too low. This led to the use of random forest regression, which provided a 95% test accuracy and was considered excellent. It is hoped that with continuing data acquisition in gas plants employing this algorithm, further modelling will become more predictive as machine learns from experience.

Keywords: Machine learning; gas leaks; pressure-based model; gas plant; forest regression; detection; training data set.

1. INTRODUCTION

"Natural gas is composed mostly of methane, the simplest hydrocarbon molecule, with only one carbon atom. But most gas at the wellhead contains other hydrocarbon molecules known as natural gas liquids, such as ethane (with two carbon atoms) and propane (with three carbon atoms). Therefore, it is sent to processing facilities, where most of the natural gas liquids are removed and sold separately" [1]. "Gas processing facilities produces consumer-grade natural gas, which is primarily made up of about 95% methane. During these operational services, gas leaks tend to occur undetected early enough. This undetected gas leakage can lead to undesirable economic loss of natural gas from installed facilities and are often accompanied by toxic air pollutants that typically pose safety and public health concern" [2]. However, for safety officers and plant managers trying to keep up with the evolution of detection technology are finding it difficult since no single system or technology is the solution to every plant's problem [3]. This research will develop a model using machine learning algorithms to detect gas leaks based on available data and present the one with highest accuracy.

2. NATURAL GAS COMPOSITION

Natural gas is a naturally occurring gas mixture, consisting mainly of methane sourced from supply basins in western Canada, the United States and Ontario producers.

Composition is an overall system average and may vary from the typical value listed below by location.

Table 1. Composition of natural gas

Component	Typical analysis (mole %)	Range (mole %)
Methane	94.7	87.0 - 98.0
Ethane	4.2	1.5 – 9.0
Propane	0.2	0.1 – 1.5
iso – Butane	0.02	trace – 0.3
normal - Butane	0.02	trace – 0.3
iso - Pentane	0.01	trace – 0.04
normal - Pentane	0.01	trace – 0.04
Hexanes plus	0.01	trace – 0.06
Nitrogen	0.5	0.2-5.5
Carbon Dioxide	0.3	0.05 -'1.0
Oxygen	0.01	trace – 0.1
Hydrogen	0.02	trace – 0.05
Specific Gravity	0.58	0.57 - 0.62
Gross Heating Value (MJ/m^3), dry basis *	38.8	36.0 - 40.2
Wobbe Number (MJ/m^9)	50.9	47 5 - 51.5

3. GAS LEAKS DURING OPERATIONS

Leaks are found relatively often in the extensive pipeline systems on industrial sites and they can be tracked back to various causes. In the case of leaking fittings, it is usually the unavoidable aging process, the lack of operation and maintenance, whereas in the case of leaky threaded connections, the use of hardening sealant can be observed.

"A natural gas leak refers to an unintended leak of natural gas or another gaseous product from a pipeline or other containment into any area where the gas should not be present" [4].

Gas leaks are invisible, unregulated and majority go unnoticed. These leaks may depend on any of the following: operation practices, equipment age and maintenance. Leaks and venting at natural gas processing plants release other pollutants (e.g., benzene, hexane, hydrogen sulfide) besides methane that can threaten air quality and public health. Hence, there is need for early detection of gas leaks by using appropriate Machine Learning models. Nigeria is a province of gas with pockets of oil [5], and the use of pipeline is considered as a major means of conveying petroleum products which serves as the major assets to the Nigeria economy and should well protected. Gas leaks can be hazardous to health as well as the environment. “Gas leaks from pipelines may give an odor of gas in the air while gas from landfills may not give an indication of odor. Affected soil from a gas leak will have a characteristic blue-black color and rotten egg odor. Roots killed by gas will be blackened and necrotic” [6].

“Natural gas leaks can also cause smaller-than-normal leaves on trees, wilted plants and yellowish patches of grass. Symptoms of exposure (Physical symptoms of natural gas poisoning) to low levels of natural gas include headaches, dizziness, fatigue, nausea and irregular breathing” [2]. “The most common cause of gas leaks is damage to underground utility lines. If you will be digging on your property, does it safely to avoid breaking gas utility lines (as well as other utilities like fiber-optic cables)” [2].

