A Novel Computational Approach for the Management of Bioreactor Landfills

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ABSTRACT

The bioreactor landfill is an emerging concept for solid waste management that has gained significant attention in the last decade. This technology employs specific operational practices to enhance the microbial decomposition processes in landfills. However, the unsupervised management and lack of operational guidelines for the bioreactor landfill, specifically leachate manipulation and recirculation processes, usually results in less than optimal system performance. Therefore, these limitations have led to the development of SMART (Sensor-based Monitoring and Remote-control Technology), an expert control system that utilizes real-time monitoring of key system parameters in the management of bioreactor landfills.

SMART replaces conventional open-loop control with a feedback control system that aids the human operator in making decisions and managing complex control issues. The target from this control system is to provide optimum conditions for the biodegradation of the refuse, and also, to enhance the performance of the bioreactor in terms of biogas generation. SMART includes multiple cascading logic controllers and mathematical calculations through which the quantity and quality of the recirculated solution are determined. The expert system computes the required quantities of leachate, buffer, supplemental water, and nutritional amendments in order to provide the bioreactor landfill microbial consortia with their optimum growth requirements.

Soft computational methods, particularly fuzzy logic, were incorporated in the logic controllers of SMART so as to accommodate the uncertainty, complexity, and nonlinearity of the bioreactor landfill processes. Fuzzy logic was used to solve complex operational issues in the control program of SMART including: (1) identify the current operational phase of the bioreactor landfill based on quantifiable parameters of the leachate generated and biogas produced, (2) evaluate the toxicological status of the leachate based on certain parameters that directly contribute to or indirectly indicates bacterial inhibition, and (3) predict biogas generation rates based on the operational phase, leachate recirculation, and sludge addition. The later fuzzy logic model was upgraded to a hybrid model that employed the learning algorithm of artificial neural networks to optimize the model parameters.

SMART was applied to a pilot-scale bioreactor landfill prototype that incorporated the hardware components (sensors, communication devices, and control elements) and the software components (user interface and control program) of the system. During a one-year monitoring period, the feasibility and effectiveness of the SMART system were evaluated in terms of multiple leachate, biogas, and waste parameters. In addition, leachate heating was evaluated as a potential temperature control tool in bioreactor landfills.

The pilot-scale implementation of SMART demonstrated the applicability of the system. SMART led to a significant improvement in the overall performance of the BL in terms of methane production and leachate stabilization. Temperature control via recirculation of heated leachate achieved high degradation rates of organic matter and improved the methanogenic activity.

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IN THE NAME OF 'ALLAH'- LORD OF THE WORLDS, THE MOST MERCIFUL AND THE MOST BENEVOLENT

DEDICATED TO

MY PARENTS, WONDERFUL WIFE NORA, AND LOVELY DAUGHTER MARYAM

TABLE OF CONTENTS

LIST OF FIGURES

List of Tables

NOMENCLATURE

AA	acetic acid
Al	aluminum
ANFIS	adaptive nuero-fuzzy inference system
ANN	artificial neural networks
ATC	automatic temperature compensation
B	boron
BA	bicarbonate alkalinity
BD	block diagram
BL	bioreactor landfill
BMP	biochemical methane potential
BOD	biological oxygen demand
Ca	calcium
CAT	alkali cation
Cd	cadmium
CH_4	methane gas
Co	cobalt
CO_2	carbon dioxide gas
COD	chemical oxygen demand
Cr	chromium
Cu	copper
ET	error tolerance
FB	fractional bias
FCM	fuzzy cognitive map

Fe	iron
FL	fuzzy logic
FLC	fuzzy logic control/controller
FP	front panel
FV	fractional variance
GSU	global sensory unit
GUI	graphical user interface
H_2	hydrogen gas
H_3O^+	hydronium ion
IA	index of agreement
ICP-AES	inductively coupled plasma atomic emission spectrometry
K	potassium
LC	logic controller
LDU	local driving unit
LFG	landfill gas
LSU	local sensory unit
MAE	mean absolute error
MBE	mean bias error
MC	mathematical calculation
MCU	main controller unit
MF	membership function
Mg	magnesium
MIMO	multi-input-multi-output
Mn	manganese

MP	methane production
MSD	mean squared deviation
MSW	municipal solid waste
Na	sodium
$NaHCO_3$	sodium bicarbonate
Na_2CO_3	sodium carbonate
NaOH	sodium hydroxide
NH_3-N	ammonia as nitrogen
Ni	nickel
OPC	object linking and embedding for process control
ORP	oxidation reduction potential
P	phosphorus
Pb	lead
PDC	primary driving controller
PID	proportional-integral-derivative
PSDP	primary sensory data processor
R	correlation coefficient
R^2	coefficient of determination
RA	required alkalinity
RMSE	root mean squared error
ROPEC	Robert O. Pickard environmental center
SISO	single-input-single-output
SMART	sensor-based monitoring and remote-control technology
TA	total alkalinity

TDR	time domain reflectometry
TKN	total Kjeldahl nitrogen
TN	total nitrogen
TOC	total organic carbon
TP	total phosphorus
TS	total solids
UAN	unionized fraction of ammonia
USB	universal serial bus
UVFA	undissociated volatile fatty acid
VFA	volatile fatty acid
VOA	volatile organic acid
VS	volatile solids
Zn	zinc

CHAPTER 1

INTRODUCTION

1.1. Background

In 2008, Canadians produced over 1,031 kg of waste per person, up 8% from 2004 (Statistics Canada, 2008). Over 75% of this waste was disposed in landfills, which translate into an annual overall production of 34 million tons of waste handled by the waste management industry; 26 million tons of that waste being sent to landfills. In the United States, about 54% of the 243 million tons generated municipal solid waste (MSW) in 2009 was disposed in landfills (U.S. EPA, 2010). Landfilling has been always considered the dominant and most economical method for the disposal of MSW worldwide. However, serious environmental impacts resulting from landfills have led to the development of new design and operation concepts to optimize the operation, mitigate the negative impacts, and maximize the potential profit. The "bioreactor landfill" is considered one of the most promising and effective developments in this field.

A bioreactor landfill (BL) is typically a sanitary landfill in which specific management activities and operational modifications are employed to transform and stabilize readily and moderately decomposable organic waste within 5 to 10 years (Warith, 2002). The BL concept provides the consortia of microorganisms within the landfill ecosystem with the optimum environmental conditions, such as sufficient moisture and nutrients, for their growth requirements. The recirculation of leachate is considered the main operational characteristic in the BL to increase moisture (Figure 1-1). In some cases, other techniques such as pH buffering, nutrient addition, microbial bioaugmentation, and temperature management have been incorporated with leachate recirculation to improve overall performance (Barlaz *et al.*, 1990; Reinhart, 1996; Reinhart and Townsend, 1998; Warith, 2002, 2005).

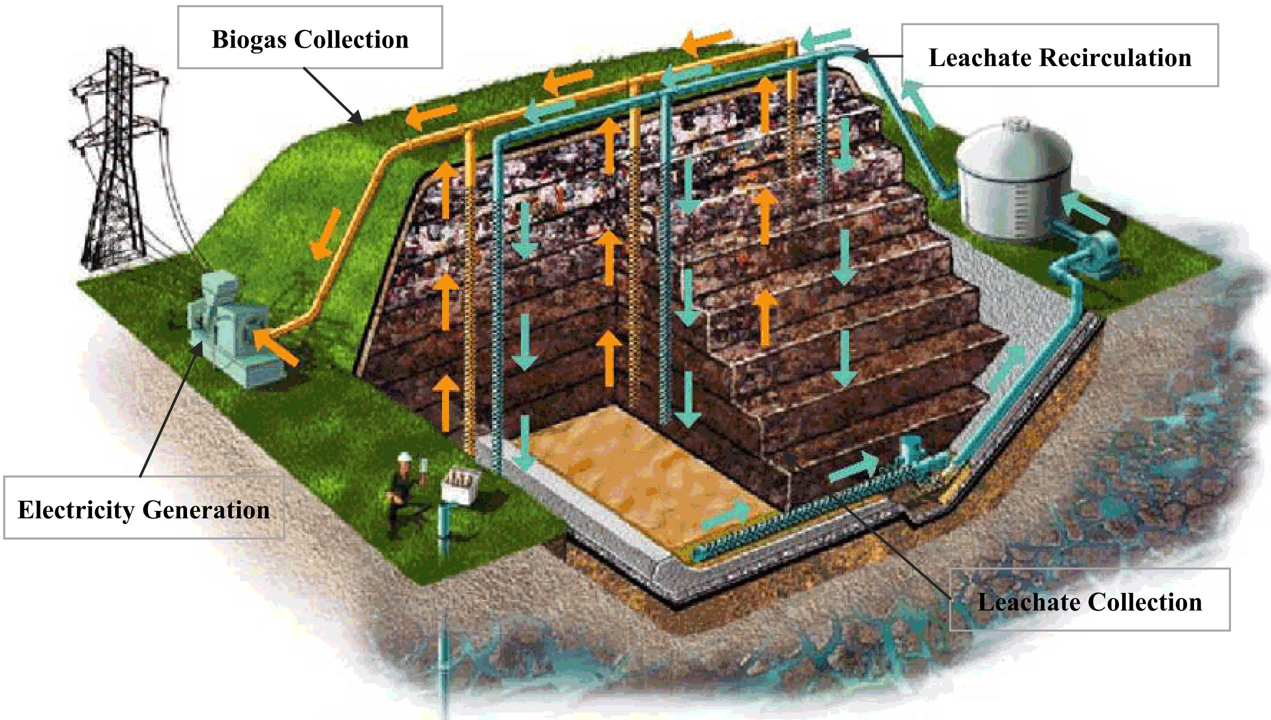

Figure 1-1 Leachate recirculation and gas collection in bioreactor landfill (Courtesy of Waste Management, Inc.)

The potential advantages of BLs include: more rapid waste stabilization, increased waste settlement rates and airspace recovery, rapid biogas production (thereby maximizes the profitability of gas collection projects), decreased leachate treatment costs, and reduced post-closure efforts. On the other hand, there are several technical issues that still need to be studied in order for BLs to achieve optimal performance.

1.2. Problem Identification

One of the most critical, yet little studied, issues in the operation of BLs is process control. In field applications, the system may suffer from serious complications as a result of improper control. Unsupervised operational procedures can disturb the dynamics of the BL processes causing serious consequences on the overall evolution of the system. This may result in unstable, and sometimes unsuccessful, transition from one operational phase to another. One of the major operational issues that hinder proper control of BLs is the lack of generic guidelines for the BL process operation, specifically leachate recirculation and manipulation processes. This is mostly due to the following:

- Lack of well-defined methodologies and field experiences of the BL;
- The optimum quantity and quality for leachate recirculation has not yet been identified;
- The large variation in the biochemical characteristics of leachate makes the leachate, as produced, an unsteady liquid for the recirculation process. This is coupled with the variable growth requirements of the population consortia inside the BL during the different operational phases.
- Using literature values of the quantities of leachate and other amendments is impractical because the applied materials, operating conditions, and application methods vary significantly between different studies. Moreover, the applied quantities and reported results are rarely, if ever, standardized, which makes them inapplicable for other cases.

