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A Supervisory Control and Data Acquisition system to mitigate fugitive methane emission in landfills

Lavanya Natarajan[1]

[1]Viera High School, Melbourne, FL, USA

ABSTRACT

Landfills are 3rd largest sources of anthropogenic methane (CH_4) emissions. Currently, as landfill gas (LFG) CH_4 measurements are inconsistent and untimely, inadvertent fugitive emissions go undetected; problems are realized late. So, there is an inherent need to monitor LFG CH_4 continuously via "Smart" systems. The goal is to design and develop a Supervisory Control and Data Acquisition (SCADA) system for real-time CH_4 detection, prediction, and remote mitigation. System includes (i) Fugitive Emissions Mitigator (FEM) with programmable WiFi microcontroller connected to gas, and environmental sensors; (ii) continuous wireless data transmission to interactive cloud through unified codes; (iii) descriptive and diagnostic analytics in cloud dashboard to inform historical events, (iv) predictive and prescriptive analytics via Machine Learning (ML) algorithms to forecast CH_4 emissions, and (v) long-distance LFG mitigation. To test SCADA system, two aspects, which influenced the magnitude of fugitive emissions in the real world were studied in lab, namely, CH_4 Transport in Soil, and CH_4 Generation conditions in waste. Per results, CH_4 transport rate was inversely proportional to soil moisture. However, CH_4 generation was directly proportional to moisture content in wastes. To further explain the complex CH_4-to-moisture relationship, a 5th-order Polynomial ML equation with 86% accuracy and greatest curve-fit was derived. Finally, LFG mitigation was achieved via a separate component, which allowed for remote pump activation to extract CH_4. Overall, this cost effective IoT solution helps solve existing and emerging fugitive CH_4 issues via real-time measurements, prediction, and mitigation to help US reduce 45% greenhouse gases by 2030.

Background

Methane generation and migration mechanism

While methane makes up only 9% of total greenhouse gases (GHG), it has the potency to trap 35x more heat versus others. Methane (CH_4) emanating from landfills is pervasive concern globally. In the US, landfills are the 3rd largest anthropogenic sources of methane emissions (USEPA, 2020). In Municipal Solid Waste (MSW) landfills, when organic material is decomposed under anerobic conditions, landfill gas (LFG) containing 40-60% methane by volume is produced at a constant rate and gets emitted for over 50 years.[1,2] Methane production is correlated with wet conditions as moisture can accelerate gas generation process. Its migration to the surrounding follows the path of least resistance in underground substrate. Saturated soil might prevent some gas from escaping into the atmosphere as voids are filled with landfill leachates. Under such conditions, gas tends to migrate laterally from landfills. Gas migration is affected by soil permeability, depth of ground water, waste conditions, moisture content, and landfill capping systems. LFG is transported via *molecular effusion* (occurs at boundary surface in absence of impervious covers), *molecular diffusion* (occurs due to gas concentration gradient, essentially, migration from high to low concentration areas), and *convection* (occurs due to pressure gradients, essentially, migration from higher to lower pressure regions). External weather conditions also influence production and migration of LFG.[3,4,5]

Problem

Today, LFG methane is captured via a series of wells spread across landfills. However, most US landfills are failing to capture or divert excess methane for energy use due to inadequate, or inconsistent CH_4 extraction processes. Instead, the CH_4 is inadvertently released into the air via fugitive emissions, which is a threat to safety, health, and especially global warming. If there is too less CH_4 extraction, impervious geomembrane covers in landfills could lead to LFG pressure build up. The restriction of outward movement of gases cause geomembrane ruptures. However, too much CH_4 extraction results in vacuum buildup in underground voids leading to oxygen intrusion, which serves as a recipe for auto combustion.[6,7] Considering these multi-dimensional problems, timely and delicate landfill maintenance is critical, which prompts the need for an optimized methane extraction process to minimize fugitive emissions. Note, per USEPA, 28% of FL landfills do not even have proper LFG measuring or collection mechanism, and 3 of top 10 methane emitting landfills in the nation are in Florida.

Current work and its Limitations

To lessen the risk of landfill gas hazards, today, engineers use two methods for comprehension, (i) LFG estimation via modeling, and (ii) LFG measurements via monitoring. Boiler plate models used today for LFG prediction has substantial variability as landfill contents and local environmental conditions are stochastic. As far as measurements, the monthly minimal and manual on-site data collected by engineers provide very little and untimely information. Engineers collect information by walking over the treacherous landfill terrain, carrying bulky Flame Ionization Detectors from gas well to gas well, which are 200 feet apart. They log the datasheets manually and feed to computers upon return to the lab. The "batch" nature coupled with large form factors does not fit "continuous" measurement necessity. Because LFG metrics are measured monthly, the problem is realized too late; LFG is inadvertently released into atmosphere via undetected fugitive emissions. Today a limited number of LFG wells collect portions of CH_4 for energy use, while others escape via fugitive emissions. So, is there is a technology dearth in today's landfills? Is it "dumb?" Yes, there is an inherent need to monitor real-time metrics in landfills cost effectively and control via "Smart" IoT networks with small form factor sensors with latest communication protocols to mitigate fugitive emissions and landfill disasters.

