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Geospatial Internet of Things: Framework for fugitive Methane Gas Leaks Monitoring

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Abstract

We present a framework for wireless sensor network monitoring and detection of methane leaks from natural gas well pads. The wireless sensor network can measure methane concentrations across a well pad and combined with advanced analytics it can locate and determine the leak rate. Simulations of the inverse and forward modeling problems indicates that methane leaks can be localized within a 1 m distance from their original locations. The wireless sensor network and real time analytics can be extended to monitor multiple methane leaks and methane background levels.

1. Introduction

Methane has a much larger global warming potential compared to carbon dioxide. Methane gas is emitted by agricultural and waste management sources, however more than 30% of emitted methane gas is coming from energy exploration sites (natural gas and petroleum system and coal mining). With more than half a million natural gas well pad sites developed in USA, understanding the impact of methane gas on human health and long term climate impact became important.

In the past, standalone high precision sensors were used to measure methane gas leaks. These measurements can offer a very precise methane concentration assessment but the spatial coverage is limited. Current methane measurement and modeling techniques are lacking the capabilities to localize leaks on a well pad (Zavala-Araiza 2015; Lyon 2015; Foster-Wittig 2015). An alternative method to detect methane leaks is using satellite observations. While the satellite methods offer a large scale geospatial observation, the spatial resolution of the detection method is too coarse for single leak detection (Turner 2015; Veefkind 2012). There is certainly a need to combine the high accuracy local wireless sensor measurements with large scale satellite observations for (1) accounting all methane leaks over a regional area and (2) attribute methane leaks to emission sources.

Here we present a novel methane monitoring solution based on wireless sensor network. Methane sensitive sensors are distributed on a 10 m grid and are measuring in real time the methane concentration. In addition, the wind direction and speed is measured as well. We note that each well pad have construction on their perimeters and an associated infrastructure (storage tanks, well heads, etc). These structures will cause turbulence to wind flow pattern. The well pad layout can be extracted from high resolution satellite or drone imagery. The layout is used for three dimensional reconstruction of a gas well pad and generate a Computer Aided Design (CAD) models. The CAD model is a necessary input into CFD for dispersion modeling. The advantage of our proposed method is that each methane leak can be identified and localization on a well pad.

The concept for large area methane measurements, across multiple well pads, in presented in Figure 1. Each of the 4 well pads have its own Wireless Sensor Network that measure methane and wind for that specific locations. Inter well pads communication is enabled using a Wide Area Network (WAN) to transfer the sensor data and computational load between well pads. Each well pad may have one or more Raspberry Pi computers that act as a computational platform and data gathering device (edge devices). If no leak is present on a well pad, the sensor values can be sampled every hour, however in case of large methane leaks the sampling rate may have to be increased to a measurement each second. Since significant amount of data may be generated on each well pad, data processing needs to be carried out on the edge device and only aggregated and processes sensor values are sent to the cloud platform.

Locations of the sensors on the well pad as well as the site layout are geospatially located. Measurement on a single well pad may be affected by a leak on a different well pad. This scenarios can