1.3. Research Rationale

Controlling the BL requires a good understanding of the system components and processes. The BL can be considered as a fixed-bed reactor in which the predominant reaction is the anaerobic decomposition of the biodegradable organic fraction of the solid waste. From the control point of view, the BL has two types of *inputs* based on the feasibility of manipulation: *controllable* and *uncontrollable*. The *controllable inputs* include the supplemental additives such as recirculated leachate, inocula, buffer, and nutrients. The *uncontrollable inputs* include climate-related conditions (such as precipitation and temperature), site-specific settings (such as collection and injection systems), and waste characteristics (such as waste composition). On the other hand, the *outputs* of the BL are mainly the leachate and the landfill gas (LFG), both of which vary significantly in quantity and quality depending on the operational phase of the BL.

Development of a control system conventionally requires an accurate model of the controlled process. Considerable efforts were made towards developing good models of the complex processes taking place within the landfill ecosystem (El-Fadel *et al.*, 1989; Findikakis *et al.*, 1988; Gurijala *et al.*, 1997; Lay *et al.*, 1998; White *et al.*, 2004). However, most of the models developed so far are very complicated and require extensive data inputs, being practically inapplicable to implement in a control system for BL field applications. Furthermore, the heterogeneity of MSW adds to the difficulty of assessing the individual and coupled effects of various system parameters. In attempt to solve these limitations, soft computational methods, particularly fuzzy logic (FL), were used to develop better models of some parameters of the system such as biogas generation (Garg *et al.*, 2006; Abdallah *et al.*, 2009) and leachate quality (Rendra *et al.*, 2007). The FL models were successful in catching the pertinent features of the modeled processes provided that sufficient knowledge is available to describe the behaviour of the system properly.

Fuzzy logic control (FLC), which uses linguistic rules capturing the know-how of the experienced human operators, proved to be robust and reliable solutions for dealing with complex and ill-defined processes, similar to those encountered in the operation of a BL. To date, there is no such application using FL in the control of BL or any other type of landfill projects. However, the relevant FLC applications in the field of solid waste management and wastewater treatment are encouraging. FL was successfully used to control municipal incinerators (Chen *et al.*, 2002; Shen *et al.*, 2005), as well as anaerobic digesters (Estaben *et al.*, 1997).

1.4. Hypotheses

1) Based on the success of FL in modeling key BL parameters and controlling analogous biological systems, it is hypothesized that incorporating FL in a BL control system would accommodate the uncertainties and complexities of the interconnected nonlinear multi-parameter BL processes;

2) The performance of BLs would be improved if the conventional open-loop control scheme is replaced by a closed-loop scheme that employs process feedback and measurements to adjust the control actions;

3) Applying automated monitoring and intelligent control techniques in the management of BLs would be advantageous since the control actions are based on the site-specific conditions and real-time measurements of the controlled system;

4) Leachate manipulation techniques, such as buffering, bioaugmentation, supplemental water addition, nutrient addition and heating, are potential control tools that adjust the characteristics of the leachate so as to provide the BL microbial consortia with their growth

requirements, correct certain process deviations, reduce impact of detrimental substances, and/or enrich concentration of beneficial compounds.

1.5. Objectives

The objectives of this research work are shown in Figure 1-2, and include the following:

1) <u>Design a new control framework for the management of BL:</u>

   The main target is to optimize the BL performance by incorporating automated monitoring and intelligent control techniques.

2) <u>Develop a knowledge-based control program for the operation of BLs:</u>

   The program is to manage the leachate recirculation and manipulation techniques in order to provide optimum conditions for waste biodegradation, and thus biogas generation.

3) <u>Develop computational models to solve the complex BL processes in the control program:</u>

   FL is to be utilized in the control program to simplify situations where nonlinearity of the BL processes as well as waste heterogeneity would hinder conventional methods from dealing with the system effectively.

4) <u>Evaluate the new control system through a pilot-scale application:</u>

   This includes studying potential improvements of the control system, assessing the effect of supplements' addition on the BL performance, and investigating the feasibility of leachate heating as a control strategy for internal temperatures of BLs.

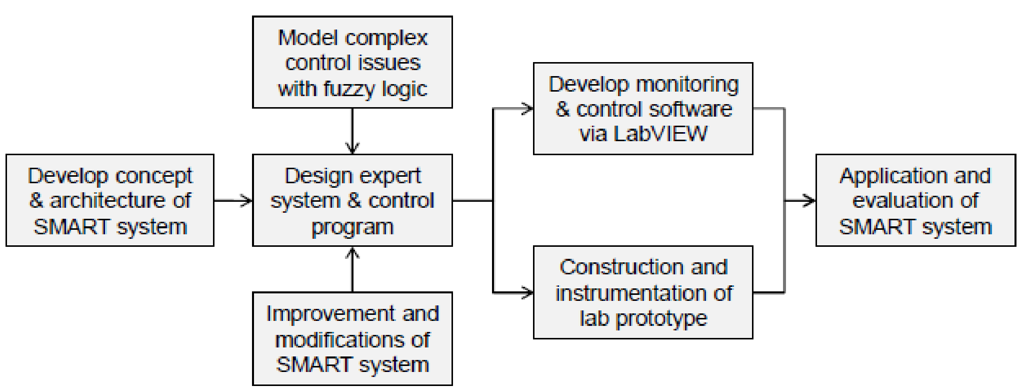

Figure 1-2 Demonstration of objective tasks

1.6. Thesis Organization

The thesis is organized as a combination of paper-based and traditional formats. Each chapter is based on one or more papers supplemented with unpublished work and additional bridging sections in order to connect the manuscripts to each other and to the thesis body. The present research work generated ***four*** (published/submitted) journal papers, and ***five*** conference papers; ***four*** of which are published in conference proceedings. The thesis organization is as follows:

Chapter 1: Introduction

Chapter 2: Literature Review

This chapter covers the fundamentals of BLs and leachate management techniques, and reviews advanced process control and computational modeling techniques.

Chapter 3: Development of Sensor-based Monitoring and Remote-control Technology (SMART) for Bioreactor Landfills

This chapter presents the conceptual framework and main components of the proposed control system. The chapter is based on a paper submitted to the Journal of Environmental Management as the first in a series of publications (Abdallah *et al.,* 2011c). An overview of the SMART system was published in the proceedings of the IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, Ottawa (Abdallah *et al.*, 2011e).

Chapter 4: SMART Control Program & Operational Guidelines

The control program and expert system of SMART are discussed in this chapter, which includes a paper submitted to the Journal of Environmental Management (Abdallah *et al.,* 2011a) as the second in a series of publications. The chapter elucidates the sequence and mathematical calculations involved in the control program.

Chapter 5: Implementation of Fuzzy Logic Control in SMART

The main theme of this chapter is the implementation of FL in solving complex operational issues in the control program of SMART. This chapter combines the work of multiple journal articles and conference papers discussing the three FLCs incorporated in SMART.

The first FLC was developed to compute the operational phase of the BL, while the second FLC was focused on the evaluation of the toxicological status of the leachate. These two FLCs were part of a paper submitted to the Journal of Environmental Management (Abdallah *et al.*, 2011a) as well as a separate paper published in the proceedings of the IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, Ottawa (Abdallah *et al.*, 2011d). In the third FLC of SMART, the estimated methane production from a BL was simulated by a FL model as well as a hybrid FL-Neural Networks model. The results of the FL and hybrid models were published in the Journal of Environmental Engineering and Science (Abdallah *et al.,* 2009), and in the proceedings of the International Conference of Modeling and Simulation in Quebec (Abdallah *et al.,* 2008), respectively.

Chapter 6: Application, Assessment, and Improvement of SMART

This chapter discusses the application and evaluation of SMART in a pilot prototype, as well as the assessment of the feasibility of temperature control in BLs. The chapter merges a paper that will be submitted to the Journal of Environmental Management as the third and last in a series of publications, as well as another paper submitted to the Journal of Waste Management & Research (Abdallah *et al.,* 2011b).

Chapter 7: Conclusions and Recommendations

This chapter summarizes the conclusions that were drawn in chapters 3, 4, 5, and 6. The recommended future work is then presented, highlighting the research topics that need further exploration and development.

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CHAPTER 2

LITERATURE REVIEW

2.1. Overview

The main target of the present study is to develop, construct and evaluate a feasible control system to better operate and control the ecological environment within bioreactor landfills (BLs). The proposed monitoring and control system as well as the subsequent modifications to various control strategies are aimed at improving the management and operational practices of the BL system. Therefore, this literature review is intended to provide sufficient background coverage and interconnection of two main topics; (1) required knowledge pertaining to the BL technology including operational stages, factors affecting BL performance, and potential control techniques, and (2) unconventional modeling and control methods applicable to the complex processes similar to the BL, particularly fuzzy logic (FL).

2.2. Bioreactor Landfill Ecosystem

Modeling and/or control of BLs requires a good understanding of the system and its data flow including inputs, outputs, and interconnecting processes. Basic principles and mechanisms of the BL are well documented in the literature (Pohland and Al-Yousfi, 1994; El-Fadel *et al.*, 1997; Hilger and Barlaz, 2002; Warith *et al.*, 2005).

2.2.1. Waste Decomposition in Landfills

The BL can be considered as a multiphase fixed-bed reactor in which the solid waste matrix represents the substrate as well as the packing media. The predominant reaction inside the BL is the anaerobic decomposition of the biodegradable organic fraction of the solid waste. All MSW landfills, including the bioreactor type, undergo the same typical stages of waste stabilization but BL accelerates the stabilization phases (Kim and Pohland, 2003; Pohland and Al-Yousfi, 1994; Reinhart and Townsend, 1998). Since landfills receive refuse continually over several years, these progressive stages occur simultaneously in different neighbouring locales. The temporal and spatial dimensions of each phase depends on many factors such as waste characteristics, landfill design, operational strategy, environmental conditions, and are characterized by temporal changes in various chemical and biochemical indicator parameters. Figure 2-1 shows the main features of the five main waste decomposition phases in terms of biogas quantity and composition as well as biochemical leachate parameters. The key characteristics of these stabilization phases are as follows:

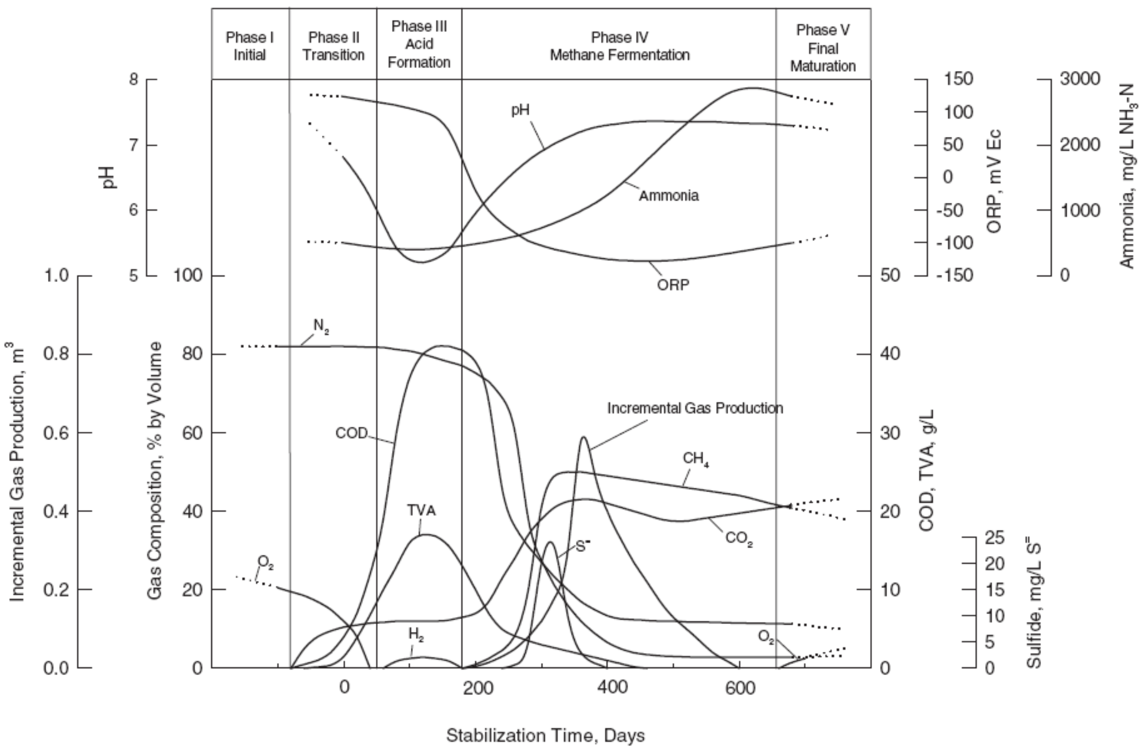

Figure 2-1 Phases of waste decomposition in bioreactor landfills (adapted from Kim and Pohland, 2003)

Phase I (Initial Adjustment)

As moisture becomes available and the microbial population density increases, biochemical decomposition under aerobic conditions is started. Lasting a few weeks or less, this stage involves the consumption of residual oxygen (O_2) present in waste at the time of placement with production of nearly equal molar quantities of carbon dioxide (CO_2) in addition to water as a by-product.

Phase II (Transition)

This stage is a transition from aerobic to anaerobic conditions. During this phase, the primary electron acceptors become nitrates and sulphates. As O_2 is depleting, anaerobic and facultative microorganisms predominate. Within this stage, CO_2 production increases and production of volatile organic acids (VOAs) and hydrogen (H_2) begins.

Phase III (Acid Formation)

In this phase, the concentration of volatile fatty acids (VFAs) in leachate increases because of the hydrolysis and acidification of the biodegradable fraction of waste, thus pH decreases from about 7.5 to 5.6 (Pohland *et al.*, 1993). The acidic fermentation intermediates, such as VFAs, result in high COD concentrations and long-chain VOAs are converted to acetic acid, CO_2, and H_2. The accumulation of H_2 is usually minimal by the end of this phase as hydrogenotrophic methanogens begin scavenging H_2 for reduction of CO_2 to methane. In this stage, the majority of organic carbon in the waste that gets converted ends up in the leachate.

Phase IV (Methane Fermentation)

Intermediary products appearing during acid formation phase (mainly acetic, propionic, and butyric acids) are converted to CH_4, H_2 and CO_2 by acetogens and methanogens. The accumulation of H_2 remains low as the hydrogenotrophic methanogens continue to scavenge H_2 for reduction of CO_2 to methane. As a result, pH increases to neutrality, the organic strength and biodegradability of the leachate decreases dramatically, and the landfill gas (LFG) production increases. This phase, together with the acid formation phase, account for the majority of waste stabilization being achieved.

Phase V (Final Maturation)

The final stage of MSW decomposition is characterized by a lower rate of biological activity due to the limiting concentrations of nutrients such as phosphorus. During this stage, CH_4 production is almost negligible. O_2 and oxidized species may slowly reappear as air permeates from the atmosphere with a corresponding increase in oxidation-reduction potential (ORP) in the leachate.

2.3. Process Enhancements of Bioreactor Landfills

The consortium of microorganisms involved in the stabilization of waste has specific environmental requirements for pH, temperature, and micro- and macro-nutrients. These parameters, among others, affect the performance and operation of landfills. Generally, the factors affecting the landfill ecosystem can be grouped to: (1) factors pertaining to the microbial environment (moisture, temperature, nutrients availability, pH, alkalinity, and toxicity), and (2) factors related to climate conditions (air temperature, precipitation), waste matrix characteristics (size, composition), as well as site operation and configuration (waste placement, compaction, liner, cover, collection and distribution systems). The BL concept is based on adapting specific management activities and operational modifications to control the influencing factors in a positive manner. The most important aspect for effective operation is liquid addition for moisture control and management. Other strategies, including pH adjustment, nutrients addition, inoculation, waste shredding, waste pre-disposal and post-disposal conditioning, and temperature management, can be integrated with liquid addition in order to optimize the BL process. The management techniques that control the first group of factors, mentioned above, are discussed in details.

2.3.1. Moisture Management

Moisture addition has been proved repeatedly to stimulate the methanogenic population; however some researchers attribute this improvement to the movement of moisture through waste as much as the water addition (Reinhart *et al.*, 2002). Moisture movement through waste can increase the methane production rate from 25 to 50%, compared to static moisture application at the same moisture levels (Klink and Ham, 1982). Leachate recirculation is considered the most effective method to increase moisture content in a controlled fashion. Pohland *et al.* (1993) suggested that leachate recirculation could reduce the time required for landfill stabilization from several decades to two to three years by maintaining optimum moisture content in the waste. Additionally, leachate recirculation has several potential advantages, beyond acceleration of waste decomposition, including; pH buffering, improving distribution of nutrients and inoculum in the waste matrix, serving as a reactant in hydrolysis reactions, dissolving metabolites, diluting inhibitory compounds, and providing onsite leachate treatment.

Leachate recirculation has been proven to achieve better BL performance in terms of biogas production by several lab-, pilot-, and full-scale studies (Reinhart, 1996; Reinhart and Al-Yousfi, 1996; Townsend *et al.*, 1996; Pohland and Kim, 1999; San and Onay, 2001; Mehta *et al.*, 2002; Bilgili *et al.*, 2007; Filipkowska, 2008; Benbelkacem *et al.,* 2010). A comprehensive demonstration of the most recent published laboratory studies pertaining to leachate recirculation is presented in Appendix A. In full-scale applications, leachate recirculation at the Trail Road MSW landfill site (Ottawa, Canada) enhanced waste settlement and resulted in 30% airspace recovery, which was used for landfilling more waste (Warith *et al.*, 2001). In another full-scale study by Morris *et al.* (2003), leachate recirculation achieved more rapid LFG production, increased settlement rates, and resulted in accelerated decreases in the concentration of certain contaminants in the leachate.

On the other hand, Lay *et al.* (1998) reported that leachate recycling alone could enhance the rate of methanogenesis, but not acetogenesis. According to Buivid *et al.* (1981), moisture increase alone does not enhance methane production. It is the nutrients, inocula and buffers, which in addition to moisture addition, enhances biodegradation to the greatest extent. He *et al.* (2005) showed that added alkalinity, dissolved oxygen level, and presence of methanogenic bacteria in the recirculated solution considerably influenced the hydrolysis rate and establishment of methanogenesis in the waste matrix. Therefore, it is suggested that, not only moisture addition, but also the quality of the leachate used affects the impact of the recirculation process, and therefore, the final outcome/results can change significantly. The quality of leachate is typically dependent on waste composition and operational phase (El-Fadel *et al.,* 1997). The large temporal variation in the biochemical characteristics of leachate, as produced, makes it sometimes unsuitable for recirculation. As a result, researchers examined the use of different leachates (mature leachate as opposed to young leachate) for recirculation. As shown in Table 2-1, the main characteristics of the leachate used are the high pH as well as the low organic load and acid concentrations.

Table 2-1 Characteristics of mature leachate used in previous studies

Parameter	pH	COD	VFA	TP	TN	ORP	Alkalinity
Units	-	mg/L	mg/L	mg/L	mg/L	mV	mg $CaCO_3$ /L
Erses and Onay (2003)	7.76	721	-	30	-	-234	4829
Jianguo *et al.* (2007)	7.37	13890	856	64	2499	-	-
Filipkowska (2008)	8.87	3915	-	21	442	-	-
Benbelkacem *et al.* (2010)	8.5	-	35	-	-	-	-

Alternatively, Erses and Onay (2003) used young and mature leachate interchangeably along the BL lifespan which was divided to four operational stages. They used young leachate in phase I, then mature leachate in phase II and when the characteristics of produced leachate became suitable, they switched back to young leachate in phases III and IV. The same concept was applied by Chugh *et al.* (1998) who rotated the recirculated leachate between fresh waste and stabilised waste reactors until a balanced microbial population was established. Other studies combined leachate with water, as simulated rainfall, which simulated field conditions and diluted the recirculated leachate (San and Onay, 2001; Sponza and Agdag, 2004). Sanphoti *et al.* (2006) demonstrated that addition of supplemental water to the recirculated leachate in early operational phases improves the BL performance in terms of cumulative methane production and reduction in required stabilization time. Supplemental water addition increases dilution of inhibitory substances and reduces leachate strength resulting in more favourable conditions for the sensitive methanogenic microorganisms.

2.3.2. pH Adjustment

Methanogenic bacteria are sensitive to pH, with an optimal range between 6.8 and 7.2, and could be inhibited by acidic conditions at pH less than 6.7. Therefore, pH of recycled leachate can have a significant effect on waste stabilization and methane production. This understanding of microbial ecology has promoted the addition of buffer to adjust the pH of leachate prior to recycling it back to a landfill. Buffering as a control option may be best used in response to changes in leachate characteristics (i.e., a drop in pH or increase in VOA concentration). Leachate recirculation with a buffering system to control the pH has been found to result in a shorter acidogenic stage leading to earlier initiation of the methanogenic stage, and concomitant higher gas production (He *et al.*, 2005; Sanphoti *et al.*, 2006; Reinhart and Townsend, 1998; Warith, 2002).

2.3.3. Bioaugmentation

Bioaugmentation or inoculating the landfill, usually through the addition of biosolids, such as anaerobic digester or septic tank sludge, has also been reported. The optimal inoculum should serve as a seed to increase the inventory of anaerobic microorganisms, as well as a source of nitrogen, phosphorous, and other nutrients. Buivid *et al.* (1981) noted the importance of the type of inoculum used; MSW mixed with anaerobically digested wastewater sludge produced three times more methane than a mixture of MSW and primary sludge. Increased methanogenesis was attributed to the greater population of the methanogenic consortia in the former combination. Rees (1980) reported similar results, and indicated that anaerobic digested sewage sludge from an active municipal digester is an excellent source of microbial inocula, whereas septic tank sludge which has a much longer sludge age and is cultivated under much lower organic loading conditions, resulted in inferior improvements in waste stabilization.

