Estimation of Fugitive Landfill Methane Emissions using Surface Emission Monitoring and Genetic Algorithms Optimization

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Abstract

As municipal solid waste (MSW) landfills can generate significant amounts of methane, there is considerable interest in quantifying fugitive methane emissions at such facilities. A variety of methods exist for the estimation of methane emissions from landfills. These methods are either based on analytical emission models or on measurements. This paper presents a method to estimate methane emissions using ambient air methane measurements obtained on the surface of a landfill. Genetic Algorithms based optimization combined with the standard Gaussian dispersion model is employed to identify locations as well as emission rates of potential emission sources throughout a municipal solid waste landfill. Four case studies are employed in order to evaluate the performance of the proposed methodology. It is shown that the proposed approach enables estimation of landfill methane emissions and localization of major emission hotspots in the studied landfills. The proposed source-locating-scheme could be seen as a cost effective method assisting landfill operators to reasonably estimate and locate major methane emissions.

Keywords: Methane emission, Solid Waste Landfill, Methane measurements, Genetic Algorithms.

1. Introduction

Global Climate Change is expected to put the world on a pathway to experience climate impacts of a dangerous and irreversible magnitude. Several spectacular aspects of these climate impacts are already noticed: global warming, sea level rise, intense rain, as well as more frequent and severe heat waves. Many nations around the world are developing innovative policies and business approaches to build low-carbon economies and adapt to changing climate. In particular, efforts are being made to control greenhouse gas emission from various sources. Therefore a global effort is being made to understand, quantify, and manage greenhouse gas emissions. Major actions aim at making measurable reduction in greenhouse gas emissions contributing thus to stabilize their concentrations in the atmosphere at a level that would prevent the dangerous anthropogenic interference with the climate system.

Methane (CH_4) is the second most important anthropogenic greenhouse gas after carbon dioxide (CO_2). Per mass of the compound, methane global warming potential has been estimated to be more than 28 times of that of carbon dioxide (IPCC, 2013). Globally, over 60% of total methane emissions come from human activities (EPA, 2010; Nisbet et al., 2014). Methane is emitted from industry, agriculture, and waste management activities. Methane emissions from waste management are dominated by the decomposition of organic matter in municipal solid waste and industrial landfills. The associated microbial anaerobic degradation of the organic fraction in waste disposed in landfills generates a mixture of hundreds of different gases. By volume, landfill gas typically contains 45% to 60% methane and 40% to 60% carbon dioxide. Waste management is estimated to be the third largest source of methane emissions in the United States (EPA, 2010). In Europe, an estimated 30% of anthropogenic methane emissions are caused by landfills (EEA, 2014). In 2010, global methane emissions from landfills accounted for approximately 11% of total methane emissions (EPA, 2014) and these emissions are projected to grow 13% between 2010 and 2030. In 2030, emissions from landfills are expected to represent 10% of the global total methane from all sources (EPA, 2014).

In the last decade, attention to methane emissions from landfills has grown significantly. The reason is that emission reduction from landfills is amongst the most feasible and cost-effective measures to reduce greenhouse gas emissions (Oonk, 2010). In addition, using landfill gas can provide a continuous source of energy. Technologies for converting landfill gas into energy include: electricity generation and production of alternate fuels (EPA, 2014).

Many large landfills are closely monitored and in many countries, authorities have the obligation to quantify landfill methane emissions and subsequently report emissions within international programs aimed at controlling greenhouse gas emissions. In addition, measurements of methane emissions may represent a good way to evaluate the efficiency of landfill gas recovering systems or biocovers (Scheutz et al., 2011). However, quantifying landfill fugitive methane emissions is problematic due to the high temporal variability and spatial heterogeneity of these emissions. Additionally, the relationship between the emission rate and the gas concentration at a given location is dependent on the meteorological conditions and local topography, preventing accurate quantification of the emission rate. Thus, development of reliable and cost-effective methods for measurements of landfill methane emissions is an important task and a challenge to the scientific community.

Several methods exist for the estimation of methane emissions from landfills. Estimation methods are either based on emission models or on measurement methods. In model-based methods, methane emissions can be estimated using existing biogas production mathematical models. These models are aimed at quantitatively describing methane formation from anaerobic waste degradation through simulating the decay of organic material deposed in the landfill. One of the largely used model is the landfill Gas Emissions Model (LandGEM) developed by the U.S Environmental Protection Agency (Alexander et al., 2005). Models also include GasSim (GasSim2.5, 2014) developed by Golder Associates for the Environment Agency of England and Wales. Besides, in the frame of the European Pollutant Emission Register (EPER) various evolving version of the European EPER models are applied in many European countries such as the French EPER model and the German EPER Model (Oonk, 2010; Rajaram et al., 2011). Spokas et al (2011) have developed an annual inventory model for landfill methane emissions that incorporates both site-specific soil properties and soil microclimate modeling. This new approach has been field-validated at two Californian sites where emission predictions were in the same order of magnitude as field measurements.

Even largely used, the landfill generation models are generally considered insufficiently accurate and not mutually comparable (Di Bella et al., 2011). Jacobs and Schraff (2005) compared several methane emission models with methane emission measurements. They showed that emission models give different results, even when the same data are entered. Jacobs and Schraff (2005) also stated that further development of methane emission measurement techniques may provide a more reliable tool in the near future than modeling.

As an alternative to model-based methods, measurement techniques are having an increasing interest for landfill methane emission estimation. Closed chamber measurement is frequently employed both for monitoring methane emissions from small parts of a landfill as well as estimating overall emissions from an entire landfill (Abichou et al., 2011; Scheutz et al., 2009). Also micrometerological measurements are used for methane emission quantification (Lohila et al., 2007). Recently, several methodologies have been proposed in order to estimate methane emissions from landfills while delivering cost- and labor-effective results (Cambaliza et al., 2015; Foster-Wittig et al., 2015). These methods include: static and mobile plume measurement methods using tracer gas (Mønster et al., 2015; Mønster et al., 2014; Scheutz et al., 2011), radial plume mapping (RPM) using optical remote sensing by means of laser infrared radiation emissions (Goldsmith et al., 2011; Thoma et al., 2010), differential absorption light detection and ranging (LiDAR) (Babilotte et al., 2010) and inverse plume modeling (Mackie and Cooper, 2009; Oonk, 2010).

In inverse plume modeling technique, methane concentrations above the landfill surface are mapped. A field survey can be done by walking a predefined grid with a portable Flame Ionization Detector or another field gas analyzer. Surface concentrations are relatively inexpensive and much easier to obtain compared to alternative experimental techniques. Mapping of methane concentration could be exploited to identify point sources of relatively high concentrations (emission hotspots) such as cracks in the landfill cover (Figueroa et al., 2009). Methane concentration data are already frequently sampled in many municipal solid waste landfills. Furthermore, employing such approaches allows for reduced costs and uncertainties associated with other experimental and model-based estimations of emissions. In this context arises the need for efficient approaches to correlate surface concentrations to emissions allowing thus for better estimation of the tendencies of methane oxidation and emission rates at landfills. Mackie and Cooper (2009) proposed an emissions prediction approach exploiting ambient air volatile organic compound measurements. They used Voronoi diagrams to predict the locations of maximum likelihood of the point sources, and emission rates are then calculated using linear regression aiming at identifying statistical best fit for solving multi-source problems.

This study presents an alternative methane emission estimation method exploiting ambient air methane concentration measurements on landfill surface. The proposed approach aims at establishing an estimation of methane emissions from a given landfill, and also to identify positions of leakage sources and to quantify the gas emission rate. An optimization-based approach using Genetic Algorithms is employed to solve the inverse problem that consists on identifying source data (locations of hot-spots and corresponding emission rates) having receptor locations and surface measurements along with meteorological conditions as input data. Stochastic search methods such as Genetic Algorithms are particularly useful in hard optimization tasks. Hard optimization problems include practical optimization tasks that are difficult (if not impossible) to solve exactly in a reasonable time (Dréo, 2006). Stochastic methods are able to efficiently explore complex and large solution space using special strategies. Although there is no guarantee of reaching a global optimum, near optimal solutions are usually obtained. Single and also multi-objective optimization schemes through Genetic Algorithms are tested in this study based on measurement data available. The optimization methodology uses atmospheric dispersion calculations to predict major methane emissions sources in a landfill. Four case-studies are presented to show effectiveness of the proposed methodology.

2. Optimization-based methane emission estimation

2.1 Description of the proposed approach

The proposed methane emission estimation technique exploits ambient air methane concentration measurements that are already frequently obtained and monitored in many municipal solid waste landfills. Single and also multi-objective optimization schemes through Genetic Algorithms are tested in this study based on surface emission monitoring data. In the optimization-based solution of the identification task (Fig. 1), the proposed methodology uses atmospheric dispersion calculations to evaluate emission source configurations on a landfill. Detailed description of the major steps of the proposed approach is presented in subsequent sections.

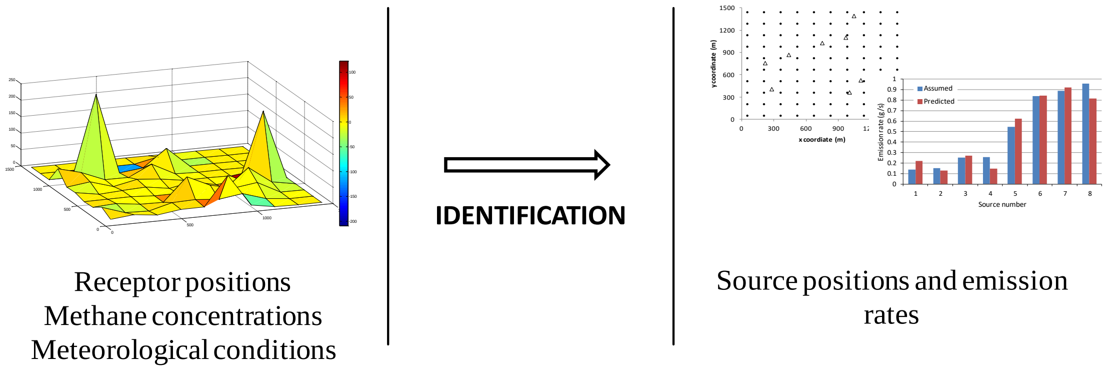

Figure 1. Identification scheme for emission estimation (prepared by authors)

2.2 Generation and evaluation of candidate models

Assuming that a field survey has resulted in a vector of methane concentration measurements denoted $C_{measured}$ performed at *m* defined measurement points in a landfill. Measurement locations or receptors are thus represented by two coordinate vectors X and Y, each having *m* components; related with the vector of gas concentration measurements.

