PROJECT
CANARY

A Quantitative Overview to Continuous Monitoring of Methane Emissions

Executive Summary

This report outlines the findings and results from Round 2 (R2) of the field-testing campaign to simulate real-world environmental conditions under a controlled setting at Colorado State University's Methane Emissions Technology Evaluation Center (METEC). We present our progress in developing, testing, and implementing methods to quantify methane emissions from oil and gas facilities using our innovative analytics platform. This platform integrates continuously monitored data from the Canary X detectors, meteorological conditions, and cloud analytics to detect and quantify methane emissions from remote locations.

We performed continual testing of methane emissions throughout the entirety of three days to investigate the diurnal effects on our quantification methods. The design of experiments included a total of 45 test conditions (experiments) that included programmed methane releases from multiple sources at a natural gas site, including gas processing units, well heads, and storage tank batteries. A total of eight CANARY sensors networks were deployed at the Fenceline of the 200 ft x 280 ft site with a detector to source distance ranging from 69 to 230 ft. The duration of each test lasted 60 minutes, followed by a 15-minute remission period when no methane was released. The goal for each test was to establish a baseline for the following test and so on. Each leak rate was repeated three times with a total of 45 experiments to examine if our quantification models could provide reproducible or consistent results. The controlled methane leaks ranged from low to high release rates between 0.05 g/s (~10 scfh) all the way up to 0.84 g/s (~160 scfh) to represent average well pad emissions on natural gas sites. The wide range of methane releases offered a great way to test the robustness of our quantification models.

As part of the quantification methods, we have developed and examined two models (Model N and Model S) for quantification to thoroughly investigate the problem and employ the best evaluation methods. The findings indicate that the quantification methods are robust under variable weather conditions when the average wind speed ranges from 0.5 m/s to 6 m/s at the site footprint and for different sensor configurations. Furthermore, both quantification methods demonstrate that they can detect methane leaks with a total site emission prediction error ranging from -16% to 3% at the mentioned release rates. Total predicted site emission is the cumulative predicted emission rates of each experiment over the total test period of three days. The true total site emission (cumulative over the full 3-day test period) was 50.22 kg of methane. The predicted values were 58.1 kg of methane released for Model S and 48.74 kg of methane released for Model N. The goal is to converge to a single analytics platform that will integrate the best features from each method.

Site Setup: Cataloging Equipment

This section describes an arrangement used at the METEC test site at Colorado State University. **Figure 1** shows the eight CANARY detectors deployed around the test site (200 ft x 280 ft) with a detector to source distance ranging from 69 to 230 ft. This detector-to-source distance was selected to reasonably ensure the detectors will be activated by the gas plume regardless of wind direction, and therefore, enable the system to operate autonomously.