“Even a small leak into a building or other confined space may gradually build up an explosive or lethal concentration of gas. Leaks of natural gas and refrigerant gas into the atmosphere are especially harmful due to their global warming potential and ozone depletion potential” [2]. Leaks of gases associated with industrial operations and equipment are also generally known as fugitive emissions.

Natural gas leaks from fossil fuel extraction and use are known as fugitive gas emissions. Such unintended leaks should not be confused with similar intentional types of gas release, such as:

a. Gas venting emissions which are controlled releases, and often practiced as a part of routine operations, or "emergency pressure releases" which are intended to prevent equipment damage and safeguard life.
b. Gas leaks should also not be confused with "gas seepage" from the earth or oceans either natural or due to human activity.

Pure natural gas is colorless and odorless, and is composed primarily of methane. Unpleasant scents in the form of traces of mercaptans are usually added, to assist in identifying leaks. This odor may be perceived as rotting eggs, or a faintly unpleasant skunk smell. Persons detecting the odor must evacuate the area and abstain from using open flames or operating electrical equipment, to reduce the risk of fire and explosion [7].

As a result of the Pipeline Safety Improvement Act of 2002 passed in the United States, federal safety standards require companies providing natural gas to conduct safety inspections for gas leaks in homes and other buildings receiving natural gas [8]. The gas company is required to inspect gas meters and inside gas piping from the point of entry into the building to the outlet side of the gas meter for gas leaks. This may require entry into private homes by the natural gas companies to check for hazardous conditions [8].

Gas leaks can damage or kill plants. In addition to leaks from natural gas pipes, methane and other gases migrating from landfill garbage disposal sites can also cause chlorosis and necrosis in grass, weeds, or trees. In some cases, leaking gas may migrate as far as 100 feet (30 m) from the source of the leak to an affected tree.

4. ANALYSIS OF GASEOUS POLLUTANTS AT PROCESSING PLANTS

“In addition to wasting a source of energy, leaked natural gas mostly methane is a powerful greenhouse gas. It is a significant contributor to climate change that makes it essential for gas utilities, and the regulators and public officials that oversee them, to act swiftly and decisively to repair and prevent all methane leaks. The gas utilities' pipe systems are just one link in the national gas supply chain that brings gas from the well to your home. Leaks are an issue at every stage, starting at the wellhead. That's why we're addressing leaks throughout the system” [9].

This research work is aimed at modeling innovative technological leak detection for gas processing plants using machine learning. The objectives are to develop a model for gas leak detection using machine learning. To generate a safety notification and improved flow system based on leak detection findings [10-12].

5. METHODOLOGY

The methodology that was followed during this study includes important steps to building a Machine learning model. The first step was to collect the required dataset and a preprocessing phase which includes cleaning the data, attempting a linear regression model and other regressions (Random Forest). The linear regression model and the random forest were used for predicting tolerance and gas leak detection.

The second step is to train the proposed model and evaluate its performance. A detailed description of the methodology is included in this paper. Fig. 2 summarizes the methodology of this study.