Engineering Goal

The goal is to develop a Supervisory Control and Data Acquisition (SCADA) system, a centralized hardware-software combo that enables timely data capture and automation for LFG detection and mitigation. This IoT holistic solution provides real-time measurements, data management, and analytics to mitigate fugitive CH_4 emissions. The first-of-its-kind system (Figure 1) components are below:

1) Fugitive Emissions Mitigator (FEM) with a microcontroller connected to ambient, gas, and soil sensors for continuous measurements of landfill metrics
2) Real time data transmission to an interactive cloud dashboard
3) Descriptive and diagnostic analytics in cloud dashboard to understand past occurrences through accurate, comprehensive, live visualization
4) Predictive and prescriptive analytics using historical patterns to predict specific outcomes using advanced machine learning algorithms, and recommend actions
5) Long-distance LFG mitigation based on prescriptive analytics

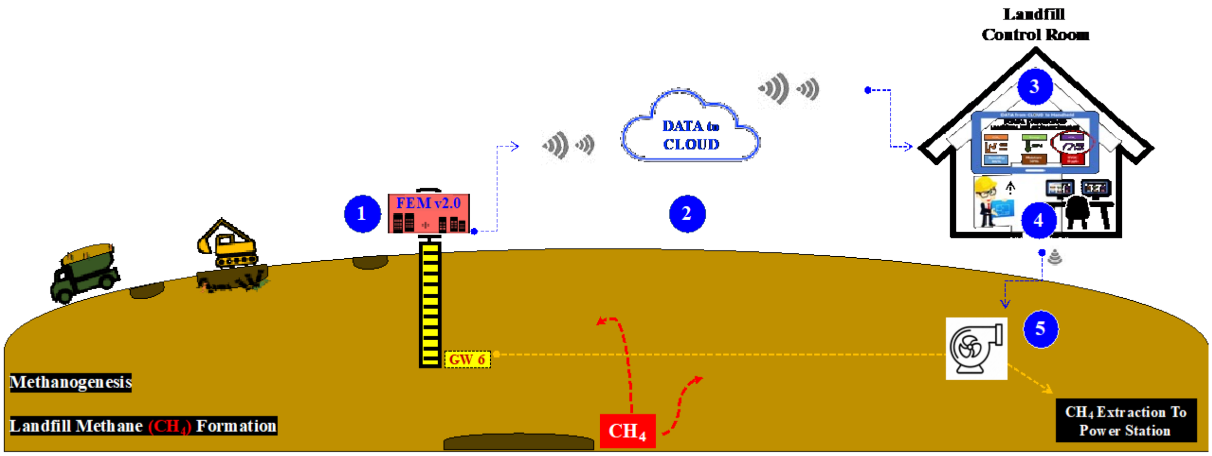

Figure 1 - Landfill SCADA Solution Schematic showing CH_4 generation, LFG Well, FEM v2.0 Sensor Bundle, Data sent to Cloud, and monitoring real-time via handheld by landfill engineer. Schematic by Researcher.

Materials and Methods

[1] Fugitive Emissions Mitigator (FEM) v2.0

To measure LFG emanating near the vicinity of gas wells and to wirelessly transmit data, a Fugitive Emissions Mitigator (FEM) sensor bundle was designed. Following an infancy prototype version, an upgraded FEM with advanced sensors and wireless capabilities using industry grade sensors and cloud compatible microcontrollers was constructed. This was FEM v2.0.

Device Design & Test: Circuitry and connectivity (Figure 2 and 3) are shown below. An Arduino MKR1000 cloud compatible microcontroller was connected to the following sensors: Adafruit BME280 (senses Temperature +1.5°C, Pressure +1 hPa, Humidity +3%, Altitude +1m), Keyestudio CCS811 digital gas sensor (for CO_2, Total VOC's), MQ-4 (for CH_4), Gikfun Capacitive sensor (for Soil Moisture), and Gikfun DS18B20 (for Soil Temp). All components were housed in a weather enclosure powered by a 5v battery. Sensors were successfully programmed to communicate with the microcontroller. This FEM can be positioned on top of the LFG well shown in the CAD drawing (Figure 4).