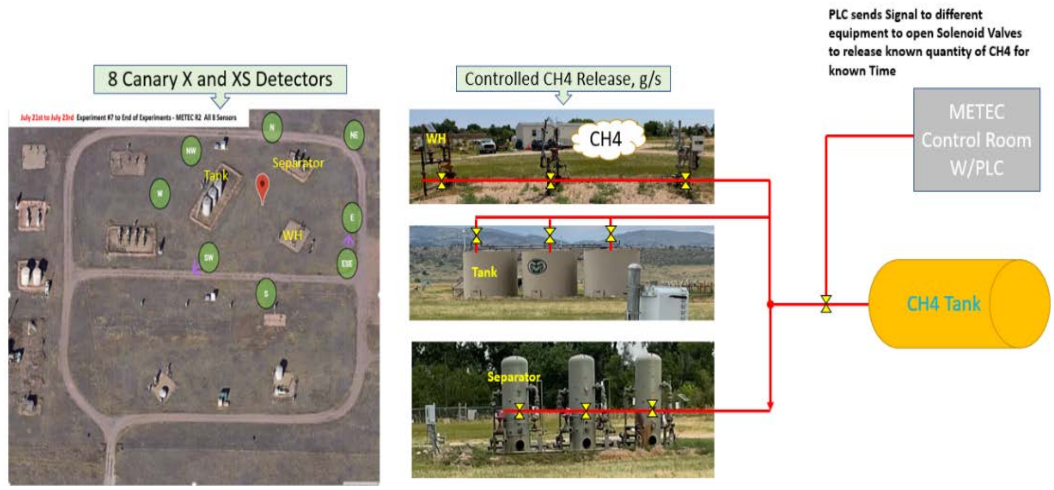

Figure 1. METEC Test Site with Detectors Deployed and Methane Release System

Wind speed and direction were measured in some of the Canary detectors if ultrasonic wind sensors were installed. The testing campaign releases a controlled volume of methane at three primary sources: wellhead, separator, and storage tanks. Emissions were released from heights ranging from 5 ft to 15 ft. The release rates ranged from 0.05 g/s on the lower end and up to 0.84 g/s on the higher end, which is a wide range for representing average well pad emissions. The METEC site has provisions to accurately regulate and measure flow rate using orifice meters, solenoids, and PLCs.

We performed continual testing of methane emissions throughout the entirety of three days to investigate the diurnal effects on our quantification methods. The design of experiments included a total of 45 test conditions (experiments) that had programmed methane releases from multiple sources at a natural gas site, including gas processing units, well heads, and storage tank batteries; see **Figure 1**. The duration of each test lasted 60 minutes, followed by a 15-minute remission period when no methane was released since the goal for each test was to establish a baseline for the following test and so on. Each leak rate ~~test~~ was repeated three times to examine if our quantification models could provide reproducible or consistent results. The controlled methane leaks ranged from low to high release rates between 0.05 g/s and 0.84 g/s to represent average well pad emissions. The wide range of methane releases offered a great way to test the robustness of our quantification models. **Table 1** shows the detailed design of experiments with the following criteria: Experiment ID, Start/End times, the release rate of methane, and emission source type.

Table 1. Design of the Experiment

Detection of Emissions Event

The Canary devices measure precise methane concentration, wind speed and direction, GPS coordinates, and various other environmental parameters, very much like the deployments in the wild, every second, and report minute-level average readings to Project Canary cloud servers over a cellular network in real-time. An event-driven processing pipeline validates and ingests the data into the Project Canary analytics platform, where it is automatically checked for data integrity and alarm conditions, aggregated spatially and temporally with existing data, made available through the Project Canary Dashboard and REST API, and passed to the localization and quantification pipeline described below.

