



Department of Mechanical Engineering
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Improvement of Predictable Model of Methane Recovery
within Landfill

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Submitted in partial fulfilment of the requirement for the degree of
MSc. in Energy Systems and the Environment
September 2004-2005

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Acknowledgements

I would like to thank the following people for their assistance in the writing of this thesis:

- ❖ Prof. Joe Clarke, ESRU Course Director, Department of Mechanical Engineering, University of Strathclyde.
- ❖ Mr. Craig Mclean, Project Supervisor, Department of Mechanical Engineering, University of Strathclyde, for acting in his professional capacity as my Project Supervisor.

Finally, my deepest thanks to my friends, and my family for their untiring support, good humour and help throughout this academic year.

I would like to dedicate this work to my parents, whom I think might have found this topic quite interesting.

Wirot Rattanawiboonsom

Glasgow, September 30th 2005

Abstract

The aim of this project was to select various landfill methane models and to provide a comparison of model outputs to actual long-term gas recovery data from suitable landfills. Another aim was to use these data to develop better estimates of confidence limits that can be assigned to model projections.

This project assessed trial model forms against data from available landfills. Data were obtained from sixteen U.S. landfills. Four landfill methane models were compared: a zero-order; a simple first order; a modified first order; and a multi-phase first order model. Models were adjusted for “best fit” to data to yield parameter combinations based on the minimized residual errors between predicted and experienced methane recovery. The models were optimized in this way using two data treatments: absolute value of the differences (arithmetic error minimization) and absolute value of the natural log of the ratios (logarithmic error minimization).

Minimization of the logarithmic error gave better results than those produced by arithmetic error minimization in the form of a narrow, more specific band of parameter combinations for best-fit optimization. Regression coefficients (r^2) were calculated to compare modelled versus actual methane recovery. The regression coefficient results indicate that the four models were similar in predictive ability.

The four landfill methane models were also compared through examination of the data distributions of the numerical ratios of the measured methane recovery values to the modelled recovery over the spectrum of data points established for the study landfills. Plots were developed to show 10 and 90 percent probability limits around median values based on minimization of arithmetic and logarithmic errors. The probability limits for the models optimized via logarithmic minimization were narrower than those established with the arithmetic optimization.

A simple computer program was developed for each of the study models based on the minimization of arithmetic error procedures, which accepts keyboard inputs for model parameters in order project methane generation over time.

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CHAPTER 1

Introduction

Landfill gas (LFG) is a mixture of mainly methane and carbon dioxide resulting from the biodegradation, in the absence of oxygen, of organic landfilled waste. Landfills are a significant source of anthropogenic methane emission. LFG is also potentially flammable or explosive in air, and its odor can cause a nuisance to people living or working near a site.

The production and accumulation of landfill gas within the landfill raises the gas pressure in the landfill above atmosphere pressure. The resulting pressure gradient acts as a driving force causing the gas to diffuse out of landfill, into the surrounding soil strata or into the air. This diffusion occurs along the path of least resistance, i.e. through cracks, the landfill cover and laterally through the surrounding topsoil.

The methane generation of landfill gas lead to four main environments: safety concerns associated with the migration of a potentially explosive gas into the surrounding areas; a detrimental effect on vegetation; odor generation and the contribution of the gas to the greenhouse effect.

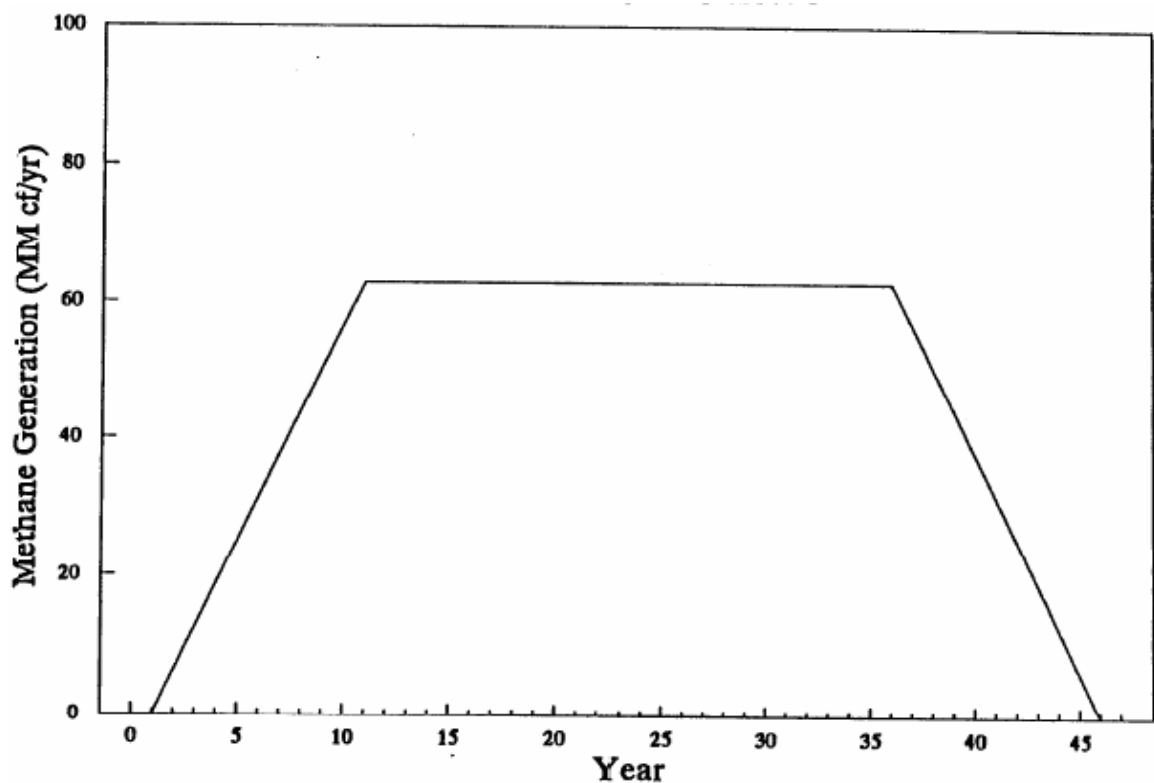
1.1 Landfill methane models

A landfill methane model is a tool used to project methane generation over time from a mass of waste. In its simplest form, a model predicts methane generation or recovery from a single batch of waste, landfilled at a single given point in time. Total methane generation or recovery from a landfill (or a portion of the waste mass) is then the sum of outputs from all batches in the landfill. Typically, the unit for the time parameter is a year.

Typical components of models may include an interval before methane generation starts (lag time) and subsequent intervals of rising, constant, and falling production, depending on the model. A simplified example of a model profile from a single waste batch is illustrated in Figure 1.1, showing a 1-year lag time and

estimated methane generation over a 45-year period. Although Figure 1.1 shows a single line for simplicity, model projections are inherently probabilistic, and confidence limits should be assigned to their projections.

Figure 1.1: Hypothetical Methane Generation profile from landfill waste

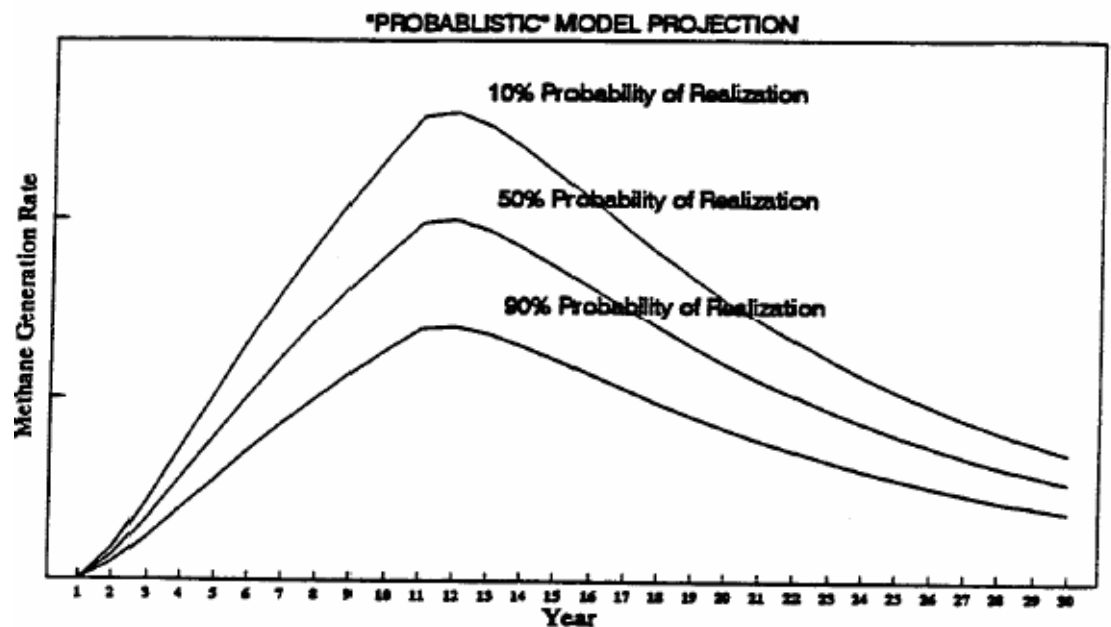


Landfill gas (LFG) models are used for:

- Sizing landfill gas collection systems. LFG collection and treatment equipment must be installed at most larger landfills in response to regulatory requirements under the Clean Air Act. In addition, landfill sites often require such systems for purposes of subsurface migration control, odour control, and other reasons. Modelling can be an effective tool to appropriately size the well field and associated LFG collection, treatment, and/or recovery equipment.

- Evaluations and projections of landfill gas energy uses. With knowledge of equipment and operating costs, unit energy revenues, and other key factors, "probabilistic" model projections can be used to estimate the LFG or methane yields of landfills, size equipment, estimate costs, and evaluate the spectrum of likely investment returns.
- Regulatory purposes. Model projections have been used to calculate landfill emissions and to support establishment of LFG and methane emission requirements.

Figure 1.2: Use of Methane Profiles to evaluate energy applications



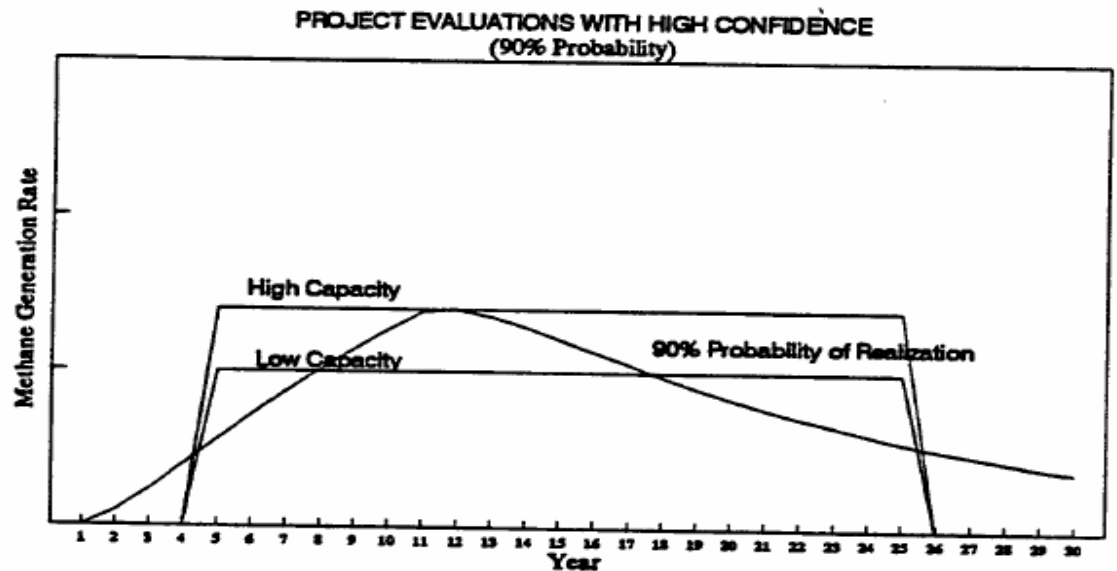
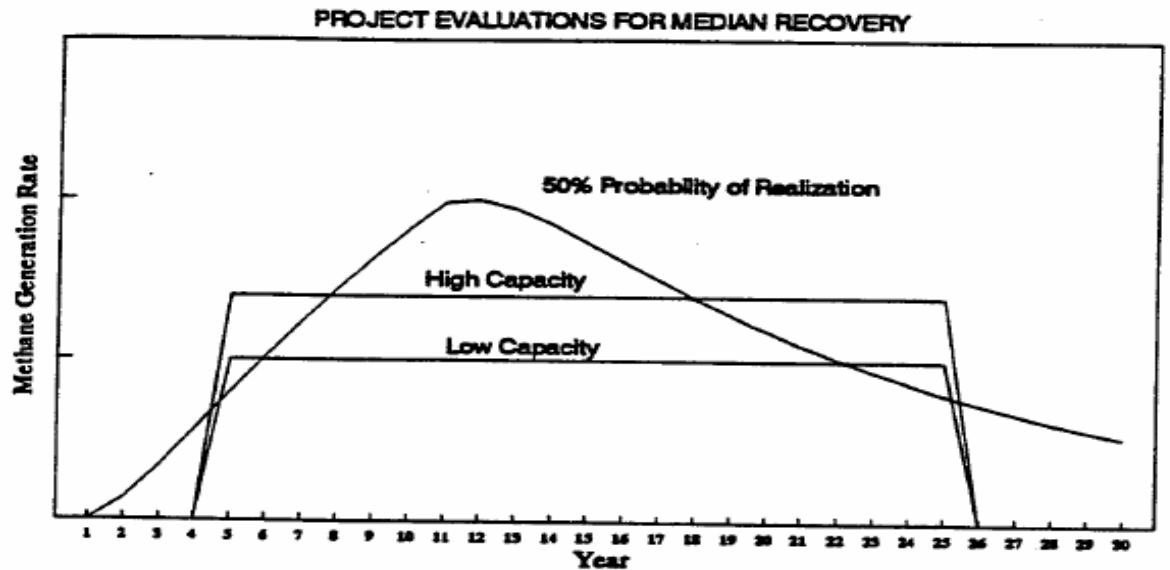


Figure 1.2 shows steps in a hypothetical model application for an energy project. The top illustration shows three curves for a hypothetical model which projects the likelihood that gas recovery will exceed given values at a landfill site. The lowest curve is a recovery value which might be exceeded 90 percent of the time; the middle curve is the median (where gas recovery might be exceeded 50 percent of the time) and the top curve is the recovery that would be attained 10 percent of the time.

The middle illustration of Figure 1.2 represents equipment performance for two different capacities (or gas usage rates) compared to a gas recovery projection at the 50 percent level. Similarly, the bottom illustration represents the same set of equipment capacities compared to more conservative gas recovery estimates (i.e., methane recovery that would be realized or exceeded 90 percent of the time).

Solid waste industry investments and expenses associated with LFG control and recovery are significant. For example, the capital cost of equipment to produce 1,000 MW of electricity from LFG would exceed \$1 billion (EPRI, 1992; EPA, 1993). Both EPA (1993) and EPRI (1992) estimate LFG electric potential at 5000 + MW, given adequate electricity sale prices. Furthermore, given the implementation of current Clean Air Act requirements, the costs for LFG controls are expected to rise in the future.

Theoretically, as landfill methane models are refined and improved, their use should reduce errors in sizing of energy and recovery equipment, yield improved cost-benefit calculations, and reduce project risks. Such models would provide significant added value annually to the LFG industry and the public.

Compared to other alternatives, models have advantages in terms of low cost and relatively rapid results. To estimate a landfill's methane generation, one alternative to models (short of installing a full-scale recovery system) is the use of test wells and the performance of a pump-test program. However, costs for pump tests can exceed \$100,000 and require three months or more to accomplish; the tests have inherent imprecision; and the field results represent points in time for the test location(s) in the landfill rather than long-term projections for the entire landfill. A goal for landfill methane models is to provide information of comparable accuracy to extrapolations of pump test results for the entire landfill.

Although models have the potential to provide these benefits, advantages of models can be realized only to the extent models are sufficiently developed. Modelling of landfill methane generation and recovery is not sufficiently advanced.

1.2 Previous Modelling Studies

Model development for prediction of gas recovery and other purposes began with the increase in sanitary landfilling in the 1970's. The first "modelling" consisted of the application of "rules of thumb", and such estimates (albeit refined) continue to be used in the LFG industry (Walsh, 1994). Qualitative descriptions of the LFG generation process also were developed by Farquhar and Rovers in 1973. Other investigators attempted more rational bases for prediction of LFG or methane on the basis of available but limited landfill data (Alpern, 1973; Ham, 1979; and Ham, et. al., 1979). Around the same time, more quantitative model predictions were first attempted in the Los Angeles base in the U. S.

Numerous variables affect waste decomposition in landfills and the subsequent production of methane. The "standard" analytical models, such as the Manod, that predict performance of microbial processes under defined temperature, nutrient, and other biological conditions, cannot be applied effectively to landfills. Many researchers have found it difficult to obtain field data from a unique batch of waste to compare with a model's predicted methane generation curve. In part, this difficulty occurs because methane recovery from landfills typically is aggregated output from many years of waste placement, rather than from individual batches of waste within the landfill.

Model development mostly has been empirical; it has consisted of the application or the testing of a wide range of postulated generation curves (i.e., variations on the curve of Figure 1.1). Forms of such curves have been assumed on various bases including mechanistic assumptions about decomposition (Van Zanten and Scheepers, 1995; Zison, 1990; Augenstein and Pacey, 1991).

The literature is not replete with landfill methane models that have been compared or calibrated with field data. The following summarizes some of the published and unpublished work:

- Several proprietary models exist and are applied by engineering firms and others. However, the development details largely are unknown and little

published information is available which compares the proprietary models' predictions with field experience.

- Oonk, et. al. (1994) examined methane recovery from landfills in Holland. This work correlated four trial models with a moderate amount of data from 12 landfills and showed good "fit" of postulated models with site data. However, methane generation data were short term- three years, maximum.
- Peer, et. al. (1992) for the U. S. EPA examined methane recovery from a set of 21 US landfills. One recovery rate was measured at a single "point in time" (the study year) for each landfill. Peer, et. al. found recovery to be correlated with waste in place, by what was termed an "emission factor": i.e., methane recoverable per unit of waste per unit of time, determined for each individual study landfill. Correlations were not made with waste age (i.e., time since filling) or other variables such as rainfall or temperature. For the study landfills, the emission factor ranged from 2.5 to 6.5 cubic meters of methane per minute per million metric tons of waste in place.
- Augenstein and Pacey (1991) showed comparisons of two landfills' data to a proprietary model, which suggests conformance of gas generation recovery to first order kinetics. This paper also presented data from Zison (1990) wherein a similar model gave reasonable results (recovery ranging from -30 to + 50 percent of predicted) for three of four Southern California landfills.