For this study, a candidate model defines a peculiar configuration of sources and emission rates. It is represented by the following data set:

- Geographic positions of a number (*n*) of sources: source positions are represented by two coordinate vectors X and Y, each having *n* components;
- Point emission rates corresponding to the *n* sources of the model: this information is represented by a vector Q of *n* components corresponding to emission rates of the model sources (expressed in micrograms per second: µg/s).

A model is evaluated through calculating the corresponding methane concentrations at receptors points. This is done by backward application of atmospheric dispersion model. Gaussian dispersion equations are used for this task. The Gaussian model is still the basic workhorse for dispersion calculations (Beychok, 2005). According to this approach, gas concentration is given by Equation (1).

$$C(x,y,z,H)=\frac{Q}{2\pi u\sigma_y\sigma_z}\exp\left(-\frac{1}{2}\frac{y^2}{\sigma_y^2}\right)\left\{\exp\left(-\frac{1}{2}\frac{(z-H)^2}{\sigma_z^2}\right)+\exp\left(-\frac{1}{2}\frac{(z+H)^2}{\sigma_z^2}\right)\right\} \qquad \text{(Eq. 1)}$$

where *C* is the steady-state gas concentration ($\mu g/m^3$) at a point (*x, y, z*), *Q* is the emission rate ($\mu g/s$), σ_y and σ_z are the horizontal and vertical spread parameters that are functions of the along wind distance *x* (Fig. 2) and the atmospheric stability, *u* is the average wind speed at stack height (*m/s*), *y* is the crosswind distance from ground level (*m*), *z* is the vertical distance above the ground (*m*), and *H* is the effective stack height (physical stack height plus plume rise expressed in m). In Equation (1) the second z-exponential term is added to account for the fact that pollutant cannot diffuse downward through the ground at $z = 0$. A virtual source located at $z=-H$ below the ground will then begin to contribute to the aboveground concentrations. This “image” term is used to account for plume reflection at the ground (Wark et al., 1998).

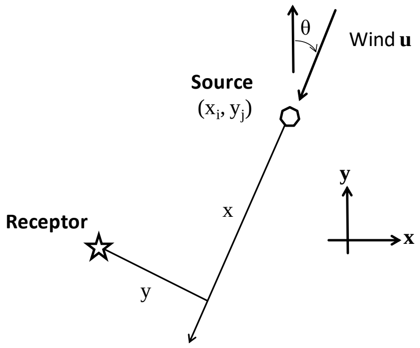

Figure 2: Source-receptor configuration (adapted from Mackie and Cooper (2009))

The Gaussian distribution equation uses relatively simple calculations requiring only two dispersion parameters (σ_y and σ_z) to identify the variation of gas concentrations away from the diffusion source. These dispersion coefficients, σ_y and σ_z, are functions of wind speed, cloud cover, and surface heating by the sun. Generally, the evaluation of the diffusion coefficients are based on atmospheric stability class (Pasquill and Smith, 1983). In this study, Pasquill-Gifford stability classes are employed and dispersion coefficients are calculated using Briggs model (Hanna et al., 1982). Details about dispersion coefficient evaluation are given in Appendix.

For ground-level sources and receptors (*z = 0* and *H = 0*), Equation (1) reduces to Equation (2):

$$C = \frac{Q}{\pi\, u\, \sigma_y \sigma_z} \exp\left[-\frac{1}{2}\frac{y^2}{\sigma_y^2}\right] \qquad \text{(Eq. 2)}$$

Under defined atmospheric conditions and wind speed, dispersion parameters are obtained and the predicted methane concentration in a receptor point *i* ($C_{i,\ predicted}$) is calculated through summing up all contributions (C_{ij}) of assumed source points *j* (*j=1,.., n*). This is expressed in Equation (3).

$$C_{i,\text{predicted}} = \sum_{j=1}^{n} C_{i,j} \qquad \text{(Eq. 3)}$$

Calculating predicted concentration for all receptor points (*i=1, .., m*) results in a vector of predicted concentrations ($C_{\text{predicted}}$).

Using ambient methane measurements, the identification task aims at locating emission sources and their emission rates. This task is formulated as an optimization problem that consists on residual minimization under bound constraints. The objective function ***R*** is thus defined as the normalized estimation error between predicted and measured methane concentrations. The problem is presented as follows:

$$\begin{aligned}
&Min\ R(X,Y,Q) = \frac{\sum_{i=1}^{n}\left(C_{i,measured} - C_{i,predicted}\right)^2}{\sum_{i=1}^{n}\left(C_{i,measured}\right)^2} \\
&under \\
&x_{\min} \le x_j \le x_{\max} \quad ;\ j = 1,..n \\
&y_{\min} \le y_j \le y_{\max} \quad ;\ j = 1,..n \\
&Q_{\min} \le Q_j \le Q_{\max} \quad ;\ j = 1,..n
\end{aligned} \qquad \text{(Eq. 4)}$$

In Equation (4), the two first constraints define the geographic limits of source positions (Limits of the landfill). The third constraint defines the lower and the upper bounds of the source emission rates.

2.3 Estimation of source number

Prior to optimization with Genetic Algorithms, an estimation of the number of potential emission sources is performed. The number of sources could be added as an optimization variable in the identification procedure. However, it would increase the complexity of the optimization task and increase drastically the running time of the optimization code. Instead, a data-driven initial guess of the number of release points could be used to simplify the optimization task. A peak picking procedure is employed to obtain an estimated number of the landfill sources. The simplest automated peak picking algorithm is based primarily on the intensity of local maxima exceeding a threshold value. The procedure employs a threshold value that represents the minimum peak height to be taken into account. Consequently, the procedure only returns peaks that exceed the threshold ignoring peaks having low intensities. Therefore, a large threshold value could result in a few number of local maxima being picked and a small threshold could result in a large number of maxima to be considered. Thus, the threshold should be tuned in order to prevent selecting too many or too few peaks.

Identifying peaks from measurement data is performed employing a Matlab® routine called *findpeaks*. This routine is able to find values and locations of local maxima in a set of data even if some peaks are very close to each other. For instance, measured methane concentrations presented in Fig. 3 are treated with the peak picking procedure in order to estimate the number of high concentration points. Fig. 4 displays results of the peak picking procedure. A two-dimensional representation is used for a better visualization of concentration peaks. In Fig. 4 measured concentration (Y axis) are displayed for each measurement location (X axis). The circular markers show the identified peaks. The threshold is fixed as 5% of the biggest measured methane concentration along all measurement points. This procedure is effective in identification of high concentration points. It is assumed that these high concentration points are likely to be close to hotspots in the landfill. In this example and also for the case studies presented in subsequent sections, the chosen value for the threshold is shown to be useful in estimating the number of potential sources. It is also assumed that source points that are likely to be ignored by the peak picking procedure are generally those associated with low emission rates which slightly affect the results of the entire methane-emission estimation.

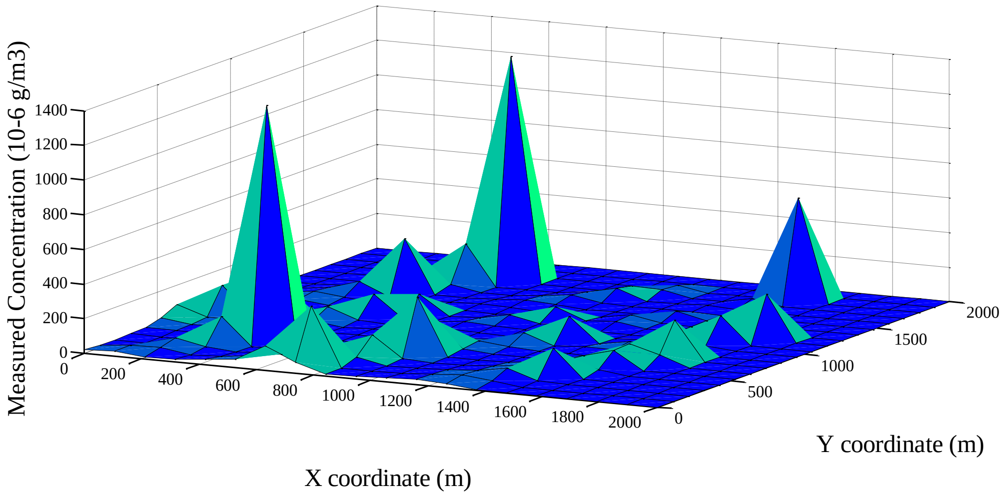

Figure 3: Sample measurement data (prepared from randomly generated data)

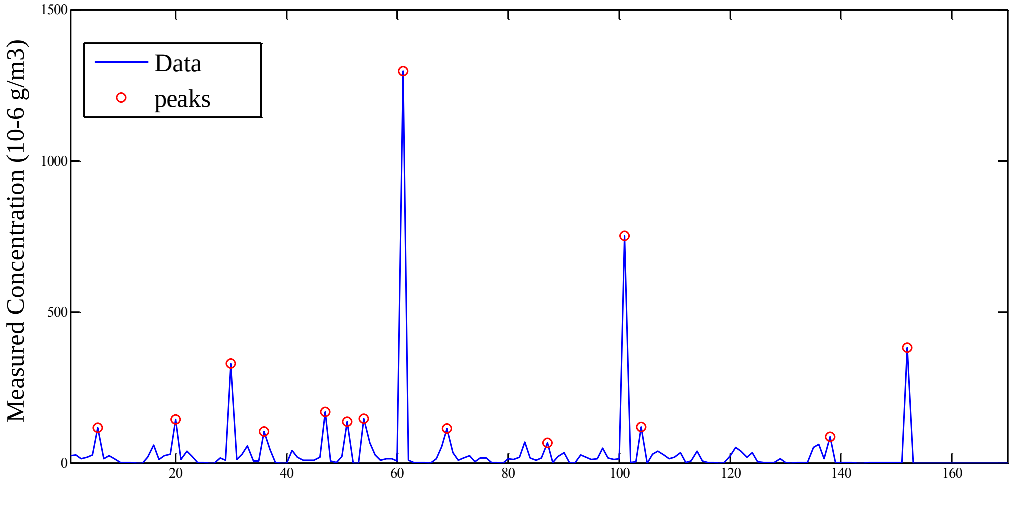

Figure 4: Detected peaks in measurement data (prepared from randomly generated data)

2.4 Identification of source configuration through Genetic Algorithms optimization

Genetic Algorithms are global search methods that belong to the class of stochastic search algorithms. They were originally proposed by John Holland, but the success of the method owes much to the work of Goldberg (1989). Genetic Algorithms have been used efficiently since the early 1990s to solve hard optimization problems with both discrete and continuous variables. This is the main reason behind using stochastic algorithms, which produce near-optimal solutions with a moderate computing effort.