Lisk (1991) also demonstrated that methanogenesis could be initiated and promoted by varying the amounts of methanogenic microorganisms added from an anaerobic sewage digester. Cossu *et al.* (1987) examined moisture saturation conditions under three cases: with digested sewage sludge, with fertilizer, and without additives. Moisture addition with sewage sludge resulted in the shortest acidogenic phase and highest gas production.

It is worth mentioning that it has been suggested that any measured beneficial effects associated with the addition of biosolids may be due to buffering or moisture addition rather than inoculation. Stegmann and Spendlin (1987) indicated that generic conclusions regarding the effect of sludge addition cannot be drawn, since different types and percentages of sludge might have been used in different experiments. They performed experiments with mixtures of MSW and anaerobic digester sludge, and reported that sludge addition did not enhance methane production, and actually prolonged the acidogenic phase. Barlaz *et al.* (1990) found that anaerobic sludge addition with buffer stimulated methane production, while addition of sludge without buffer was not stimulatory because of the acid accumulation associated with it, resulting in pH drop and methanogenic bacterial inhibition.

2.3.4. Temperature Management

The rate of metabolism of anaerobic microorganisms involved in MSW decomposition is highly affected by temperature, but to different degrees with methanogens generally more sensitive to temperature than acidogens. Therefore, temperature is considered to affect MSW decomposition in two ways: acute short-term effects on reaction rates and chronic longer-term effects on the microbial population balance (Hartz *et al.,* 1982). Temperature effects on microbial growth bio-kinetics parameters, including reaction rate constants, can be described by the Arrhenius equation, which is by far the most commonly used empirical model for this relation. It can be written as,

$$k = A \times e^{-\left(\frac{E_a}{RT}\right)} \tag{2-1}$$

Where k is rate coefficient (d^{-1}), A is proportionality constant (d^{-1}), E_a is activation energy ($J \cdot mol^{-1}$), R is universal gas constant ($J \cdot {}^{\circ}K^{-1}.mol^{-1}$), and T is temperature (°K). The Arrhenius model was incorporated by El-Fadel *et al.* (1996) in their model to estimate methane generation rate from MSW landfills. Model simulations showed that temperature has a significant effect on the modeled system at early phases, but after methanogenesis was established, temperature impacts were minimal.

The biological reactions occurring during anaerobic digestion in MSW landfills are either endothermic (biosynthesis) or exothermic (decomposition). Since biosynthesis is typically much less than decomposition in the anaerobic landfill environments, exothermic reactions prevail, yet much of the heat released is absorbed as latent heat in the produced LFG (Pohland, 1968). Rees (1980) summarized the major contributors to the thermal regime of a typical MSW landfill as: heats of reaction and neutralization, solar radiation, anaerobic metabolism, specific heat of water/refuse mixtures, and heat losses to air and soil. Thus, the temperature attained by a landfill will be determined by the balance between the rates of heat production and addition (solar energy) from one side and the rate of heat loss to the surrounding soil and atmosphere from the other side.

The optimum temperature for methane production in mesophilic waste decomposition is in the range of 30 to 40ºC, whereas 55ºC is the optimum temperature for thermophilic waste decomposition (Barlaz *et al.*, 1990). However, there are upper and lower limits to the beneficial impact of temperature on waste decomposition. Significantly reduced gas generation rates are expected at temperatures below 20°C and above 75°C (Tchobanoglous *et al.,* 1993). Low temperatures in landfill inhibit methanogenesis, and results in lower conversion of organic acids to methane and carbon dioxide (Rees and Grainger, 1982). This effect is exacerbated by the differential change in metabolism rate with temperature of the acidogens (small) and methanogens (large), which can lead to accumulation of VFAs and potential souring of the landfill (Speece, 2008).

Internal temperatures in landfills are also highly affected by seasonal and operational conditions. Waste temperatures at shallow depths (up to 8 m depth) and near the landfill edges (within 20 m) conform to seasonal temperature variations, whereas elevated temperatures (23 to 57°C) can be reached at deep and central zones (Yesiller *et al.*, 2005). In a deep and well-insulated landfill, temperatures of 40°C could be achieved (Rees and Grainger, 1982). The operational aspects over a 30-month period for the Tucuman BL (in Argentina) demonstrated the ability to maintain the process in the mesophilic range (McBean *et al.*, 2007). These optimal conditions are unlikely to be achieved in cold climates. In a full scale BL studied by Zhao *et al.* (2008), sub-zero ˚C temperatures persisted within the lifts filled during winter for over the one year monitoring program, and the gas production was minimal during this period. These low temperatures resulted primarily from the cold weather placement of the refuse, the insulation effects of the landfill, and the recirculation of low temperature leachate. The researchers concluded that after increasing the moisture content in a BL, temperature becomes the most important factor controlling the biological decomposition processes.

Baldwin *et al.* (1998) investigated the effect of temperature on two full-scale landfills, one located in Florida (southern climate) and the other in Wisconsin (northern climate). The Florida landfill (30˚C) had a more rapid rate of decomposition and methane generation compared to the Wisconsin landfill (22˚C). Kasali and Senior (1989) found in bench-scale test that increasing the temperature of MSW with 60% moisture content from 18.7 to 30˚C caused a 2.6 fold increase in the methanogenic rate, while a 7.8 fold increase was achieved when the temperature rose from 18.7 to 40˚C. However, further temperature increase to 55°C was inhibitory, and caused a fermentation imbalance that led to accumulation of volatile fatty acids. It has also been demonstrated that by raising the temperature of waste from 22 to 33°C the gas production rate increased by 70% (Rees and Grainger, 1982). The positive effects of temperature on landfill processes motivated some research work to investigate potential temperature management and control techniques. Rees (1980) maintained temperatures of about 45°C in an anaerobic landfill by allowing water into the bottom and maintaining an insulating layer of refuse above the water table in the landfill. Rees and Grainger (1982) described a waste emplacement strategy by which mesophilic temperature could be attained. They suggested that, initial refuse layers should be placed at low density to promote aerobic catabolism and thus temperature increase that could stimulate the decomposition rates in the more compacted waste placed above. Temperature control via heating the recirculated leachate was explored in the Swedish SORAB test cells, known as Energy Loaves. Leachate was heated by the LFG-fuelled boilers, and was then used to raise the system temperature to 30 to 40˚C. Gas production was reported to be an order of magnitude higher than typically obtained without heat supplementation (Brundin, 1991).

2.3.5. Nutrients Addition

Nutrient requirements for waste degradation in landfills are generally met by the waste in-situ during early degradation phases; however some nutrients, such as phosphorous, may sometimes be limited at later stages (Reinhart and Townsend, 1998). In fact, all the necessary nutrients are typically available in most MSW landfills, but heterogeneity and insufficient mixing of the wastes may result in nutrient-limited environments (Rees, 1980). These limitations are likely circumvented in part by the application of leachate recirculation.

Some studies found that the addition of nitrogen and phosphorous stimulated methane production, rapidly decreased organic load of leachate, and shortened the initial phase before methane generation (Warith, 2002; Pohland, 1992). However, other studies found that nutrients addition had no significant effect on stabilization of the waste especially after reaching the methanogenic stage (Pohland, 1975; Tittlebaum, 1982).

2.4. Process Control of Bioreactor Landfills

The biological processes occurring in the landfill are largely anaerobic. Similar to anaerobic digesters, the landfill ecosystem is sensitive to environmental conditions such as pH, temperature, moisture content, toxic compounds, and the presence of oxygen. In fact, much of what is known or assumed concerning processes in landfills has primarily come from experiences with anaerobic digesters (El-Fadel *et al.*, 1997). For this reason, the required control for an anaerobic BL is analogous to that of an anaerobic digester, with the latter more easily to control being a well-mixed reactor (Reinhart and Townsend, 1998).

There are various control mechanisms that can be applied in managing chemical and environmental engineering systems. The most widespread control schemes are: feedback, feed-forward, and open-loop control. Feedback control is a control mechanism that uses information from measurements to manipulate a variable so that the desired result is achieved. Alternatively, feed-forward control mechanism predicts the effects of measured disturbances and takes corrective action to achieve the desired result. On the other hand, the open-loop controller does not utilize feedback to determine whether the input achieved the desired goal or not, and can neither engage in machine learning nor correct any errors that it could make. Thus far in landfill sites, process control is accomplished, if ever, based on a non-feedback scheme. Therefore, the present study aims at applying feedback control in the management of BLs.

2.5. Feedback Control Scheme

In feedback control, the variable being controlled is measured and compared with a target value. The difference between the measured and desired value is called the *error*. Feedback control manipulates inputs of the system to minimize this error. Figure 2-2 shows a generic component block diagram of an elementary feedback controller. The output of the system is measured by a *sensor* and the control element represents an actuator or control device. The error in this system would be the *Measured Output - Desired Output.*

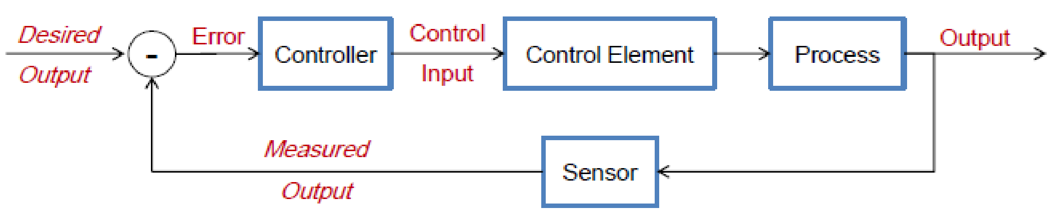

Figure 2-2 Block diagram of a basic feedback control loop

The potential advantages of feedback control lie in the fact that it obtains and utilizes data at the process output (Kim *et al*., 1997). Therefore, the controller takes into account unforeseen disturbances in the process. Feedback control architecture ensures the desired performance by altering the inputs immediately once deviations are observed regardless of their reason. Thus, it reduces operator workload by eliminating the need for human adjustment of the control variable. An additional advantage is that by analyzing the output of a system, unstable processes may be stabilized. Feedback controls do not require detailed knowledge of the system and, in particular, do not require a mathematical model of the process. The controller can be easily duplicated from one system to another.

On the other hand, the time lag in the system is potentially the main disadvantage of feedback control. A process deviation occurring near the beginning of the process will not be recognized until the process output. The feedback control will then have to adjust the process inputs in order to correct this deviation. This results in the possibility of substantial deviation throughout the entire process (Kim *et al*., 1997). The system could possibly miss process output disturbances and the error could continue without adjustment resulting in a steady state error. When the feedback controller proves unable to maintain stable closed-loop control, operator intervention is then required. Finally, feedback control does not take predictive control action towards the effects of known disturbances, and depends entirely on the accuracy with which the controlled output is measured.

2.6. Fuzzy Logic Control

No conventional controller has been successfully developed for the operation of a BL because it is practically impossible to satisfactorily identify its behaviour. In the field of wastewater treatment, the average trained operator can handle the operation of a reactor even without any fundamental understanding of the underlying principles. This shows that to control a complex system it is often enough to have qualitative knowledge about its behaviour. Complex industrial processes are often better controlled by an experienced human controller than by conventional automatic control. This property is successfully used in fuzzy logic control (FLC), where instead of exact equations, fuzzy rules are used. FLC has a less ambitious approach than the traditional control in modeling the system; it simply strives to mimic the functioning of a human operator.