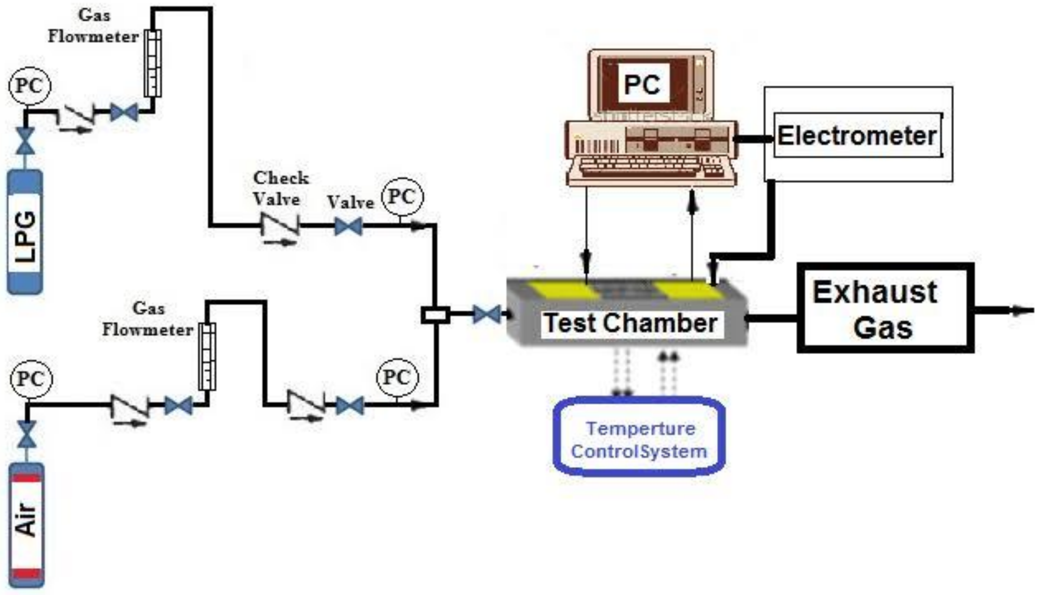

Fig. 1. Schematic diagram of detection unit for gas sensor performance

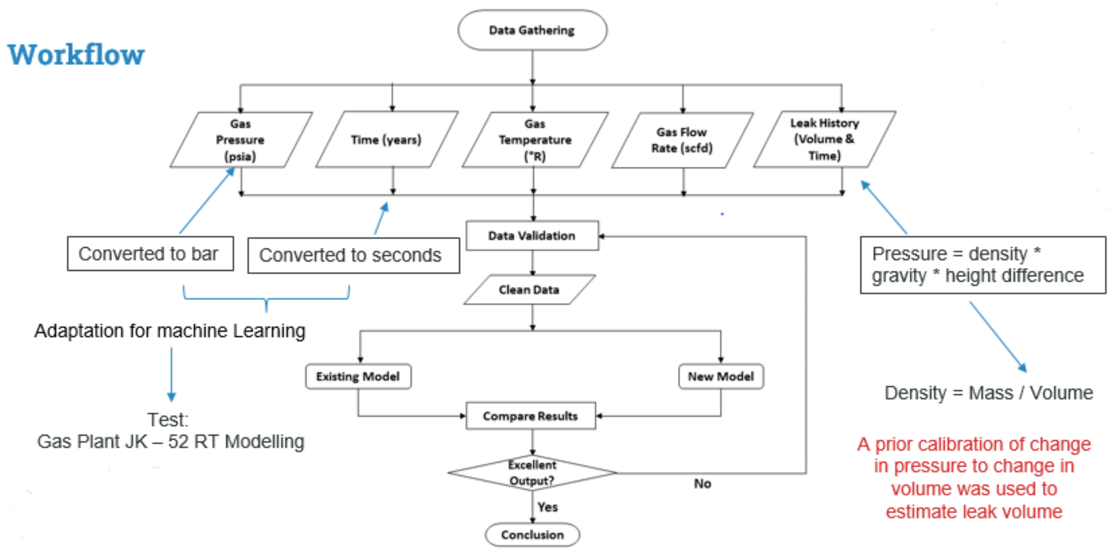

Fig. 2. Summary of the methodology

5.1 Data Collection

Data were collected with the help of the company. The data of different gas plant Operators with the sample data from 2010 to 2017 was collected. The dataset contains 48 features and 2795 instances, and it contains both categorical and numerical attributes. Additionally, the dataset could be used for regression and classification problems, and it is split into training and testing sets.

5.2 Formulations

This research made use of machine learning algorithms based on the general gas flow equation with input parameters such as pressure drop in a gas pipeline, taking into account the pipe diameter, length, elevations along the pipe, gas flow rate, generate a safety flow procedure for curbing leak detection based on findings and the gravity and compressibility of the gas. This was used to establish a reference by understanding the normal behavior of the process inflow. Consequently, any process flow that deviates from the reference signifies an anomalous behavior

The general flow equation is given as

$$Q = 77.54\left(\frac{T_b}{P_b}\right)\left(\frac{P_1^2 - P_2^2}{GT_f LZf}\right)^{0.5} D^{2.5}$$

Where:

Q = gas flow rate, standard, ft3/day (SCFD)
L = Pipe length, mi
D= inside diameter pf pipe, in.
P1 = upstream pressure, psia.
P2 = downstream pressure, psia.
Pb = base pressure, psia (usually 14.5 psia)
Tb = base temperature, R (usually 60+460 = 540 R)
Tf = average flowing temperature of gas, R
G = gas specific gravity (Air = 1.00)
Z = gas compressibility factor at the flowing temperature and pressure, dimensionless
F = friction factor, dimensionless

6. MACHINE LEANING MODELS FOR EARLY GAS DETECTION

6.1 Set Up of the JK - Gas Processing Plant

The following steps were carried out to describe the setting up of the JK-Gas Processing Plant. Fig. 2 describes the set up diagrammatically.