Genetic Algorithms are modeled based on the principles of the evolution of generations via natural selection, mutation and crossover. Biological evolution is simulated by encoding potential solutions (a *population* of *individuals* in genetic terminology) using a chromosome-like data structure and the search is guided by the results of evaluating the objective function for each individual in the population (Raphael and Smith, 2013). New individuals are generated in the population through reproduction using crossover and mutation operators. Individuals that have higher *fitness* (i.e., represent better solutions) can be identified, and these are given more opportunity to breed. The genetic algorithm evolves, in successive generations, the composition of the population; enabling thus convergence towards near-optimal global solutions. Furthermore, even if stochastic search methods do never guarantee to obtain the optimal solution for whatever an optimization problem, these techniques are able to converge to near-optimal solutions that are most of the time satisfactory from an engineering point of view.

As formulated in this study, the estimation of landfill methane emission is based on the identification of the source configuration that permits obtaining the best fit between measured and inferred methane concentrations. A source configuration involves positions and emission rates of a definite number of source points. The number of source configurations generated for an identification case increases rapidly with increasing estimated number of sources. This is the main reason behind choosing Genetic Algorithms to solve such identification task since this method is generally capable of traversing large and complex search space to provide near-optimal solutions.

The identification procedure is described in the flowchart presented in Fig. 5. The main steps of the estimation of methane emission from landfill are summarized as follows:

1. The inputs of the estimation procedure are related to the geometry of the landfill, the meteorological conditions and the surface emission measurement data (concentration values and measurement locations).
2. The peak picking procedure described in section 2.3 is performed in order to have an estimation of the number of potential emission sources in the landfill. This is a key step since the estimated number of sources is a prerequisite for the optimization-based identification procedure.
3. The Genetic Algorithms based identification procedure begins with a randomly generated set of source configurations. This set constitutes the initial *population* of *individuals* in Genetic Algorithms terminology. Each source configuration consists on a number of emission sources with defined positions and emission rates.
4. The meteorological conditions are used to determine the Pasquill stability class. The predicted methane concentration in each receptor position is calculated by summing-up contributions of all assumed emission hotspots in the source configuration. This is performed through forward application of the Gaussian dispersion equation. Each of the generated source configurations is evaluated and assigned a *fitness* value based on the objective function defined in Equation (4). The difference between predicted and measured concentration vectors (the residual) defines the performance of a source configuration. Thus, the minimum value of the residual function corresponds to the best fit between measurements and predictions. The up-coming steps are targeted to minimize the objective function in order to identify a source position that represents the best fit between measurements and predictions for receptor methane concentrations.
5. Based on the evaluation step (step 4), the source configuration set is handled through Genetic Algorithms operators. New source configurations are generated through the Biology-inspired operators that characterize the Genetic Algorithms optimization technique. A proportion of the existing source configuration set is selected to breed new source configurations. Source configurations are selected through a fitness-based process, where fitter solutions (as measured by the previously defined objective function) are typically more likely to be selected. The new source configuration set is obtained from selected configurations through a combination of genetic operators: crossover and mutation. These processes ultimately result in a new source configuration set that is different from the initial set. Generally the average fitness will increase by this procedure for the configuration set (population), since only the best solutions from the first configuration set are selected for breeding, along with a small proportion of less fit solutions.
6. The generational process is repeated until a termination condition has been reached. For this application, the process terminates when a fixed number of iterations (*generations* in Genetic Algorithms terminology) is reached. Genetic Algorithms optimization process evolves, in successive iterations, the composition of the source configuration set; enabling thus convergence towards near-optimal global solutions. The source configuration having the best fitness (the minimum value of the objective function) is taken into account as the solution of the identification task.

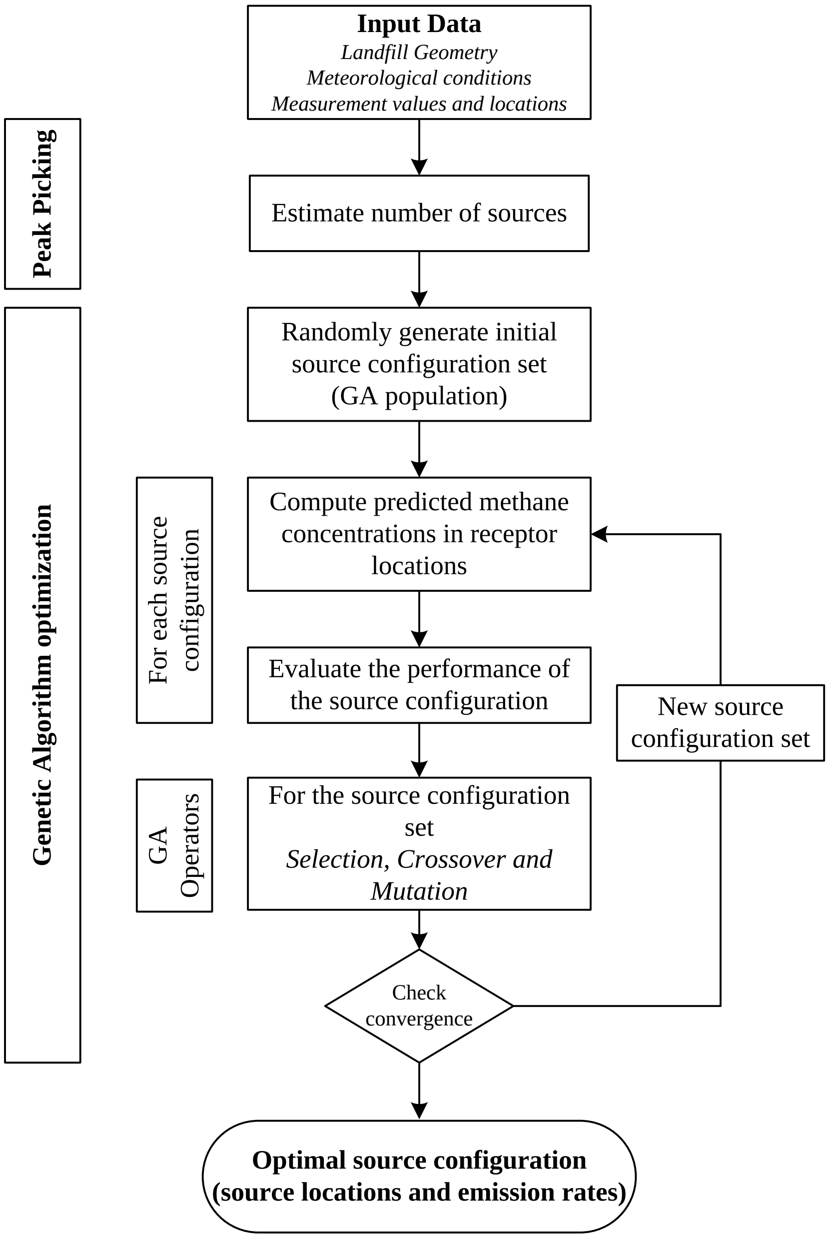

Figure 5: A flowchart of the Genetic Algorithms based identification procedure (prepared by authors)

3. Case studies

In order to illustrate the proposed approach for landfill methane emission estimation, four case-studies are presented. The first two examples are hand-generated case-studies with defined configurations of sources and receptors. These case studies simulate two landfill configurations with 8 and 16 sources, respectively. For the two cases, measurement data are generated through application of the Gaussian dispersion equations. For the case study with 16 sources, receptor concentrations are calculated for two distinct atmospheric conditions simulating, hence, measurement data obtained through two distinct field campaigns. A single objective Genetic Algorithms optimization is employed for the first case study since the objective is to minimize the error between measured and predicted methane concentrations for a unique monitoring round. In contrast, for the second case study, two measurement rounds are available and the objective is to search for the best fit between predicted methane concentrations with two distinct measurement data. This is formulated as an optimization task with two objective functions leading to a multi-objective case study. The third and fourth case studies correspond to actual municipal solid waste landfills. The outcomes of the proposed methodology are compared with the results obtained using Tracer-based method for the first actual case study.

3.1 Test case with 8 sources

For the first case study, a simplified configuration of sources and receptors is simulated. Eight sources with predefined emission rates and 100 receptors are considered. Positions for sources are randomly generated assuming a square-shaped landfill having 1.5km sides. Source emission rates are also randomly generated between zero and 1g/s. Receptor positions are uniformly distributed over the landfill area. Table 1 shows source positions and assumed emission rates (Q) for all eight sources. Receptor and source positions are displayed in Fig. 6. Receptor concentrations are determined based on Gaussian dispersion model assuming a wind speed of 2m/s and wind direction of 35° and stability class C. The Briggs model is employed for determining horizontal and vertical dispersion spread parameters (see Appendix for more details).

Table 1: Source data for case study 1 (hand generated data)

Source number	x position (m)	y position(m)	Emission rate Q (g/s)
1	1001.6	363.3	0.13862
2	967.1	1101.8	0.14929
3	747.7	1028.7	0.25428
4	277.7	407.1	0.25751
5	436.4	869.4	0.54722
6	216.6	758.3	0.84072
7	1043.1	1393.6	0.89090
8	1106.6	526.5	0.95929

In addition to receptor positions, simulated concentrations obtained through application of the dispersion equation are the input data employed to estimate number, positions and emission rates of landfill sources.