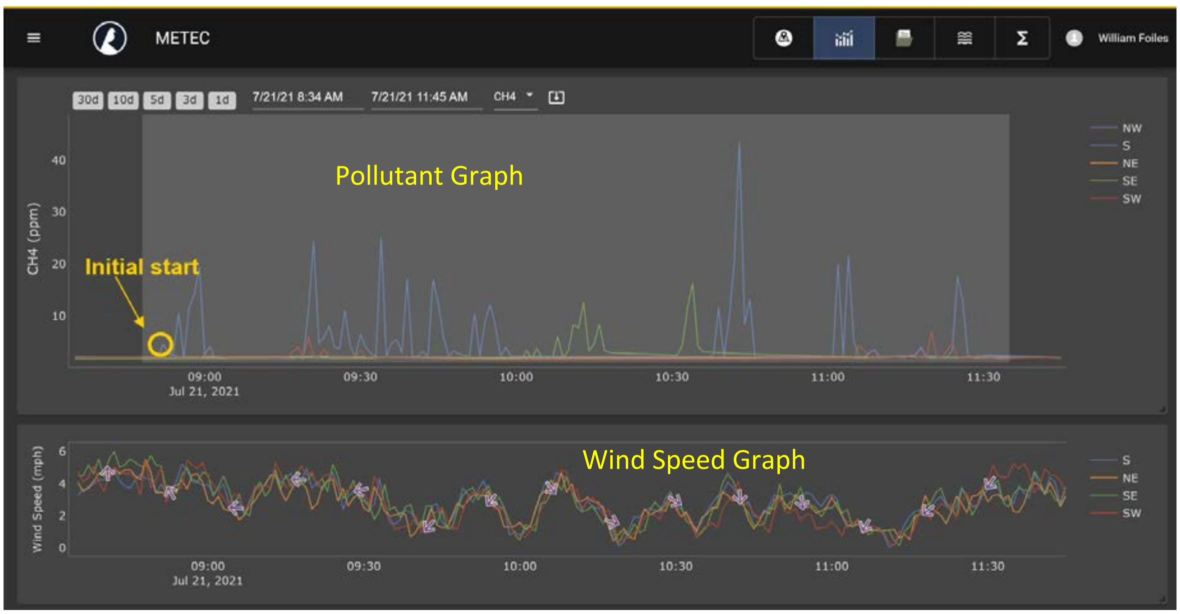

Figure 2: Data generated by the Project Canary Continuous Monitoring Dashboard

Visualization of time series and hourly aggregated statistics of concentration, wind speed, and wind direction from all detectors and weather sensors enable the user to assess node engagement and to adjust the experimental setup, if necessary, to maximize alignment of sensors with the dominant methane dispersion directions by the prevailing wind as shown in **Figure 2.**

Quantification Model

Concentration to Mass Physics Models

The concentration-to-mass physics models are developed using the Gaussian plume principles to model the advection and diffusion properties. In this paper, we present two models: Model N and Model S. Both models are based on the Gaussian Plume Model (GPM) with some variations in pre- and post-data processing and dispersion coefficients, to mention a few.

The overarching problem of Model S is to detect, localize, and quantify leaks for short-range dispersion effects. To begin, the problem is projected to the radial coordinate system to look at the radial distance and angle between every source and detector. The following step is to perform hourly Signal-to-Noise Ratio (SNR) to filter out concentration data from each detector that is not significantly above the baseline, i.e., it does not signify that an event occurred. Next, the baseline is corrected to the median concentration over the duration of the data. The filtered concentration data is then inputted into the event detection and duration algorithm to find when and how long an event occurred. Next, model S performs source localization during the event to find the likeliest emitting source using the wind data and a probabilistic approach. Next, the stability class is calculated every 10 minutes to see how much spreading or dispersion occurred in the Gaussian plume using the Brookhaven National Laboratory (BNL) stability class coefficients. Finally, Model S calculates the flux for each detector based on the GPM and BNL stability class coefficients. The last step is to perform bootstrapping to sample the flux profiles from all detectors and summarize the calculations. Bootstrapping the flux profiles from all detectors provides uncertainty quantification in confidence intervals with error bars on the bootstrap mean flux.

In Model N, ambient methane concentrations are calculated using the median measured value over a rolling 7-day window. This calculation is done independently for each sensor and each hour of the day to account for diurnal and seasonal variations in background concentration and automatically correct for sensor drift and calibration errors. The U.S. Nuclear Regulatory Commission's sigma theta method is used to determine the Pasquill stability class, based on a 10-minute standard deviation of wind direction measurements. A buoyant plume dispersion model (Beychok) is used to calculate the leak flux. Due to the poor performance of the commonly used Pasquill-Gifford and Klug dispersion coefficient functions at distances less than 100 meters downwind of the leak source, the interpolation method used by Stanford University's FEAST model is adopted by Model N for short-range distances.