The basic structure of a FLC is illustrated in Figure 2-3. The typical components include: (1) *fuzzification unit*, (2) *data base*, (3) *rule base*, (4) *fuzzy inference engine*, and (5) *defuzzification unit*.

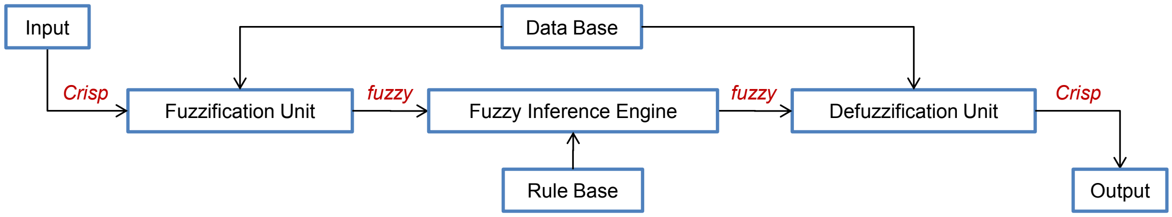

Figure 2-3 Typical structure of a fuzzy logic controller

First, the *fuzzification unit* acquires the measured input variables, and performs two processes: (a) map each crisp (numerical) input value into its corresponding universe of discourse (range), and (b) convert the mapped value into linguistic terms so as to make it compatible with the fuzzy sets representation. This crisp/fuzzy conversion is achieved through *membership functions* (MFs) which are defined for each system variable. MFs are represented by a real number ranging between 0 and 1 in order to describe the partial truth of the value of input variable in a given fuzzy set. The *Data Base*, shown in Figure 2-3, contains all the MFs defined for each input or output system variable.

Next, the *fuzzy inference engine* acquires the input fuzzy values and generates the output fuzzy values. This process uses the *Rule Base* which consists of a number of fuzzy rules that define the behaviour of the modeled system and replace conventional mechanistic mathematical modeling of the system. The rules are stated as IF-THEN statements that describe the expected fuzzy output corresponding to various fuzzy inputs. These rules may include several variables both in the condition (IF part) and the conclusion (THEN part) of the rules; thereby FL is applicable to both single-input-single-output (SISO) and multi-input-multi-output (MIMO) problems. The *fuzzy inference engine* processes the fuzzy inputs based on their relevant fuzzy rules, and determines the fuzzy output.

The *defuzzification unit* then acts as part of the last stage of fuzzy inference. Typically, it incorporates a number of fuzzy sets in a calculation that gives a single numeric value for each output. A fuzzy controller can use one of several mathematical methods to perform the defuzzification, including: *center of gravity*, *center of sums*, *center of maximum*, or *mean of maximum*.

2.7. Applications of FLC in Environmental Engineering

In recent years, intelligent control of large-scale industrial processes has brought about a revolution in the field of advanced control (Manesis *et al.,* 1998). Knowledge-based techniques, such as FL, have been proved to be robust and reliable. Because there is no such application in the BL projects, the following section will be focused on relevant processes in the solid waste management and wastewater treatment sectors. Interpretations can be made from such processes as much of what is known or assumed concerning processes in landfills has primarily come from experience with these applications (El-Fadel *et al.,* 1997). FLC was applied successfully in municipal incinerators (Chen *et al.*, 2002; Shen *et al.*, 2005), anaerobic digesters (Estaben *et al.*, 1997), anaerobic treatment reactors (Garcia *et al.*, 2007; Puñal *et al.*, 2003), and aerobic treatment reactors (Bae *et al.,* 2006; Ciappelloni *et al.,* 2006). The followings are some examples of FL controlled systems:

Shen *et al.* (2005) designed an adaptive FL control strategy to stabilize the combustion temperature in incinerators. The results indicated that incorporating adaptive parameters in the control strategy was a good method to achieve the target incineration temperature. In another study by Estaben *et al.* (1997), a FLC was developed to control an anaerobic digester based on pH and flow rate measurements. The control algorithm operated the digester effectively around a setpoint that was selected to ensure an optimum COD reduction efficiency was maintained.

Garcia *et al.* (2007) developed a FL-based system for diagnosis and control of a hybrid anaerobic reactor. The selected control variables were methane production, hydrogen gas concentration, and intermediate alkalinity/total alkalinity ratio. The control system was designed to compute the feed flow rate for adjusting the organic load applied to the reactor. The system correctly diagnosed different situations, and demonstrated high reliability in supplying adequate control actions to achieve the desired setpoint as well as to manage sudden changes in influent COD load. Also, Puñal *et al.* (2003) developed a FL-based control law for an anaerobic wastewater treatment process. The controlled variable was the VFA concentration in a fixed bed upflow reactor and the manipulated variable was the input flow rate. The derivative of the controlled variable was used as a second input of the system in order to increase or decrease the speed of the control action. The FL control law proved to be reliable in making adequate control actions to achieve the desired setpoint, and also, in managing disturbances in COD influent concentrations.

Scherer *et al.* (2008) developed a FLC system for the operation of biogas reactors running on energy crops. Three measured parameters were set to be the model input variables: pH, methane content, and specific gas production rate. The objective was to avoid the need for pH stabilization by the addition of buffering supplements, like lime or manure. The developed FL system achieved a successful start-up process and recovery strategy after reactor failure. In another study that compared FLC with the classical proportional-integral-derivative (PID) approach, Traore *et al.* (2005) examined the control of dissolved oxygen in a sequential batch reactor. They reported that adjusting the PID parameter was very difficult due to the non-linearity of the process. On the other hand, FLC was able to control the reactor, and improved the performance significantly.

2.8. Summary

It is clear that there is a lack of knowledge and practice in the process control of BLs as well as in the implementation of unconventional control techniques for their management. However, based on the literature reviewed, it is evident that BL's process control can be achievable by employing the BL control techniques as adjustable control tools to manipulate the system. It is also suggested that the BL process can be optimized if a feedback control scheme is adapted, and that FL can be a potential effective technique for modeling and controlling the complex, nonlinear processes in the BLs as well as accounting for waste heterogeneity. The following chapters present research work that targets the development and application of these prospective ideas.

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CHAPTER 3

DEVELOPMENT OF SENSOR-BASED MONITORING AND REMOTE-CONTROL TECHNOLOGY (SMART) FOR BIOREACTOR LANDFILLS

This chapter is based on the following publications:

1. *Abdallah, M., Warith, M., Petriu, E., Kennedy, K., Narbaitz, R. (2011)* ***Sensor-based Monitoring and Remote-control Technology (SMART) for bioreactor landfills: I) conceptual framework****. Submitted to the Journal of Environmental Management.*

2. *Abdallah, M., Petriu, E., Kennedy, K., Narbaitz, R., Warith, M. (2011)* ***Intelligent control of bioreactor landfills.*** *Proceedings of the IEEE International Conference on Computational Intelligence for Measurement Systems and Applications, Ottawa, ON.*

3.1. Abstract

One of the most critical issues in the operation of bioreactor landfills is process control. In field applications, unsupervised management of bioreactor processes leads to serious consequences on the system performance. The present research work introduces an innovative approach that uses automated monitoring and expert control to operate bioreactor landfills in an efficient manner. The proposed Sensor-based Monitoring and Remote-control Technology (SMART) replaces the conventional open loop control with an intelligent feedback control scheme (see Figure 3-1). SMART features a knowledge-based expert system that cooperates with the human operator in making decisions and controlling complex situations. This technology aims to provide optimum conditions for the biodegradation of municipal solid waste, and also, to improve the bioreactor efficiency in terms of enhanced biogas production and more rapid space recovery. This chapter discusses the conceptual framework of SMART system including its structure, main components, and instrumentation.

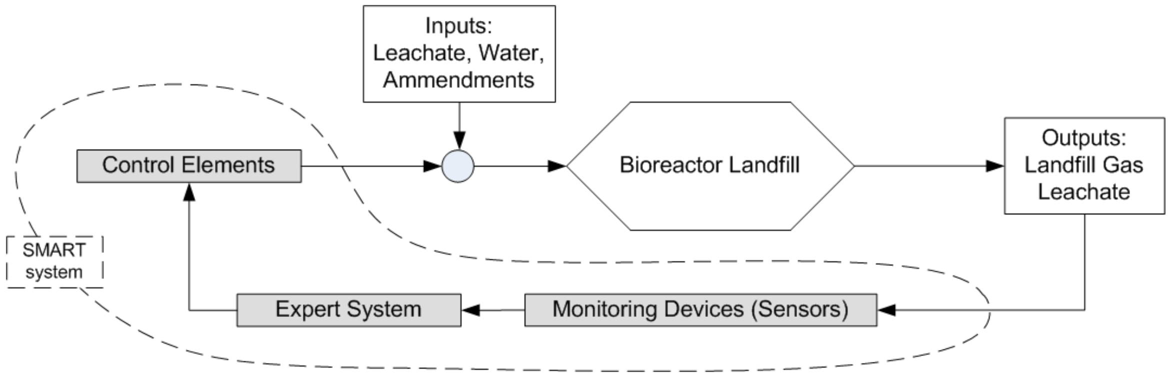

Figure 3-1 Schematic for the proposed control framework

3.2. Introduction

Despite recent increases in recycling, composting, and incineration, sanitary landfills remain the predominant and most economical municipal solid waste (MSW) management alternative. Modern MSW landfills strive to optimize the design, construction, and operation processes in order to mitigate many of the potentially negative impacts, and improve the profitability. The bioreactor landfill (BL) is considered one of the promising developments that have recently gained significant attention. This waste-to-energy technology requires specific management activities and operational procedures that enhance the microbial decomposition processes inside the landfill resulting in higher production of landfill gas (Warith, 2002).

The potential benefits of the BL technology have been demonstrated in laboratory studies since the 1970s (Pohland, 1975). The advantages include increased waste settlement rates and airspace utilization, decreased costs for leachate treatment, more rapid gas production (which improves the economics of gas recovery), and more rapid waste stabilization (which may reduce the post-closure maintenance period). These potential benefits have led to many full-scale BL applications in the last decade, mostly in the United States, resulting in the generation of design and operation data. In 2004, the Solid Waste Association of North America conducted an inventory that identified over 70 BLs in North America (SWANA, 2004). Many of these experiences have revealed scale-up issues and technical limitations that merit further research and development (Reinhart *et al.*, 2002; Warith *et al.*, 2001; Zhao *et al.*, 2008). One of the main operational issues, which are particularly addressed in the present work, is the large variation in the biochemical characteristics of the produced leachate, which makes the fresh leachate an unstable solution for the recirculation process. At the same time, the physical, chemical, and biochemical growth requirements of the population consortia inside the BL change significantly during the different operational phases. It is therefore necessary to manipulate the collected leachate before recirculation in order to suit the prevailing reactions and conditions inside the BL. Several techniques have been tested in laboratory studies to enhance the performance of BLs either directly or indirectly through the manipulation of the recirculated leachate: pH adjustment, nutrients addition, biosolids addition, and temperature management (Cossu *et al.*, 1987; Brundin, 1991; Reinhart and Townsend, 1998; Warith, 2002; He *et al.*, 2005). However, these techniques are rarely applied in field applications due to lack of well-defined methodologies and operational guidelines. Applying advanced process control techniques offers an alternative solution for this problem. Developing a control system that optimizes the leachate recirculation and manipulation processes can provide a flexible engineered solution to be applied in any typical system based on the real-time conditions of the controlled system.