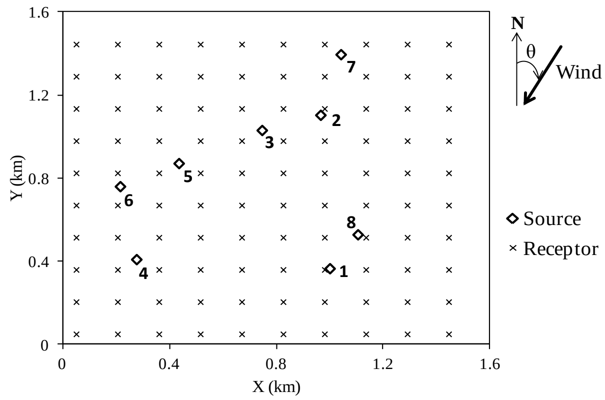

Figure 6. Source and receptor positions for 8 source case study (hand generated data)

The proposed approach is used to obtain the optimal solution for the landfill configuration. Peak picking is first performed to obtain an estimation of the number of sources. Several tests were carried out to fix the Genetic Algorithms parameters. For the case study presented here, optimization results were satisfactory employing a source configuration set with 200 solutions (population size in Genetic Algorithms terminology) evaluated over 3000 iterations. Beyond this fixed number of iterations, simulations showed no improvement of the best generated solution. Convergence is thus assumed and the best solution in the last iteration is stored. Several runs are performed in order to overcome the stochastic nature of the optimization method. The best solution obtained over a sequence of 5 optimization runs is considered as the optimal configuration.

Optimization results are displayed in Fig. 7 and 8. These results are obtained with 8 sources as an estimated number of point sources in the landfill. Fig. 7 shows position of 8 predicted sources compared to assumed source positions. Fig. 8 shows assumed and predicted emission rates for the eight sources. The two figures show good agreement between simulated and predicted results. The identification errors for source positions are below 5% (the assumed positions are taken as the base values). Emission rates for most sources are also well identified. For the overall emission in the landfill, optimization results into a total value of 4.1g/s which can be considered as an accurate approximation of the assumed total emission flux (4.0g/s).

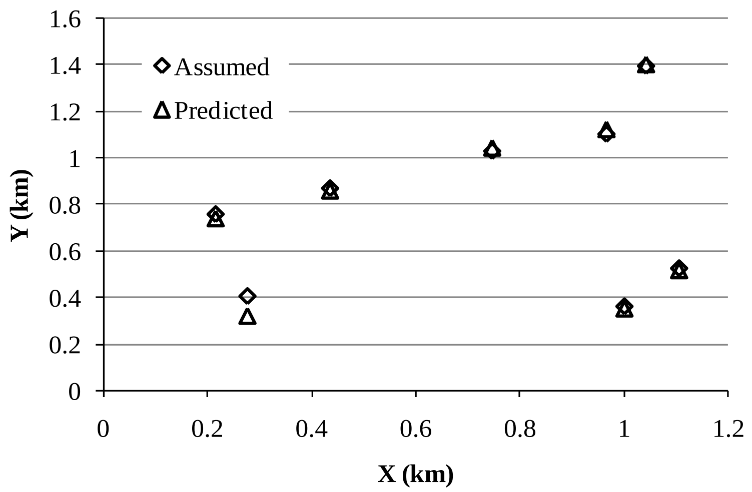

Figure 7. Assumed and predicted source positions for case study 1 (identification results)

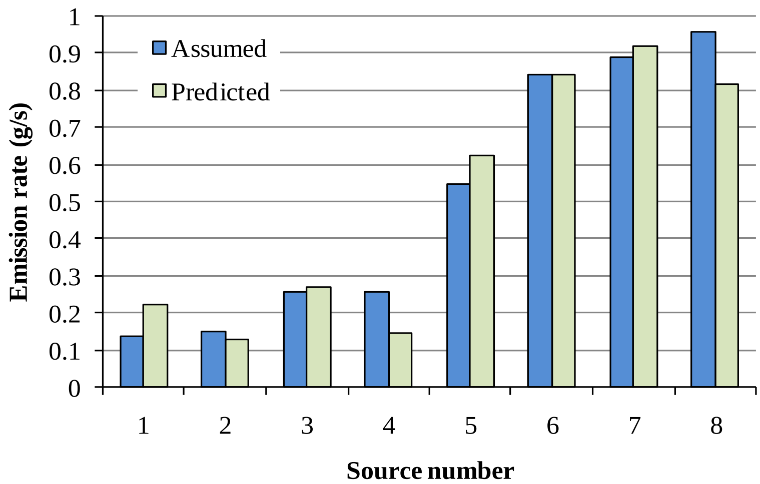

Figure 8. Assumed and predicted source emission rates for case study1 (identification results)

- **Influence of the estimated number of sources**

In order to evaluate the influence of the estimation of the number of sources on optimization identification efficiency, the identification procedure is performed assuming a number of sources equal to 7. This is to simulate situations where the peak picking procedure under-estimates the number of sources in the landfill. Results for this case are displayed in Fig. 9 and

10. Obtained results show that the proposed procedure is still able to identify positions and emission rates even if the number of sources is not accurately estimated. The source number 4 is ignored through identification. Compared to other sources, source 4 has relatively low emission rate. Moreover, taking into account wind direction, downwind receptor points for this source are relatively few. Not more than 5 receptors are directly influenced by emission from source point 4. The latter arguments could explain the results. For the 7 identified sources, the identification errors for source positions are below 5%. As for emission rates, identification errors depends up-on emission level. For the sources having highest emission rates, identification errors are below 20%. For the overall emission in the landfill, the optimization results into a total value of 3.7g/s which indicate an estimation error below 7%. Estimation errors are calculated as the ratio of the difference between predicted and assumed values to the assumed value. This holds for all hand generated case studies.

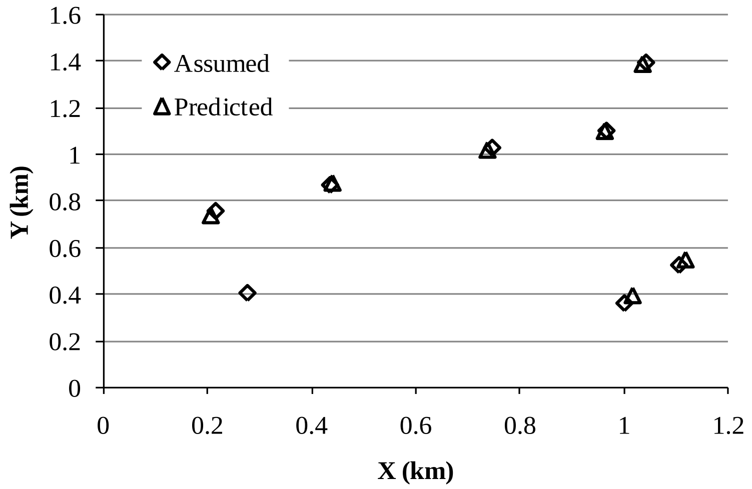

Figure 9. Assumed and predicted source positions for case study 1 with 7 sources (identification results)

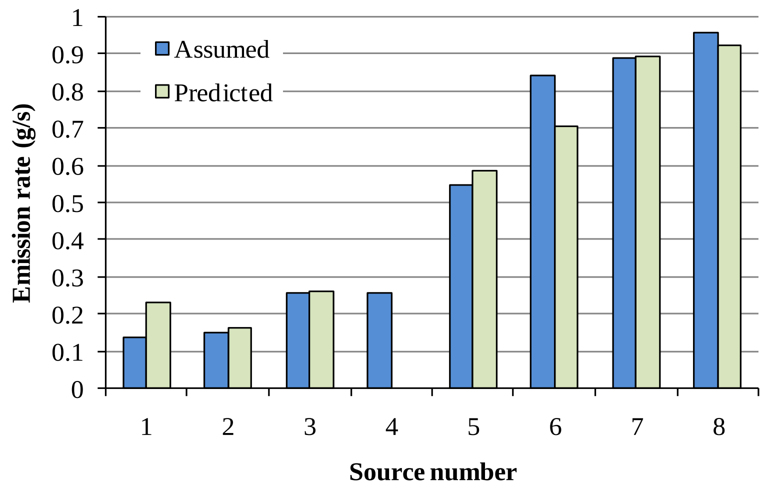

Figure 10. Assumed and predicted source emission rates for case study 1 with 7 sources (identification results)

In order to further investigate the efficiency of the proposed identification procedure, optimization-based identification is performed with an estimated number of 4, 9 and 16 sources, respectively. Again, the objective of using deliberately inaccurate estimated number of sources is to evaluate the identification efficiency in case the peak picking procedure fails at accurately estimating the number of sources in the landfill.

Results for all simulation cases are summarized in Table 2. Results show the total emission rate over the entire landfill. The best result obtained over five runs of the optimization procedure is given. Estimation error for each case is also given (values in parentheses in Table 2). Estimation error evaluates the estimation deviation from the reference assumed total emission flux (4.0g/s). In all cases, the proposed identification procedure is shown able to estimate the total emission rate even if the number of sources is not accurately estimated. The error on the total emission flux does not exceed 12.5%. In the case of a good estimation of the number of sources, the identification procedure is able to pinpoint source positions and emission rates and consequently the total emission rate of the entire landfill is well estimated.

Table 2: Emission predictions for varying number of estimated sources (identification results)

	Number of estimated sources				
	4	7	8	9	16
Predicted landfill emission [g/s](error)	3.7 (7.5%)	3.7 (7.5%)	4. 1 (2.5%)	4.1 (2.5%)	4.5 (12.5%)

- **Influence of the meteorological conditions**

The uncertainties related to meteorological conditions are investigated. Genetic Algorithms based identification is performed with modified values for the Stability class, the wind speed and the wind direction. This is aimed to take into consideration the variability of wind speed and wind direction during measurement campaigns. In addition, the Pasquill stability class which is highly affected by the meteorological conditions is not always easy to establish.

For the three studied parameters, the percentage errors on the identified methane emission from the landfill are displayed in Fig. 11. For all cases the estimation error ranges between 3 and 30%. The wind speed is shown to be a key parameter in the estimation procedure. A modification of only 1m/s in wind speed causes an estimation error that is over 20%. Results showed that wind direction uncertainty have a bigger effect on estimation results. In fact, when wind direction is decreased or increased by 60°, the error in the methane emission estimation ranges between 14% and 30%. Finally, the Pasquill stability parameters have also an important role in the estimation accuracy of the proposed method. It is shown in Fig. 11 that if a wrong stability class is taken into account the estimation error may rise over 15%.