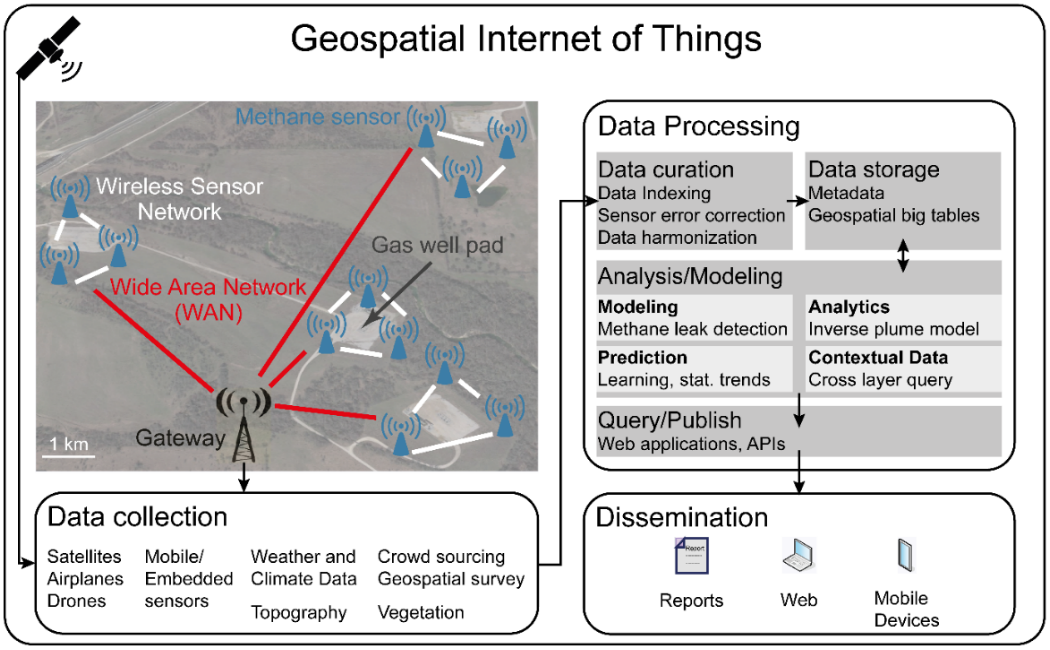

Figure 1 Geo-spatial Internet of Things architecture for methane leak sensing, modeling, and visualization.

be only addressed if the analytics models will utilize geospatial data; e.g. proximity of well pads are included into modeling along with topography and/or local vegetation. In our approach, wireless sensor network on a well pad is explored and the sensor point measurements are spatially linked with geospatial data (Klein, 2015). In the future, the IoT sensor measurement with GIS based analytics (Veefkind 2012) framework could be extended to multi pad methane leak monitoring.

2. Approach

A wireless mesh sensor network based on volatile organic compound sensors (VOC) is currently tested for 20 ppm methane plume detection sensitivity. Sensor analytics is developed to self-calibrate each sensors and compensate sensor reading for ambient temperature, humidity, and wind flow variations. The diffusion and transport of gas in the atmosphere strongly depends on local wind conditions. This fact plays a critical role in the detection and localization of gas sources. The modeling approaches described below assume that wind speed and direction are uniform within 10 m x 10 m. In order to get a better understanding of the statistical behavior of the wind, the distribution of wind speed and direction was calculated from two simultaneously acquired wind sensor readings (Figure 2 and 3). The angle mismatch between two sensors can be determined by calculating the maximum of the cross-correlation of two wind direction readings. The related difference in the angles is used to compensate for the mismatch.

The turbulence is homogeneous across the spatial length that separates the two wind sensors, although there are short term fluctuations. In case the sensors are separated by a building or infrastructure, these measurements for similarity in detected values would change significantly due to the local turbulence. Furthermore, the auto-correlation time of the wind speed and direction are between 2-3 s, meaning that the wind speed and direction stay constant within this time frame and will determine the required sampling rates for methane sensors. Hence, this quantity is critical when locating gas sources, since it implies that methane sensor sampling interval needs to be close to the autocorrelation time.

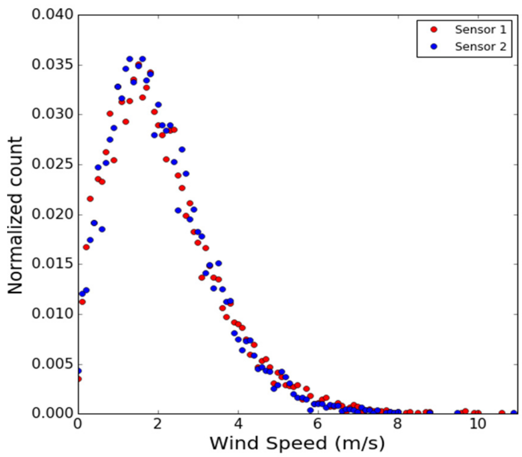

Figure 2. Distribution of wind speed for two sensors .

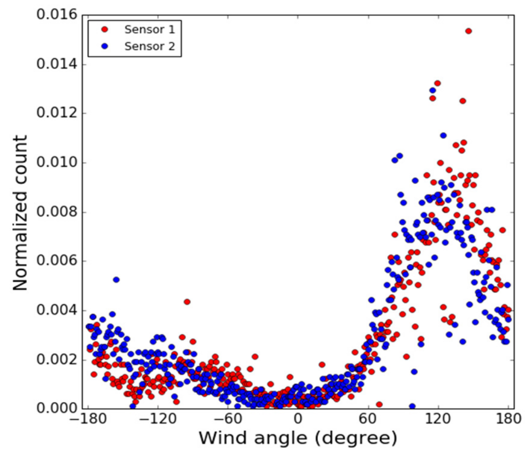

Figure 3. Distribution of wind directions compensated for 5 degree mismatch.