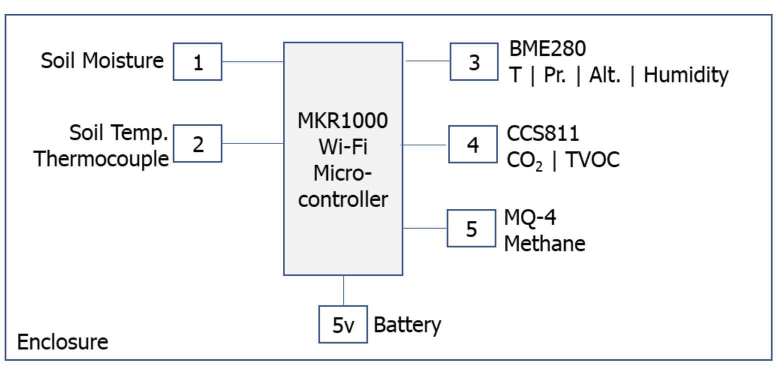

Figure 2 - Fugitive Emissions Mitigator (FEM) v2.0. Schematic by researcher

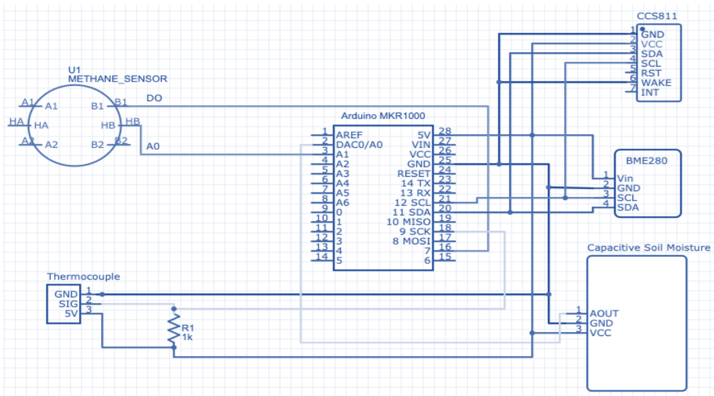

Figure 3 - Fugitive Emissions Mitigator (FEM) v2.0 Circuit diagram using EasyEDA. Schematic by Researcher.

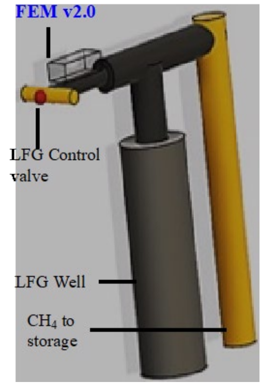

Figure 4 - CAD drawing by researcher showing LFG well and placement of FEM v2.0

[2] Realtime Data Transmission

Environmental sensors were connected to the digital pins on the WiFi microcontroller supported by 2-way I^2C communication protocol.

Cloud Testing: The microcontroller was programmed to connect to a local WiFi for wireless connectivity. An "open source" cloud IoT platform, Thinger.io, was narrowed down for the purposes of real-time data collection. Landfill Engineers suggested design and placement of widgets (LFG metrics) on Thinger.io. Cloud testing was successful.

Device and Cloud Testing: A unified C++ code was compiled to connect the FEM v2.0 to Thinger.io. The revolutionary IoT platform allowed for cloud data visualization, showed runtime LFG metrics, alerts, geolocation, interactive charts with on-demand downloadable reports for diagnostics and desktop predictive analytics.

Laboratory Analysis Testing (LAT): Prior to conducting field LFG measurements using FEM v2.0 bundle, LAT in controlled environment was conducted to determine if sensors, electronics, hardware assembly and software codes (to control the sensors from microcontroller remotely) were robust. The purpose of LAT was also to better understand major factors influencing fugitive emissions in landfills. Two aspects, namely (i) CH_4 transport behavior and (ii) CH_4 generation itself, which influenced the magnitude of emissions were studied and experiments were conducted as below.

Aspect 1 (CH_4 Transport Experiment): Setup is as shown in Figure 5. A calibration gas tank containing 15% CH_4 in inert Nitrogen was used for the experiment. A regulator to control the gas flow was attached to the top of the gas tank. Regulator was opened for 30 seconds for each test. Using a flexible hose, the regulator was connected to a stabilization tank to balance the gas pressure and to avoid sudden puffs of CH_4. The methane was then passed to a 40cm x 10cm x 10cm plexiglass physical model. FEM v2.0 was placed on top of the physical model, which gathered and continuously transmitted data from sensors wirelessly, and displayed on the interactive dashboard. Gas from the physical model was channeled to another methane capture tank. Here, for safety reasons, gas was bubbled through a water before ambient escape. This also symbolized the fugitive emissions emanating from the landfills. Tests were executed with no medium in the physical model followed by a known volume ($100cm^3$) of substrate F40 Florida sand type with a known hydraulic conductivity (K) of 7.0 m/day. The Hydraulic conductivity (K) was calculated separately by conducting a Falling Head test using a permeameter and a single water column manometer and applying Darcy's equation, $K = (aL/At) + Ln(h0/h1)$, where a=pipe area; L= soil column length; A=soil column area; h0=initial height of water; t=time for head drop from h0 to h1; h1=final height of water. Varying quantities of water were added to F40 soil medium in the physical model to observe gas transport behavior at different moisture conditions. Prior to each trial, it was ensured that CH_4 levels reached equilibrium in the simulator.