Current landfill methane models are uncertain. These uncertainties are due to several factors, including:

- Sparseness and quality of the data used for model development and Calibration;
- Limited time frames for the available field data used;
- Inappropriate application of available data;
- Varying geographic/climatic conditions; and
- Other factors specific to the landfill design and operations such as landfill depth, liners, and leachate recirculation.

As more LFG collection systems are installed and operated within lined landfills, better landfill data likely will become available for modelling. As a result, model uncertainties probably can be reduced.

1.3 Project Objectives

The purpose of this project is to compile information and select various landfill methane models from existing of previous data in group project (part B) (in Appendix A) and to provide a comparison of model outputs to actual gas recovery data. Specific objectives as following;

1. Compile and select US. Landfill site information which is suitable for model comparison with available operational and gas recovery data from the existing group project (Part B);
2. Select trial model forms to test against landfill data;
3. Use landfill data to adjust model parameters and assess the reasonableness of the trial models;
4. Identify confidence limits which can be assigned to models;
5. Assess the effect of site variables on methane generation and recovery;
6. Make available the study's findings in the form of an easy-to-use computer program; and
7. Make recommendations for future study.

Comparison of landfill methane models involves a number of complex issues and choices as to procedures to be used. This project provides detail on the background and reasoning as to why certain approaches were taken and discusses advantages and limitations of the findings with respect to methane model users in the LFG industry.

1.4 Organization and Content

The remaining chapters of the dissertation are organized as follows:

- Chapter 2 presents background on landfill methane generation and the selection of landfill methane models for further evaluation.
- Chapter 3 discusses the approach used for comparison of model outputs to actual gas recovery data.
- Chapter 4 presents results of the model comparisons and derivations for parameter values of the optimized models. It also presents error and confidence limits based on data from the study landfills.
- Chapter 5 discusses the computer program developed for users to create outputs from the four models evaluated.
- Chapter 6 presents recommendations for further study, based on the findings and analytical results; and
- Chapter 7 References.

1.5 Contribution of the Project

The anticipated contribution of this study will be useful to potential developers of LFG projects, landfill operators and regulators. Moreover, this study of this review is to provide information on the current status of energy recovery from LFG.

CHAPTER 2

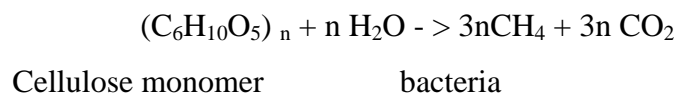
Literature Review

2.1 Introduction

This chapter provides the literature review about the landfill gas generation as it relates to predictive model. The variables and uncertainties inherent in both the development of models and their application are discussed. Moreover, the criteria used in to select this study's landfills for model development. Finally, this chapter discusses the basis for the landfill methane models selected for further examination.

2.2 Landfill Gas Generation

Landfill gas is the mixture of carbon dioxide and methane, and other trace components, generated from waste by bacterial decomposition of waste organics. For cellulose, the principal source of gas from landfilled waste, the conversion reaction is:



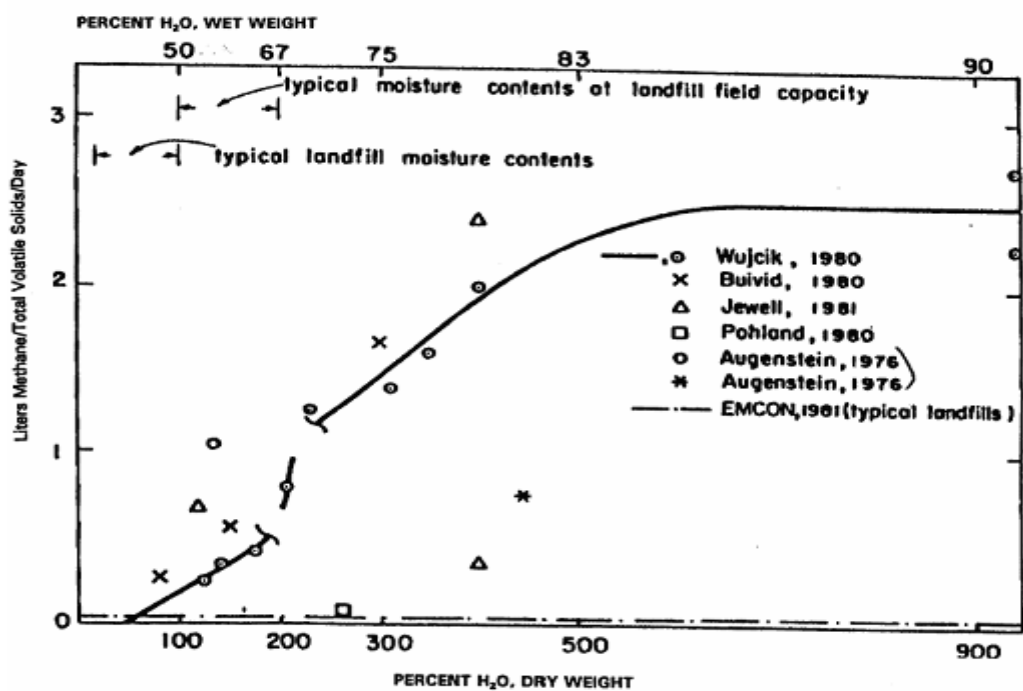
Discussions on landfilled waste decomposition are found in a number of references, including Halvadakis, et. al. (1983), Barlaz (1990), Ham and co-workers (several papers), Pohland and co-workers (several papers), and Augenstein and Pacey (1991).

Several factors govern waste decomposition. Moisture level commonly is considered of greatest importance. Another factor, well-established on fundamental grounds and from laboratory tests (but largely neglected in modelling), is temperature. Figures 2.1 and 2.2 show the pronounced effects of moisture and

temperature, respectively, from work of Halvadskis, et. al. (1983) and Ashate, et. al.(1993), respectively.

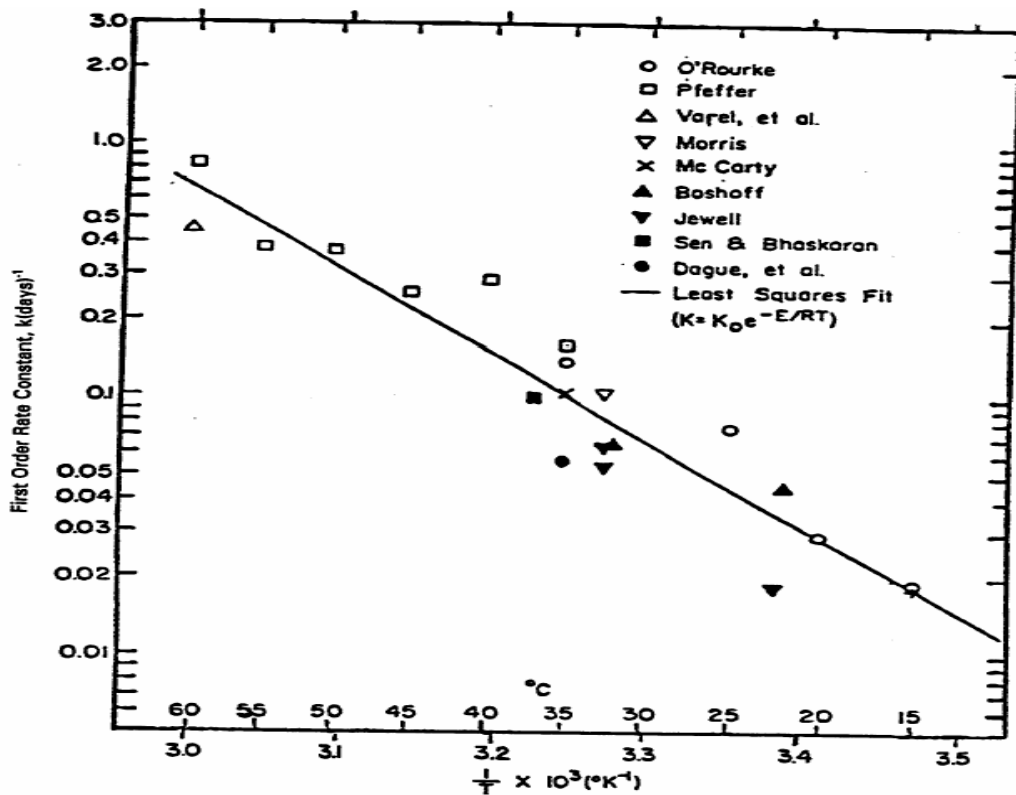
Other factors also affect the rate and quantity of methane generation from wastes. These can include waste composition, waste nutrient level, and the presence or absence of buffering agents (which may be provided from such sources as cover soils). Landfill operational factors, such as air intrusion, landfill covers, waste compaction, and leachate recirculation also can impact methane generation. Because factors tend to vary from landfill to landfill, some degree of modelling uncertainty is a given.

Figure 2.1: Effects of moisture on methane generation



Source: Halvadskis, et. al. (1983)

Figure 2.2: Effects of temperature on methane generation



Source: Ashate, et. al. (1993)

2.3 Source of Uncertainty in Model Development and Application

Factors giving rise to uncertainties in methane models include:

- Variation in generation due to factors mentioned above;
- Measurement inaccuracies or errors;
- Recovery efficiency variables;
- Substantial variation of relevant parameters spatially within the landfill, becoming more significant with increasing moisture and temperature in certain 'pockets' or zones; and
- Discrepancies between the model form chosen and the "true" underlying average generation within a given dataset used to estimate model parameters.

For example, recovery efficiency is a source of variability. It likely varies with the landfill geometry; liner and cover materials (e.g., clay or membrane); cover maintenance; design, installation, and maintenance of the LFG extraction system; and other factors. Recovery efficiency can change with time during active landfilling, with lower recovery expected in the first few years, higher recoveries expected after closure, and levels somewhere in between during the interim years.

Landfill-to-landfill variations in methane generation and recovery occur for reasons that are evident. For example, precipitation/infiltration through cover soils may be greater into some landfills than others, and subsequent methane generation may be accelerated where there is more infiltration. However, excessive oxygen infiltration into the waste mass impedes methane production. Also, warm region landfills decompose more rapidly than cold region landfills. While landfills self-warm as methane generation occurs, heat dissipation rates vary.

What is important for modelling is not so much the source of uncertainties but their effect in the aggregate. In aggregate the uncertainties create deviations between any model's prediction and subsequent field experience. This deviation is referred to as "model error" or "uncertainty" in this report. The degree of model error intrinsic to a given model is important to describe, but has not been explicitly characterized for any large database in landfill methane model work to date. There exist "probabilistic" ways of expressing probability of methane recovery lying within any given set of bounds. Identification and expression of these bounds were project objectives.

Some uncertainties can be reduced. One way is to select landfills with superior data. Uncertainties also can be compensated for or reduced by establishing correlations between site factors and gas recovery.

The value of reliable methane recovery data and corresponding reliable site factors was illustrated by Oonk, et. al. (1994). Using data from 12 Dutch landfills with good apparent recovery and good knowledge of site history and site factors (e.g. annual waste placement, design, extraction monitoring, etc.), three different trial models "fit recovery with similar accuracy (by statistical indices). Maximum error of about 30 percent was reported, generally better than reported by U.S. experience¹.

¹ Such 'Goodness of fit' may relate to the relative uniformity of Dutch landfill and wastes, but nonetheless supports use of the best site data.

2.4 Selection of Study Landfills

Candidate landfills for this study ("study landfills") were sought with the following characteristics:

- Gas recovery efficiency is maximized. This was considered associated with as many as possible of the following features:
 - Scavenging of LFG for energy-limited equipment;
 - Well-maintained covers (clay or synthetic) and frequent well monitoring;
 - Good well density;
 - 'Efficient' well configuration in terms of close spacing, greater (rather than lesser) depth;
 - Wellhead and header pipeline methane contents at 40 to 50 percent (rather than 50 to 60 percent), suggesting tuning of wells for maximum recovery;
 - Maintenance of methane below regulatory limits by surface scan (now mandated in many regions of the country); and
 - Maintenance of odours below odour thresholds.
- Accurate waste gate receipt and placement history.
- Methane recovery over significant durations. Typically, methane has been recovered at US landfills for only a portion of the time needed for complete generation. Also, little information exists on methane recovery after closure of the landfill. Consequently; study landfills were sought with long-term recovery data.
- Other site features known. These include waste composition (for example, presence of unusual quantities of inert or degradable materials), knowledge of leachate quantities (a surrogate for waste moisture], degrees of compaction, internal temperature, site geology/soils (for example, clay layers which would tend to prevent lateral migration), rainfall, and other features which might affect or correlate with methane generation and recovery.
- Measurements of methane recovery by methods accepted as accurate.

- Ready accessibility of records.

Several factors were grounds for exclusion of a landfill from the study. The principal (and frequently encountered) reason for exclusion of a landfill was that methane recovery was not maximized (for many landfills, only enough methane was recovered to support energy equipment. These landfills were unsuitable because total recoverable methane was unknown). Another reason was absence of gate tonnage data (volume receipts alone were not considered accurate enough for study purposes).

Of the 16 landfills considered to have acceptable characteristics for inclusion in the study. Waste placement data obtained for each site are given in Appendix A.

Because this study represents a limited set of landfills. However, efforts were made to include a cross-section of U.S. landfills (with the normal uncertainties and methane recovery variations) so as to allow basic comparisons in model outputs (including predictive ability and confidence limits) to "average" or "typical" U.S. landfills. Models limited to this predictive ability still represent a significant advance over previous published work.

2.5 Selection of Landfill Methane Models

Landfill methane models considered for the study were based on previous studies and usage in the LFG industry. Some models were not selected for inclusion (examples are certain model forms proposed in Zison [1990]. Kinetic estimates (which have significant "guess" components, precedent, and experience) are important model forms in the industry. Model forms that are commonly considered are discussed in Van Zanten and Scheepers (1995) and in Augenstein and Pacey (1991).

A goal of the project is to select landfill methane models with fairly simple structures that are easy to use. In part, this is because any model of sufficient complexity-with sufficient adjustable parameters-can be fit to any dataset. Yet, ability to obtain a perfect fit does not confirm a model's correctness.

Certain field measurements should (in principle) provide ideal methane generation profiles upon which to base model forms. For example, an ideal

measurement for purposes of model development would be of long-term methane generation/recovery for a landfill cell filled over a short interval, with known relevant parameters (such as moisture content, etc.). The cell could be monitored closely over time so that total methane output could be assumed to represent a batch methane generation profile and thus, provide a "true" model curve for landfilled wastes under a given set of conditions.

There have been some measurements of methane generation from single batches along these lines. The results are informative, but less than helpful with respect to ideals of modellers. In one case a completely enclosed control cell was operated as part of a landfill test project (Augenstein and Pacey, 1991). The generation curve from this enclosed cell is shown in Figure 2.3.

In another case, gas recovery data were collected from five waste cells at a California landfill (Yolo Central) over a six-year interval. These data yield normalized methane per year per ton of waste in place for each of the five cells as a function of time since waste placement. These results are depicted in Figure 2.4.

Both Figures 2.3 and 2.4 should represent a close match of an ideal batch generation profile (i.e., the "model curve") for the particular waste masses measured. However, the generation and/or recovery field data are irregular over time, with many short-term variations that are difficult to explain. In essence, field data typically do not match mathematical model curves in the published literature.

Figure 2.3: Methane recovery from Mountain View landfill test cell

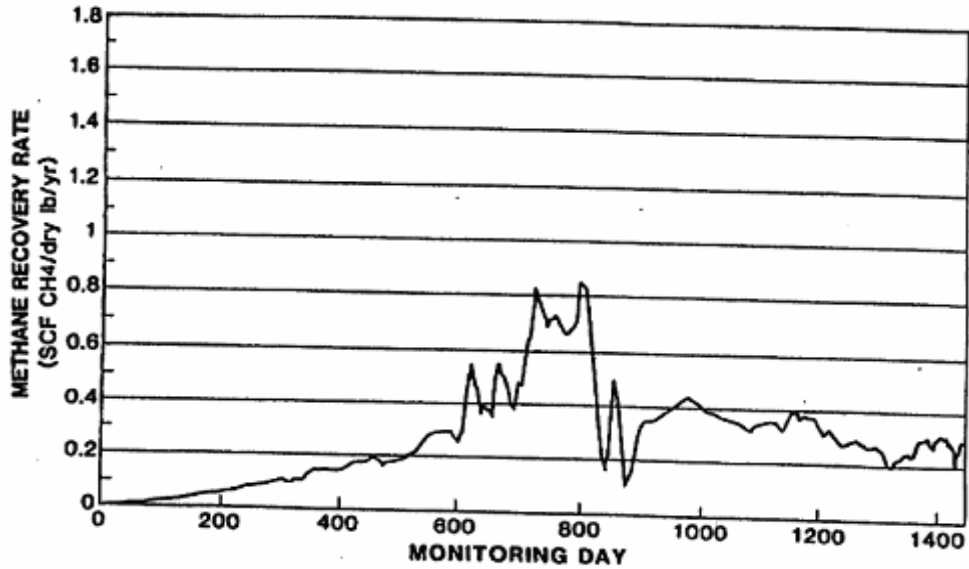
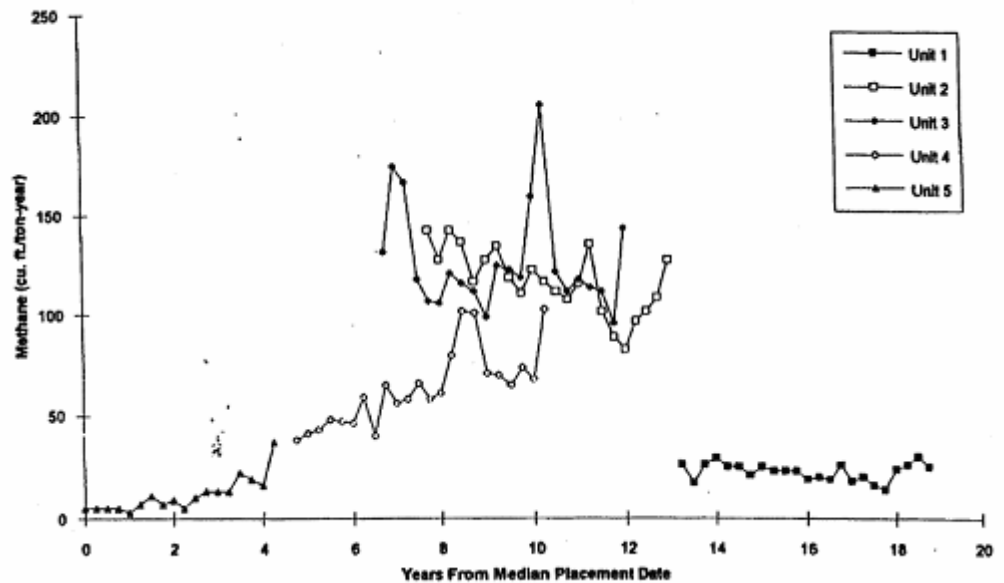


Figure 2.4: Methane recovery from YOLO county landfill test cells



As landfilling proceeds over a longer time and more waste is added which contributes to the landfill's generation/recovery profile, short-term fluctuations in generation from individual waste lots average out. Even if a postulated model form

does not match the generation profile of a single waste batch exactly, it can be useful to replicate to replicate the longer term generation profiles of "real" landfills.