The analytics of source attribution from various types and length scales of geospatial data is dependent to some extent on the length scale of observation. The simplest and most studied model corresponds to the well-known Gaussian plume that establishes itself from a source when steady wind and atmospheric conditions remain stationary over a sufficient length of time and are spatially homogeneous. In the case of a planar terrain in a x-y plane, the plume dispersion characteristics for a source of strength q at $(0,0,h)$ are described by

$$c(x,y,z) = \frac{q}{2\pi u \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right)\left\{\exp\left(-\frac{(z-h)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+h)^2}{2\sigma_z^2}\right)\right\} \tag{1}$$

where, c is the pollutant concentration, q is the mean wind speed, and $\sigma_x$and σ_y are the dispersion parameters in the lateral and vertical directions and depend on atmospheric turbulence characteristics and distance downwind from the leak source, x. The x direction coincides with wind direction. For a spatially distributed network of sensors, and a non-local leak, the recorded concentrations are given by

$$s_i = A_{ij} q_j, \qquad i = 1,2 \ldots m \tag{2}$$

where, A is the discretized Green's function and $\{q_j\}$ with $j = 1, \ldots, n$ are source strengths at spatial grid point j. The discretized Green's function A_{ij} represents the concentration at sensor i arising from a unit source at spatial grid point j and depends on wind speed as well as wind direction. This is the so called *forward problem*. The *inverse problem* consists of determining the source distribution $\{q_j\}$ with $j = 1, \ldots, n$ from a knowledge of the sensor readings measured in a gas leak scenario. Since the number of sensors, m is typically less than the number of spatial grid points, n multiple wind directions are needed to make the inverse problem well –posed. To illustrate the source attribution, a network of 25 sensors were placed in a rectangular 10 m x 10 m grid. The forward problem was solved to predict the concentrations at the sensors for 6 different wind conditions. To mimic experimental Gaussian noise a signal-to-noise (SNR) of 10 was added to the sensor readings. The resulting sensor data were used to locate the leak by solving the inverse problem using least-squares with regularization.
Thus the source vector, $\boldsymbol{q}$, is determined by a minimization of

$$||\boldsymbol{Aq} - \boldsymbol{s}||^2 + \lambda||\boldsymbol{q}||^2 \tag{3}$$

where, λ, is a small regularization parameter. Figure 4 shows the result of inversion for a scenario where source is positioned 0.5 m above the ground. The distribution of normalized counts (sum of all counts is equal to 1) for the inversion is successful, most of the time, with a mean source location error of about 1.04 m (Figure 5).

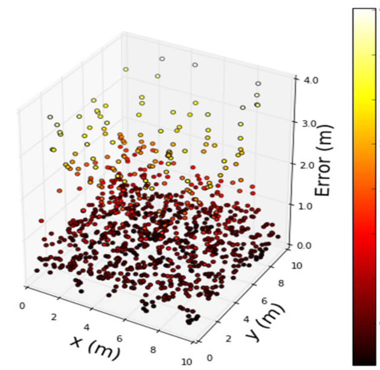

Figure 4. Randomly generated 1000 leak coordinates (x, y) and the error in source location from the inverse problem.

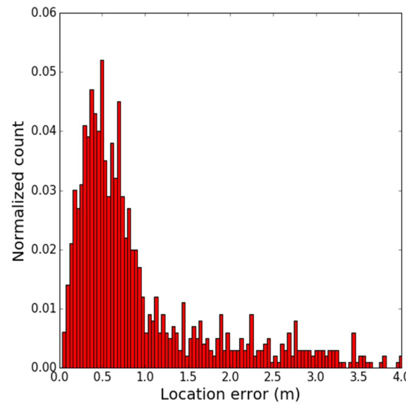

Figure 5. Histogram of source location errors for 1000 simulations.

While a simple scenario has been used for illustration, the method can be generalized to realistic situations such as gas well pads by using a Green's function appropriate for the situation. Such Green's functions can be obtained for instance by computational fluid dynamics (Crank 1975) and integrated into edge devices analytics that carry out methane leak calculation on well pad sites.

3. Conclusion

A scalable solutions to monitor methane leaks is proposed based on wireless sensor network and advanced analytics. We demonstrated that inverse and forward modeling can locate methane leaks with an accuracy of 1 m and quantify emission rates on individual well pad sites. Distributed computing on edge devices and cloud platforms require integration of GIS with IoT sensor data to pinpoint methane leaks and to distinguish small leaks from background methane fluctuations. The solution can be easily adaptable to other industries like agriculture, livestock or waste management where methane emission has a significant impact.

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