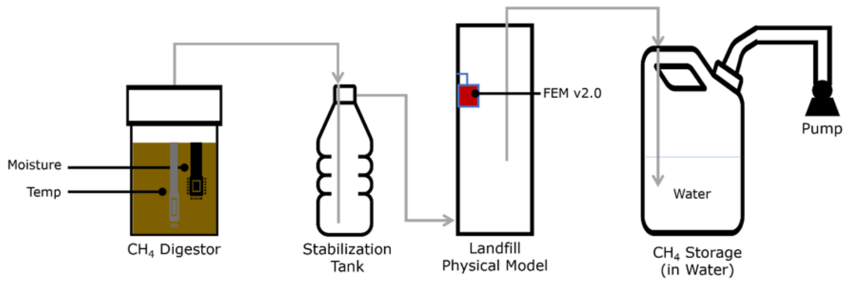

Figure 5 - Methane Transport Experiment (Aspect 1). Schematic by researcher.

Aspect 2 (CH_4 Generation Experiment): Setup is as shown in Figure 6. Landfill conditions were simulated to determine the magnitude of CH_4 generation in pilot scale. Six pounds of organic wastes (Black Kow cow manure from Home Depot to accelerate methanogenesis) was placed in an air-tight digester. LFGs were generated by wastes under anerobic conditions. A foam jacket was placed around the digester for steady temperature. Soil moisture and temperature probes were inserted in the digester to measure LFG metrics real-time. The digester was then connected to a stabilization tank and gas was channeled to the plexiglass physical model, which housed the FEM v2.0. Gas from the plexiglass physical model was channeled to another CH_4 capture tank for safety. To execute, varying quantities of water were added to the digester to observe CH_4 generation levels. LFG metrics were wirelessly transferred from FEM v2.0 to the cloud real-time. Lab tests were conducted for over 2 weeks. Data was downloaded from Thinger.io cloud platform. Descriptive and diagnostic analysis were produced.

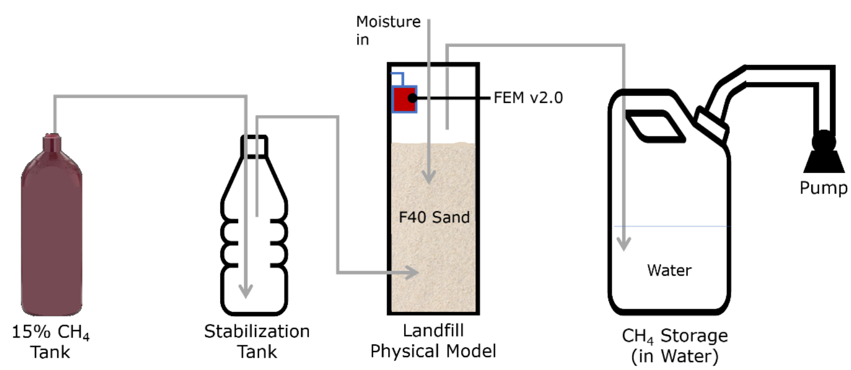

Figure 6 - Methane generation Experiment (Aspect 2). Schematic by researcher.

Field Testing: In real world, metrics can be accessed ubiquitously by engineers for diagnostics and control of landfill health on cloud dashboard and database. Field tests (Figure 7 and 8) was conducted in Brevard County landfill with engineer assistance. FEM v2.0 was strategically placed above the LFG well. Metrics measured were aligned with existing field equipment, proving that SCADA solution was applicable in existing landfills. FEM v2.0 wirelessly transmitted LFG metrics to engineers' handheld.

Figure 7 - FEM Sensor Bundle Field Test/Demo/Discussions with Landfill Engineers

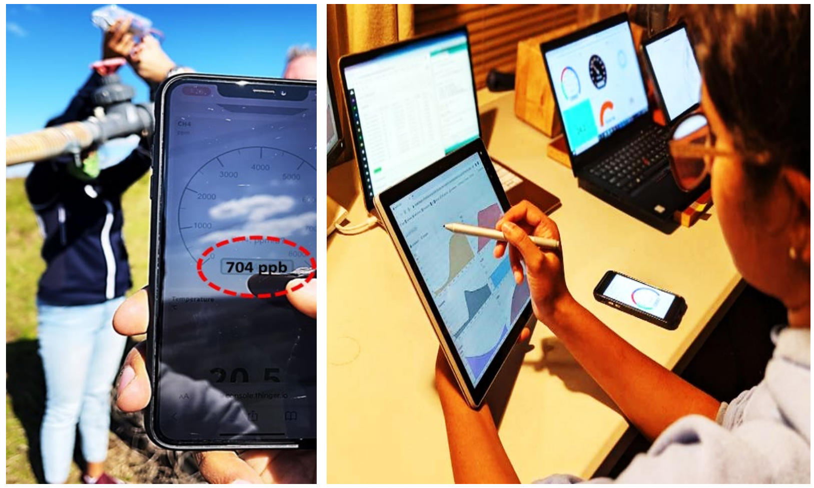

Figure 8 - Real-time display of LFG CH_4 metrics on a mobile handheld

Results and Discussions

[3] Descriptive and Diagnostic Analysis: Aspect 1 and 2 experimental results studied to determine the magnitude of fugitive emissions are as follows:

Aspect 1 (CH_4 Transport Analysis): Based on LAT, gas transport rate was observed to be inversely proportional to the moisture content. CH_4 peak concentrations declined as moisture levels increased (Figure 9). It was also observed that CH_4 six-hour decay rate on soils with no moisture was about 12.5 ppb/hour. This was substantially higher than decay rate on fully saturated liner conditions, which was about 3.3 ppb/hour as shown in Figure 10. Fugitive emissions on saturated soils was essentially 74% lower versus dry soil due to lower diffusion and absence of void spaces, which facilitated gas transport in dry soil.[1] Further, based on the statistical Box-Whisker plot (Figure 11), mean CH_4 levels (fugitive emissions) under dry soil conditions were higher versus wet soil.