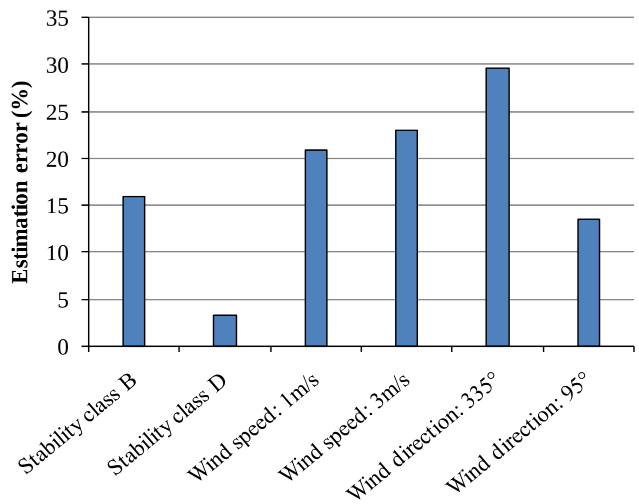

Figure 11. Emission estimation with varying model parameters (identification results)

3.2 Multi-objective case study with 16 sources

For the second case study, a more comprehensive configuration of sources is simulated. Sixteen sources with predefined emission rates and 170 receptors are considered. Positions for sources are randomly generated assuming a square-shaped landfill having 2km width. Source emission rates are also randomly generated between zero and 1g/s. Receptor positions are uniformly distributed over the landfill area. Table 3 shows source positions and assumed emission rates (Q) for all sixteen sources. Receptor and source positions are displayed in Fig. 12. For this case study, receptor concentrations are calculated for two distinct atmospheric conditions simulating, hence, measurement data obtained through two distinct field campaigns. In a first configuration, receptor concentrations are determined by forward application of the Gaussian dispersion model assuming a wind speed of 2m/s, wind direction of 40° and stability class C. A second configuration simulates a measurement campaign where the wind speed is 3m/s, the wind direction is 135° and the stability class is D. For the two configurations the Briggs model is employed for determining horizontal and vertical dispersion spread parameters.

Table 3: Source data for case study 2 (hand generated data)

Source number	x position (m)	y position (m)	Emission rate Q (g/s)
1	0.4851	1.4495	0.16351
2	1.7817	0.8157	0.92110
3	0.2808	0.9608	0.79466
4	1.4016	1.0353	0.57739
5	1.246	1.8496	0.44004
6	1.5913	0.4563	0.25761
7	0.6868	1.7599	0.75195
8	1.4372	1.4173	0.22867
9	1.5952	1.8152	0.6419
10	0.8466	0.2055	0.76733
11	1.0717	0.7102	0.67120
12	1.8614	1.2759	0.71521
13	1.0662	0.5708	0.64206
14	0.4613	0.4762	0.41905
15	1.196	1.3656	0.39076
16	0.7172	1.2055	0.81614

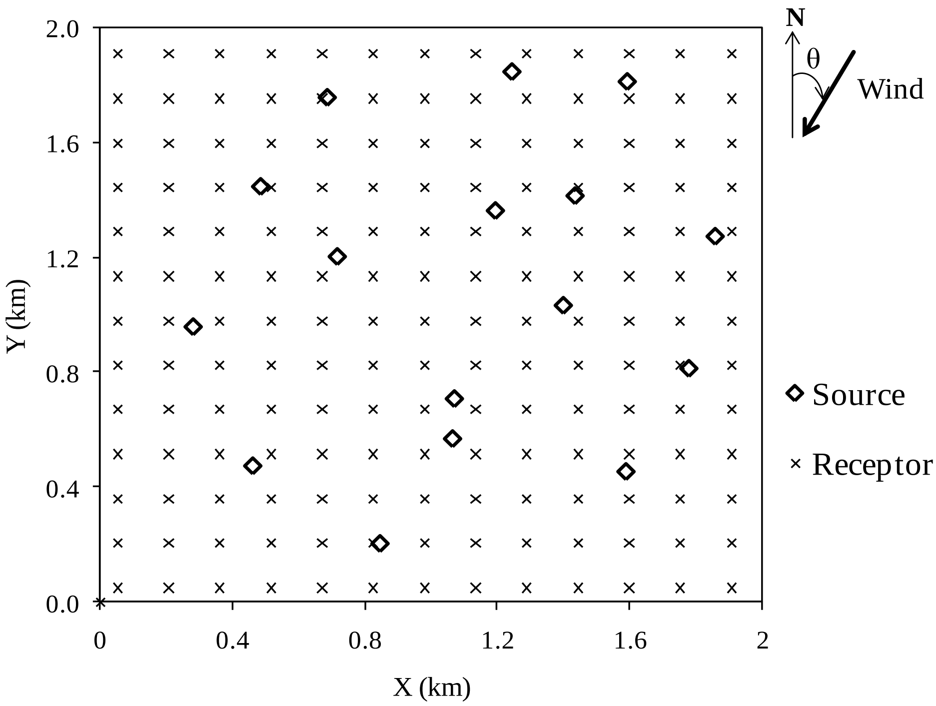

Figure 12. Source and receptor positions for 16 source case study (hand generated data)

In addition to receptor positions, two vectors of simulated concentrations obtained through forward application of the dispersion equation are the input data that are employed to estimate number, positions and emission rates of landfill sources. In order to efficiently exploit the measurement data collected separately through the two simulated campaigns, a multi-objective optimization scheme is now employed. Minimization of two objective functions (Eq.(4)) is targeted. The objective functions represent the error (residual) between measured and predicted methane concentrations using the two available measurement data sets. The multi-objective optimization procedure aims at identifying the source configurations that fits the best the two objectives.

Peak picking is first performed to obtain an estimation of the number of sources. Peak picking resulted in an estimated number of sources of 15 sources for the first simulated data set and 16 sources for the second simulated data set. The threshold of the peak picking procedure is fixed as 5% of the biggest measured methane concentration along all measurement points. It is conjectured that discrepancy in source number estimations arises because of some closely spaced sources. When two or more source points are too close the peak picking procedure may not be able to distinguish separate source points leading to identification of a unique potential source. However, this is shown to have minor influence on the overall estimation results since the physical behavior of two close source points is hardly distinguished from that of a unique source point having an emission rate that is the sum of the two sources emission rates. Using multi-objective optimization, results were satisfactory for a source configuration set of 200 solutions evaluated over 3000 iterations. The best solution set obtained over a sequence of 5 runs is considered as the optimal one.

As a multi-objective problem, the addressed identification task requires the generation of a set of possible solutions, defined as those able to satisfy best and with different performances the two objectives taken into account for source configuration evaluation. These solutions are known as Pareto optimal or nondominated solutions. In a multi-objective minimization task, a solution S* is said to be Pareto optimal if no feasible vector of optimization variables can be found to improve the values for any objective function without causing a simultaneous decline in other objectives. The solution is then selected between mutually nondominated candidates. The Pareto optimal solutions obtained through GA optimization are presented in Fig. 13 with respect to the two objectives. The results displayed in Fig. 13 are obtained assuming existence of 16 source points.

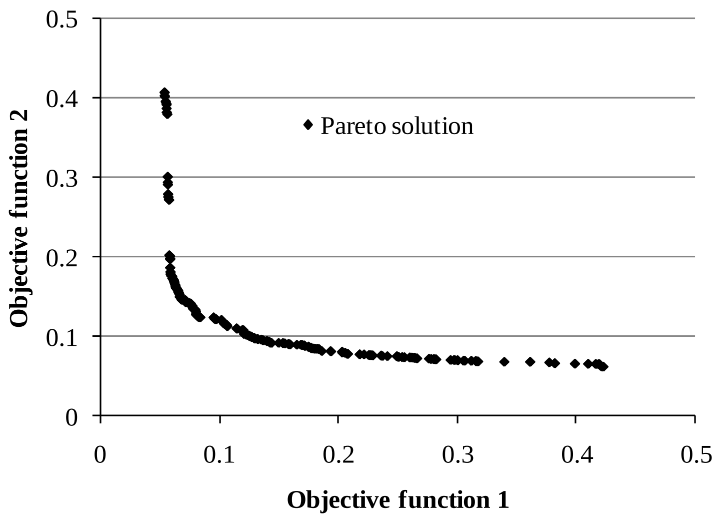

Figure 13. Pareto optimal solutions generated for case study 2 (identification results)

In order to extract maximum information from the entire set of Pareto solutions, a clustering procedure is performed to come with a unique solution for the identification of source positions and emission rates. As defined in the field of *Data Mining*, clustering is a division of data into groups of similar objects. Each group, called cluster, consists of objects that are similar between themselves and dissimilar to objects of other groups (Han et al., 2011).When applied to the set of Pareto optimal solutions, clustering enables grouping closely spaced source positions to represent the Pareto solution set by a unique source configuration.

Clustering is performed on source positions and an average value of emission rate is calculated for each cluster corresponding to a potential source position. The resulting source positions are displayed in Fig. 14. Identification results show good agreement between simulated and predicted source positions. Sources that were not detected (3 out of 16) correspond to the sources with relatively low emission rates. For all other source points, emission hotspots are approached. The averaged emission rates corresponding to each one of the detected source point are displayed in Fig. 15. Once again, predicted emission rates are in good agreement with assumed data. For the overall emission in the landfill, optimization and clustering result into a total value of 8.6g/s which correspond exactly to the assumed total emission flux (8.6g/s).

It is noticed that identification efficiency for some source point is influenced by the geometric position of the source in the landfill and also by the number of corresponding downward receptor points. Obtained results emphasize the importance of having several measurement data-sets to overcome insufficient information. It is important to notice that for any measurement campaign, there is no guarantee that receptors are placed at the most informative locations. Moreover, the variability of the meteorological conditions during measurement campaigns should be kept in mind. Having several measurement data would overcome uncertainties related to the model parameters and lack of information. For this case study, when a unique data set is used and a single objective optimization is performed, the overall methane emission is estimated to be 8.4g/s which represents an estimation error that is below 3%. Even if the difference between single and multi-objective optimization is not large in this case, it is the author's belief that a multi-objective scheme greatly enhances reliability of the optimization-based emission estimation.