- In the gas plant of study, the effluent (a mix up of water, oil and gas) was pumped into the gas plant from nearby oil well.
- Crude stored in a Floating Production Storage and Offloading Offshore may also be tapped from a Tanker offloading / Lifting buoy and transported to the Gas Plant
- There is also provision for piped crude from multiple well clusters in the field to ensure constant source of hydrocarbon.
- The crude passes through a water-oil-and-gas separator, a purifier or a compressor as part of the refining or treatment process before delivering the final gas product

7. NEW PRESSURE-BASED MODELLING APPROACH FOR MACHINE LEANING

- Gas pressure measurement units in the industry may be in Bars or Psi or in other units. In the current work, pressure in the unit of Bars was adopted
- While most leakages become catastrophic and visible in months or years, the current work have reduced the time lapse of interest for detection in seconds
- Temperature affects gas considerably, so it was taken into consideration by not using direct volume measurement which changes with heat and expansion
- Due to limitation of direct estimation of volume, a linear relationship was sought to estimate leak volume from pressure drop in the flow system
- Gas leak volume result was presented in bars and in standard cubic feet (scf)

8. A CASE STUDY OF THE JK-52 GAS PLANT

8.1 Gas Plant JK – 52 Real-Time Case Modelling Analytics

The analytics in the modelling involves:

1. Lag Time: delay in reading between the Inlet and the outlet gauge
2. Tolerance: acceptable window of pressure gauge difference in normal flow
3. Leakage: increase in pressure gauge difference higher than the tolerance
4. Machine then learns the process to detect leakage automatically
5. The acceptable window of tolerance is also a way of checking that the gauges and flow are accurate, a Quality Control (QC) method termed Consistency.

6. The leak volume is then estimated based on a prior established calibration between the pressure drop and volume changes.

9. CALIBRATION OF INPUT GAS PRESSURE DATA

- Process 1: The gas plant stabilises and strips lighter gas or condensates to produce purified dry gas ready as end product
- Process 2: The alternate process processes crude effluent by first separating the water and trace or associated oil, before it is treated to remove impurities such as Carbon dioxide and sulphides). The resulting gas is then compressed or liquified (Liquified Natural Gas – LNG) for storage and eventual supply.
- In both cases, initial sensors and gauges are placed at the upstream (sourcing section) and at the downstream (receiving section) of the products.
- Inlet and outlet pressure gauges are placed across intervals with tendency of gas leak.

10. RESULTS AND DISCUSSION

10.1 Evaluation of Consistency in Real-Time

The real-time data is consistent if it plots within the tolerance window, set by the upper and lower limits of calibrated fluctuation, without leak.

10.2 Estimation of Lag-Time

The lag-time is given by the delay between the upstream and the downstream gauges, or the inlet and the outlet gauges, and must be taken into consideration in matching the plotted events.

10.3 Tolerance Computation

The tolerance window is earlier established in the residual and ramp up phases, usually close to 1 (when the value of the inlet and outlet pressure reading match) and much less or much higher than 1 when the reading indicate leakage or lifting / supply of the gas.

For gas detection result, the steps followed are Identification of Phases, Calibration of System (QC), Evaluation of Lag Time, Checking for Tolerance, Checking for Consistency, and Detection of Leakage. From Fig. 4, the red line represents inlet gauge while the blue line represents the outlet guage. Residual phase occur between 3500 and 5500 seconds below the pressure of 12bars. Residuals can be used to identify potentially problematic instances. For most models, residuals should express a random behavior with certain properties (like, e.g., being concentrated around 0). Having a negative residual means that the predicted value is too high, similarly if you have a positive residual it means that the predicted value was too low. The ramp phase occurs between 3500 and 6500 seconds above the pressure of 12 bars but below the pressure of 30 bars. The word ramp is used here as a sloping surface joining two different levels. So the ramp phase is the phase between the residual phase and lifting phase. Lifting or stabilization phase as is used here is a general term to denote all forms of gas collection which could be sampling, supply, pumping, etc. Fig. 4 showed that the gas sample can be collected at pressures between 30 bars and 40 bars. Fig. 5 showed the lag time as approximately 250 seconds. This occurred between the first and second lifting. Lag time is defined as the time interval between two lifting. Lag time creates a delay between two tasks that share a dependency. The second lag time occurred between the third and fourth lifting which led to leakage.