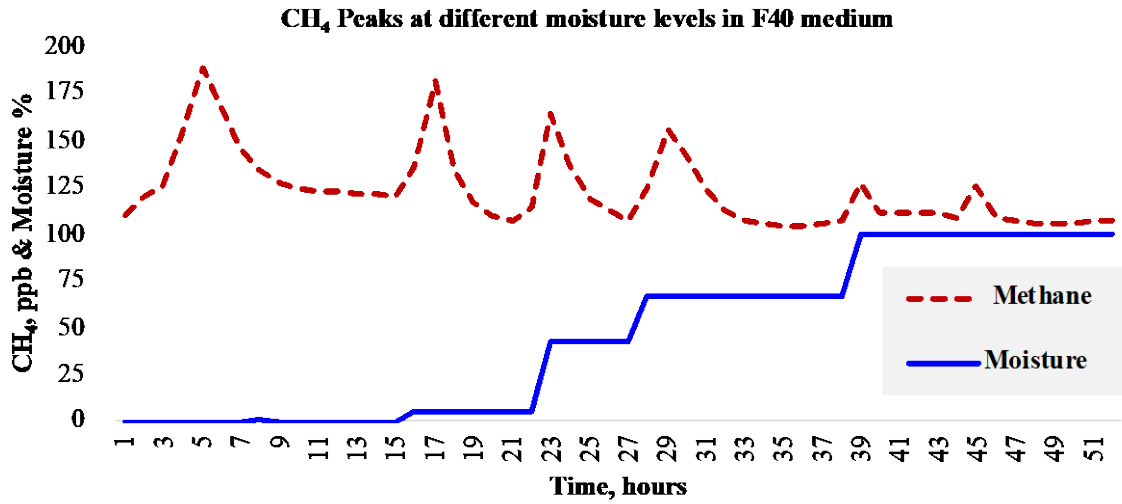

Figure 9 - Methane Peaks at different moisture levels in F40 medium [Aspect 1 CH_4 Transport]

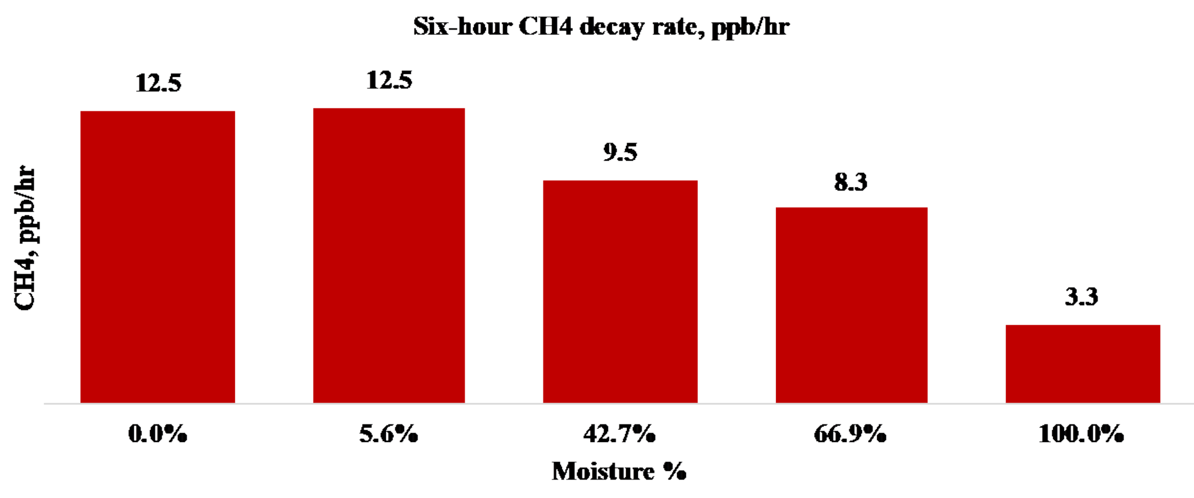

Figure 10 - Six-hour CH4 concentration decay rate [Aspect 1 CH4 Transport]