With these issues in mind, four model forms (taking the form of mathematical expressions) were selected for evaluation and comparison. The background and basis for each model choice are discussed briefly below.

With each model, parameters which can be adjusted to optimize the model are shown in boxes beneath the model equations. Each model requires input values for adjusted waste placement data and the noted parameters to make projections for a given model year. Because the model equations for the value G (methane generation by volume) are for individual "batches" or years, the batches must be summed for the years desired to provide the gas generation time curve. Mathematical expressions for the models are as follows:

Model 1: Zero Order Model

$$G = \frac{WL_0}{(T_1 - T_f)} \text{ for } t_1 \leq t \leq t_f$$

Where:

G = methane generation, million cubic feet per year;

W = waste in place, tons;

L₀ = methane yield potential, cubic feet methane per ton of waste;

t = time, years;

t₁ = lag time (between placement and start of generation); and

t_f = time to endpoint of generation.

Parameters adjustable to fit field data for optimization: t₁ and t_f (or the interval t₁-t_f)

This model is used fairly extensively in the landfill gas industry.

Model 2: Simple First Order Model

$$G = WL_0 k e^{-k(t-t_1)}$$

Where:

G = methane generation, million cubic feet per year;

W = waste in place, tons;

L₀ = methane yield potential, cubic feet methane per ton of waste;

t = time after waste placement, years;

t₁ = lag time (between placement and start of generation); and

k = first order rate constant.

Parameters to vary initially for best fit to field data: k and t₁

Variants of this model are used extensively. A public domain computer version is available from EPA.

Model 3: Modified First Order Model

$$G = WL_0 \frac{K+S}{S} (1 - e^{-s(t-t_1)} (k e^{-k(t-t_1)}))$$

Where:

G = methane generation, million cubic feet per year;

W = waste in place, tons;

L₀ = methane yield potential, cubic feet methane per ton of waste;

t = time after waste placement, years;

t₁ = lag time (between placement and start of generation);

k = first order decay rate constant; and

s = first order rise phase rate constant.

Parameters to adjust to fit field data: t₁, k, and s

This model is described by Van Zanten and Scheepers (1995). The model form assumes that methane generation/recovery initially may be low (i.e., there is a "lag"). Recovery then rises to a peak before declining in what is essentially exponential fashion.

Model 4: First Order Multi-Phase Model

$$G = WL_0 \left[F_{(r)}(k_{(r)}e^{-k_{(r)}(t-t_1)}) + F_{(s)}(k_{(s)}e^{-k_{(s)}(t-t_1)}) \right]$$

Where:

G = methane generation, million cubic feet per year;

W = waste in place, tons;

L₀ = methane yield potential, cubic feet methane per ton of waste;

t = time after waste placement, years;

t₁ = lag time (between placement and start of generation);

k_(r) = first order decay rate constant for rapidly decomposable waste;

k_(s) = first order decay constant for slowly decomposable waste;

F_(r) = fraction of rapidly decomposable waste; and

F_(s) = fraction of slowly decomposable waste.

Parameters to adjust to fit field data: t₁, k_(r), k_(s), F_(r), F_(s)

Model 4 is a refinement of Model 3 (the modified first order model) above. Its assumptions are the same, except that differing waste fractions are assumed to decompose at different rates. Variants of this model are applied commercially. This model gave the best results (by narrow margin) in modelling work of Oonk, et. al. (1994).

2.6 Parameter Sensitivity

To estimate annual methane emissions, each model accepts inputs for the refuse filling history and methane generation parameters. Some input parameters are used by several models; others are specific to one particular model. To illustrate model outputs and the effects of varying parameters, trial runs of the four models were used to estimate methane emissions from an example landfill. Parameter sensitivity was ascertained by varying one parameter with selected values while keeping other parameters constant.

The example landfill for this parameter sensitivity effort received 100,000 tons of refuse per year for 10 years (i.e., resultant waste-in-place is 1 million tons).

Model 1

The Zero Order Model has two parameters: the methane yield potential (L_0) and duration of methane generation (time in years). A graphic summary of the sensitivity for these two parameters is shown in Figure 2.5 (for L_0) and Figure 2.6 (for time).

As shown in Figure 2.5, the impact of varying L_0 in Model 1 is direct: during peak methane generation periods (i.e., the flat peak of the curve), cubic feet of methane per year vary inversely with L_0 .

Figure 2.5: Model 1 (Zero Order Model) effects of varying L_0 on methane generation

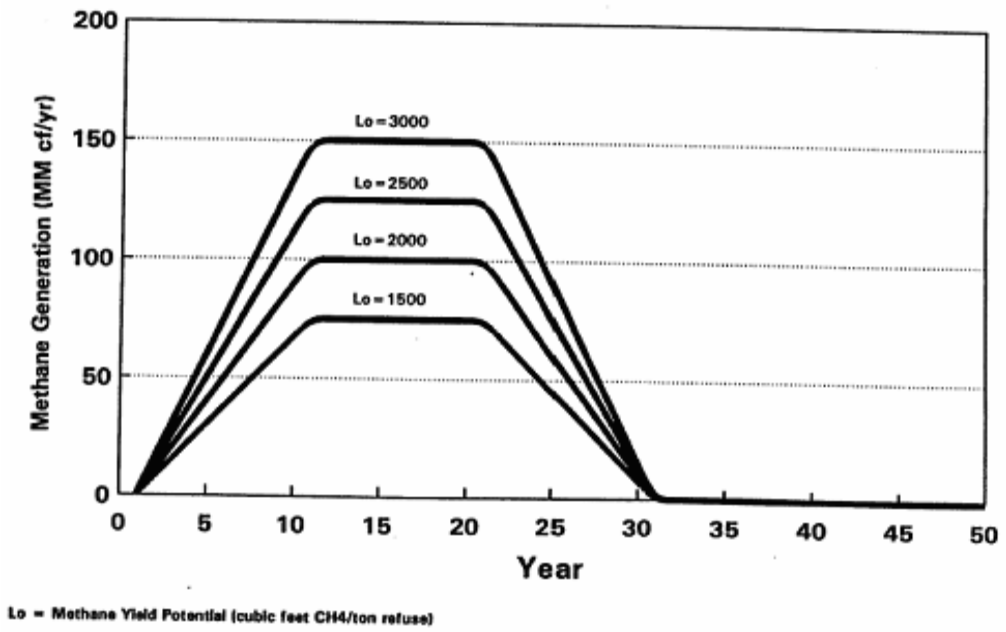
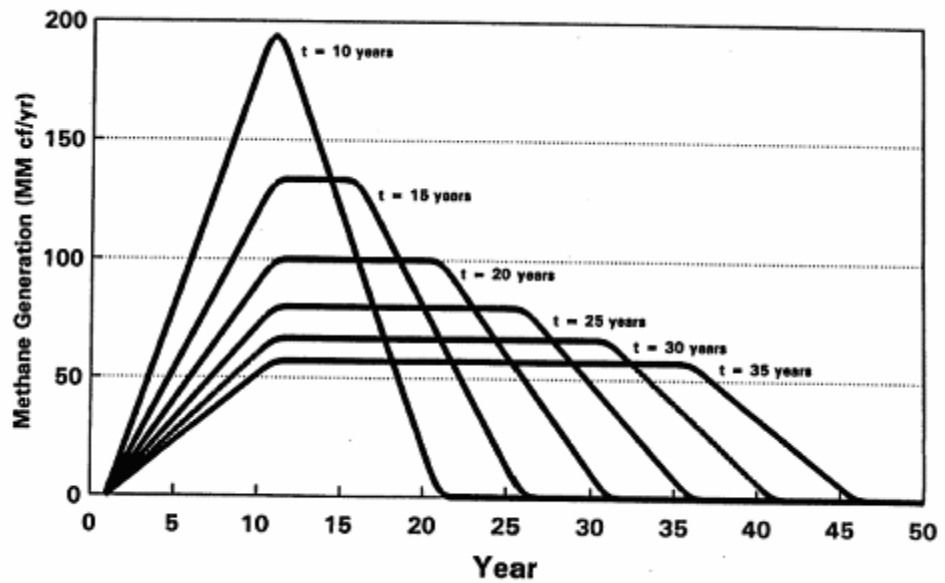


Figure 2.6: Model 1 (Zero Order Model) effects of varying time on methane generation



Model 2

The Simplified First Order Model has two parameters: the methane yield potential (L_0) and the decay rate (k). Figures 2.7 and 2.8 show sensitivity to the parameters L_0 and k .

As shown in Figure 2.7, the impact of varying L_0 in Model 2 is significant: the estimated rate has a direct relationship to the selected value for L_0 . Similarly, Figure 2.8 shows that as k is increased, recovery increases and time span decreases. The rate of falloff for methane generation increases markedly with increasing k .

Figure 2.7: Model 2 (Simple First Order Model) effects of varying L_0 on methane generation

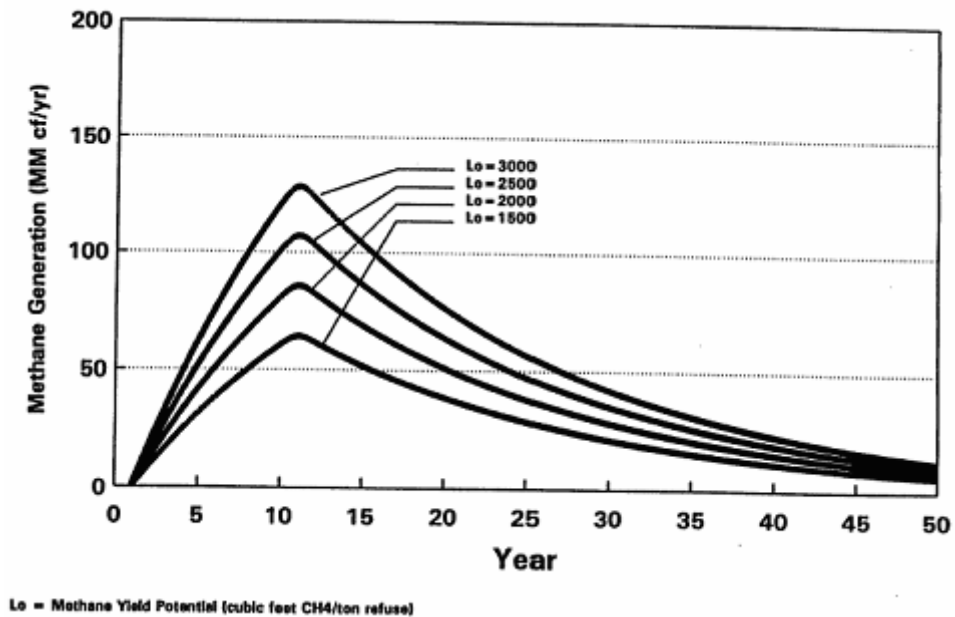
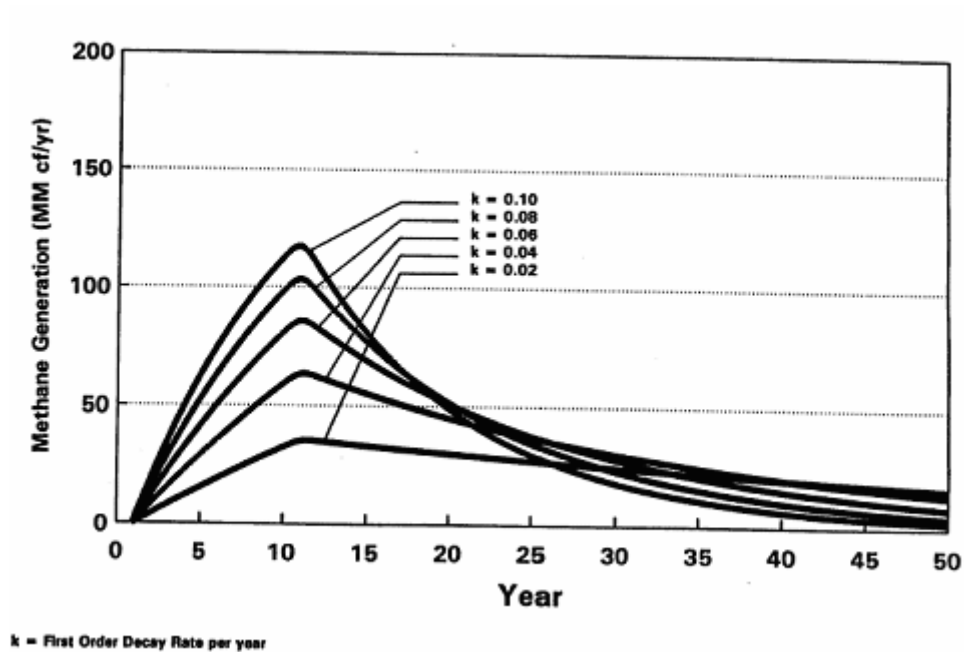


Figure 2.8: Model 2 (Simple First Order Model) effects of varying k on methane generation



Model 3

The Modified first Order Model has three parameters: the methane yield potential (L_0), the decay rate (k), and the rise phase constant (s). Sensitivity testing is illustrated as follows:

Figure 2.9 depicts the effects of varying L_0 ;

Figure 2.10 depicts the effects of varying k ; and

Figure 2.11 depicts the effects of varying s .

The impact of varying L_0 in Model 3, as with Model 2, is to increase generation proportionally to L_0 . Effect of varying k in Model 3 is similar to the effect exhibited in Model 2. These results are not surprising, given similarities between Models 2 and 3.

Figure 2.11 depicts the effect of varying “s” in the Modified First Order Model. In this model, values for “s” fix the rate of rise in methane generation/recovery after filling. (As noted above, the justification for this model form is that such a rise from initially low rates of recovery is commonly observed in the field.) Figure 2.11 shows the effect of the rise phase constant “s” on the time to reach peak generation, and the peak rate at which methane is generated. The rise phase constant also has a minor effect in the rate of decay from peak generation

Figure 2.9: Model 3 (Modified First Order Model) effects of varying L_0 on methane generation

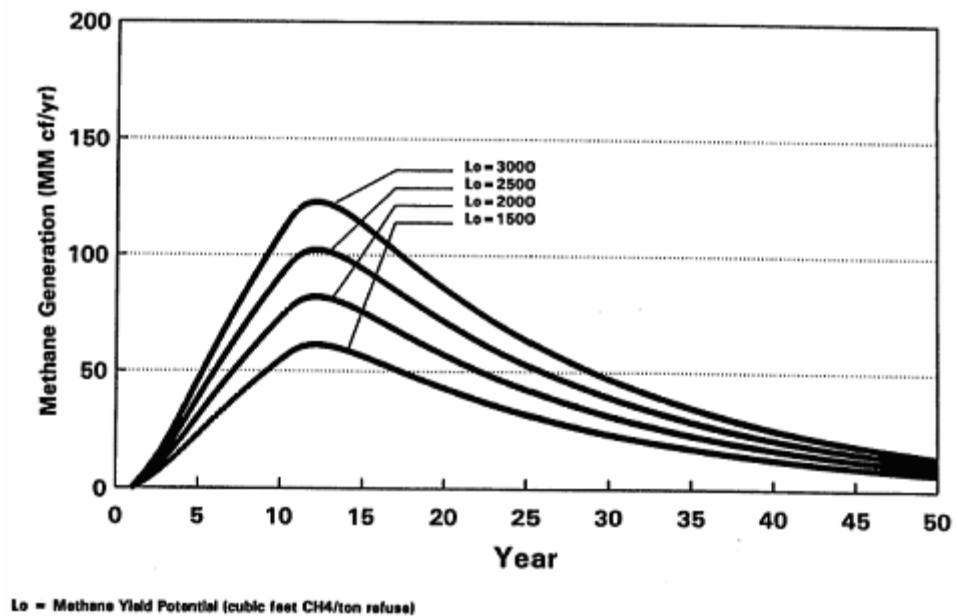
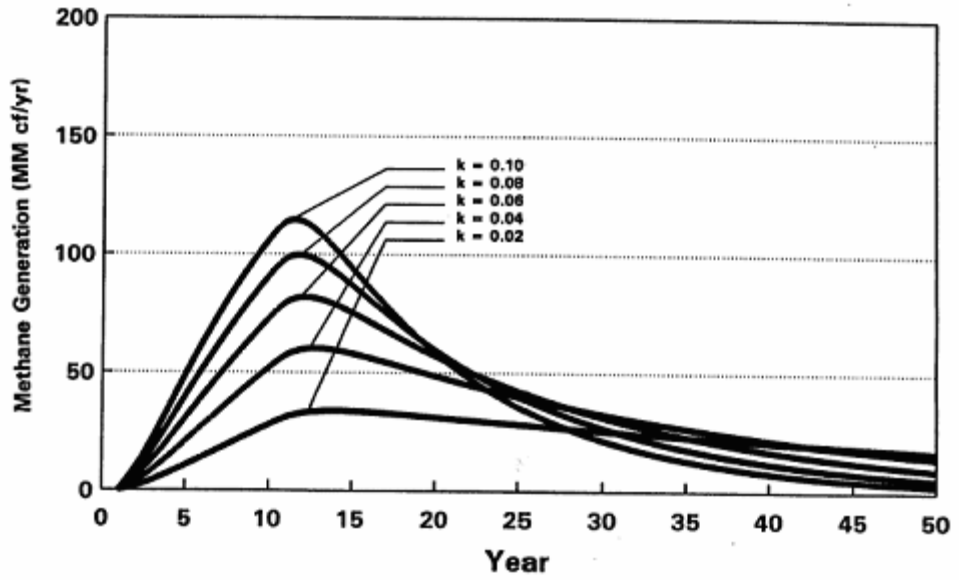
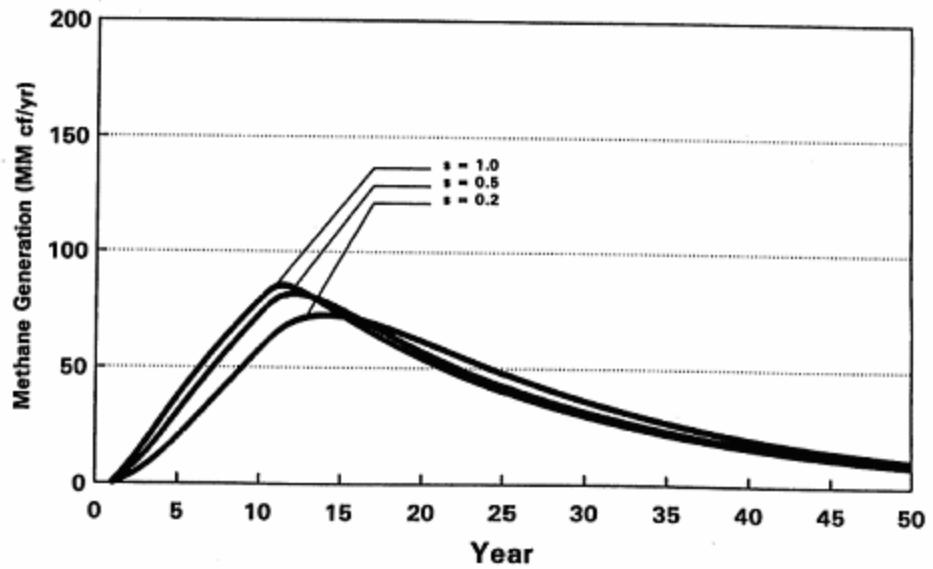


Figure 2.10: Model 3 (Modified First Order Model) effects of varying k on methane generation



k = First Order Decay Rate per year

Figure 2.11: Model 3 (Modified First Order Model) effects of varying s on methane generation



s = First Order Rise Phase Rate Constant per year

Model 4

The Multi-Phase First Order Model has four parameters: the methane yield potential (t_0); the fraction of rapidly decomposing refuse, $F(r)$; the decay rate of rapidly decomposing refuse, $k(r)$; and the decay rate of slowly decomposing refuse, $k(s)$.