In recent years, intelligent control of large-scale industrial processes has brought about a revolution in the field of advanced process control (Manesis *et al.*, 1998). Knowledge-based techniques, such as fuzzy logic (FL) which uses linguistic control rules capturing the know-how of the experienced human operators, proved to be robust and reliable solutions for dealing with complex and ill-defined processes, such as those encountered in the operation of a BL. In fact, no conventional controller could efficiently operate such a complex process because it is practically impossible to predict its behaviour. In the field of environmental engineering, FL has been used successfully to control various biological treatment systems (discussed in chapter 2). Recently, FL was used to model key parameters of the landfill ecosystem such as biogas generation (Garg *et al.*, 2006; Abdallah *et al.*, 2009) and leachate quality (Rendra *et al.*, 2007). The FL models were successful in catching the pertinent features of the modeled processes provided that sufficient knowledge is available to describe the system behaviour.

Inspired by the success of FL in modeling landfill parameters as well as controlling analogous biological systems, the present work introduces a new approach for the operation of BLs via an expert system that employs FL in its decision making process. The proposed system is named the Sensor-based Monitoring and Remote-control Technology (SMART).

The SMART system features an intelligent controller that manipulates the controllable variables of the bioreactor process based on online monitoring of key system parameters. The objective of this technology is to provide the optimal operational conditions for the biodegradation of the MSW, and also, to enhance the performance of the BL in terms of biogas production. In this chapter, a comprehensive analysis of the process control of bioreactor landfills is presented, followed by the conceptual framework for SMART, including system structure, main components, and instrumentation.

3.3. Process Analysis

3.3.1. Bioreactor Landfill Ecosystem

The concept of the BL is based on the application of specific design, construction, and operation practices in order to achieve the biodegradation of the readily and moderately decomposable organic waste constituents within 5 to 10 years (Warith, 2002). Controlling the BL requires a good understanding of the system and its dataflow including inputs, outputs, and interconnecting processes. The basic principles and mechanisms of the BL are well documented in the literature (Pohland and Al-Yousfi, 1994; El-Fadel *et al.*, 1997; Hilger and Barlaz, 2002). A simplified dataflow diagram for an anaerobic BL is shown in Figure 3-2. The BL can be considered as a fixed-bed reactor in which the solid waste matrix represents the substrate as well as the packing media. The predominant reaction inside the BL is the anaerobic decomposition of the biodegradable organic fraction of the solid waste. From the control point of view, the BL system has two types of inputs based on the feasibility of manipulation: *controllable* and *uncontrollable*. The controllable inputs include the quantity and quality of supplemental additives, such as the recirculated leachate, inocula, buffer, and nutrients. The uncontrollable ones include climate-related conditions (such as temperature and precipitation), site-specific settings (such as the collection and injection systems), and waste characteristics (such as particle size and waste composition). On the other hand, the outputs of the BL are mainly the leachate and the landfill gas (LFG). These outputs vary significantly in quantity and quality depending on the operational phase of the landfill.

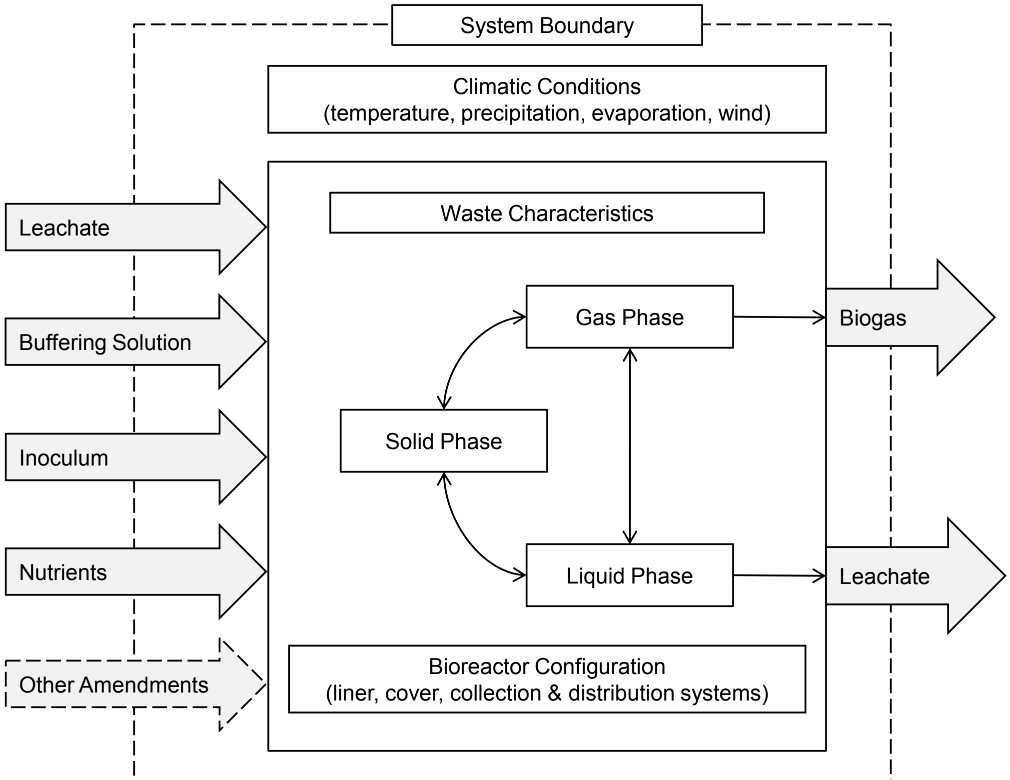

Figure 3-2 Data flow diagram of the bioreactor landfill ecosystem

The reactions within the BL ecosystem involve a consortium of microorganisms that require specific environmental conditions such as moisture, temperature, pH, and nutrients, among others. The BL concept is based on optimizing these conditions via specific management activities and operational modifications. Strategies, such as liquid addition, pH adjustment, nutrients addition, bioaugmentation, waste shredding, waste pre-treatment, and temperature management, are used to enhance the performance of the BL. The techniques employed as control tools in the SMART system are discussed in chapter 2.

3.4. Control Strategy

In an anaerobic BL, the main control tool is clearly the leachate recirculation which provides optimal moisture content and even distribution of the additives. In order to achieve the benefits of leachate recirculation, leachate has to be recycled at optimal rates to achieve sufficient contact with waste. Jianguo *et al.* (2007) suggests that leachate recirculation rate should be adjusted according to the phases of waste stabilization. Moreover, the quality of the produced leachate poses a potential problem since its characteristics vary significantly with the age of the BL; for example, the concentrations of dissolved organic substances in fresh leachate are much higher than in older leachate. Also, the specific growth requirements of the landfill bacterial consortia changes with time. As a result, leachate may not always be favoured to be reintroduced to the landfill ecosystem in its original form. Leachate should therefore be manipulated before recirculation in order to suit the prevailing reactions and conditions inside the BL. In the proposed control strategy, adjusting the characteristics and rate of the recirculated leachate according to the requirements of each operational phase is hypothesised to provide the optimum conditions for waste biodegradation in BLs. The biochemical, chemical, and physical characteristics of the recirculated leachate can be adjusted using the control techniques previously mentioned; buffering, bioaugmentation, nutrient addition, supplemental water addition, and heating.

The pH of the recirculated leachate can be adjusted by adding buffer solutions. Inoculum, namely anaerobic digested sludge, can also be used as a basic buffer and a rich source of methanogenic bacteria. At later phases of operation, nutrients can be added to provide the bacterial population with its nutritional needs. Supplemental water can be added to dilute highly concentrated leachate (as a remedy for toxicity) and to cover any shortage in available recyclable leachate. The rate of application of these amendments can be decided based on the measured parameters of leachate and the specific requirements of each operational phase in the BL. In the SMART control system, leachate heating is employed as a temperature control tool to overcome the negative effects of cold leachate recirculation.

In conjunction with the recirculation practices, certain parameters, such as the pore water pressure and landfill internal temperature, are to be monitored. These parameters are highly affected by the recirculated liquids, and at the same time, they can affect the BL operations significantly. Finally, performance indicators, like methane production and leachate pH, can be employed to evaluate the control actions taken by the control system, and also to detect operational problems. In this way, the system can incorporate a detection, diagnosis, and correction strategy in response to the process performance deviations and problems.

3.5. Sensor-based Monitoring and Remote-control Technology (SMART)

The design philosophy of SMART's expert system is inspired by the concept of man-computer symbiosis that was introduced by Licklider (1960). This concept can describe the relationship between BL operators and the expert system such that: (1) the computer facilitates the solution of formulated problems for the operator, and (2) the operator cooperate with the expert system in making decisions and managing complex situations. In SMART, conventional open-loop control is replaced by a feedback control scheme which uses process measurements to determine whether the input achieved the desired goal or not, and then cannot correct any errors that could result.

3.5.1. Control Framework

The SMART system features software and hardware interacting components that provide automated monitoring and expert control of BLs. Figure 3-3 shows a general diagram of the SMART control system. The dashed lines indicate the sensory data, while the dot-dashed lines represent the commands.