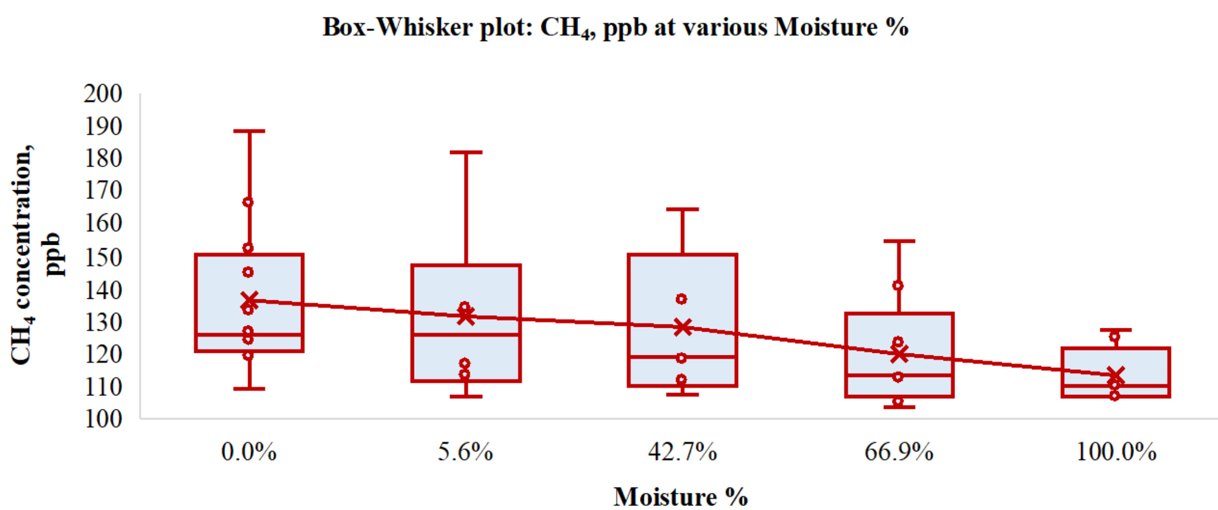

Figure 11 - Box-Whisker plot: CH_4, ppb at various Moisture % [Aspect 1 CH_4 Transport]

Aspect 2 (CH_4 Generation Analysis): Based on LAT, it was observed that as moisture level increases, the CH_4 generation increased (Figure 12). Methane generation followed a linear profile at certain temporal intervals. Despite subtle intermittent variations, there was an increasing trend between CH_4 and moisture.

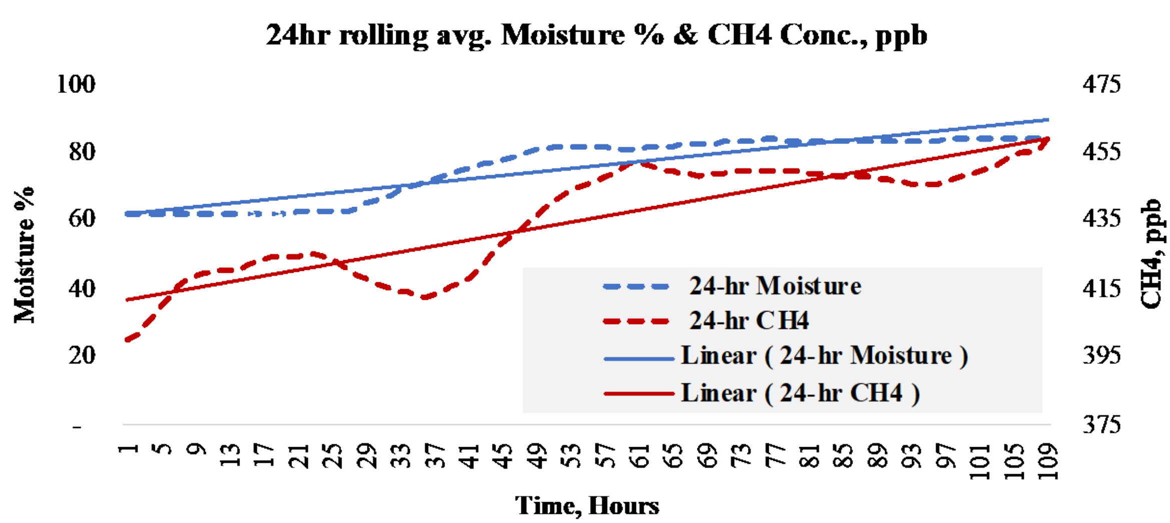

Figure 12 - 24-hr rolling avg. Moisture % & CH_4 Conc., ppb [Aspect 2 CH_4 generation]

[4] Predictive and Prescriptive Analytics

Per Figure 13, relationship between CH_4 concentration and moisture could be explained by the linear regression equation: *Methane concentration = 1.53*Moisture% + 319.35.* An R^2 of 0.78 suggested reasonable correlation between CH_4 and other parameters.