A graphic summary of sensitivity testing for this model is summarized by parameter as follows:

Figure 2.12 depicts the effects of varying L_0 ;

Figure 2.13 depicts the effects of varying $k(r)$;

Figure 2.14 depicts the effects of varying $k(s)$; and

Figure 2.15 depicts the effects of varying waste composition.

Figure 2.12: Model 4 (Multi-Phase First Order Model) effects of varying L_0 on methane generation

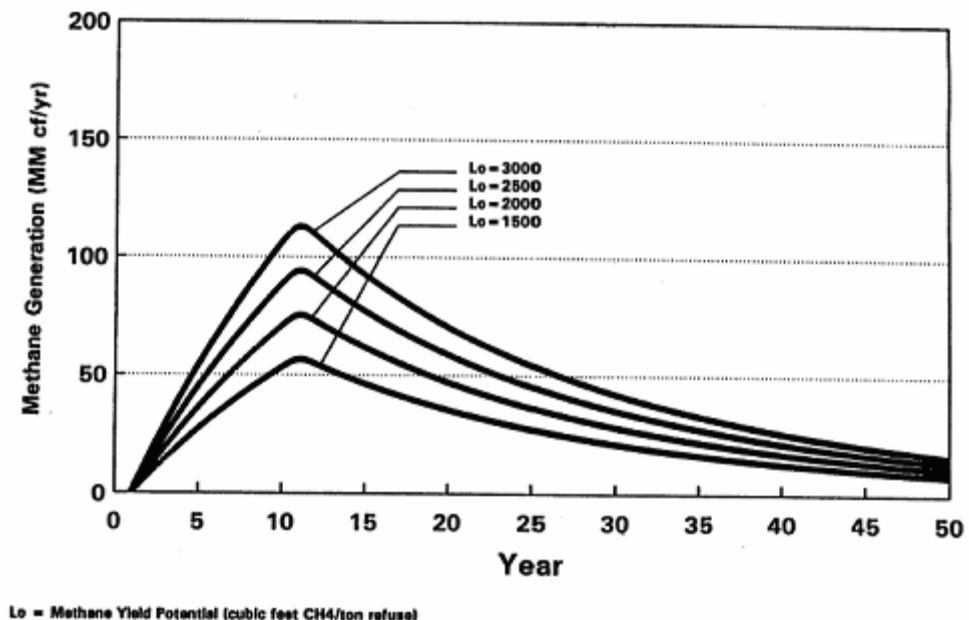


Figure 2.13: Model 4 (Multi-Phase First Order Model) effects of varying $k_{(r)}$ on methane generation

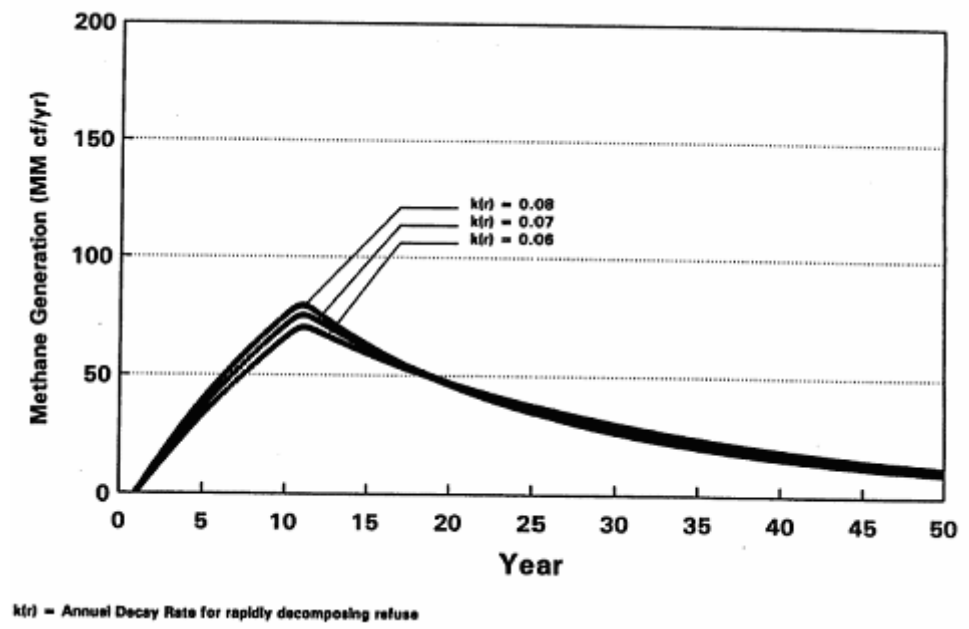


Figure 2.14: Model 4 (Multi-Phase First Order Model) effects of varying $k_{(s)}$ on methane generation

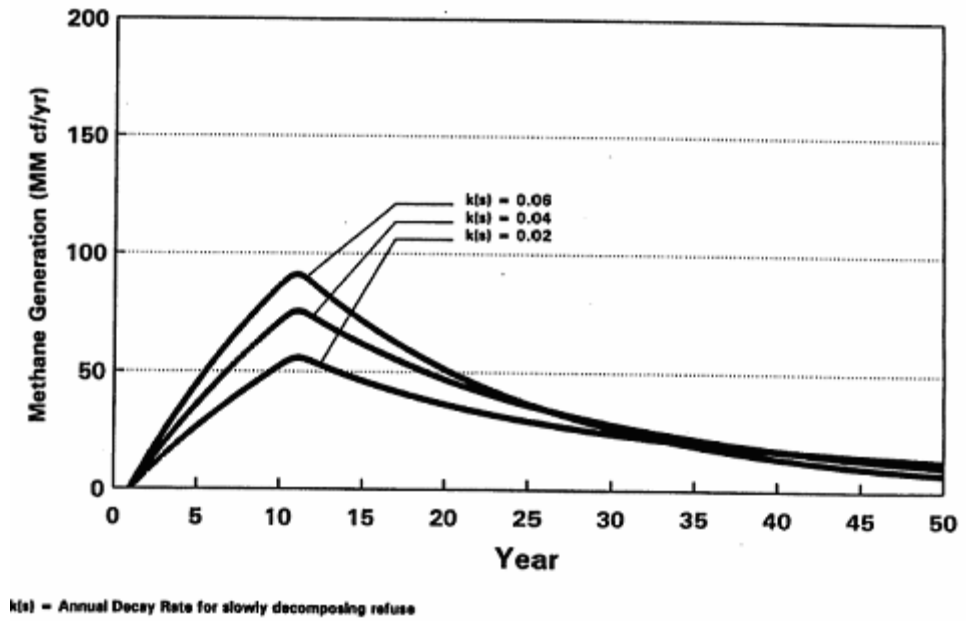
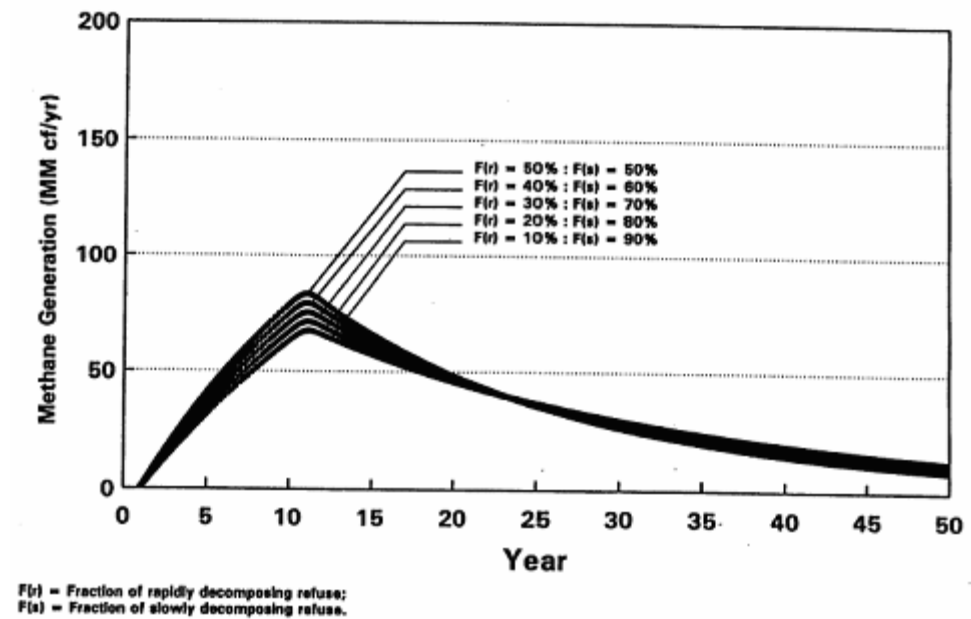


Figure 2.15: Model 4 (Multi-Phase First Order Model) effects of varying waste composition on methane generation



Methane recovery at any given time is directly proportional to L_0 ; that is, doubling the selected value for L_0 will double the estimated peak generation rate. Of

the two decay values, a variation in $k(r)$ has a minimal effect on the generation pattern while changes to $k(s)$ have a more pronounced effect on model results.

As might be anticipated, Model 4 will be sensitive to changes in waste composition. As the selected value for $F(s)$ is increased, peak generation (and time to reach this state) is decreased. However, the rate of tail-off in recovery is correspondingly less pronounced when a high fraction of slower decaying waste is assumed.

The procedures to estimate “best” values for model parameters and to allow comparisons between the four models are discussed in Chapter 3

CHAPTER 3

Approach for Model Optimization and Comparison

3.1 Overview of Approach

This chapter presents the approaches considered for model optimization and subsequent methods for model comparison. Model optimization sought to calibrate the selected landfill methane models through varying key model parameters to obtain the "best fit" to results for each model.

There can be different definitions of "best fit", and several approaches exist for this kind of data analysis and model calibration. Typical optimization functions are based on the differences (or residuals) between projected methane recovery and actual methane recovery data, or on the ratios of projected methane recovery to actual methane recovery data. Model optimization approaches considered for this study were:

- Use of absolute filling and recovery data;
- Use of normalized filling and recovery data;
- Fitting of filling/recovery data to trial models;
- Minimization of arithmetic error:
 - Use of absolute value of the differences;
 - Use of square of the differences (i.e., least squares);
- Minimization of logarithmic error:
 - Use of the natural log of the ratios;
 - Use of absolute value of the natural log of the ratios; and
 - Use of square of the natural log of the ratios.

Of these data treatment choices considered, two were selected for application and subsequent model comparisons in accordance with the scope of the study. The first calibration method was minimization of arithmetic error through use of the

absolute value of the differences; the second method was minimization of logarithmic error through the use of the absolute value of the natural log of the ratios.

Minimization of arithmetic and logarithmic residuals has certain advantages and disadvantages. Minimization of arithmetic residuals weights according to actual waste quantities and gas recoveries. For example, large model errors at high recovery rates are more important than smaller model errors at lower recovery rates. In contrast, an advantage of the logarithmic optimization is in normalizing, so that both large and small landfills' data count equally. But, logarithmic optimization might give less weight to an important discrepancy between prediction and experience. For example, it will give equal weight to the \log_{10} spreads between a 50,000 cfm predicted versus 5,000 cfm experienced ratio and to a 500 cfm predicted versus 50 cfm experienced ratio.

Another consequence of minimizing logarithmic rather than arithmetic residuals is that the optimized prediction will tend toward the log mean rather than the arithmetic mean of projections. For data with a significant amount of scatter, the log mean recovery may be significantly less than the arithmetic. One consequence is that the model obtained by minimizing logarithmic residuals may under predict recovery.

3.2 Model Optimization Procedure

Each model calibration method adjusted parameters for each of the four models to minimize model error (and thus, obtain one form of "best fit") between predictions of the trial model at hand and the gas recovery data set from the 16 landfills. The calibration methods weighted data in accordance with waste placement magnitude and methane recovery.

Modelled methane generation for a landfill site was assumed to be equivalent to methane recovery experienced. In addition, a time mesh or interval of one year for methane recovery was used for model optimization. Lastly, it was assumed that for each-landfill site, gas recovery during any one-year period would count as one value

in the optimization process. Thus, landfills with fewer recovery values contributed less to the project results than landfills with more recovery values.

For minimization of arithmetic error, the model optimization procedure was:

- Based on the waste filling history for each of the study landfills, establish parameter values for time (t) and waste in place (W). For each model calculate methane generation (G) over time using a probable combination of remaining parameter values (e.g., k and L_0). (Parameters varied for each model were identified in Chapter 2.)
- Run iterative calculations of G over time for the varied parameters through small adjustments of the parameters over a wide range of numerical values. These iterations yield a series of model recovery projections, one for each combination of model parameters.
- For each trial model and parameter combination leading to a projection, calculate the absolute arithmetic difference between the model projection data points for methane generation (G) and the experienced methane gas recovery from the study Landfill dataset.
- Sum the arithmetic differences (or residuals) between projections and experienced methane recoveries for the study landfill to obtain a total "sum of residuals" or total arithmetic error. The "calibrated" (or optimized) model is simply the trial model form with parameter Combinations that give the minimum arithmetic error, and thus, the "best" predictions.

Procedures for minimization of logarithmic error were similar to the above except that the logarithms of waste placement and gas recovery were used, and minimization was performed on the absolute values of the residuals (differences in the natural logs of the ratios of gas recovery predicted versus gas recovery experienced).

3.3 Illustration of Trial Model Optimization

As noted earlier, each of the four models (zero order, simple first order, modified first order, and multi-phase first order) was tested by the above procedures. For illustration of how the two optimization functions were applied, Figures 3.1 and

3.2 show examples carried out for Model 2 (simple first order model) with the study landfill data set.

For Model 2, parameters which can vary are the estimated recovery yield, L_0 , and the first order decay rate constant, k . (Note that for Models 1, 2, and 4, the lag time was set at zero to simplify the evaluation. This does not result in significant error). For Figures 3.1 and 3.2, the values of L_0 were varied within a range considered likely (i.e., from 1,500 to 3,000 cubic feet of methane per ton of refuse, at intervals of 100), and the values for k were varied between 0.02 year^{-1} and 0.10 year^{-1} , at intervals of 0.02.

Examination of Figure 3.1 for the arithmetic optimization function shows that several L_0 and k parameter combinations yielded similar minimized residuals, at around 30,000 (the units of error are arbitrary). Calculated values for the same (not shown in Figure 3.1) allowed more specific comparisons. For example, the lowest sum of arithmetic error obtained for Figure 3.1 was with $L_0 = 2,000$ and $k = 0.08$; the sum of residuals was 26,767. Other parameter combinations had low sums of arithmetic error as well: the residuals sum at $L_0 = 2,200$ and $k = 0.06$ was 26,993; and a similar residual value was obtained for L_0 of 2,500 and k of 0.04. While an advantage could be assumed because error was minimized with L_0 and k at 2,000 and 0.08, respectively, it is not likely this parameter combination is unique or statistically significant for establishment of the only or "best" parameter set for Model 2.

Examination of Figure 3.2 for the logarithmic optimization function shows greater specificity for establishment of the "best" parameter set for Model 2. As shown, the sum of the natural log of the ratios was minimized at 24 (again, units of error are arbitrary) and this occurred with L_0 at 2,200 and k at 0.04. Figure 3.2 is useful because it indicates that values of $k = 0.06$, 0.08, and 0.10 do not yield best fits under any combinations within the range of L_0 values tested, that $k = 0.02$ may yield a best fit combination outside of the L_0 range tested (i.e., at L_0 values greater than 3,000), and that $k = 0.04$ provides several L_0 values with minimized error near the best fit parameter combination (e.g., $L_0 = 2,100$ or 2,300).

Based on these examples, the optimization process leaves some uncertainty as to "best" parameter combinations. Ambiguity as to the best L_0 and k combinations

arises because of the relatively short term of much of the gas recovery data for the study landfills. Longer term gas recovery data would tend to provide improved values of L_0 , which would in turn fix k values more exactly. This is true because L_0 by definition becomes better defined as gas is recovered over a greater fraction of the generation cycle.

For purposes of this study, the parameter combinations which resulted in minimum error (even if the combination has only a small advantage over other combinations for the same trial model) were used to describe the best fit for the model at hand and for further comparative purposes.