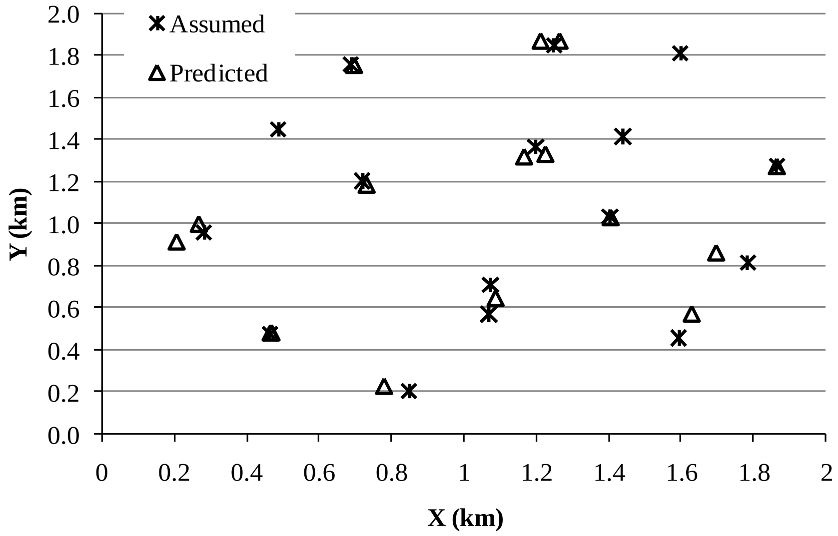

Figure 14. Assumed and predicted source positions for case study 2 (identification results)

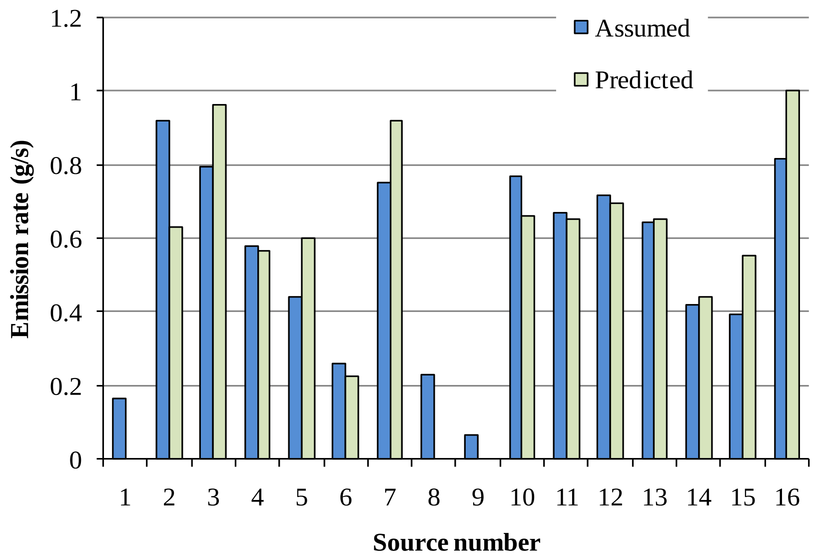

Figure 15. Assumed and predicted source emission rates for case study 2 (identification results)

- **Influence of the estimated number of sources**

In order to show robustness of the proposed identification procedure, the multi-objective Genetic Algorithms based identification is also performed with an estimated number of sources of 8, 15, 17 and 32, respectively. Again, the objective of testing deliberately modified estimated number of sources is to evaluate identification robustness in cases the peak picking procedure over or under estimates the number of sources in the landfill.

Results for all simulation cases are summarized in Table 4. Results show the total emission rate over the entire landfill. The best result obtained through clustering of the Pareto optimal set of solutions is given along with the emission value averaged over all Pareto solutions. Values in parentheses in Table 4 express the estimation deviation from the reference assumed total emission flux (8.6g/s). In all cases, the proposed identification procedure is shown able to estimate the total emission rate even if the number of sources is not accurately estimated. Extreme cases where the number of sources is estimated double (half, respectively) of the actual number of sources in the landfill showed that the estimation error is below 35%. The identification results show that even if the number of sources is largely over estimated, the proposed methodology is still able to identify major hotspots in the landfill. This demonstrates methodology robustness with respect to the estimated number of potential sources and the use of the peak picking procedure.

Table 4: Emission predictions for varying number of estimated sources (identification results)

	Number of estimated sources				
	8	15	16	17	32
Total predicted emission for the best run [g/s](error)	6.0 (30.2%)	8.2 (4.6%)	8.6 (0.0%)	7.9 (8.1%)	11.0 (28.0%)
Total predicted emission averaged over all Pareto solutions [g/s] (error)	6.3 (26.7)	8.0 (7.0%)	8.4(2.3%)	7.4 (13.9%)	11.5 (33.7%)

- **Influence of the meteorological conditions**

As for the first case study, the uncertainties related to meteorological conditions are investigated for the second case study. Genetic Algorithms based identification is performed with modified values for the stability class, the wind speed and the wind direction. The percentage errors on the identified methane emission from the landfill are displayed in Fig. 16. For all cases the estimation error is below 15%.

All parameter modifications are made for the first simulated configuration. The reference configuration is simulated assuming a wind speed of 2m/s, wind direction of 40° and stability class C. Six additional cases are tested. For the first two cases the objective is to estimate the robustness of the proposed method if a wrong stability class is taken into account. A stability class B (D, respectively) is considered rather than the actual stability class (C). Two other cases simulate uncertainty on wind speed (1m/s and 2m/s rather than 3m/s). The two last cases are intended to evaluate the effect of wind direction variability (340° and 100° rather than 40°).

The methane emission estimation error is displayed for all six studied cases (Fig. 16). Results show that if a wrong stability class is taken into account the estimation error may rise over 12%. For wind speed, it is shown that a modification of 1m/s in wind speed causes an estimation error that is slightly over 10%. Results also showed that for this case study wind direction uncertainty has a minor effect on estimation results. For instance, if wind direction is decreased or increased by 60°, the error in the methane emission estimation is below 8%.

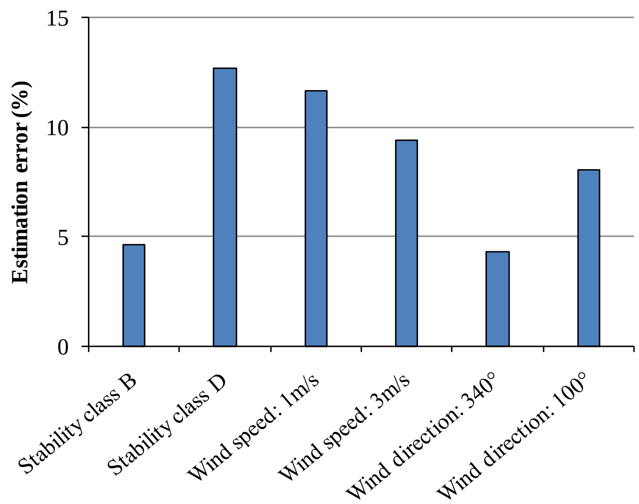

Figure 16. Emission estimation with varying model parameters (identification results).

3.3 SW landfill case study

The Genetic Algorithms based identification methodology was applied to an existing municipal solid waste landfill named *SW landfill* in order to estimate fugitive methane emissions. The studied case is a closed landfill that covers an overall area of about 202,345 m². Along with a surface emission measurement campaign, tracer test campaigns were performed in the same period for *SW landfill* as described by (Foster-Wittig et al., 2015; Green et al., 2012; SCS, 2010). This allowed comparing outcomes of the two methodologies.

3.3.1 Surface emission monitoring: Data and Results

According to the surface emission monitoring report (SCS, 2010), approximately two hours were needed to collect surface methane concentrations across the walking path in 463 measurement locations. The temperature and the wind speed were measured twice: in the beginning and by the end of monitoring. A Flame Ionization Detector was used to perform surface monitoring with data collected every 15 seconds. The Flame Ionization Detector was calibrated at the beginning of monitoring event, prior to use, in accordance with the regulations. In order to screen surface methane concentrations a funnel-shaped probe was directly put on the landfill surface and via an integrated pump the emitted gas was drawn through the Flame Ionization Detector. The equipment allows quantifying the methane concentrations in the air at sampling locations that are the result of mixing of methane released upwind with locally released gas. A GPS unit was used to indicate measurement positions along the monitoring path. The surface emission monitoring route provided coverage of all waste disposal of the landfill. Additionally, if surface defects or passive vents were encountered, concentration readings were performed around such features.

Table 5 shows general data and climate conditions for the surface emission measuring campaign. Based on monitoring conditions a stability class C is assigned for this case. As for earlier case studies the Briggs model is employed for determining horizontal and vertical dispersion spread parameters. The proposed approach is used to estimate methane emissions and locate potential sources. Peak picking is first performed to obtain an estimation of the number of sources. Based on the peak picking procedure, the number of potential emission sources in the landfill is estimated to be 11 sources.

Table 5: General conditions for the SEM in SW landfill (SCS, 2010).

	SEM conditions (SCS, 2010)
Date	September 17, 2010
Time	18:05 to 20:00
Sky	overcast
Ground	dry
Temperature (°C)	15
Wind direction	NW
Wind speed (m/s)	2.22
Pressure (Pa)	101795
Number of measurement points	463

For the measuring campaign, methane concentrations are measured in 463 points. Fig. 17 shows receptor positions and measured methane concentrations.

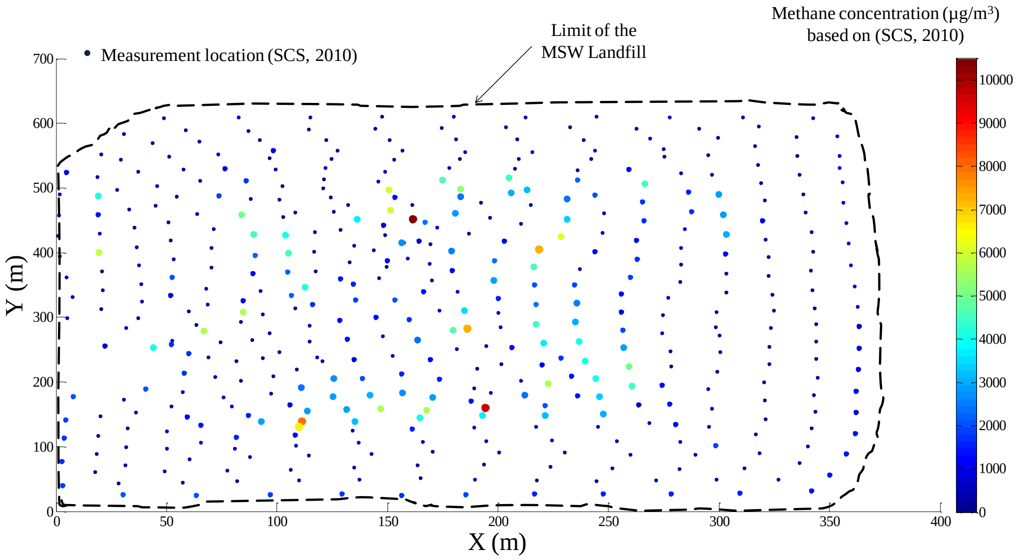

Figure 17. Receptor positions for SW Landfill (SCS, 2010).