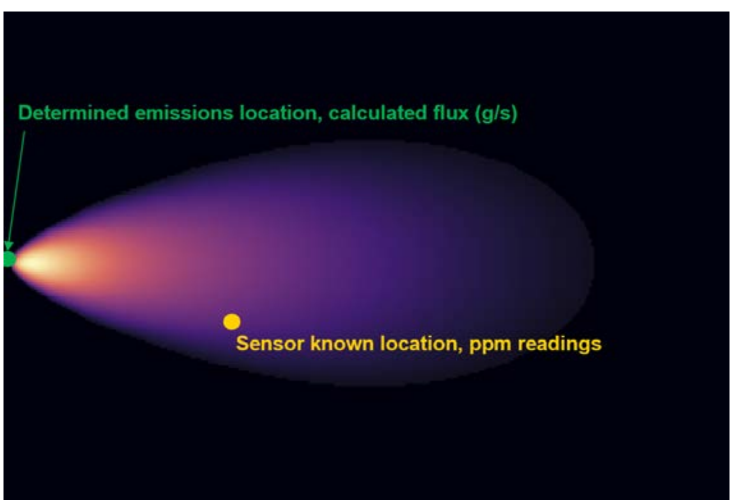

Figure 3: Gaussian Plume model

Event Duration Algorithms

The event detection algorithm in Model N is designed to combine time-adjacent sensor readings determined by the localization algorithm to have originated from the same source. It also estimates leak rates during periods where atmospheric conditions are such that accurate concentration readings are not possible, such as when no sensors are downwind of leak sources or when wind speed is too low or too high to obtain reliable measurements. This serves two purposes; a) increasing the accuracy of leak flux calculations by increasing the number of measurements used in the calculation and b) allowing for accurate estimation of the mass of methane emitted during an event.

To determine if low concentration measurements are due to the absence of a leak or from unfavorable atmospheric conditions, the system calculates the minimum detectable flux from each known leak source every minute under the measured atmospheric conditions. Suppose the minimum detectable flux is greater than the lower 95% confidence interval of an adjacent emission event. In that case, the event is assumed to have been occurring at the same emission rate as the adjacent event during the period of inconclusive data.

The event duration algorithm in Model S has two functionalities: (1) event detection and (2) event duration. The event detection algorithm searches for sudden jumps in the concentration profile that would signify a leak. Once a jump or spike is detected, the event duration algorithm then detects when and for how long this event occurred.

Source Localization Algorithms

Source localization is critical during the quantification and detection of leaks. However, this is a difficult task because many uncertainties stem from variable weather conditions, obstacles blocking the wind upwind or downwind of the source, and much more. Therefore, the source localization algorithms in Models N and S are different. In Model S, a source localization algorithm is a probabilistic approach that uses the radial distance and angle between the sources and detectors to determine which source is most probable or likeliest to be emitting. The source localization algorithm finds the probabilities every minute over the course of a presumed event.

In Model N, leak source locations are found using a geometric localization technique based on angle-of-arrival (AoA) measurements. First, AoA is estimated using a concentration-weighted circular mean of measured wind directions. The algorithm then examines the intersection points of rays emitted from each sensor at the AoA and the proximities of the rays and intersection points to known positions of potential leak sources to pinpoint the location of the emission. This method had a 93% success rate with METEC experiments, correctly identifying the leak source for 41 of 45 experiments. experiments, correctly.