Figure 3.1: Example Sum of Residuals: Arithmetic

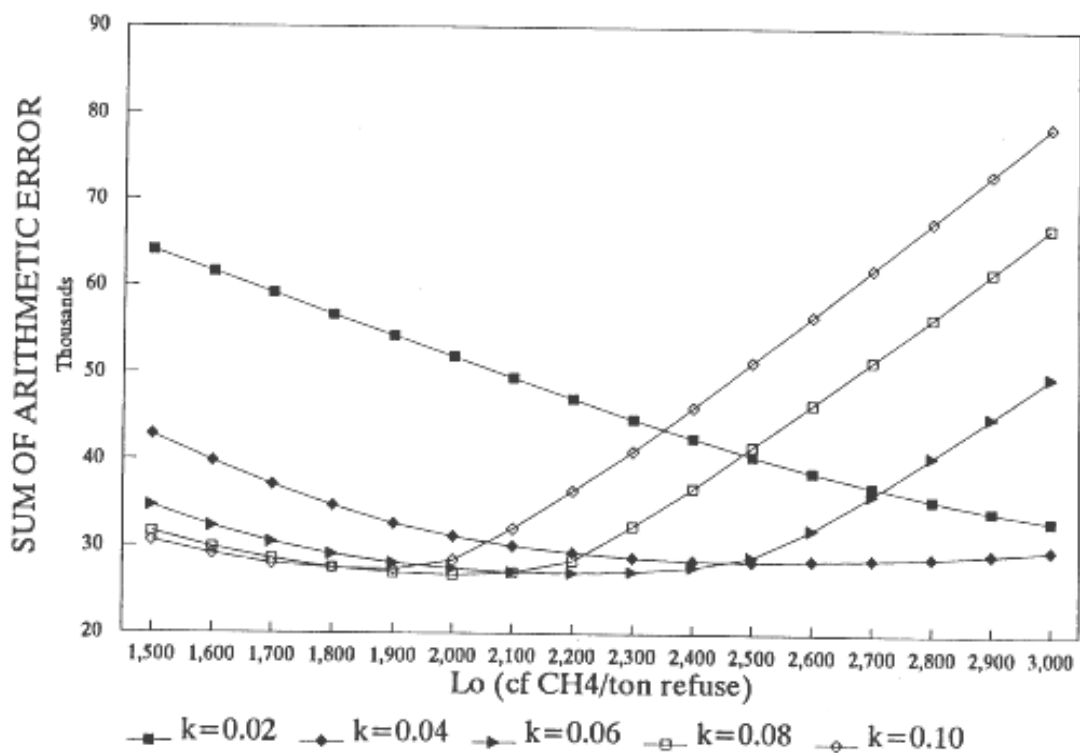
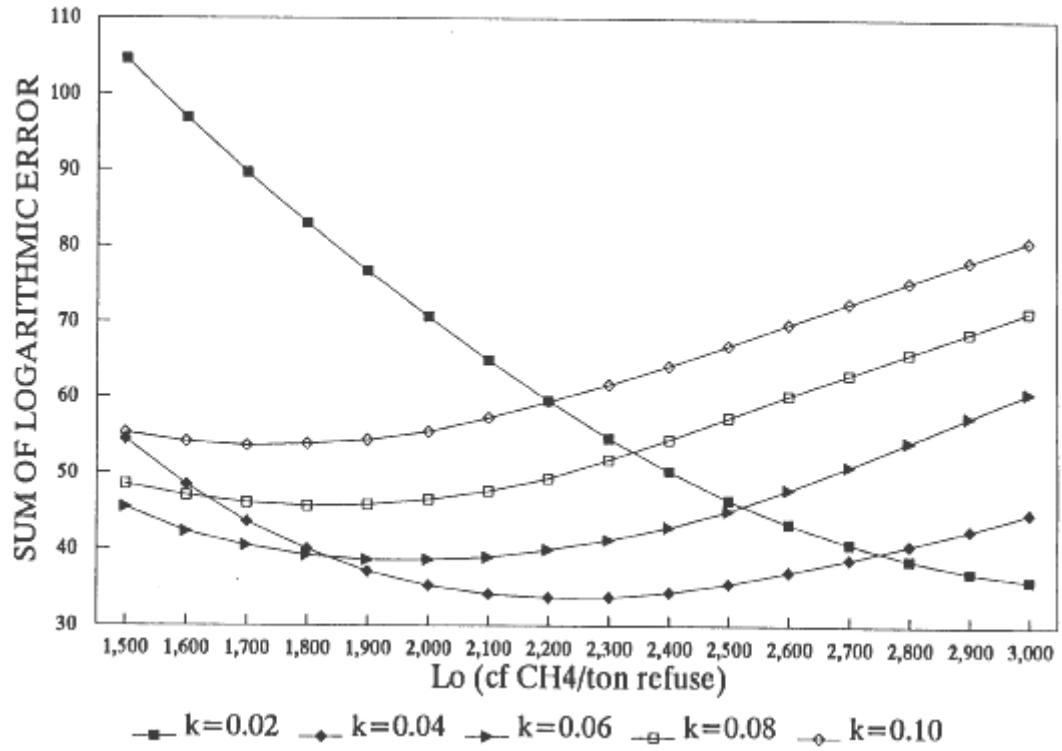


Figure 3.2: Example Sum of Residuals: Logarithmic



CHAPTER 4

Results

4.1 Parameter Combinations Derived from Minimized error

Numerous computer runs were made to calculate the residuals for possible parameter combinations for:

- the ranges of parameter values selected;
- the four models and 16 landfill sites evaluated in this study; and
- the two optimization functions selected.

Results from these computer runs were scanned visually for optimal results and compared numerically for the lowest minimized error. Table 4.1 presents the resulting parameter combinations by landfill methane model and by optimization function. Application of the data treatment of absolute value of the logarithmic error produced two different parameter combinations (each had an equivalent lowest minimized error) under each of Models 1, 2, and 3.

As indicated in Table 4.1, values for L_0 , the methane yield potential, were consistent for the three first-order models (i.e., Models 2, 3, and 4) under the arithmetic error optimization function, ranging from 2,100 to 2,200 cubic feet of methane per ton of landfilled waste. Under the logarithmic function, at least one parameter combination for each of the four models resulted in an L_0 within the 2,000 to 2,200 cubic feet of methane range.

Values for k , the first order decay rate constant, were more varied and model dependent. Under the arithmetic optimization function, k values ranged from 0.05 year⁻¹ to 0.08 year⁻¹ for Models 2, 3, and 4; under the logarithmic optimization function, k values ranged from 0.03 year⁻¹ to 0.06 year⁻¹.

Table 4.1 Methane Model Parameter Combinations Yielding Minimized Error

Optimization Function	Parameter Combinations*			
	Model 1: Zero Order	Model 2: Simple First Order	Model 3: Modified First Order	Model 4: First Order Multi-Phase
1. Minimization of Absolute Value of Arithmetic Error	$L_0 = 1,600$ $t = 20$ years	$L_0 = 2,100$ $k = 0.07 \text{ year}^{-1}$	$L_0 = 2,200$ $k = 0.05 \text{ year}^{-1}$ $s = 1.0$	$L_0 = 2,100$ $k(r) = 0.08$ $k(s) = 0.06$ $F(r) = 40\%$ $F(s) = 60\%$
2. Minimization of Absolute Value of Logarithmic Error	$L_0 = 1,700$ $t = 35$ years AND $L_0 = 2,200$ $t = 45$ years	$L_0 = 2,200$ $k = 0.04 \text{ year}^{-1}$ AND $L_0 = 2,500$ $k = 0.03 \text{ year}^{-1}$	$L_0 = 2,000$ $k = 0.05 \text{ year}^{-1}$ $s = 0.2$ AND $L_0 = 2,500$ $k = 0.03 \text{ year}^{-1}$ $s = 1.0$	$L_0 = 2,200$ $k(r) = 0.06$ $k(s) = 0.04$ $F(r) = 20\%$ $F(s) = 80\%$

* Units for L_0 , methane yield potential, are cubic feet methane gas per ton of waste landfilled.

4.2 Model Comparisons

Comparisons of the study landfill data to the optimized (or best fit) models were developed. In brief model parameter combinations obtained through minimization of arithmetic residuals (see Table 4.1) were used to develop generation curves; these data sets then were plotted against the actual methane recovery data from the 16 study landfills. Results of these plots are shown in Figures 4.5 through 4.8 for Models 1 through 4, respectively. In these figures the fit of each model is

illustrated by comparison of optimized model predictions for methane generation with the measured methane recovery for all data points obtained from the study landfills. The model parameter combinations from Table 4.1 used to develop the predicted methane generation data (i.e., the x-axis) are shown on the figures as well.

Similarly, comparisons were made for each of the four models to show the results of Optimization via minimization of logarithmic residuals, as described in the previous chapter. Figures 4.1 through 4.4 provide tabular and graphic results from the optimization procedure for Models 1 through 4, respectively. The parameter combinations derived from minimizing logarithmic error (given for each model in Table 4.1) are indicated on the figures as well.

This use of differing weighting yielded, in several cases, similar parameter combinations to the arithmetic results. Furthermore, minimization of logarithmic error gave better results than those demonstrated by arithmetic error minimization by producing a narrow, more specific band of parameter combinations for best fit optimization. As a result, other combinations could be eliminated. For example, parameter combinations which included values of $t = 15$ years and $t = 25$ years for the zero order model (Model 1) clearly could not result in the lowest minimized error (see Figure 4.1). The same conclusion could be drawn for parameter combinations which included:

- Values of $k = 0.07, 0.08, 0.09$, and 0.10 for Model 2 (see Figure 4.2);
- Values of $k = 0.07$ and 0.09 for Model 3 (see Figure 4.3); and
- Values of $k(r)$ and $k(s) = 0.06$, $k(r) = 0.07$ and $k(s) = 0.06$, and $k(r) = 0.08$ and $k(s) = 0.06$, for Model 4 (see Figure 4.4).

Figure 4.1 Model 1: Zero Order

Summary of Logarithmic Error Minimization

Lo	Sum of Absolute Natural Logs of (Predicted/Actual)							
	t = 10 yrs	t = 15 yrs	t = 20 yrs	t = 25 yrs	t = 30 yrs	t = 35 yrs	t = 40 yrs	t = 45 yrs

1,500	147*	105*	88*	63*	45*	43	53	64
1,600	150	108	91	64	45	40	48	58
1,700	153	111	94	65	46	39*	44	52
1,800	156	115	97	67	47	40	41	48
1,900	159	119	100	70	48	40	40	44
2,000	162	123	103	73	50	41	40*	41
2,100	165	127	107	75	52	43	40	40
2,200	169	131	111	79	54	44	41	39*
2,300	172	135	116	83	57	46	42	40
2,400	175	139	120	87	60	48	43	40
2,500	178	144	125	91	63	50	44	41
2,600	181	148	129	96	66	52	45	42
2,700	184	152	133	100	70	54	47	43
2,800	187	156	137	104	74	57	49	44
2,900	190	159	141	108	78	60	51	45
3,000	193	163	145	112	82	63	53	47

- Denotes the minimum sum for each value of t

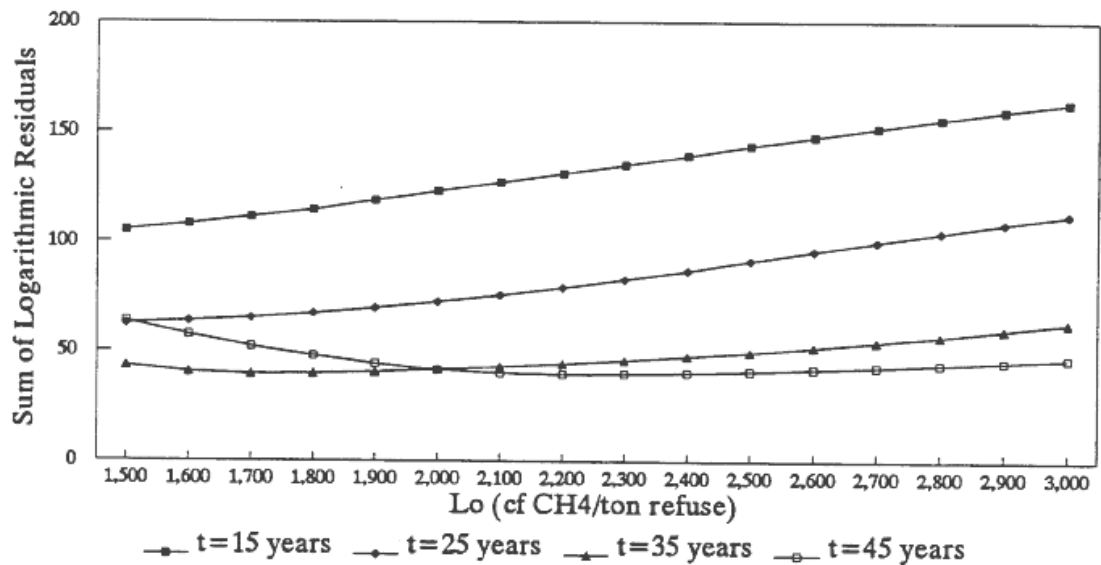


Figure 4.2 Model 2: Simple First Order

Summary of Logarithmic Error Minimization

Lo	Sum of Absolute Error								
	k = 0.02	k = 0.03	k = 0.04	k = 0.05	k = 0.06	k = 0.07	k = 0.08	k = 0.09	k = 0.10
1,500	105	72	54	47	46	46	49	52	55
1,600	97	65	48	43	42	44	47	50	54
1,700	90	58	44	40	40	43	46	50	54*
1,800	83	52	40	38	39	42	46*	50*	54
1,900	77	46	37	36	39	42*	46	50	54
2,000	71	42	35	36	39*	42	46	51	55
2,100	65	39	34	36*	39	43	48	52	57
2,200	60	36	34*	36	40	45	49	55	59
2,300	55	35	34	37	41	46	52	57	62
2,400	50	34	34	38	43	49	55	60	64
2,500	47	34*	36	40	45	51	57	62	67
2,600	43	34	37	42	48	54	60	65	70
2,700	41	35	39	44	51	57	63	68	73
2,800	39	35	41	47	54	60	66	71	75
2,900	37	36	43	50	58	63	69	74	78
3,000	36*	37	45	54	61	67	72	76	81

* Denotes the minimum sum for each value of k

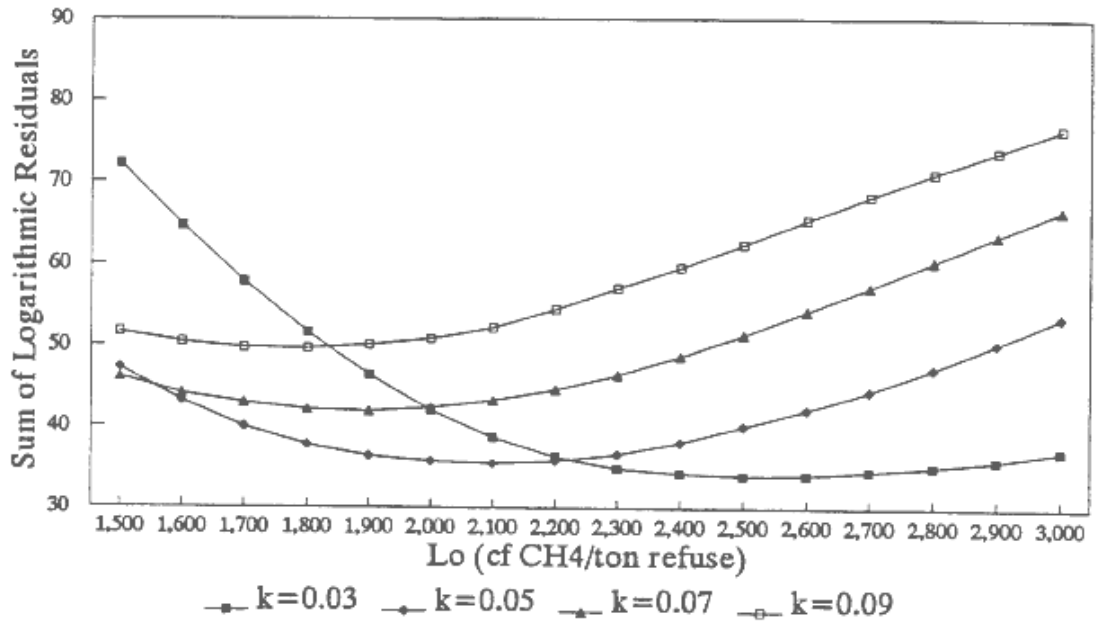


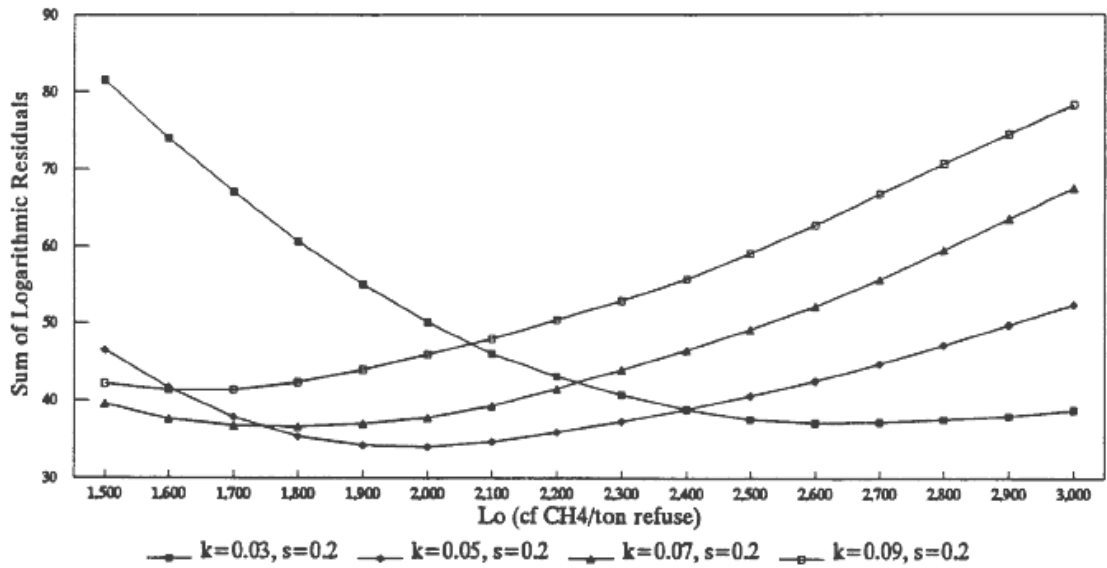
Figure 4.3 Model 3: Modified First Order

Summary of Logarithmic Error Minimization

Lo	Sum of Absolute Natural Logs of (Predicted/Actual)											
	k = 0.03			k = 0.05			K = 0.07			k = 0.09		
	s = 0.2	s = 0.5	s = 1.0	s = 0.2	s = 0.5	s = 1.0	s = 0.2	s = 0.5	s = 1.0	s = 0.2	s = 0.5	s = 1.0
1,500	82	73	71	46	44	45	40	42	44	42	47	49
1,600	74	65	64	42	40	41	38	40	42	41*	46*	48
1,700	67	58	57	38	38	38	37	40	41	41	46	48*
1,800	61	52	51	35	36	37	37*	39*	41*	42	47	49
1,900	55	47	45	34	35	35	37	40	41	44	48	50
2,000	50	42	41	34*	35*	35*	38	41	42	46	50	51
2,100	46	39	38	35	35	35	39	43	44	48	52	53
2,200	43	37	36	36	36	36	41	45	45	50	55	56
2,300	41	35	35	37	37	37	44	47	47	53	58	59
2,400	39	35	34	39	39	39	46	49	50	56	61	62

2,500	38	35*	34*	41	41	41	49	52	53	59	64	65
2,600	37*	35	34	42	44	44	52	56	56	63	67	68
2,700	37	35	35	45	46	46	56	59	60	67	71	71
2,800	37	36	36	47	49	49	59	63	63	71	74	74
2,900	38	37	37	50	52	52	64	67	66	75	77	77
3,000	39	38	38	52	55	56	68	70	70	78	81	80

- Denotes the minimum sum for each value of k and s.