Starting from measurement data and meteorological conditions, identification through Genetic Algorithms is performed. For each generated source configuration, receptor concentrations are determined based on Gaussian dispersion model assuming a wind speed of 2.22m/s, wind direction of 315° and stability class C. Plume reflection is taken into account when methane concentrations are calculated for each receptor position. This is achieved by simply doubling the simulated concentrations since both emission and measurements occur at ground level.

Table 6: Predicted emission rate for varying number of assumed sources (identification results)

	Assumed number of sources		
	10	11	12
Total predicted emission for the best run [g/s]	12.7	13.6	14.3
Averaged emission rate [g/s]		**13.5**	

Five optimization runs are performed and the best solution set obtained over all runs is considered as the optimal source configuration. An overall description of optimization results is presented in Table 6. The total emission methane rate predicted assuming existence of 11 emission sources in the landfill is presented. In addition, results obtained with 10 and 12 assumed sources are also presented in order to take into account uncertainty in the identification of the number of sources.

The identification results obtained with 11 sources as an estimated input number of sources are displayed in Fig.18 and 19. Fig.18 shows positions of the predicted sources whereas Fig. 19 shows predicted emission rates for the 11 sources.

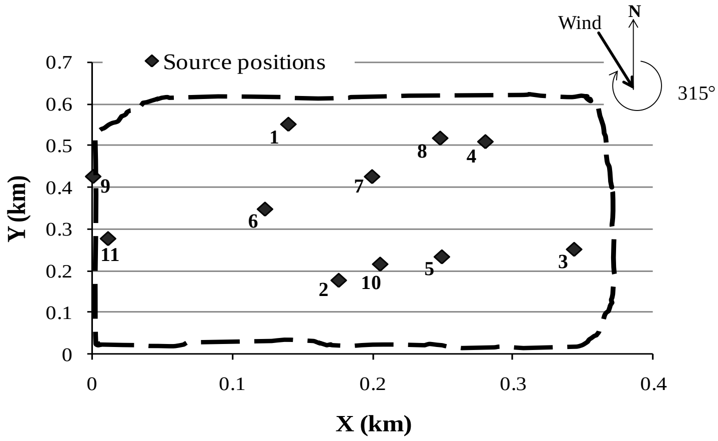

Figure 18. Predicted source positions for SW landfill (identification results)

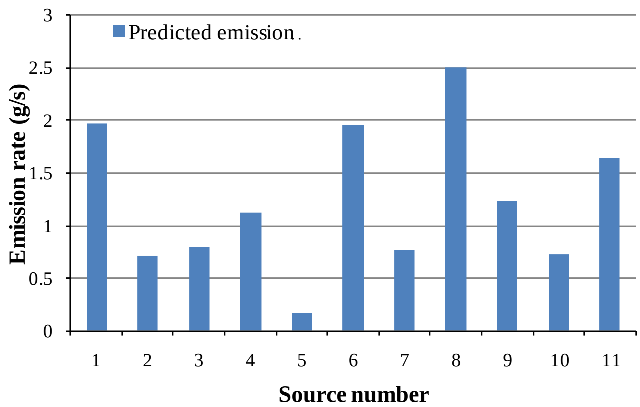

Figure 19. Predicted source emission rates for SW landfill (identification results)

3.3.2 Mobile and stationary plume measurement with Tracer Based Method

One day before the surface emission measuring campaign, an Acetylene Tracer-Based approach was performed in order to quantify methane emissions from the SW landfill. Tracer methods allow for quantitative measurements to be made using a single, mobile gas analyzer located in the far field of the source. In the SW landfill, mobile and stationary plume measurements were made on September 16, 2010 (Green et al., 2012; SCS, 2010). Mobile transect measurements were made by driving the analyzer along roads located around the landfill. Stationary measurements were performed by positioning the analyzer downwind from the landfill where concentrated measurements are performed (Foster-Wittig et al., 2015; Green et al., 2012).

Tracer-based methods involve the release of an inert tracer gas from some selected points along the upwind edge of the emitting surface to simulate gas emission. If the released tracer gas is well mixed in a source "plume" and the methane concentration in the plume differs sufficiently from background atmospheric methane, then the emission rate can be obtained directly, using a ratio method. Tracer methods has the advantage of looking at the entire landfill and avoid the issue of spatial heterogeneity by integrating the whole area flux and are therefore a preferred method for estimating emissions for whole landfills.

According to (SCS, 2010), a Picarro Model G1203 analyzer was used to measure concentrations of acetylene (tracer gas) and methane at parts per billion (ppb) and parts per thousand (ppt) levels. The unit was mounted in an SUV fitted with an external snorkel for gas sample collection. The analyzer was integrated with a GPS (Hemisphere R100) and a compact weather station including self-aligning sonic anemometer (Climatronics AIO Compact Weather Station). Concentration, position, and meteorological data are recorded in a time-synchronized data file.

Continuous measurements of acetylene and methane concentration were recorded as the analyzer makes transects through the plumes. The emission rate of methane was determined as the product of the release rate of the tracer and ratio of line integrals of the concentrations of acetylene and methane in the plume transects as:

$$Q_m = Q_t \left(\frac{\Delta C_m}{\Delta C_t} \right) \quad \text{(Eq. 5)}$$

Where: Q_m = CH_4 emission rate, Q_t = Tracer gas release rate, ΔC_m = CH_4 observed in the plume, relative to background, and ΔC_t = Tracer concentration in the plume, relative to the background.

Stationary measurements were performed by positioning the analyzer downwind from the landfill and performing an extended time series of methane and acetylene concentration measurements. An assumption of this approach is that the tracer and methane plumes are of essentially the same shape at the point of measurement. The emission rate of methane is calculated by plotting the methane concentrations versus the acetylene concentrations and determining the best-fit line. The slope of this line represents the ratio of the total methane emissions to the total acetylene emissions over the period of measurement. For the mobile transects, care was taken to ensure that the entire plume was transected, with sufficient data collected outside the plumes to establish a clear baseline.

The mobile and stationary plume measurements resulted into an estimated mean emission rate of 12.6g/s and 11.8g/s, respectively. The standard deviations for the two measurements are equal to 1.27g/s and 1.42g/s, respectively. Compared with the proposed approach, the Traced-based method gave slightly underestimated values of methane emissions. Comparing outcomes of the two methods shows that the discrepancy between estimation results is below 15% (Taking the Traced-based results as the base values). These results confirm the potential of the proposed methodology as a cost effective method for the estimation of landfill methane emissions. It is also supposed that the overall coverage of the landfill offered by surface emission monitoring enabled the proposed method to determine a more representative whole site methane emission.

3.4 SF landfill case study

The methodology presented earlier was applied to a second existing municipal solid waste landfill named *SF landfill* in order to estimate methane emissions. The studied case is a closed landfill that covers an overall area of about 225,000 m². The surface emission measuring campaign equipment and procedure were similar to that described for SW landfill case (SCS, 2010). The surface emission monitoring route provided coverage of all waste disposal area.

Approximately one hour was needed for collecting surface methane concentrations across the walking path for the measurement campaign.

Table 7 shows general data and climate conditions for the surface emission measuring campaign. Based on monitoring conditions a stability class B is assigned for this case. As for earlier case studies the Briggs model is employed for determining horizontal and vertical dispersion spread parameters. The proposed approach is used to estimate methane emissions and locate potential sources. Peak picking is first performed to obtain an estimation of the number of sources. Based on a threshold value of 5% of the biggest measured methane concentration, the estimation number of sources is 15 sources.

Table 7: General condition for the SEM in SF landfill (SCS, 2010).

	SEM conditions (SCS, 2010)
Date	September 16, 2010
Time	12:00 to 13:00
Sky	cloudy
Ground	moist
Temperature (°C)	23.3
Wind direction	SW
Wind speed (m/s)	5.36
Pressure (Pa)	101016
Humidity	70%
Number of measurement points	258

Methane concentrations are obtained from 258 measurement points. Fig.20 shows receptor positions and methane concentrations. For each generated source configuration, receptor concentrations are determined based on Gaussian dispersion model assuming a wind speed of 5.36m/s and wind direction of 225° and stability class B. It should be also highlighted that some measurement points in the south limit of the landfill were associated with relatively high methane concentrations (Fig.20). This influenced identification results as explained in the next paragraph.

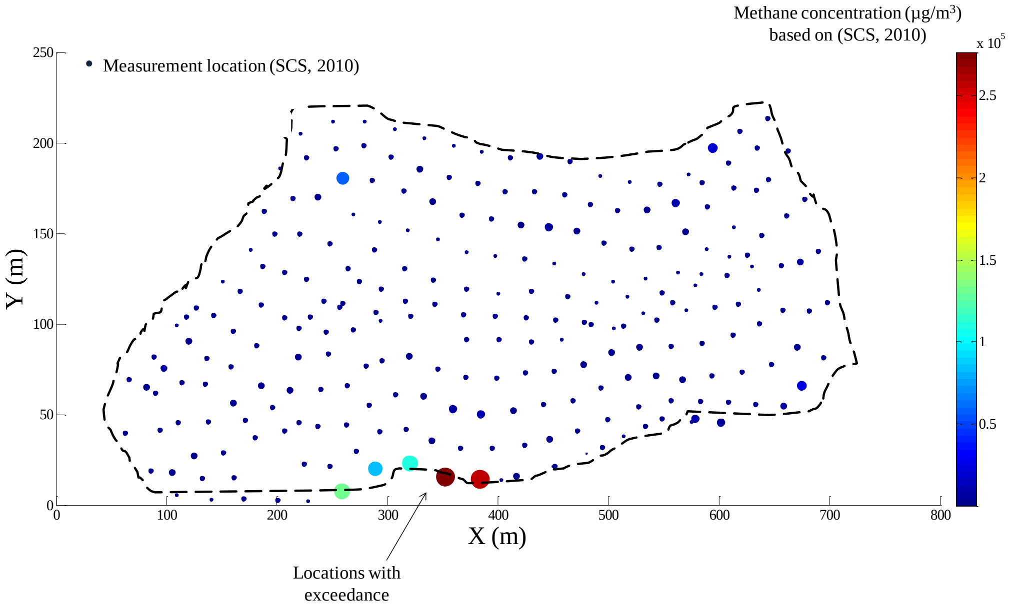

Figure 20. Receptor positions for SF Landfill (SCS, 2010).