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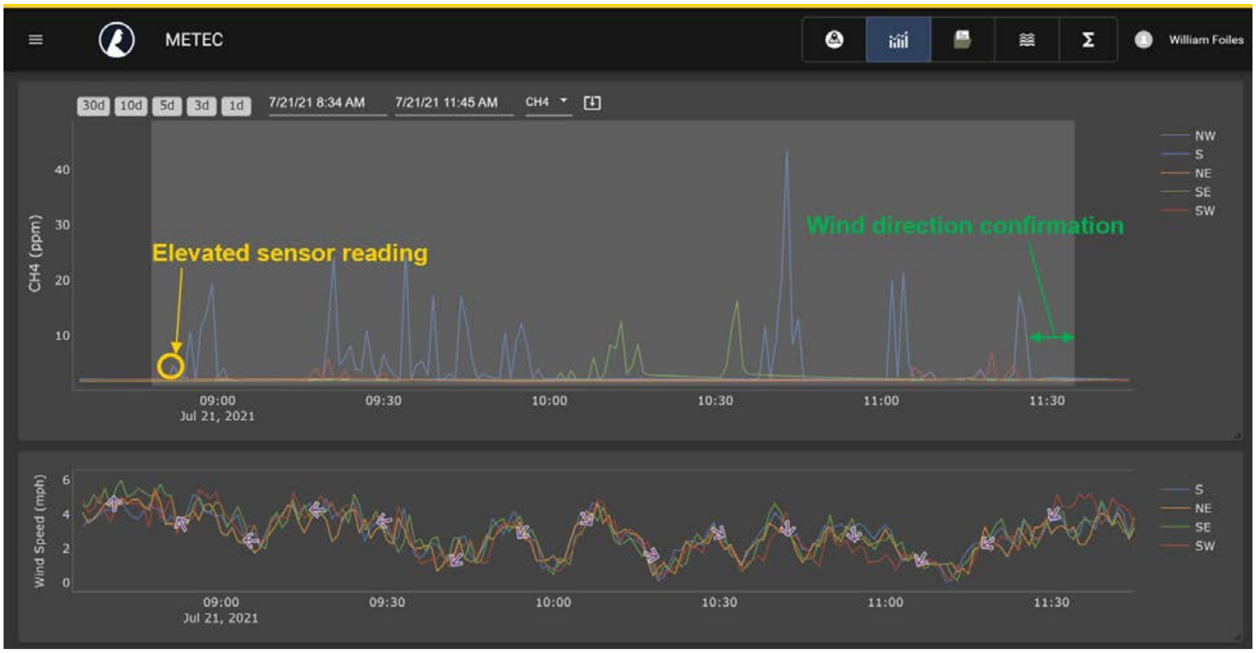

Figure 4: Event Duration confirmations

Statistical Methods

Bootstrap Sampling

Bootstrapping is a statistical procedure involving the generation of random samples from a population with replacement to quantify the mean and standard deviation of the population using multiple sampling distributions. These bootstrap statistics are used to compute the confidence interval, which provides a statistically significant bound for the lower and upper values from the bootstrap mean and standard deviation. Thus, the confidence intervals provide an assessment of the estimates as to how confident you are that 90%, 95%, etc., of your data, is contained within these lower and upper bounds. In other words, it provides a form of uncertainty quantification about your results.

In addition, as the bootstrapping algorithm samples from all the predicted fluxes, it provides summary statistics, such as mean and standard deviation. The summary statistics provide error bars, as shown in **Figure 5**. The error bars are critical in determining the width of uncertainty in the bootstrapping mean for the release rate, e.g., flux.