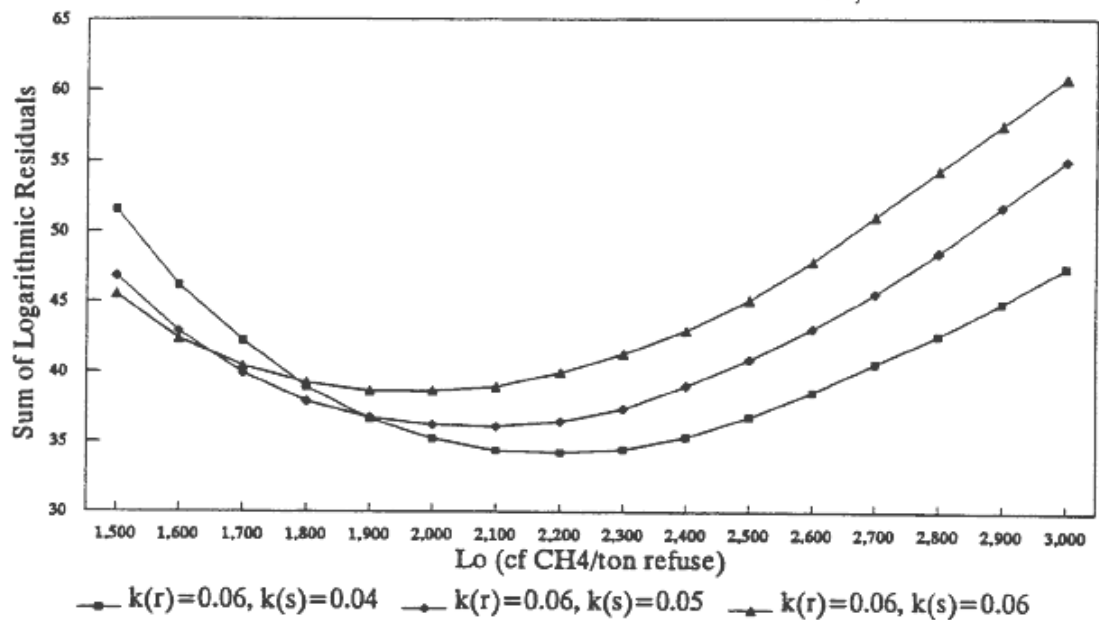


**Figure 4.4 Model 4: First Order Multi-Phase
Summary of Logarithmic Error Minimization**

Lo	Sum of Absolute Natural Logs of (Predicted/Actual)											
	k(r) = 0.06			k(r) = 0.07			k(r) = 0.08					
	k(s) = 0.04	k(s) = 0.05	k(s) = 0.06	k(s) = 0.04	k(s) = 0.05	k(s) = 0.06	k(s) = 0.04	k(s) = 0.05	k(s) = 0.06			
2,500	38	35*	34*	41	41	41	49	52	53	59	64	65
2,600	37*	35	34	42	44	44	52	56	56	63	67	68
2,700	37	35	35	45	46	46	56	59	60	67	71	71
2,800	37	36	36	47	49	49	59	63	63	71	74	74
2,900	38	37	37	50	52	52	64	67	66	75	77	77
3,000	39	38	38	52	55	56	68	70	70	78	81	80

1,500	52	47	46	51	47	46	51	47	46
1,600	46	43	42	46	43	43	46	43	43
1,700	42	40	40	42	40	41	42	40	41
1,800	39	38	39	39	38	40	39	39	40
1,900	37	37	39	37	37	39*	37	38	40*
2,000	35	36	39*	36	37	39	36	37*	40
2,100	34	36*	39	35	37*	40	35	37	40
2,200	34*	36	40	35*	37	41	35*	38	42
2,300	34	37	41	35	38	42	35	39	43
2,400	35	39	43	36	40	44	36	40	45
2,500	37	41	45	37	42	46	38	42	47
2,600	39	43	48	39	44	49	40	44	50
2,700	41	46	51	41	46	52	42	47	53
2,800	43	48	54	43	50	55	44	50	56
2,900	45	52	58	46	53	59	46	54	60
3,000	47	55	61	48	56	62	49	57	63

- Denotes the minimum sum for each value of $k_{(r)}$ and $k_{(s)}$.



4.3 Comparisons by Correlation

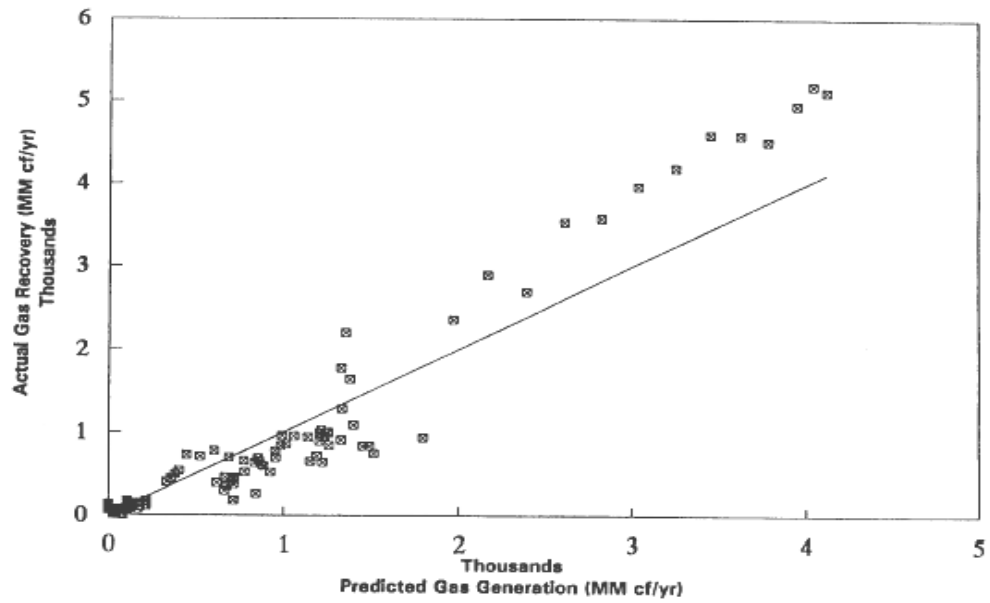
Figures 4.5 through 4.8 also allow model comparisons of predicted versus actual methane recovery in terms of the variance of landfill data points from the straight line (the straight line represents an exact correlation). A commonly-applied statistical measure for good correlation or "goodness of fit" for modelled data is the regression coefficient, r^2 . Regression coefficients were calculated for the plots shown in Figures 4.5 through 4.8 (based on arithmetic optimization) and for similar data based on logarithmic optimization. Results are presented in Table 4.2.

Generally, regression coefficient values based on arithmetic optimization were similar for all four models, ranging from 0.928 to 0.937, depending on the model. This could be considered reasonable correlation. By one interpretation, such a regression coefficient might indicate that from 92.8 to 93.7 percent of the variation in methane recovery could be attributed to parameter values and inputs of the optimized model. Table 4.2 shows that regression coefficients for the logarithmic data treatment showed high correlations as well, ranging from 0.914 to 0.955. Similarity of the regression coefficient results indicates that the four models are similar in predictive ability.

However, the assumptions implicit in the use of the regression coefficient may not correspond exactly to landfill methane modelling. Where the regression coefficient is applied, an assumption is that an underlying "true" model exists, correlated to the extent indicated by r^2 to model variables. Deviations between the model prediction and measured methane recovery are otherwise assumed to be due to unknown factors or random errors (such as in field measurements made).

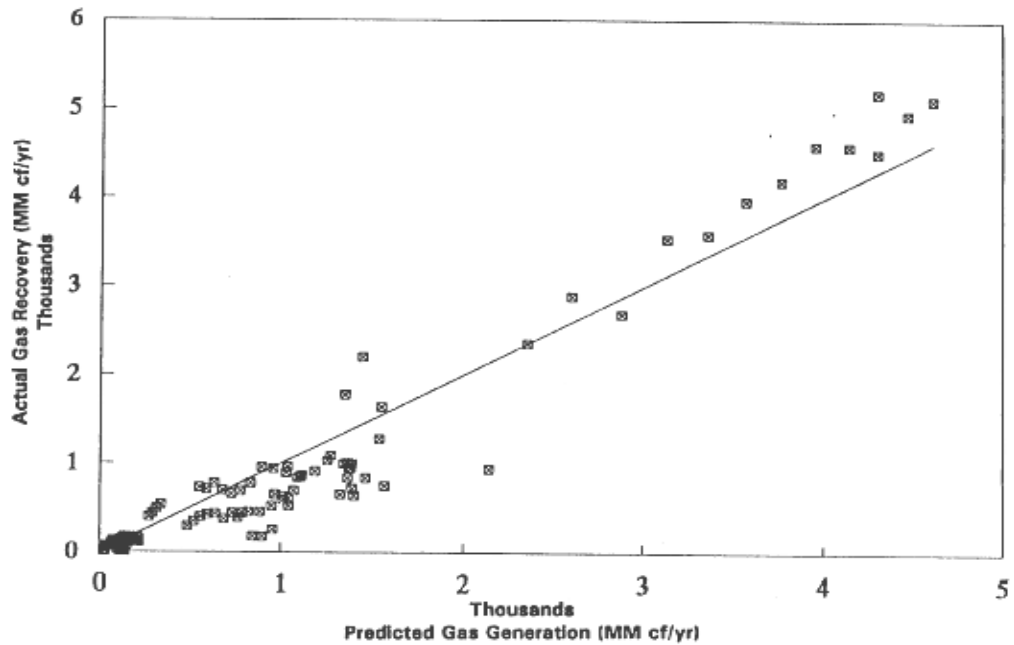
This base assumption may not be valid if a much higher fraction of the discrepancy between the modelled and experienced values is not random, but due to unquantified real biases. An example of such bias that could show as "random" error would be where one landfill yields much greater methane recovery over time (essentially, a greater L_0 value) than another because of greater moisture infiltration and distribution within the waste mass.

Figure 4.5: Model 1: Zero Order Predicted Gas Generation versus Actual Gas Recovery



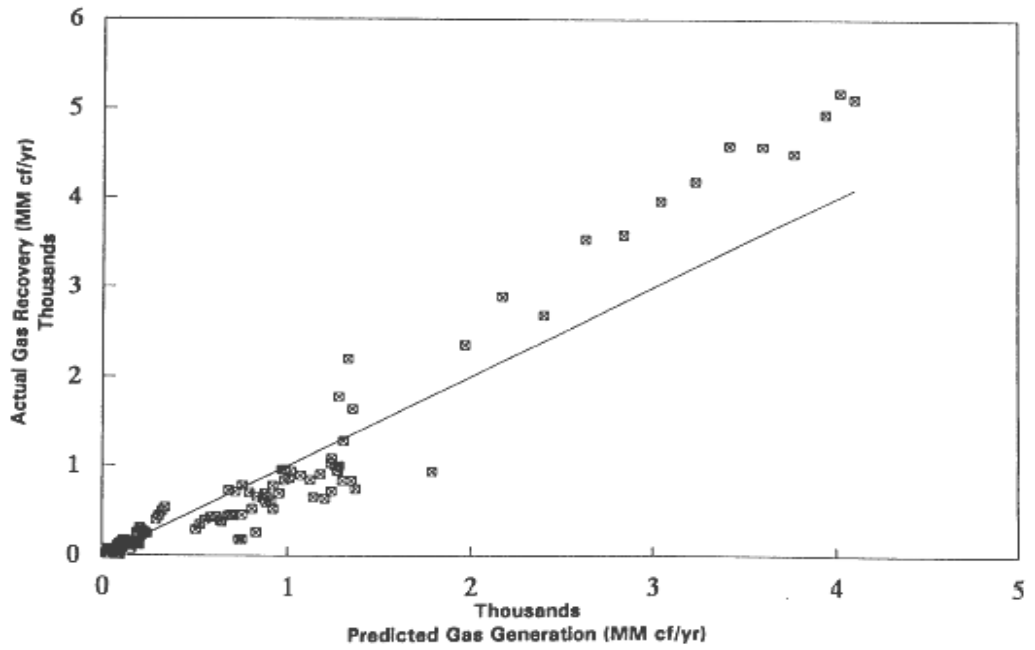
Minimizing Parameters: $L_0 = 1,600$ of CH_4 / ton refuse; time = 20 years.

Figure 4.6: Model 2: Simple First Order Predicted Gas Generation versus Actual Gas Recovery



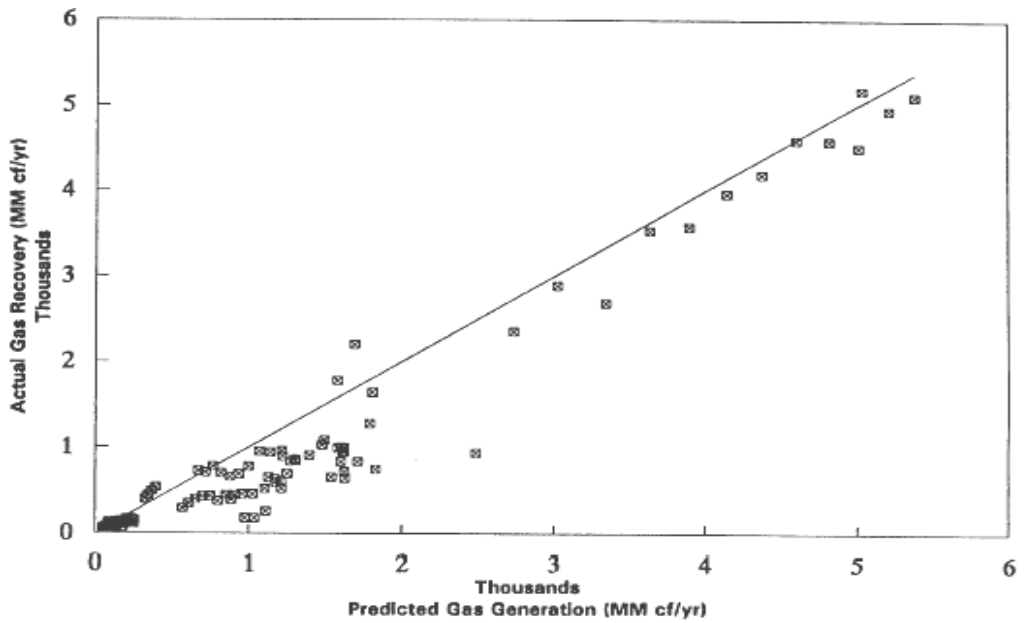
Minimizing Parameters: $L_0 = 1,600$ of CH_4 / ton refuse; time = 20 years.

Figure 4.7: Model 3: Modified First Order Predicted Gas Generation versus Actual Gas Recovery



Minimizing Parameters: $L_0 = 1,600$ of CH_4 / ton refuse; time = 20 years.

Figure 4.8: Model 4: First Order Multi-Phase Predicted Gas Generation versus Actual Gas Recovery



Minimizing Parameters: $L_0 = 1,600$ of CH_4 / ton refuse; time = 20 years.

Table 4.2 Regression Coefficient Values for Methane Model Comparisons

Landfill Methane Model	Regression Coefficient (r^2) by Optimization Function	
	Arithmetic	Logarithmic
Model 1: Zero Order	0.928	0.914
Model 2: Simple First Order	0.937	0.955
Model 3: Modified First Order	0.937	0.918
Model 4: First Order Multi-Phase	0.937	0.939

4.4 Comparisons by Probability Limits

The four landfill methane models also were compared through examination of data distributions of the numerical ratios of the measured methane recovery values to the modelled recovery over the spectrum of data points established for the study landfills. For each model and each optimization function, plots were developed to show distributions around median values for modelled versus actual methane recovery values.

Figures 4.9 through 4.12 provide distribution plots for Models 1 through 4, respectively, based on the minimization of logarithmic error.

For these figures, a "perfect" model correlation would be represented by a vertical line of the landfill data points at 100 percent of actual recovery (the x-axis). Data 'scatter' or dispersion from perfect correlation are illustrated on the figures with

bounds shown by vertical lines. These bounds represent the 10 and 90 percent probability (or confidence) limits. In other words, the cumulated fraction of points lying within any particular boundary, in terms of percentages of the modelled prediction, indicates the dispersion of experienced recovery about the model prediction.

Overall, Figures 4.9 through 4.12 show rather wide probability limits for the set of study landfills, meaning the models could project methane recovery within a factor of about 1.5 for 80 percent of the landfill data points. The spread or dispersion was greater for the remaining data points. Note that this is the first time that methane recovery probability limits have been developed in association with projections for US landfills. (Where landfills share common filling histories and operational features, a narrower range for the limits might be expected).

Comparison of figures representing data treatments indicates that the probability limits for the models optimized via logarithmic minimization are narrower than those established with the arithmetic optimization.