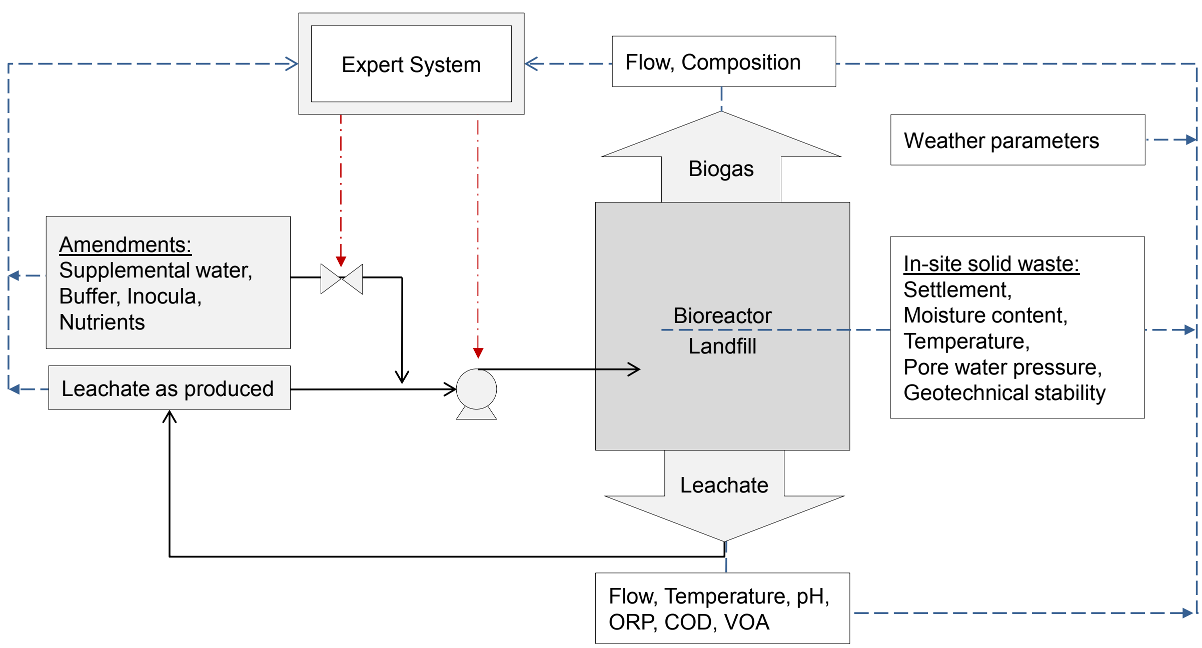

Figure 3-3 Schematic of the SMART control system

The control system has a geographically and functionally distributed architecture in which the BL is divided into basic blocks. Each block has its own local sensory data acquisition and control units. In addition, global sensory units are to provide measurements for the landfill body altogether as one block. All these local and global components are connected and remotely controlled by a global data processing and decision making unit. The controller continuously monitors two types of sensory data: process parameters (such as moisture and temperature), and returned feedback from performance indicators (such as biogas production and settlement). The decision made by the control algorithm is transmitted to the actuators, after authorization from the site operator, to inject the computed volumes of the selected amendments in order to manipulate the characteristics of the recirculated leachate. This batch control process runs continuously along the lifetime of the BL cell.

3.5.2. System Components

The SMART system incorporates six interacting components: (1) Local Sensory Unit, (2) Global Sensory Unit, (3) Primary Sensory Data Processor, (4) Main Controller Unit, (5) Primary Driving Controller, and (6) Local Driving Unit. The main components of the system are shown in Figure 3-4, and described in detail below.

3.5.2.1. Local Sensory Unit (LSU)

The LSU is placed in each block, i.e., n sensory units for the n blocks. Each unit includes a set of analog sensors which quantify the values of different system parameters, such as temperature, moisture content, pH, oxygen reduction potential (ORP), and pore water pressure, in the corresponding block. The installed units form a three dimensional grid in order to show the spatial dynamic status of the main parameters within the BL. All LSUs are designed to send the measured data to the Primary Sensory Data Processor.

3.5.2.2. Global Sensory Unit (GSU)

The GSU provides global measurements for the landfill body altogether as one block. These measurements include the parameters that are impractical to be determined for each block individually such as leachate characteristics, settlement, geotechnical stability, hydrostatic head on the liner, as well as biogas quantity and quality. Other examples of global measurements are the weather condition parameters such as air temperature, wind speed and direction, humidity, solar radiation, precipitation, and evaporation. All GSUs are connected to the Main Controller Unit through the Primary Sensory Data Processor.

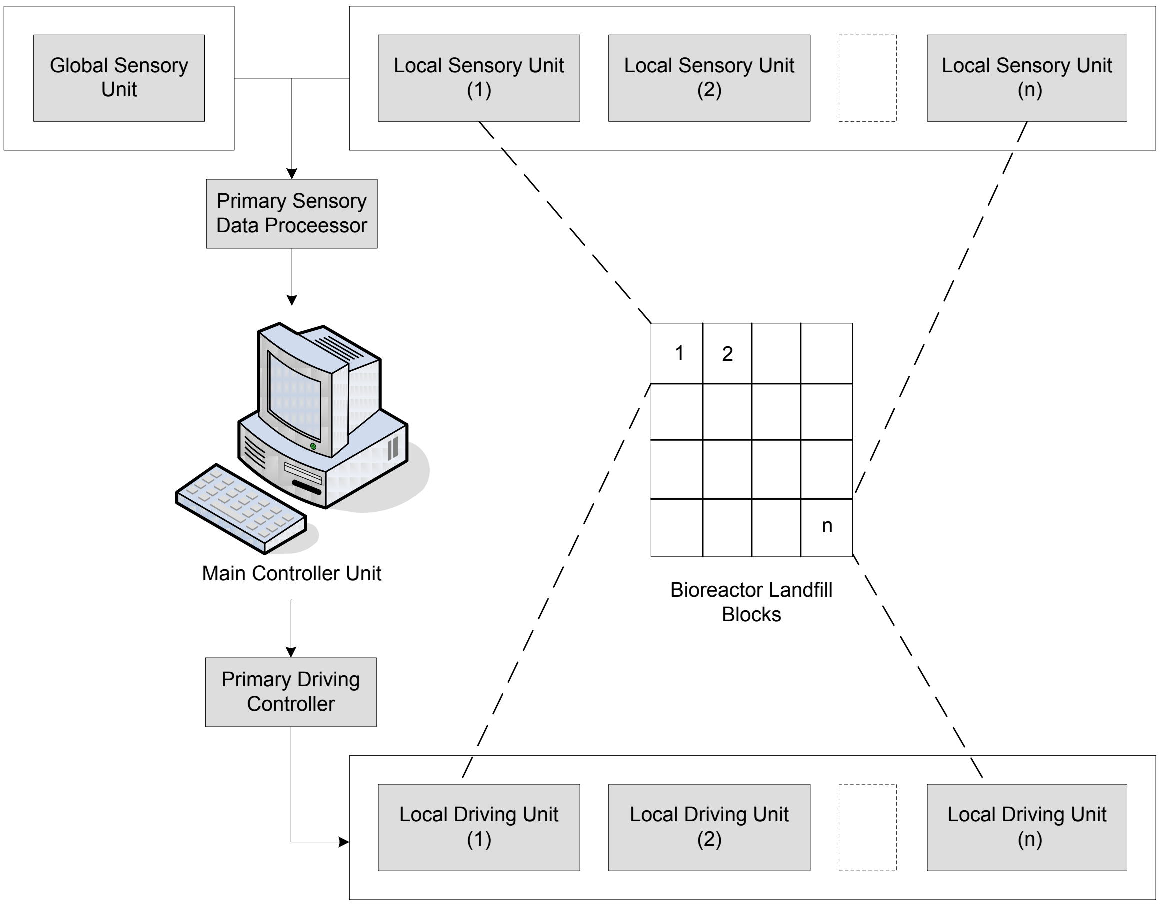

Figure 3-4 Main components of the SMART control system

3.5.2.3. Primary Sensory Data Processor (PSDP)

The PSDP is responsible for analyzing the acquired data from the Local and Global Sensory Units, and arranging them in a new frame to be delivered to the Main Controller Unit. In addition, this unit performs basic aggregate processing such as basic statistical measures (average, maximum, minimum) and error checks (standard deviation, variance). Although this work could be done by the Main Controller Unit, employing an intermediate device here provides more modularity and flexibility to the system by providing an interface between the software of the Main Controller Unit from one side, and the LSUs from the other side.

3.5.2.4. Main Controller Unit (MCU)

The MCU is considered the driving brain of the control system. It receives the measured data (inputs), processes them within the developed expert system, and makes the control decision. The operator is prompted with the decision made by the MCU in order to evaluate it, and then approves it to be sent to the Primary Driving Controller in the form of quantified commands. In certain operational situations, such as any unconsidered scenario in the expert system, the operator can overwrite the decision to deal with the unexpected problem. This unit features two interacting software components: the monitoring interface, and the controller. The monitoring and control parts are programmed using the LabVIEW™ graphical programming platform by National Instruments. The developed program offers a user friendly interface through which the different components of the system including the acquired measurements, delivered commands, and corresponding feedback of the system are displayed and analyzed. Furthermore, dynamic three dimensional graphical representations can be generated by graphics software, such as the Visualization Toolkit (VTK). Finally, for remote access purposes, the front panels of the control program are accessible on the internet via a common web browser. Only personnel with privileges can access and control the site using the LabVIEW™ Run-Time Engine installed on the computer. The control program and expert system of the MCU are discussed in detail in chapter 4.

3.5.2.5. Primary Driving Controller (PDC)

The PDC receives the commands from the MCU and distributes it to the different Local Driving Units. Basically, it is a device that de-multiplexes the received data set which holds the commands for all the driving units, and then delivers the commands to each unit separately. This unit combines analog/digital conversion, signal conditioning, and signal connectivity.

3.5.2.6. Local Driving Unit (LDU)

The LDU receives the commands and performs the required action by driving the corresponding actuator (motorized valves and/or pumps). Similar to the LSU, each of these units is responsible for controlling a single block, i.e., n driving units for the n blocks. Each actuator receives from the PDC the exact quantity required of the amendment it controls.

3.5.3. Knowledge Requirements

In order for the SMART expert system to make logical decisions, sufficient knowledge must be compiled to describe the behaviour of the BL. The knowledge, on which the SMART system relies, is based on fundamental theories and empirical data. The main information that had to be compiled: (1) parameters through which the start and end time of each bioreactor operational phase can be identified, (2) setpoints (i.e., target values) for the physical, chemical and biochemical characteristics of the recirculated leachate during different bioreactor operational phases, (3) optimum addition rates of recirculated leachate and other amendments throughout BL lifetime, and (4) optimal trends of the performance indicators (i.e., biogas quantity, methane content) during the different operational phases of the BL. This information is used to create the knowledge-base rules for the FL control program of SMART discussed in chapters 4 and 5.

3.5.4. Instrumentation

In order to build the on-line monitoring and real-time control system, all sensors and control elements must be adaptable to automatic operation. Also, because of the aggressive environment of landfills, instruments have to be durable, chemical and corrosion resistant, automatable, and robust (especially against overburden pressure). The instrumentation requirements for a generic block in the SMART system are shown in Figure 3-5. The basic set of sensors collects data for in-place waste, leachate, and LFG. In this instrumentation system, measurements are acquired by analog sensors that are controlled remotely by the PSDP, whereas the final control elements are controlled by the PDC. The PSDP/PDC unit transmits/receives the input/output signals via standard communication protocols (such as RS-232 or RS-485) to/from the main monitoring and control unit.

In-place waste is monitored by the Local Sensory Units (LSUs) which are evenly distributed in the BL body forming a three-dimensional grid. Each unit is designed to measure moisture content, temperature, and pressure. Different moisture content sensors have been examined in the field (Gawande *et al.*, 2003; Hettiaratchi *et al.*, 2007; Zhao *et al.*, 2008). Of those technologies, electrical resistivity and capacitance/frequency domain technology were found suitable for landfill conditions, and compatible with automated monitoring systems. Time domain reflectometry (TDR) sensors can also be used, but they require specialized data loggers compared to standard data loggers used by the other two technologies. A comprehensive review of landfill moisture sensors can be found in Imhoff *et al.* (2007). Temperature measurements can be obtained using thermocouples or thermistors. Many commercial moisture and pressure sensors have built in thermistors. However, thermocouples are still the preferred stand-alone temperature monitoring devices because they are less expensive and the higher accuracy of thermistors is not needed in landfill applications. Thermocouples of types T (-250 to 350°C) or K (-200 to +1350°C) or J (-40 to +750°C) are widely used in landfill applications. Pore water pressure is measured using vibrating wire or solid state piezometers.