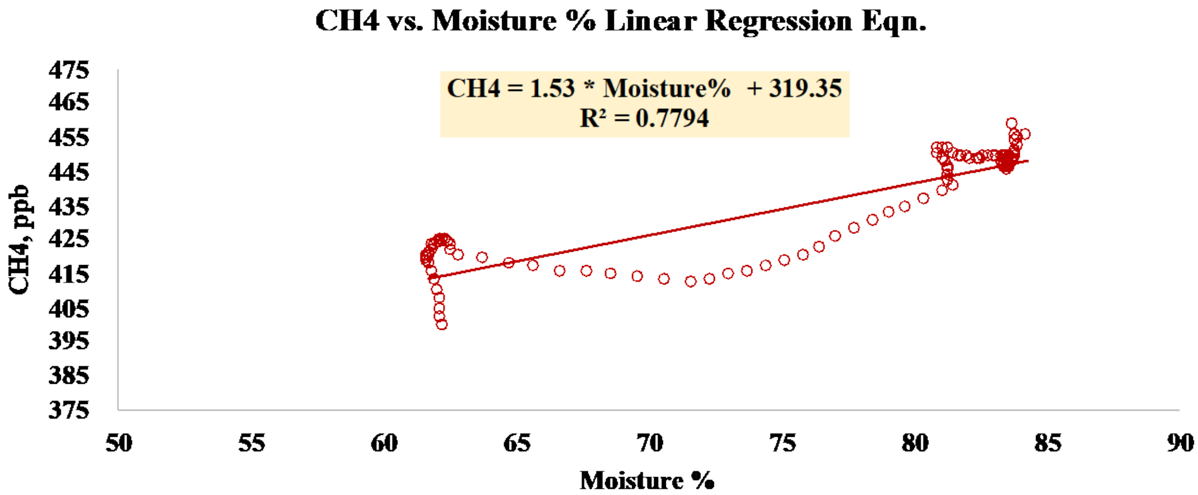

Figure 13 - Methane vs. Moisture % scatter plot with linear regression equation [Aspect 2 CH_4 generation]

To enhance the predictive power of traditional statistical models, Machine Learning (ML) models were trained for better adaptation. ML models were generated to determine the correlation and to predict CH_4 concentrations (dependent variable) based on moisture (independent variable). A 60-20-20 split was assumed for this experimentation to train, validate, and test the data. The first type of regression analysis attempted used Gaussian basis function. Eight hyperparameter tuning tests were conducted for the benchmark model.

$$f(x) = \frac{1}{\sigma * \sqrt{2\pi}} * e^{-0.5*\frac{(x-\frac{\mu}{20})^2}{\sigma}}$$

However, even after many trials of hyperparameter tuning, models did not fit the curve in a balanced manner. The second benchmark model attempted used Polynomial basis function as it can better explain nonlinear patterns per below formula:

$$f(x) = x^M + x^{(M-1)} + x^{(M-2)} \ldots$$

Five hyperparameter tuning tests were conducted for the Polynomial Basis Function benchmark model. It was observed that the best regression model obtained during hyperparameter tuning was a 5th order polynomial basis function below:

$$f(x) = 406.3 + 9.45(x-100) + 1.59 * (x-100)^2 + 0.076(x-100)^3 + 0.00141(x-100)^4 + 9.1 * 10^{-6}(x-100)^5$$

Based on the curve fit (Figure 14), the model has a relative error of 12% which translated to an accuracy of over 86% as determined by dividing the Mean Absolute Error of CH_4 concentration (33.5) by the Range of CH_4 (277 ppb). Additionally, the mean squared error on the validation set was found to be 3007.79; the mean absolute error was 33.50; the root mean squared error was 54.84.

```
 Best Model applied to Test set

M =  5
The r^2 score is on the Val set is 0.009273495075387328
The mean squared error on the Val set is 3007.789349560137
The mean absolute error  on the Val set is 33.50456073680564
The root mean squared error  on the Val set is 54.84331636179688
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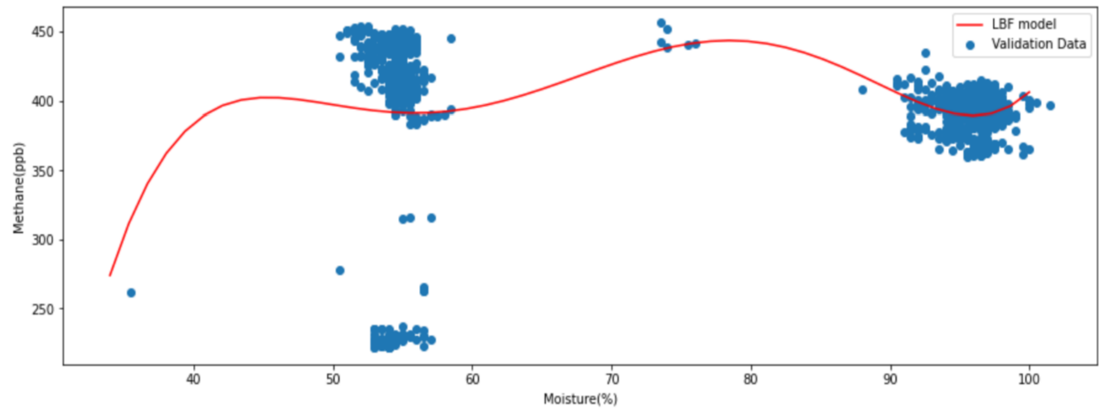


```
# return polynomial basis functions for d=1
def myBasisFunction(M):
    def polynomialM(x):
        # create an empty array
        out = np.array([])