$$\text{Tolerance} = \frac{inlet\ guage}{outlet\ guage}$$

Min Cut-Off is 0.8 while Max Cut-Off is 1.2. From Fig. 6, it can be observed that tolerance was below minimum between 1300 and 5500 seconds which was acceptable due to residual gas in the system. Tolerance is above minimum between 6500 and 9500 seconds. This led to unexplained relative peaks which could lead to a leak.

Fig. 7 shows the combination of Fig. 5 and Fig. 6. It can be clearly seen that pressure of the tolerance is higher than the lifting pressure. Fig 8 gives the result for random forest regression, which showed that it provided a 95% test accuracy and was considered excellent.

10.4 From Volume-Based to Pressure-Based Gas Leak Detection Solution

Limitations of volume-based gas leak detection are:

1. Gas is not visible and leakage cannot be seen by physical observation
2. Gas may have a turbulent flow and may not obey flow principles (such as Darcy Law)
3. Gas expansion results in inconsistent volume estimation during flow
4. Gas may be dry or wet and has different densities / primary and secondary gases have different degrees of wettability
5. Gas (volume) is highly impacted by temperature and pressure.

Mitigation in the current work = Pressure-based gas leak detection model

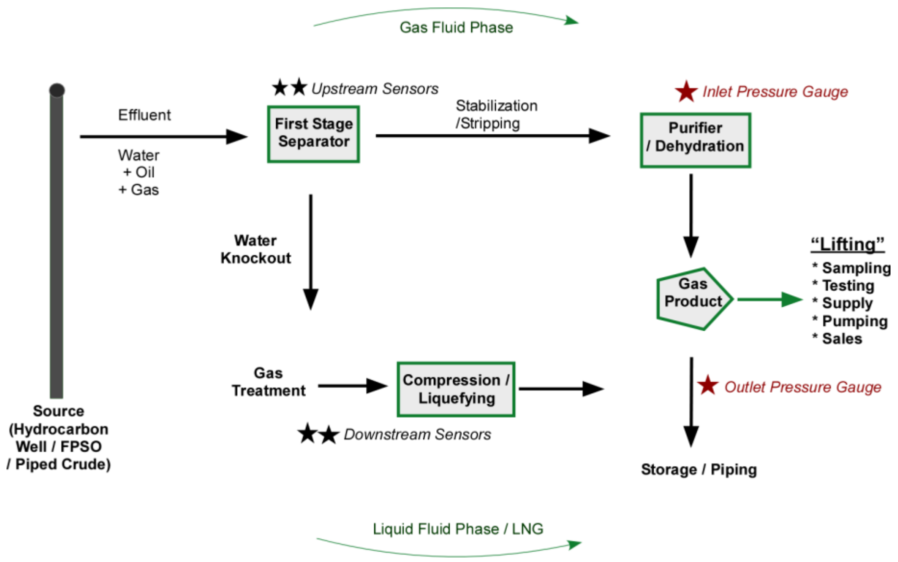

Fig. 3. Gas plant JK – 52 processing layout

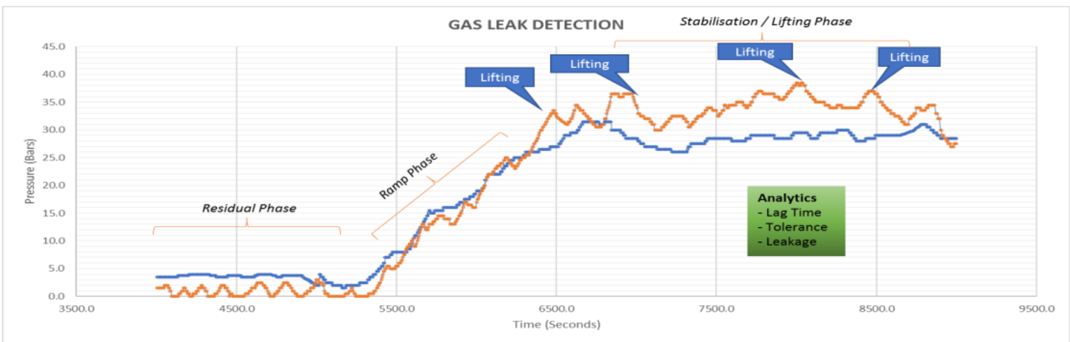

Fig. 4. Gas plant JK – 52 real-time case modelling