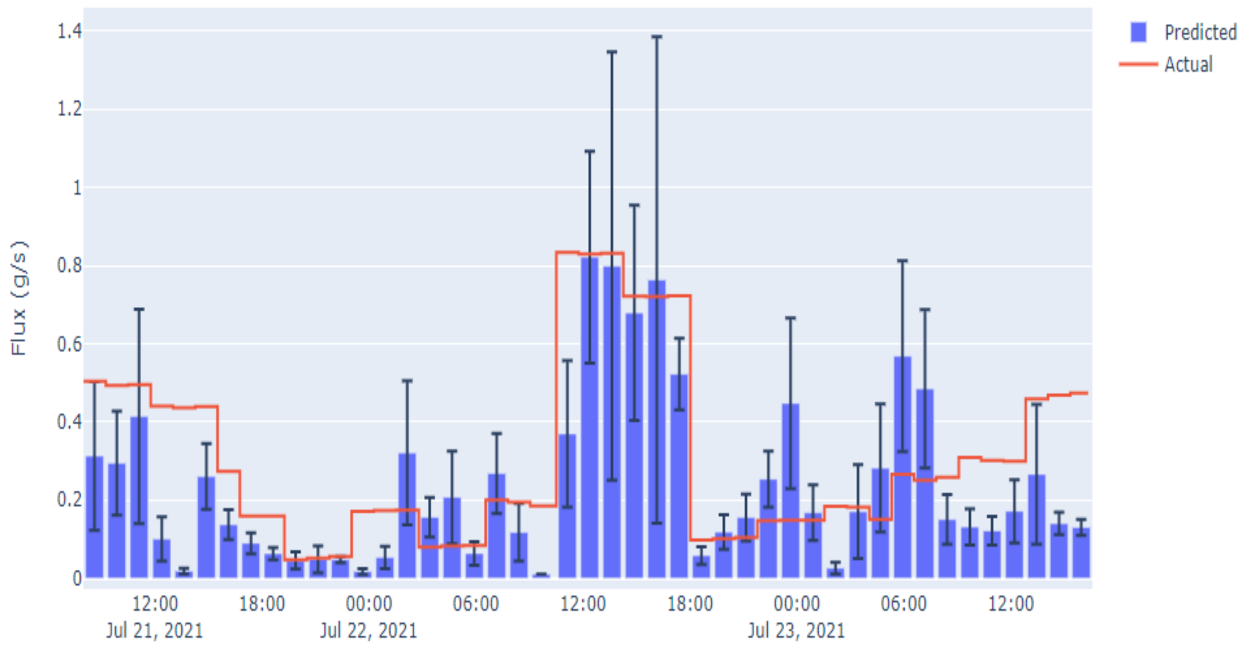

Figure 5: Bootstrapping solution to true release rate.

METEC Results

As mentioned earlier, we have developed and examined two models (Model N and Model S) for quantification to thoroughly investigate the problem and employ the best evaluation methods. Both models are based on the Gaussian Plume Model (GPM) with some variations from each other in terms of pre-and post-data processing and dispersion coefficients.

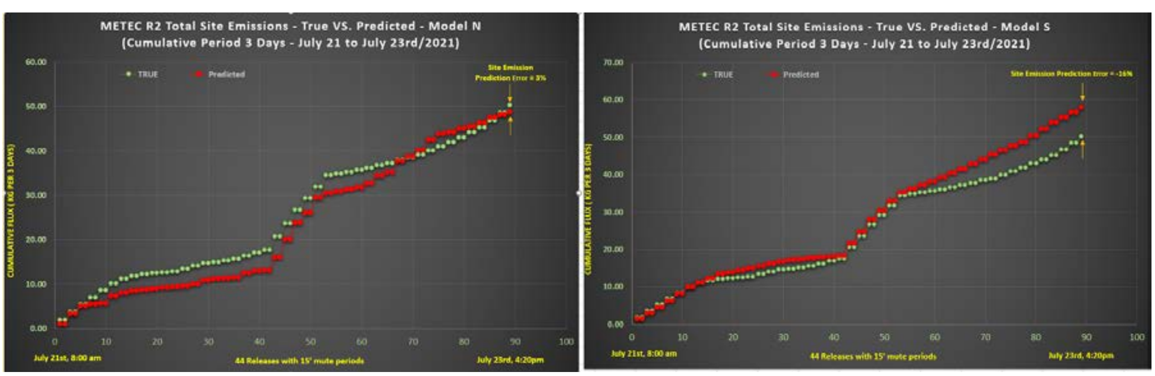

Figure 6: Total METEC Site CH4 Emissions in kilograms over 3 Days of Testing

Figure 6 shows the cumulative predictive emissions for METEC Site Emissions over the course of three days as compared to true emissions. The quantification methods have demonstrated that it can detect methane leaks in the range of 0.05 g/s up to 0.85 g/s with a total site emission prediction error ranging from -16% to 3% at an average wind speed ranging from 0.5 m/s to 6 m/s at the site footprint and sensor configuration mentioned earlier. Total predicted site emission is the cumulative predicted emission rate of each experiment over the total test period of three days. The True total site emission was 50.22 kg of methane, whereas the predicted values were 58.1 kg of methane using Model S and 48.74 kilograms of methane using Model N.