        # create the output
        for i in range(M+1):
            sigma = 200
            shift = 100
            # append -2i cos ((1/29.4)*(1/(i+1))x) - trial and error here
            # modified gaussian function (bell curve)
            # out = np.append(out,10/(sigma*np.sqrt(2*np.pi))*np.exp(-
2*((x-i/20)/sigma)**2)) # This was obtained by trial and error
            out = np.append(out,(x-shift)**i)  # polynomial

        # return the polynomial values
        return out

    # return the polynomial function
    return polynomialM
```

Figure 14 - Best Machine Learning model applied to test set [Aspect 2 CH4 generation]

[5] LFG Mitigation

The final element in the SCADA system development dealt with fugitive emissions mitigation. This was achieved by remotely activating a pump to extract LFG methane based on prescriptive analytics (ML model) output. For this step, a separate pump, relay, and activator switch circuitry as shown in Figure 15 was constructed. When the CH_4 threshold exceeded in the physical model (landfill simulator), the pump was activated enabling LFG extraction. A balloon was attached to the downstream of the pump, where inflation represented the LFG extraction and capture. In landfills, the captured CH_4 is used as a power source.

Continuous Improvement: Overall, the SCADA system was able to successfully measure LFG metrics with FEM v2.0. However, managing the hardware connections and wires were challenging as the design did not lend itself for tough usage. Hence, a FEM v2.1 (Figure 16) was subsequently designed and constructed. Surface mount sensors were soldered to a custom PCB. This v2.1 proved to be tougher, modular, extensible, smaller by 93%, cheaper by 95%, and achieved highest field performance.

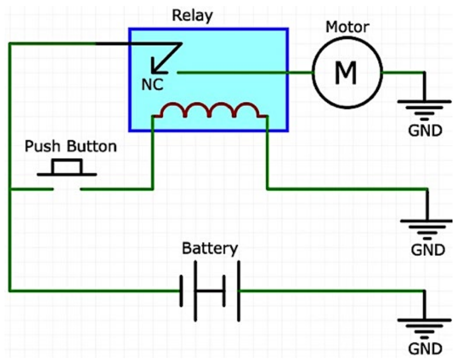

Figure 15 - Mitigator Circuit diagram using EasyEDA. Schematic by Researcher.

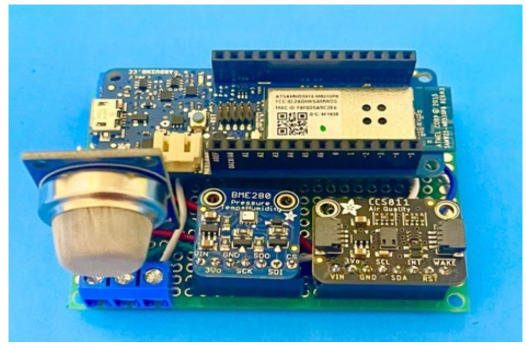

Figure 16 - FEM v2.1. Picture by researcher.

Conclusions

Overall, this end-to-end informed analytics solution provided detection of fugitive methane emissions, data visualization real-time, data analytics capabilities, and eventually lead to optimizing methane extraction in landfills. The Fugitive Emissions Mitigator (FEM) v2.0 with a microcontroller connected to ambient gas, and soil sensors continuously measured landfill metrics. Real time data transmission to an interactive cloud IoT dashboard was successively achieved using C++. Descriptive and diagnostic analytics in cloud dashboard to understand past occurrences were visualized. Both Lab Analysis Test (LAT) and Field Analysis Test (FAT) passed. Two aspects that influenced CH_4 fugitive emissions significantly, namely (i) *methane transport* in soil liners and (ii) *methane generation* conditions were studied. First, it was observed that fugitive emissions were inversely proportionally to moisture content. Essentially, gas transport in saturated soils was 74% lower versus dry soils. This was due to lower and slower gas diffusion through water and due to the absence of void spaces. Next, on CH_4 generation test, it was observed that moisture levels were directionally proportional to CH_4 production at certain intervals. Predictive and prescriptive analytics were executed using more complex ML algorithms using historical patterns to predict specific outcomes and recommend actions. This was executed because of a complex behavior exhibited in landfills, namely, moisture was proportional to CH_4 generation, but inversely proportion to fugitive emissions. A 5th order Polynomial equation provided the best curve-fit to explain the relationship between methane and moisture. This model showed 86% accuracy with respect to CH_4 emissions prediction. Finally, long-distance LFG mitigation based on prescriptive analytics was executed based on a separate circuitry component. Lab test simulations were successful in remotely activating a pump via a switch to extract LFG methane. This solution can be applied to the real world to minimize GHG CH_4 fugitive emissions, harvest more CH_4 for energy and consequently putting the US on path for 1.5°C reduction by 2030. This novel, cost-effective, compact, and holistic system is a compelling and necessary alternative to current low-tech manual measurement methodologies.

Acknowledgements

The researcher would like to thank the Engineers and Field Technicians at Brevard County Solid Waste management district for providing access to landfills, highlighting major issues, helping with concurrent field testing and comparisons of FEM v2.0 versus current instrumentation.

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