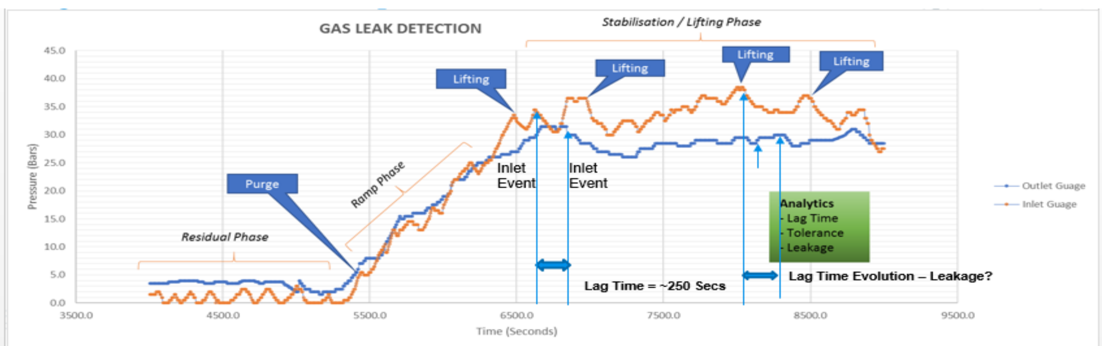

Fig. 5. Lag time evolution and implication

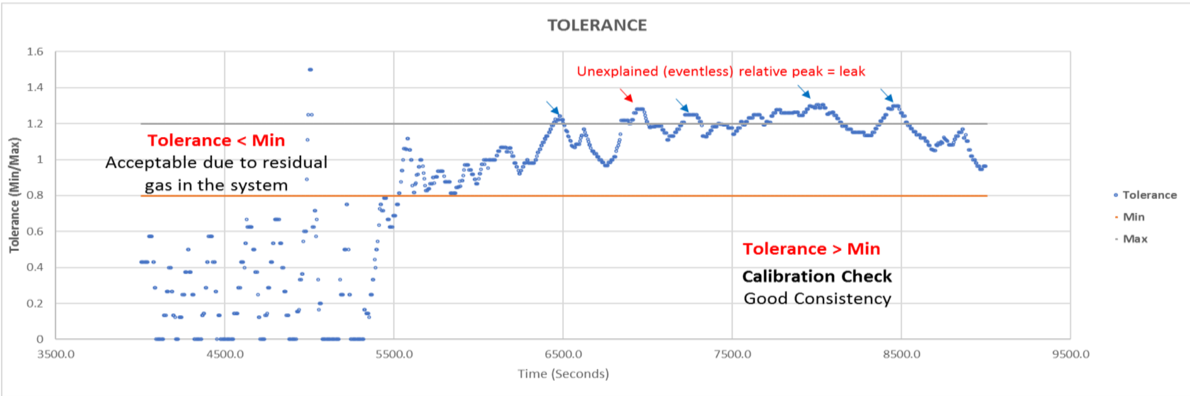

Fig. 6. Tolerance and implication for leakage

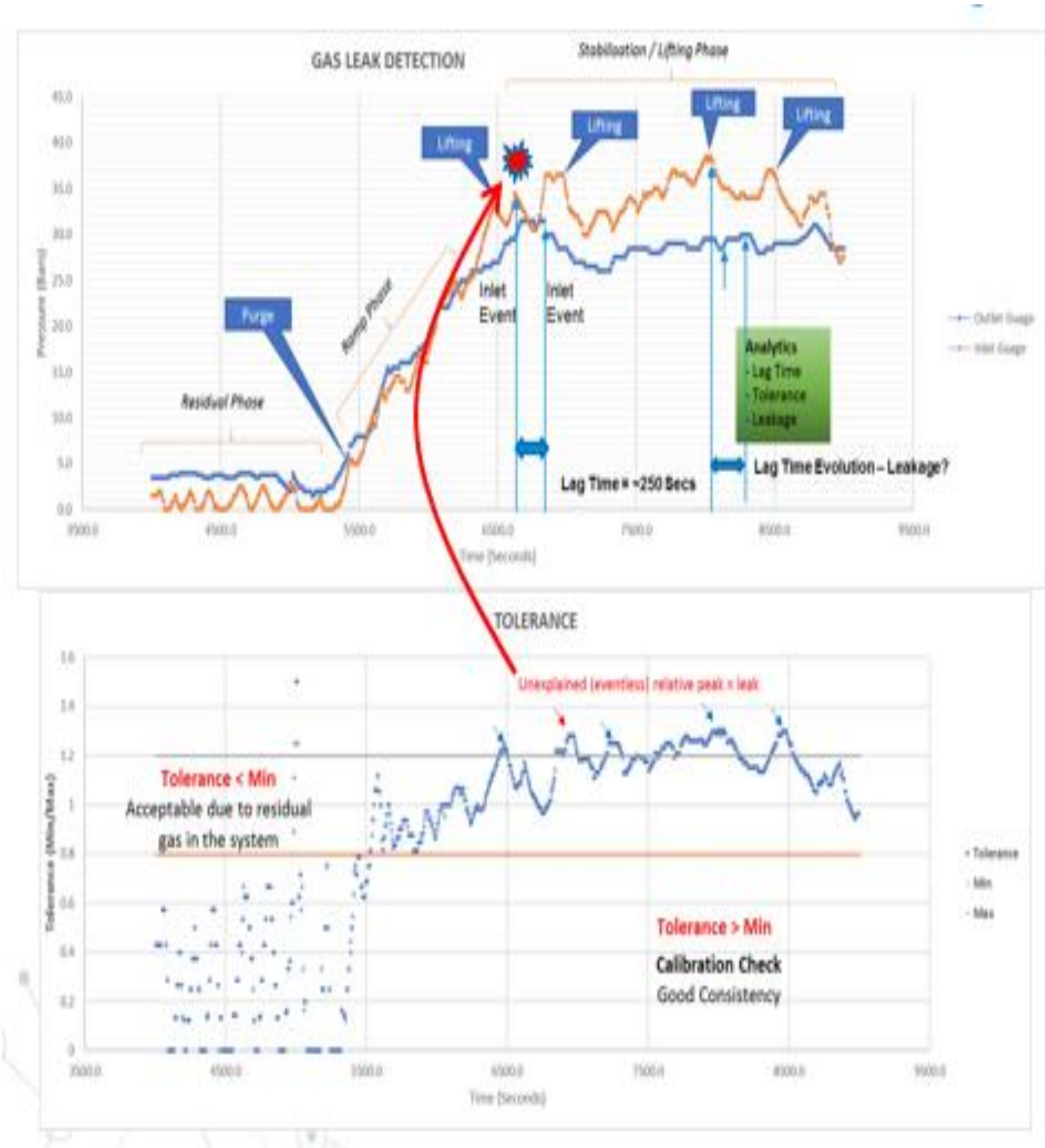

Fig. 7. Detection technics for machine learning

Table 2. Sample data

Time	Pr_final	Pr_initial	Events	Tolerance
4005	3.5	1.5	Residual s	0.428571
4010	3.5	1.5		0.428571
4015	3.5	1.5		0.428571
4020	3.5	1.5		0.428571
4025	3.5	1.5		0.428571
4030	3.5	1.5		0.428571
4035	3.5	1.5		0.428571
4040	3.5	1.5		0.428571
4045	3.5	1.5		0.428571
4050	3.5	2		0.571429
4055	3.5	2		0.571429
4060	3.5	2		0.571429
4065	3.5	2		0.571429
4070	3.5	2		0.571429
4075	3.5	1.5		0.428571
4080	3.5	1.5		0.428571
4085	3.5	1		0.285714
4090	3.5	1		0.285714