Table 3 provides the breakdown of total site emissions per source against the true emitted quantities of methane in kg for each quantification method. Both models predicted reasonably well except for a few cases when unfavorable wind conditions affected the transport of emissions. Since this continuous monitoring technology relies on wind to advect air-borne methane molecules to a detector, unfavorable wind conditions occasionally result in the detector being upwind of a given emission source, which creates a weak signal-to-noise ratio. As a result, the detector is inhibited from receiving the correct information on the emitted source concentration when the methane plume is upstream or out of reach. As a direct result, the plume dispersion model is unable to predict methane emissions accurately.

	TRUE (kg)	Pred. N (kg)	Pred. S (kg)	% ERROR - N	% ERROR - S
WH	14.70	10.80	16.82	27%	-14%
Tank	19.81	19.73	18.65	0.41%	6%
Separator	15.71	18.22	22.62	-16%	-44%
Total	50.22	48.74	58.10	2.9%	-15.7%

Table 2: METEC Results using N-model and S-model.

Additional testing planned on September at METEC would further estimate the error distribution, prediction interval width, and overall emission rate prediction trend.

Conclusions and Next Steps

From July 21st to July 23rd, 2021, the CANARY sensing and analytics platform has been tested in a real-world environment at Colorado State University's METEC facility as a practical test site. The platform integrates detector data and cloud analytics to offer a complete IoT solution for remote locations, where power availability and communications to the cloud may be challenging.

As part of the quantification roadmap, we have developed and examined two models, Model N and Model S, to thoroughly investigate the problem and employ the best evaluation methods. The quantification models are adept at handling average wind speeds ranging from 0.5 m/s to 6 m/s at the 200 ft x 280 ft site and for a detector-to-source distance ranging from 69 to 230 ft. The quantification methods have demonstrated that they can detect methane leaks in the range of 0.05 g/s up to 0.85 g/s with a total site emission prediction error ranging from -16% to 3%. The total predicted site emissions are the cumulative predicted emission rates of each experiment over the entire test period of three days. The total METEC site emissions (i.e., cumulative over the whole 3-day test period) was 50.22 kg of methane. In contrast, the predicted values were 58.1 kg of methane using Model S and 48.74 kg of methane using Model N. As expected, variability in wind speed and direction and test duration and sensor placement also led to some variability amongst replicates for the same flow rate. The next steps will focus on a more extended testing campaign at METEC to include a broader range of operating and test site conditions to allow a deeper understanding and assessment of conditions that impact model performance. In other words, we aim to fine-tune Model S and Model N for optimal prediction accuracy and tighter prediction interval width of methane leaks from unknown source locations.

References

- Stockie, J.M. (2011): “Mathematics of Atmospheric Dispersion Modelling” Society for Industrial and Applied Mathematics (SIAM) Review, 53(2): 349-372pp.

- MacDonald, R. (2003): “Theory and Objectives of Air Dispersion Modelling” Modelling Air Emissions for Compliance, MME 474A Wind Engineering (course notes), University of Waterloo, Canada. 27pp.

- Alkadi, N.E, etl.,: “Ubiquitous Sensing Network for Continuous Monitoring and Quantification of Methane Emissions”, SPE Offshore Europe Conference and Exhibition, Aberdeen, UK, September 2019, Paper Number: SPE-195703-MS. https://doi.org/10.2118/195703-MS

- Beychok, M.T. (1996). Air-dispersion modeling and the real world. Environmental Solutions, 9.

- F. A. Gifford. (1961). Use of Routine Meteorological Observations for Estimating Atmospheric Dispersion. Nuclear Safety 2.4, 47–51.

- U.S. Nuclear Regulatory Commission (1972). Meteorological Monitoring Programs for Nuclear Power Plants. Regulatory Guide 1.23, 6.

- C.E. Kemp, and A.P. Ravikumar (2021). New Technologies can Cost-effectively Reduce Oil and Gas Methane Emissions, but Policies will Require Careful Design to Establish Mitigation Equivalence. EarthArXiV.

- C.E. Kemp, A.P. Ravikumar, and A.R. Brandt (2016). Comparing Natural Gas Leakage Detection Technologies Using an Open-Source “Virtual Gas Field” Simulator. Environ. Sci. Tech. 50 4546.