The collected data from the surface emission measuring campaign are employed to estimate the methane emission from the landfill using the proposed methodology. As for the previously presented case studies, the best solution obtained over five runs is considered as the optimal source configuration. The total emission methane rates predicted with varying assumed number of sources are presented in Table 8. The averaged methane emission throughout the landfill is estimated to be equal to 15.8/s. Once again, the obtained results illustrate that the assumed number of sources has a minor effect on the total methane emission estimation. This confirms results obtained for previously presented case-studies and shows robustness of the proposed optimization-based methodology.

Table 8: Predicted emission rate for varying number of assumed sources (identification results)

	Assumed number of sources			
	15	16	17	18
Total predicted emission for the best run [g/s]	14.3	15.7	17.9	15.5
Averaged emission rate [g/s]		**15.8**		

As for the identification of the major gas leakage points or regions in the landfill, Fig.21 shows source point locations identified through various runs. The identification results show the existence of some closely spaced emission sources at the southern limit of the landfill. These results could be understood since this region was associated with high methane concentrations in the measurement campaign.

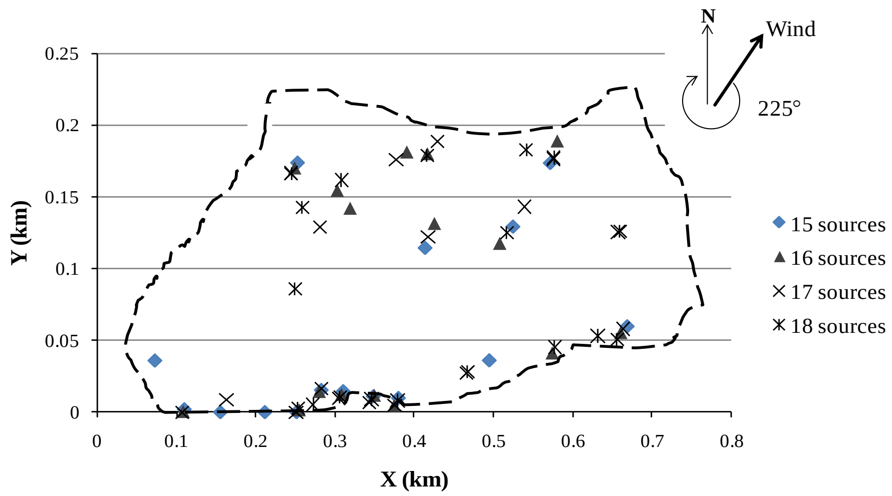

Figure 21. Source positions for varying input source number (identification results)

Sample results are displayed in Fig.22 and 23. These results are obtained with 15 sources as an estimated input number of sources in the landfill. Fig.22 shows positions of the predicted sources whereas Fig.23 shows predicted emission rates for the 15 sources. Again, these results indicate the existence of a source set at the southern limit of the landfill (sources number 3, 4, 14 and 15). These source points could indicate the existence of a crack in the landfill soil cover. It is important to notice that the identification of these sources at this peculiar position is enabled by the wind direction (South-West). This to emphasize that the identification of a source point is strongly related to the existence of associated downwind receptors. Furthermore, an overall coverage of the entire landfill area is crucial for the accuracy of emission estimation and identification of source locations.

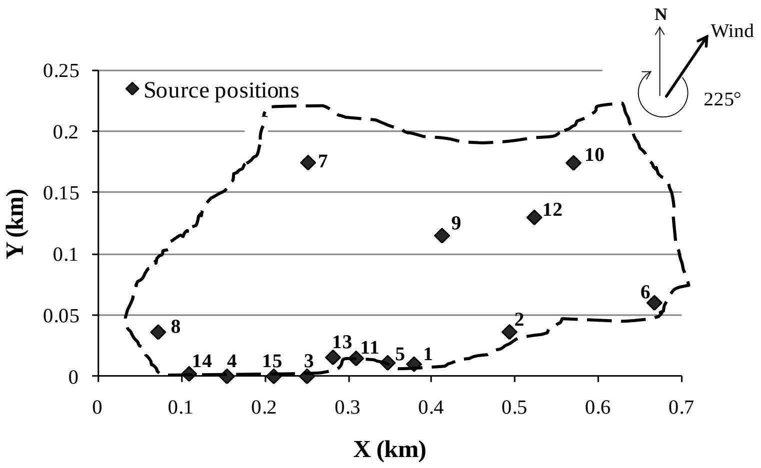

Figure 22. Predicted source positions (identification results)

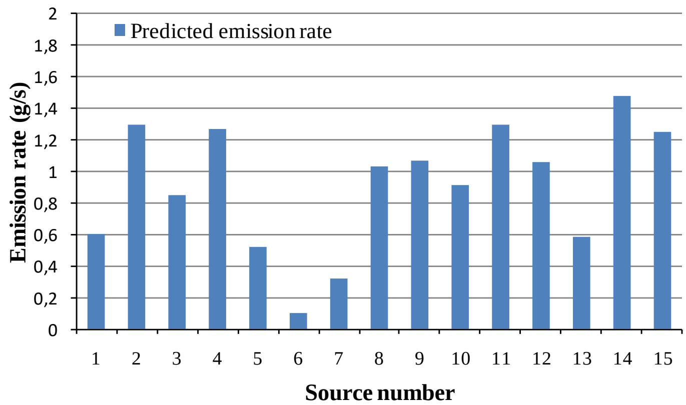

Figure 23. Predicted source emission rates (identification results)

Conclusions

This paper presents a method to estimate fugitive landfill methane emissions using ambient air methane measurements. Genetic Algorithms based optimization combined with the standard Gaussian dispersion model is employed to identify locations as well as emission rates of potential emission sources throughout a municipal solid waste landfill. It is shown that the proposed approach enables estimation of landfill methane emissions and localization of major emission hotspots in four different case studies. In addition, the use of the proposed technique is cost effective and will lead to less emission in the long term since landfill operators can use the technique with little to no cost. Using the collected surface scanning data to better estimate fugitive emissions is beneficial even for comparison purposes (between areas of landfills, between seasons, before and after an operational change is implemented, etc…). Such technique can also be very useful to regulate and improve the efficiency of gas collection systems especially known that landfill gas is recognized as a green power source.

Results of the four case studies showed the importance of having an overall coverage of all waste disposal of the landfill when surface concentration measurements are performed. Additionally, the influence of the variability of the meteorological conditions is studied. Results showed that the identification procedure is robust with respect to meteorological conditions. Based on obtained results it is highly advised to perform measurement campaigns in stable climate conditions with minimum variability during measurement campaigns. An ideal situation is to have weather data (wind speed and direction, etc.) for each individual measurement point. Furthermore, case study 2 showed that if more than one set of measurement data could be available, using a multi-objective optimization leads to accuracy enhancement especially for landfill with large number of leakage points. Having several measurement data would also overcome uncertainties related to model parameters and lack of information. In the third case study, emission estimations obtained with the proposed methodology are compared with those obtained using Traced-based method. Results showed that the outcomes of the two methods are comparable confirming the effectiveness of the proposed methodology. For the fourth case study, the Genetic Algorithms identification helped identifying the hotspots in the southern ridge of the landfill. This emphasizes the importance of having a wide coverage of the landfill in order to guarantee that receptors are placed at all informative locations.

The proposed methodology could be seen as a good step toward assisting landfill operators to reasonably estimate and locate major methane emissions. The authors believe that the described source-locating-scheme is promising and could be part of future endeavors. The proposed approach should be sufficiently field tested to resolve uncertainties and develop best implementation practices. Consistency and accuracy of the method need to be explored more intensively especially through different landfill case studies involving various geographical and meteorological conditions. The number of release points could be added as an optimization variable to overcome limitations of the peak picking procedure. In addition, in order to verify the accuracy of the method, comparison with established methods, such as DiAL, Tracer Gas and/or Radial Plume Mapping should be performed.

Appendix

Atmospheric stability classification

For dispersion estimation and modeling purposes, Pasquill developed a simple quantitative rating scheme consisting of six atmospheric stability classes. These levels of stability are based on simply observable parameters (surface wind speed, daytime insolation, and nighttime cloudiness). These stability classes are referred to as Pasquill-Gifford stability classes and are presented in Table A-1.

Table A-1: Meteorological conditions defining Pasquill stability classes

Surface wind speed (m/s)	Daytime insolation			Nighttime conditions	
	Strong	Moderate	Slight	low cloud	low cloud
<2	A	A-B	B	-	-
2-3	A-B	B	C	E	F
3-5	B	B-C	C	D	E
5-6	C	C-D	D	D	D
>6	C	D	D	D	D

Determination of the dispersion parameters

In Gaussian models, gas dispersion away from the diffusion source is represented by dispersion coefficients, σ_y (horizontal) and σ_z (vertical).These have been measured as a function of distance from the source in numerous field studies. From dispersion parameter curves reported by Pasquill (Pasquill and Smith, 1983), several researchers have worked out analytical power-law formulas for σ_y and σ_z. One of the most used analytic expression is that proposed by Briggs (Hanna et al., 1982) and displayed in Table A-2.

Table A-2: Briggs model for dispersion coefficients

Pasquill stability class	σ_y (m)	σ_z (m)
A	$0.22x(1+0.0001x)^{-0.5}$	$0.20x$
B	$0.16x(1+0.0001x)^{-0.5}$	$0.12x$
C	$0.11x(1+0.0001x)^{-0.5}$	$0.08x(1+0.0002x)^{-0.5}$
D	$0.08x(1+0.0001x)^{-0.5}$	$0.06x(1+0.0015x)^{-0.5}$
E	$0.06x(1+0.0001x)^{-0.5}$	$0.03x(1+0.0003x)^{-1}$
F	$0.04x(1+0.0001x)^{-0.5}$	$0.016x(1+0.0003x)^{-1}$

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