Figure 4.9: Zero Order Model: Logarithmic Dispersions and Confidence Limits

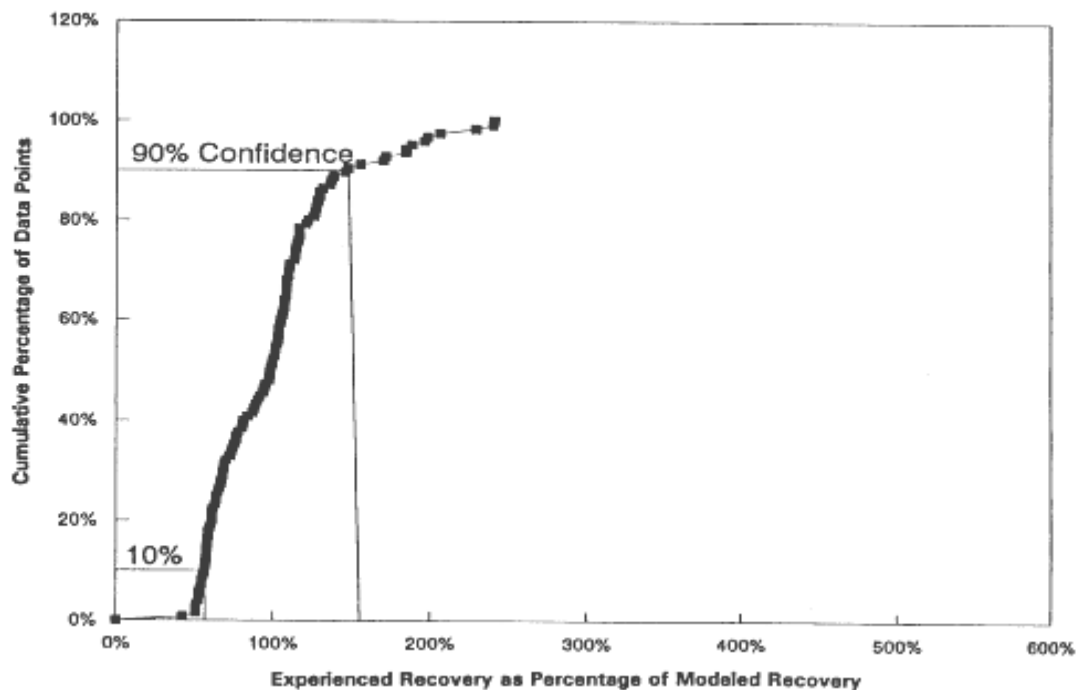


Figure 4.10: Simple First Order Model: Logarithmic Dispersions and Confidence Limits

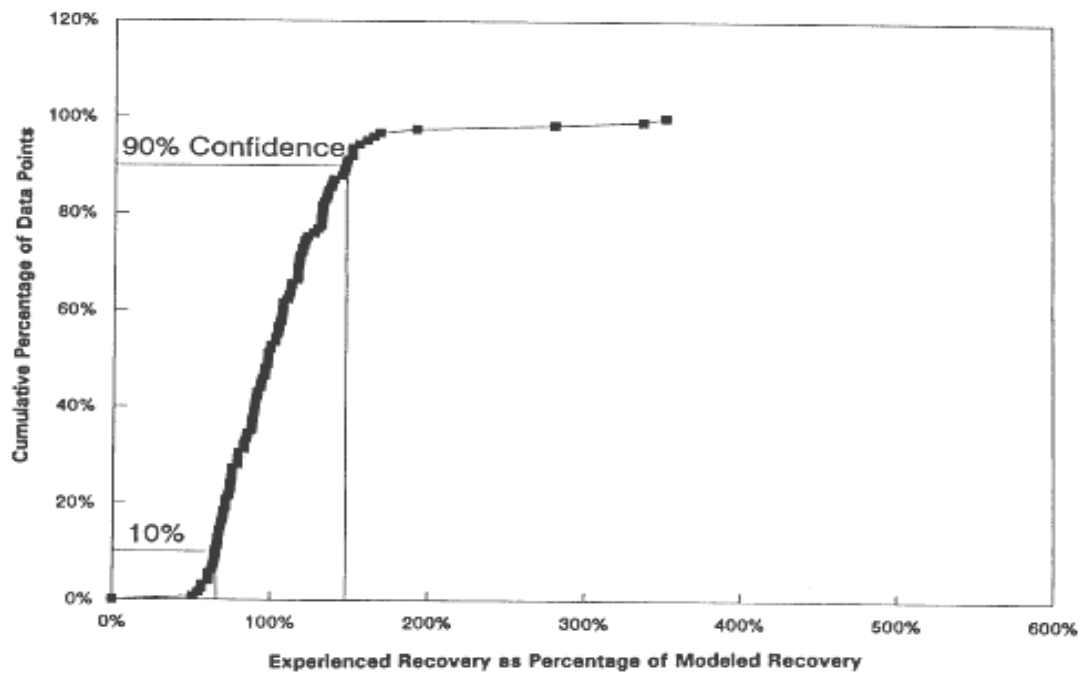


Figure 4.11: Modified First Order Model: Logarithmic Dispersions and Confidence Limits

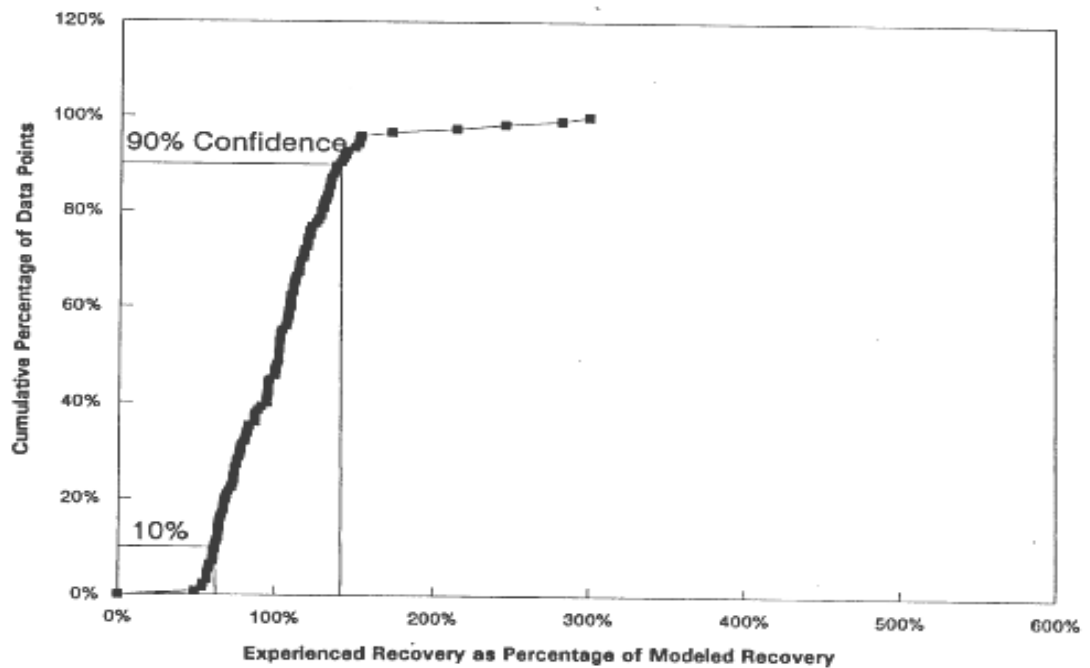
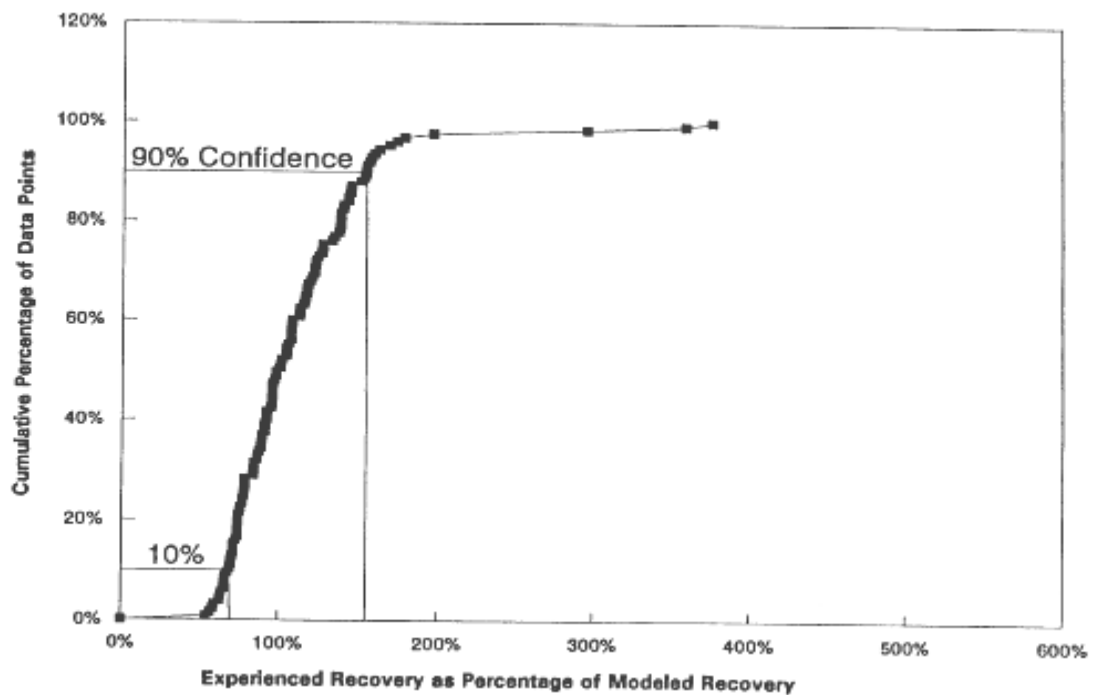


Figure 4.12: First Order Multi-Phase Model: Logarithmic Dispersions and Confidence Limits



4.5 Comparison of Model Parameters with Other Work

Parameter combinations developed for the study landfill data set were compared in a limited manner with other published values. As shown in Table 4.1 for the Simple First Order Model (Model 2), study landfill results had three parameter combinations associated with minimized error: $Lo = 2,100$ and $k = 0.07 \text{ year}^{-1}$; $Lo = 2,200$ and $k = 0.04 \text{ year}^{-1}$; and $Lo = 2,500$ and $k = 0.03 \text{ year}^{-1}$. The U.S. EPA has published regulatory values based on studied literature values for Lo and k and its first order landfill methane emissions model. The regulatory values are $Lo = 4,010$ cubic feet methane per refuse ton, k (for wet sites) = 0.04, and k (for dry sites) = 0.02, from Compilation of Air Pollutant Emission Factors, Stationary Point and Area Sources, July 1993 (AP-42). It is assumed that EPA's Lo value was selected to be

higher than reported typical landfill values in order to be conservative for regulatory purposes.

For other published model work, some interpretive calculations were made to compare with this work's findings. For example, Oonk, et. al. (1994) based methane yield on an assumed waste degradable carbon content. Based on average Dutch waste composition, the first order L_0 from Oonk can be calculated to be about 2,200 cubic feet of methane per ton, and a first order rate constant, k , of 0.09 year^{-1} .

Another commercial model studied by Augenstein (1992) and (Augenstein and Pacey, 1991) based projections on dry waste of assumed composition. An assumed 25 percent waste moisture content for this model gave an L_0 value 2,100 cubic feet of methane per ton, and k values near 0.07 year^{-1} .

CHAPTER 5

Computer Program for Landfill Methane Models

Based on this study's findings, a simple computer program was developed for each of the four models discussed herein. The program presumes a landfill has characteristics typical of the study landfills. This program is included herein as in Appendix B.

The file can be read into similar spreadsheet programs. User inputs include the landfill waste in place (tons), and parameter combinations for each selected model. The user can input model parameter combinations from Table 4.1 (as derived from the project's procedures to optimize models through minimization of error), or other parameter combinations as desired.

Outputs from each of the four models are tabular data and plots for estimated methane generation over time. For purposes of the program, methane generation estimates were treated as equivalent to expected methane recovery. Program outputs for the four models are presented in Appendix B.

CHAPTER 6

Recommendations for Further Work

This section recommends further work that could be carried out to improve the utility and confidence limits of the landfill methane models discussed herein.

6.1 Continue Accumulation of Data for Study Landfills

Collection of study landfills' data should continue, particularly waste filling and methane recovery information. Working relationships established with the landfill owners/operators should help with collection of future data as they become available. Such future data will better define "real" parameter combinations; that is, those that best explain the long-term methane generation/recovery profile.

6.2 Add More Landfills to the Study Data Set

Addition of landfills to the study's data set will expand the usefulness and application of the model comparisons. Furthermore, model calibration is needed for groups of landfills located in distinct geographic/climate regions. A larger data set should allow better evaluation for such groups of landfills, such as those in Eastern regions and hot, humid climate regions.

6.3 Examine Other Data Treatment Approaches

Four landfill methane models were compared through the use of two optimization functions. Other optimization functions were identified but not applied (such as minimization of arithmetic error by least squares, minimization of logarithmic error by the natural log of the ratios or the square of the natural log of the ratios). These choices for data treatment may be a useful step to further compare methane models and to better distinguish predictive abilities.

6.4 Examine Other Landfill Methane Models

Other trial model forms could be examined similar to the procedures presented in the study. Examples include multi-phase zero-order and second order models. It is possible that other models could be better in terms of reducing the discrepancies between model projections and field experience.

6.5 Incorporate Estimates for Methane Recovery Efficiency

The landfill methane models examined treated methane generation as equivalent to methane recovery; estimates for actual methane recovery efficiencies are not model parameters. Because recovery efficiency can affect significantly the actual methane recovered, users of methane models should be experienced and familiar with LFG collection systems so as to apply proper judgement to the model results obtained. Incorporation of the parameter, methane recovery efficiency, to the study's computer program is recommended as an initial step to allow users of methane models to discount predicted methane generation as appropriate.

CHAPTER 7

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APPENDIX A:

Data from previous group project (part B)

Landfill A

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1967	310,000	
1968	310,000	
1969	310,000	
1970	310,000	
1971	310,000	
1972	310,000	
1973	310,000	
1974	310,000	
1975	310,000	
1976	470,000	
1977	470,000	
1978	470,000	
1979	470,000	
1980	720,000	
1981	750,000	
1982	770,000	
1983	800,000	
1984	830,000	
1985	1,260,000	
1986	1,490,000	
1987	1,530,000	
1988	1,050,000	
1989	870,000	
1990	900,000	652
1991	1,200,000	637
1992	1,700,000	1,281
1993	850,000	1,637
1994		2,201
1995		1,776

Landfill B

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1973	213,000	
1974	232,000	
1975	232,000	
1976	232,000	
1977	232,000	

1978	232,000	
1979	508,000	
1980	711,000	
1981	1,114,000	
1982	1,265,000	
1983	1,528,000	
1984	1,484,000	
1985	593,000	
1986	287,000	179
1987	41,000	180
1988		441
1989		443
1990		373
1991		433
1992		426
1993		400
1994		344
1995		293

Landfill C

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1973	10,000	
1974	30,000	
1975	40,000	
1976	50,000	
1977	70,000	
1978	90,000	
1979	100,000	
1980	190,000	
1981	210,000	
1982	250,000	
1983	200,000	
1984	320,000	
1985	450,000	
1986	70,000	
1987	90,000	
1988	40,000	
1989	10,000	
1990		
1991		154.50
1992		169.50
1993		166.83
1994		171.86

Landfill D

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1974	24,000	
1975	25,000	
1976	27,000	
1977	74,000	
1978	72,000	
1979	74,000	
1980	77,000	
1981	82,000	
1982	82,000	
1983	88,000	
1984	94,000	
1985	99,000	
1986	105,000	
1987	109,000	
1988	108,000	
1989	100,000	88.44
1990	100,000	60.20
1991	69,000	85.39
1992	63,000	70.89
1993	62,000	72.07
1994	60,000	89.19

Landfill E

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1973	10,000	
1974	30,000	
1975	40,000	
1976	50,000	
1977	70,000	
1978	90,000	
1979	100,000	
1980	190,000	
1981	210,000	
1982	250,000	
1983	200,000	
1984	320,000	
1985	450,000	
1986	450,000	
1987	70,000	
1988	90,000	

1989	40,000	
1990	10,000	
1991		112.67
1992		118.44
1993		118.44
1994		119.63

Landfill F

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1965	26,000	
1966	27,000	
1967	27,000	
1968	28,000	
1969	28,000	
1970	29,000	
1971	30,000	
1972	30,000	
1973	31,000	
1974	32,000	
1975	32,000	
1976	33,000	
1977	34,000	
1978	34,000	
1979	35,000	
1980	36,000	
1981	36,000	
1982	37,000	
1983	38,000	
1984	39,000	
1985	39,000	
1986	40,000	
1987	41,000	
1988	46,000	
1989	38,000	
1990		
1991		
1992		
1993		66.83
1994		61.39

Landfill G

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1970	300,000	
1971	300,000	

1972	300,000	
1973	300,000	
1974	300,000	
1975	300,000	
1976	300,000	
1977	300,000	
1978	300,000	
1979	300,000	
1980	400,000	
1981	400,000	
1982	400,000	
1983	459,000	
1984	440,000	
1985	411,000	
1986	111,000	
1987		
1988		
1989		
1990		
1991		532.81
1992		492.56
1993		440.56
1994		399.52

Landfill H

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1975	50,000	
1976	50,000	
1977	50,000	
1978	195,000	
1979	195,000	
1980	195,000	
1981	195,000	
1982	195,000	
1983	195,000	
1984	195,000	
1985	195,000	
1986		
1987		
1988		
1989		
1990		
1991		142.50
1992		130.92
1993		107.85
1994		114.35

Landfill I

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1958	25,000	
1959	25,000	
1960	25,000	
1961	25,000	
1962	25,000	
1963	25,000	
1964	25,000	
1965	25,000	
1966	25,000	
1967	25,000	
1968	25,000	
1969	119,000	
1970	138,000	
1971	160,000	
1972	134,000	
1973	122,000	
1974	119,000	
1975	101,000	
1976	71,000	
1977	102,000	
1978	160,000	
1979	155,000	
1980	143,000	
1981	174,000	
1982	216,000	
1983	206,000	
1984	228,000	
1985	213,000	
1986	57,000	
1987		
1988		
1989		
1990		
1991		102.67
1992		71.56
1993		147.62
1994		132.16

Landfill J

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
------	-------------------------	--

1960	34,000	
1961	669,000	
1962	379,000	
1963	519,000	
1964	929,000	
1965		
1966		
1967		
1968		
1969		
1970		
1971		
1972		
1973		
1974		
1975		
1976		
1977		
1978		
1979		
1980		
1981		
1982		
1983		
1984		115
1985		131
1986		111
1987		107
1988		79
1989		72
1990		67
1991		62
1992		66
1993		72
1994		65
1995		59

Landfill K

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1957	86,000	
1958	161,200	
1959	194,800	
1960	220,950	
1961	317,800	
1962	477,700	
1963	683,300	

1964	878,350	
1965	852,100	
1966	703,300	
1967	785,450	
1968	998,572	
1969	1,355,925	
1970	1,215,841	
1971	1,045,424	
1972	1,044,948	
1973	1,062,961	
1974	1,002,844	
1975	983,190	
1976	938,401	
1977	1,052,020	
1978	1,187,187	
1979	1,176,457	
1980	1,177,953	746
1981		833
1982		836
1983		1,083
1984		907
1985		841
1986		896
1987		939
1988		957
1989		778
1990		686
1991		654
1992		697
1993		778
1994		708
1995		728

Landfill L

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1957		
1958		
1959		
1960	34,000	
1961	669,000	
1962	379,000	
1963	519,000	
1964	929,000	
1965		
1966		
1967		

1968		
1969		
1970		
1971		
1972		
1973		
1974		
1975		
1976		
1977		
1978		
1979		
1980		
1981		
1982		
1983		
1984		115
1985		131
1986		111
1987		107
1988		79
1989		72
1990		67
1991		62
1992		66
1993		72
1994		65
1995		59

Landfill M

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1961	205,000	
1962	334,000	
1963	394,000	
1964	481,000	
1965	493,000	
1966	495,000	
1967	512,000	
1968	495,000	
1969	499,000	
1970	475,000	
1971	458,400	
1972	453,000	
1973	453,000	
1974	431,000	
1975	462,000	

1976	493,000	
1977	440,700	
1978	498,500	
1979	610,300	
1980	691,400	
1981	750,800	
1982	817,500	
1983	867,700	
1984	895,300	
1985	879,000	
1986	1,062,900	
1987	1,527,100	
1988	1,620,200	
1989	683,900	718
1990	763,012	993
1991	653,697	942
1992	607,714	952
1993	611,901	1,002
1994	532,240	995
1995		1,032

Landfill N

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1957	34,560	
1958	75,300	
1959	75,300	
1960	75,300	
1961	89,250	
1962	122,621	
1963	152,404	
1964	160,412	
1965	166,768	
1966	157,428	
1967	147,900	
1968	162,022	
1969	177,606	
1970	184,304	
1971	183,223	
1972	196,010	
1973	205,116	
1974	187,832	
1975	179,883	
1976	178,004	
1977	206,995	
1978	251,992	
1979	283,572	

1980	286,528	
1981	341,519	
1982	364,070	
1983	422,212	
1984	490,617	
1985	553,469	
1986	774,962	
1987	709,519	
1988	770,192	
1989	915,626	387
1990	808,052	452
1991	862,684	456
1992	909,172	519
1993	913,908	632
1994	706,255	602
1995		652

Landfill O

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
1975	220,000	
1976	220,000	
1977	110,000	
1978	275,000	
1979	275,000	
1980	275,000	
1981	441,667	
1982	166,667	
1983	166,667	
1984	100,000	
1985	100,000	
1986	100,000	
1987		
1988	250,000	
1989	250,000	
1990	250,000	268.2605
1991	250,000	243.2414
1992		241.8708
1993		262.1037
1994		227.9036
1995		205.8382

Landfill P

Waste Placement Data

Year	Refuse (tons / year)	Methane recovery (MM cubic feet/year)
------	-------------------------	--

1962	80,000	
1963	82,000	
1964	84,000	
1965	86,000	
1966	88,000	
1967	90,000	
1968	92,000	
1969	94,000	
1970	96,000	
1971	98,000	
1972	100,000	
1973	102,000	
1974	104,000	
1975	106,000	
1976	108,000	
1977	110,000	
1978	112,000	
1979	114,000	
1980	116,000	
1981	118,000	
1982	120,000	
1983	122,000	
1984	124,000	
1985	103,428	
1986	110,944	
1987	175,000	
1988	168,766	
1989	190,657	
1990	202,000	
1991	204,000	
1992		284
1993		310
1994		228
1995		257

APPENDIX B:

Methane Gas Recovery Program

- Example Program Input Forms and Outputs

This program, designed to make estimates for methane gas recovery from landfills, is organized as follows:

Introductory Screen (Introduction)

Model 1: - Methane Generation Coefficients (Gas Coefficients 1, From Table 4.1)
- Inputs Data (Input 1)
- Graph of Estimated Methane Generation (Model 1)

Model 2: - Methane Generation Coefficients (Gas Coefficients 2, From Table 4.1)
- Inputs Data (Input 2)
- Graph of Estimated Methane Generation (Model 2)

Model 3: - Methane Generation Coefficients (Gas Coefficients 3, From Table 4.1)
- Inputs Data (Input 3)
- Graph of Estimated Methane Generation (Model 3)

Model 4: - Methane Generation Coefficients (Gas Coefficients 4, From Table 4.1)
- Inputs Data (Input 4)
- Graph of Estimated Methane Generation (Model 4)

Comparison: - Comparison Graph of Estimated Methane Generation of Model 2, 3 & 4.