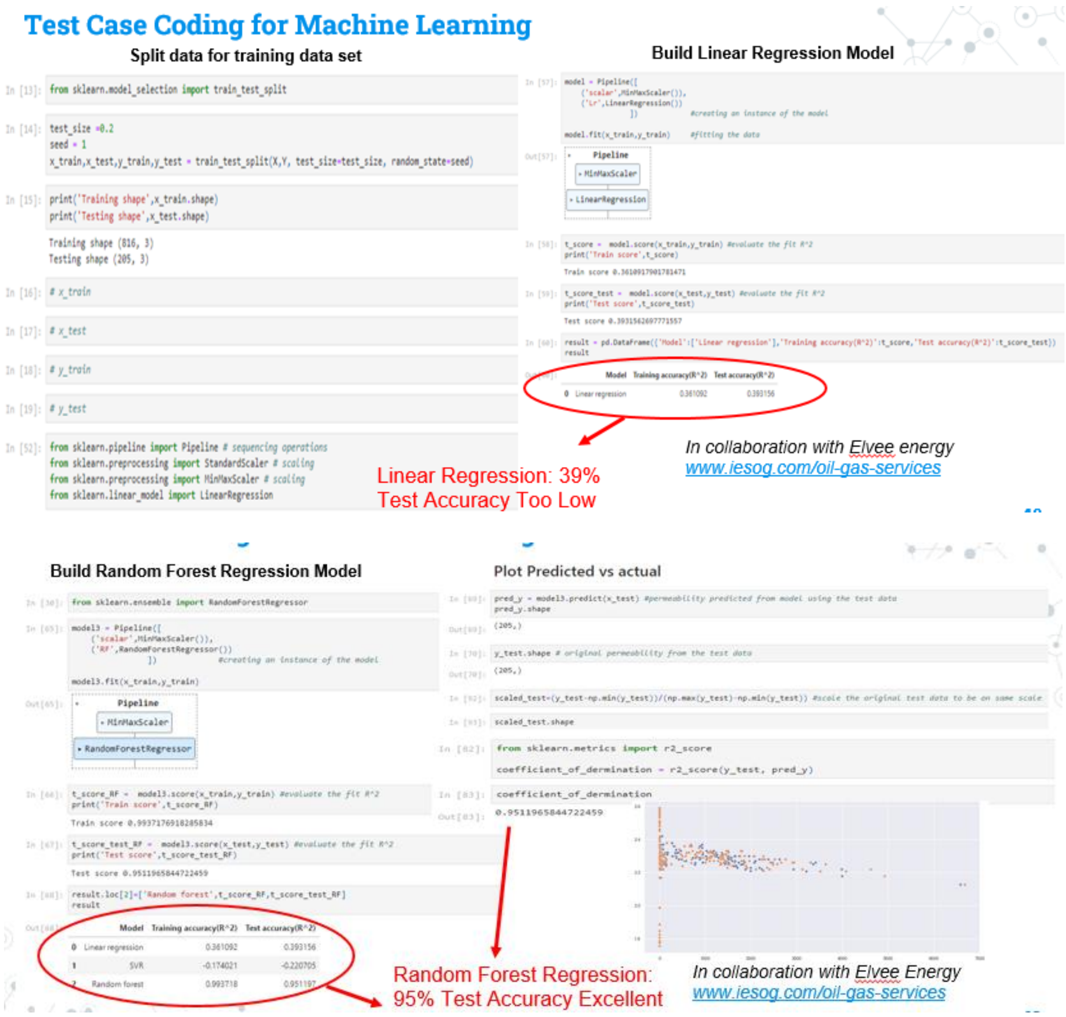

Fig. 8. Random Forest Regression Model

11. CONCLUSION

The following conclusions can be made from this research:

Input gas data is calibrated and evaluated for consistency in real-time. The data is then corrected for lag and used to compute Tolerance. Minimum and Maximum Tolerance Cut-Off is set based on machine training dataset. Where value is higher than maximum cut-off, machine sets off alarm.

Time of alarm is checked against events such as lifting, residual gas, e.t.c. Where alarm is eventless, leak is suspected and eventually confirmed. Leaked volume is estimated using a prior calibration relation. Action may taken to mitigate against the leakage. Further modelling becomes predictive as machine learns from experience.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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