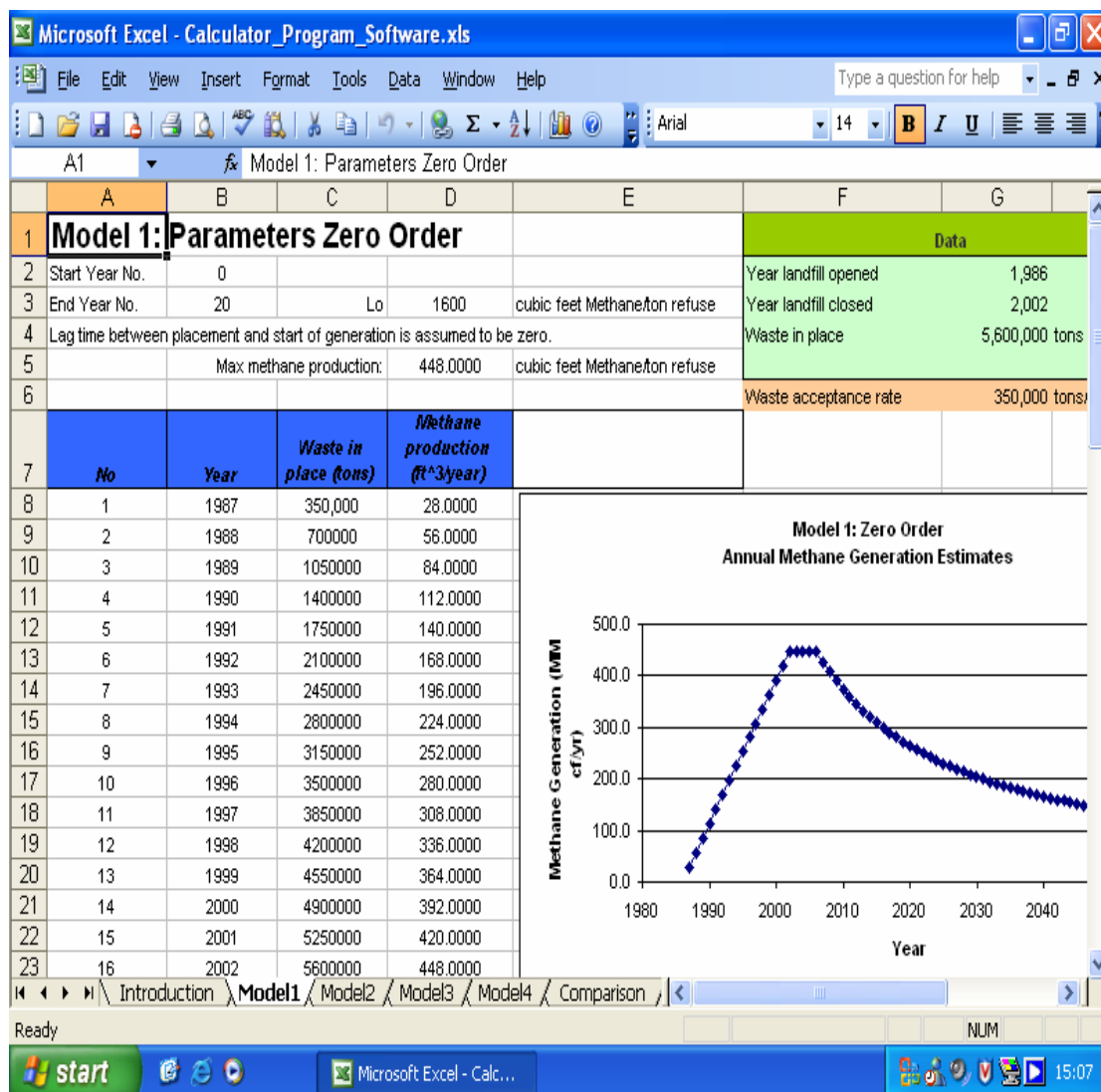
Introduction

The screenshot displays a Microsoft Excel spreadsheet titled "Calculator_Program_Software.xls". The spreadsheet content is as follows:

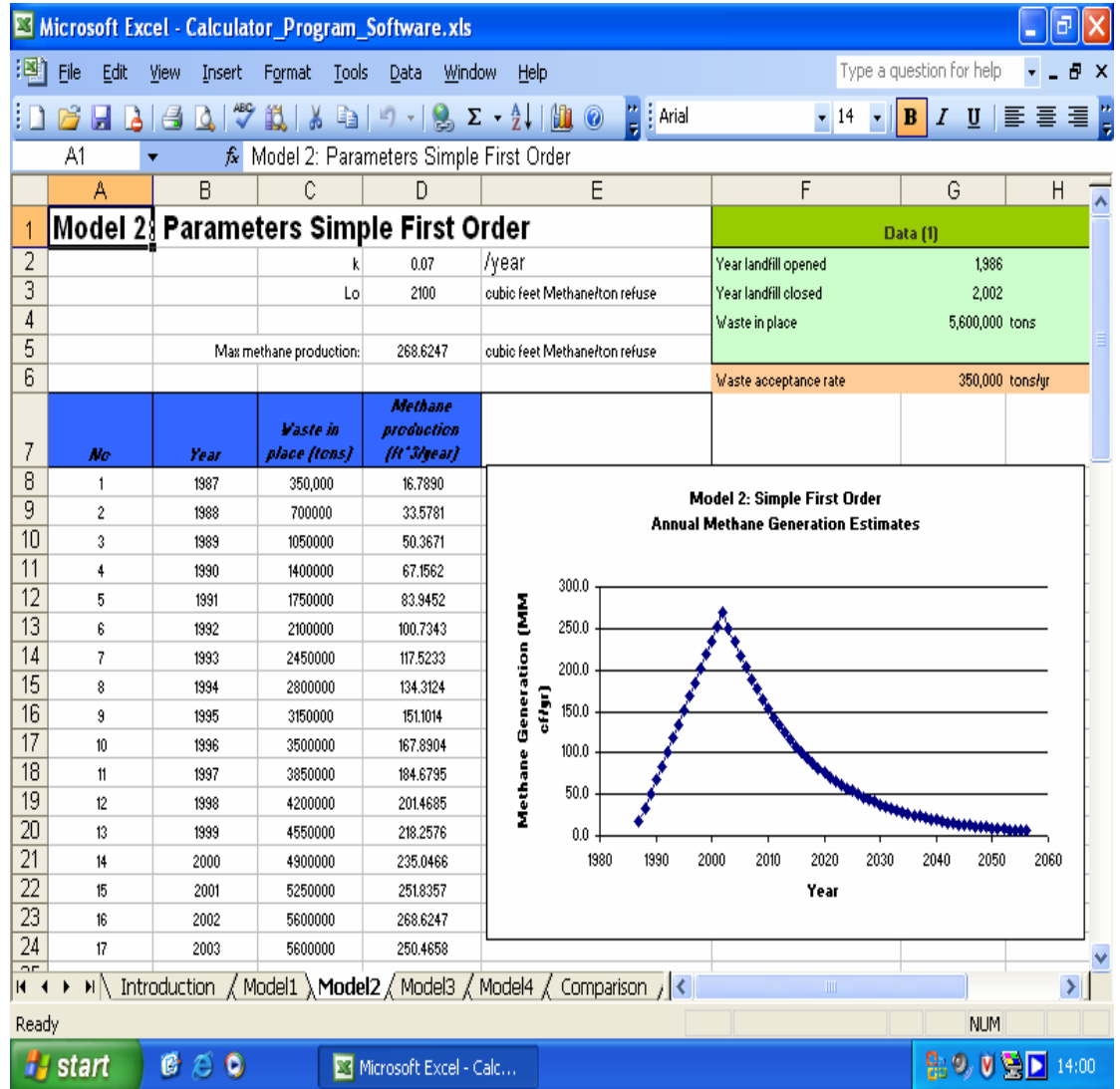
1	University of Strathclyde												
2	MSc Energy System and the Environment												
3													
4													
5	Introduction Methane Recovery Calculator						Instructions for use program						
6													
7	Model 1:	Methane Generation Coefficient (From Table)					Input your site data in the green box. - Years landfill opened - Years landfill closed - Waste in place						
8		Inputs Data											
9		Graph of Estimated Methane Generation											
10													
11	Model 2:	Methane Generation Coefficient (From Table)											
12		Inputs Data											
13		Graph of Estimated Methane Generation											
14													
15	Model 3:	Methane Generation Coefficient (From Table)											
16		Inputs Data											
17		Graph of Estimated Methane Generation											
18													
19	Model 4:	Methane Generation Coefficient (From Table)											
20		Inputs Data											
21		Graph of Estimated Methane Generation											
22													
23	Comparison:	Comparison Graph of Estimated Methane Generation of First Order Model 2 , 3 & 4											
24													
25													
26													
27													
28													
29													
30													

At the bottom right of the spreadsheet, the text "By Wirot Rattanawiboonson" is visible. The Excel interface includes a menu bar (File, Edit, View, Insert, Format, Tools, Data, Window, Help), a toolbar, and a status bar showing "Ready" and "NUM". The Windows taskbar at the bottom shows the Start button, several application icons, and the system clock displaying "13:59".

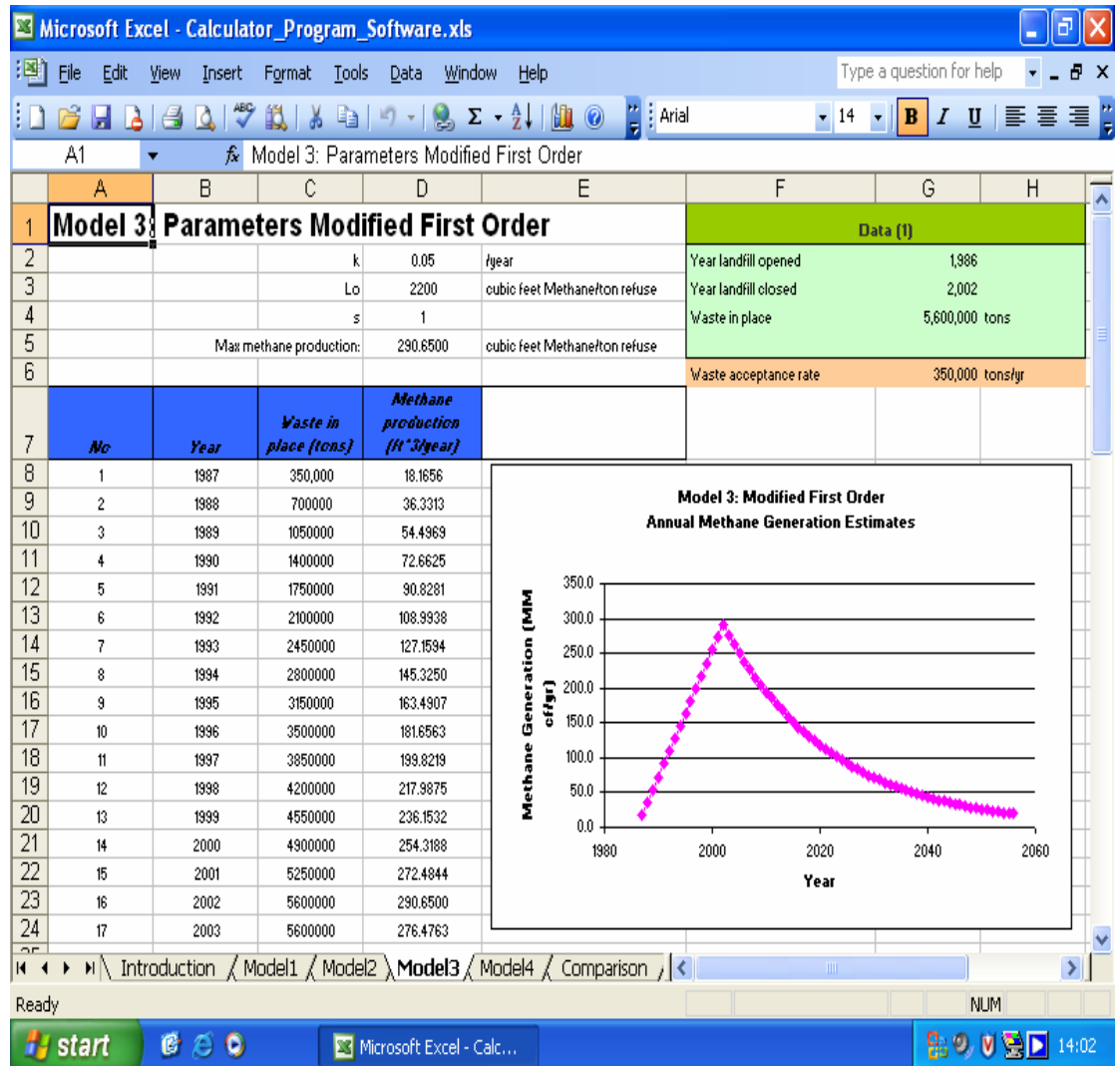
Model 1: Zero Order Model



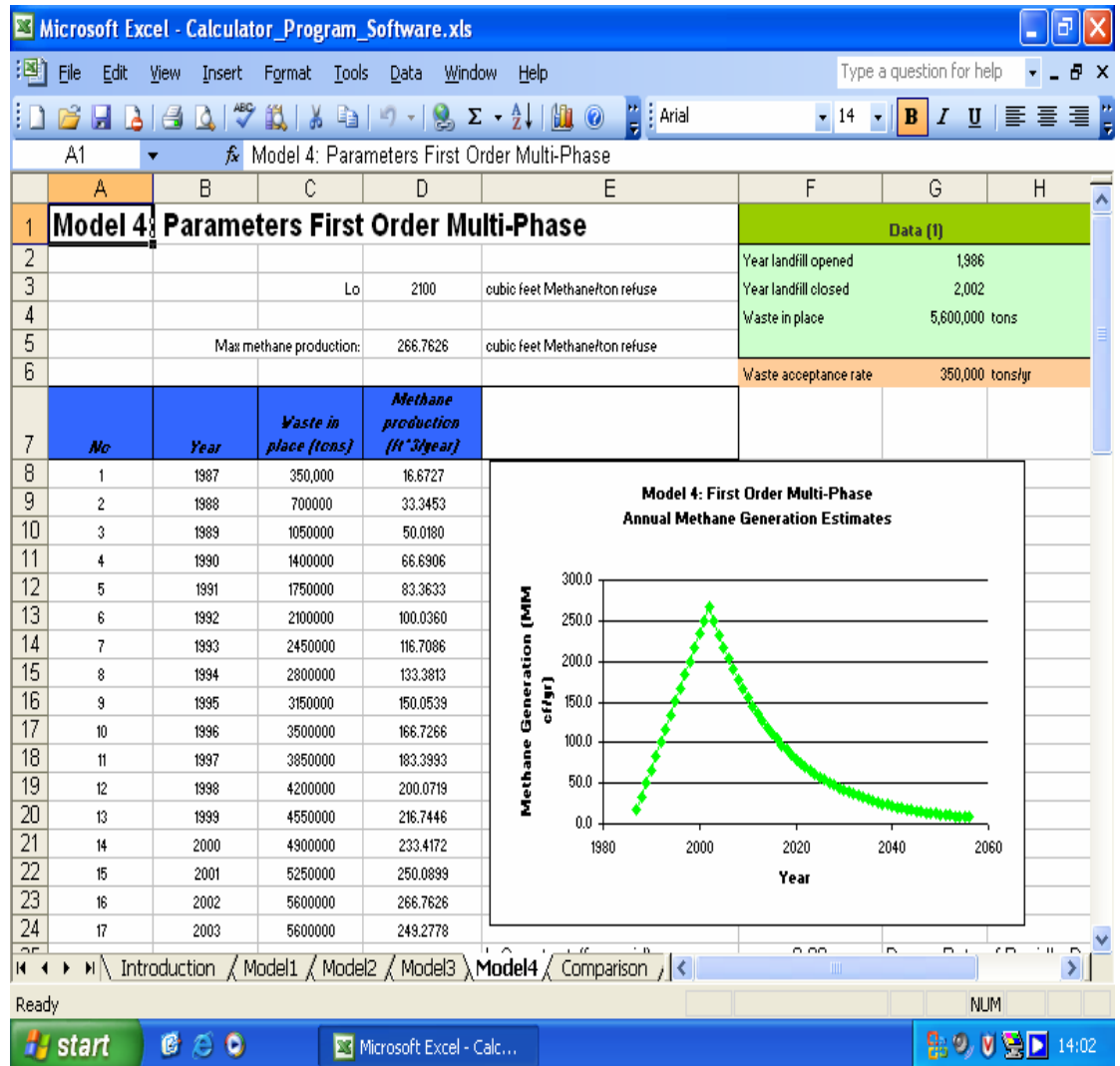
Model 2: First Order Model



Model 3: Modified First Order Model



Model 4: First Order Multi-Phase Model



Comparison: Comparison First Order Model 2, 3 & 4