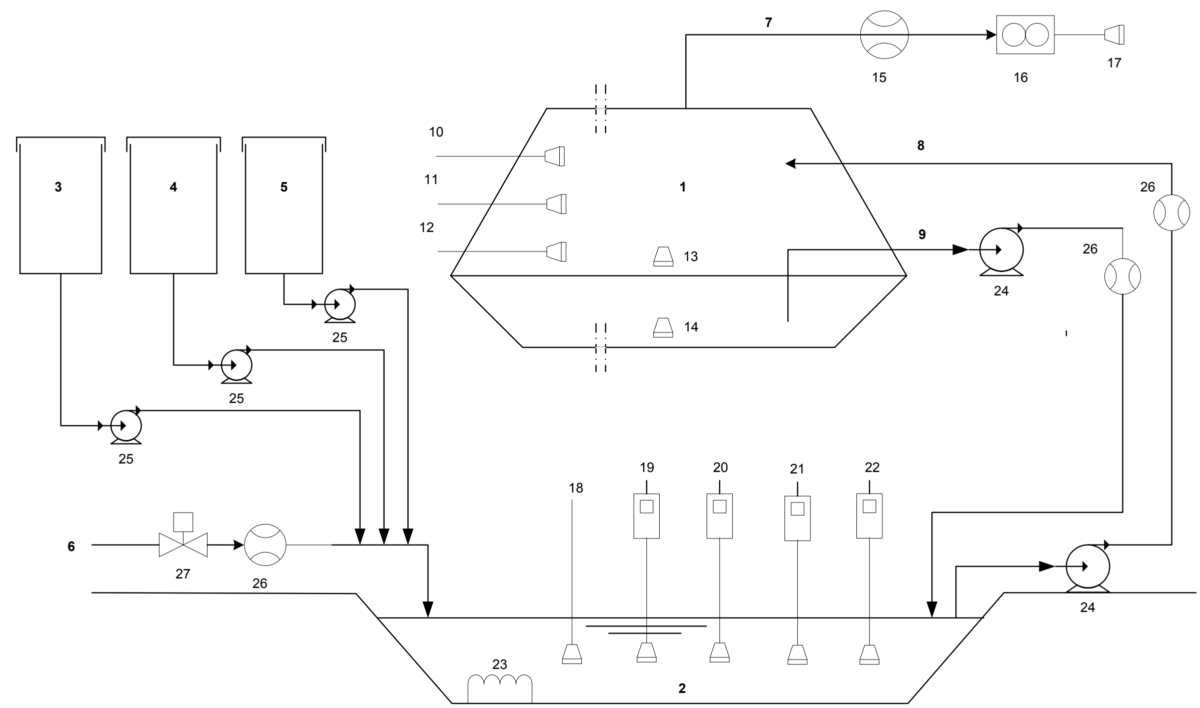

Figure 3-5 Schematic instrumentation diagram of the SMART system

(1) bioreactor landfill cell; (2) leachate storage and preparation site; (3) buffer tank; (4) inocula tank; (5) nutrient tank; (6) water supply; (7) collected biogas flow line; (8) recirculated leachate flow line; (9) collected leachate flow line; (10) moisture sensors; (11) thermocouples; (12) piezometers; (13) settlement plates; (14) pressure transducers; (15) gas flow meter; (16) online gas analyzer; (17) gas thermistor; (18) liquid thermistor; (19) pH probe and meter; (20) ORP electrode and meter; (21) Ammonia-selective electrode and meter; (22) online analyzers for leachate parameters; (23) heating unit; (24) pumps; (25) dosing pumps; (26) liquid flow meters; and (27) electrically actuated valves.

Collected leachate is analyzed for COD, VFA, TOC, TN, TP, pH, ORP, alkalinity, and ammonia. The pH, ORP, and ammonia are measured by inline double-junction temperature-compensated pH, ORP, and ion-selective electrodes, respectively connected to a transmitter. Continuous measurements of COD, TOC, TN, TP, VFA, and alkalinity are commercially available, however due to the high capital and maintenance costs of online analyzers as well as the slow reaction time in landfill processes, determination of these parameters by standard offline analytical methods is still the most economic and practical approach.

The flow of produced and recirculated leachate is measured and totalled via Coriolis mass flow sensors and totalizers, respectively. Alternatively, leachate production can be measured at the collection/ storage facility by measuring the level using noncontact ultrasonic level transmitters or capacitance switches. Settlement is measured using settlement plates, whereas hydrostatic head on liners is monitored by differential pressure transducers. LFG flow is metered and analyzed onsite. Carbon dioxide and methane are measured through dual wavelength infrared gas analyzers, whereas, oxygen is monitored via zirconium dioxide sensors. The flow rate of LFG is measured and totalized via turbine or thermal dispersion flow meters.

Final control and driving instruments include pneumatically or electrically actuated diaphragm valves, and double-diaphragm or peristaltic pumps that can safely handle particulate-laden and corrosive liquids.

3.6. Conclusions

The proposed control framework employs state of the art automated monitoring and intelligent control in operating BLs more efficiently. The system controls the manipulation processes of the produced leachate manipulation in order to produce an optimized recirculation liquid that provides the bacterial population with their growth requirements. This chapter discussed the system structure and main components for the anaerobic type of BLs. However, the knowledge-based decision making of SMART can be customized to operate and control other configurations, such as aerobic, hybrid, or facultative BLs. In fact, these configurations contain more controllable inputs, such as air injection, and more operational scenarios that would benefit from the SMART technology.

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CHAPTER 4

SMART CONTROL PROGRAM & OPERATIONAL GUIDELINES

This chapter is based on the following publication:

Abdallah, M., Kennedy, K., Narbaitz, R. Warith, M., Petriu, E. (2011) ***Sensor-based Monitoring and Remote-control Technology (SMART) for bioreactor landfills: II) control program****. Submitted to the Journal of Environmental Management.*

4.1. Abstract

The operational guidelines of bioreactor landfill processes, specifically leachate manipulation and recirculation, have not been established due to lack of well-defined methodologies and limited field experience. These limitations have led to the development of SMART, an expert control system that employs real-time monitoring of key system parameters in the management of bioreactor landfills so as to optimize their performance. This chapter describes the system's Main Control Unit which makes the decisions regarding the quantity and quality of the solution to be recirculated (see Figure 4-1). The expert system determines the required quantities of leachate, buffer solution, make-up water, and nutritional amendments in order to provide the bioreactor landfill microbial consortia with their growth requirements. The discussion elucidates the data flow and hierarchy of SMART's control program, which is composed of multiple cascading logic controllers and mathematical calculations.

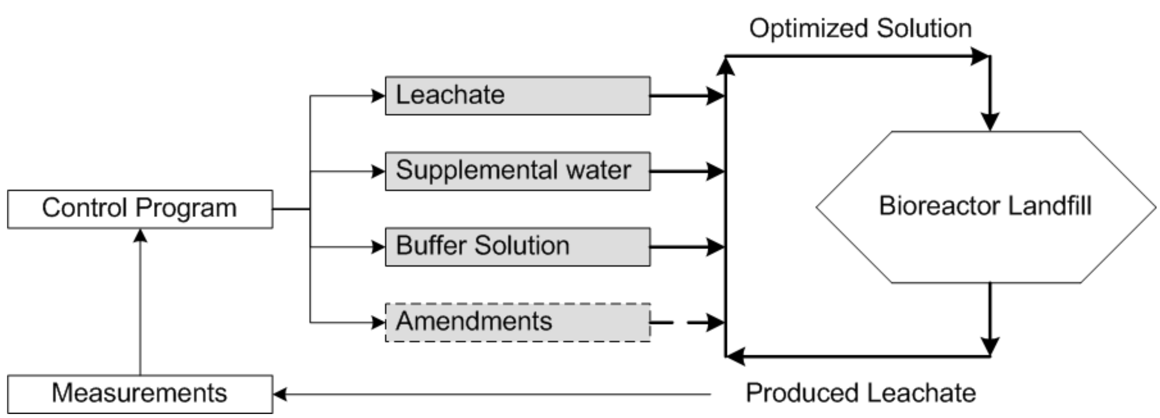

Figure 4-1 Schematic representation of control system

4.2. Introduction

The reactions within the landfill ecosystem involve a consortium of microorganisms which require specific environmental conditions, such as moisture, temperature, pH, and nutrients, among others. The bioreactor landfill (BL) concept is based on optimizing those conditions via specific management activities and operational modifications. Recirculation of leachate as produced is considered the main operational practice in the BL so as to increase moisture content. In some cases, other techniques such as pH buffering, nutrients addition, bioaugmentation, and temperature management have been incorporated with leachate recirculation to improve BL performance (Leuschner, 1987; Reinhart and Townsend, 1998; Warith, 2002; He *et al.*, 2005; Brundin, 1991). However, generic guidelines for the optimal leachate manipulation and recirculation processes have not been established yet due mainly to the lack of well-defined methodologies and field experiences (Jayasinghe *et al.,* 2010). To overcome these limitations, the authors have developed SMART (Sensor-based Monitoring and Remote-control Technology), an expert control system for real-time monitoring of key system parameters and for the management of leachate recirculation so as to optimize waste biodegradation. The SMART system manipulates the controllable variables of the BL process in order to provide optimal operational conditions for the biodegradation of the waste, and also, to enhance biogas production. In this chapter, the focus is the Main Control Unit (MCU) which includes the expert control program of SMART. The MCU makes the control decisions regarding the ***quantity*** and ***quality*** of the recirculated solution to the BL.

The ***quantity*** of the leachate generated is site-specific and a function of water availability, weather conditions, characteristics of the waste, as well as the liner and cover design (El-Fadel *et al.*, 1997). In order to achieve the benefits of leachate recirculation, leachate has to be recycled at optimal rates that achieve sufficient contact with waste. The effect of varying leachate recirculation rates was studied in lab simulations (Chugh *et al.,* 1998; San and Onay, 2001; Filipkowska, 2008; Benbelkacem *et al.,* 2010). These studies proved that higher recirculation rates result in better BL performance in terms of biogas production. Jianguo *et al.* (2007) suggests that leachate recirculation should be adjusted according to the phases of waste stabilization. This practice was applied successfully by San and Onay (2001) as well as Erses and Onay (2003) who varied the leachate recirculation rates in lab scale BLs based on

7 and 4 operational stages, respectively. Unsupervised high rate of recirculation may result in: (1) washout of large amounts of organic matter before the methanogenic phase, thereby reducing the biological methane potential, (2) production of leachate containing high concentrations of short chain fatty acids which either inhibits methanogenesis directly or by lowering the pH, (3) excessive accumulation of leachate within the landfill, which may breakout from landfill slopes, (4) increase of pore water pressure and decrease of the shear strength of the waste matrix which affect the geotechnical slope stability, (5) increase in the hydrostatic head on the base liner, leading to higher risk for ground water contamination, and (6) drop in the internal temperature of the landfill especially in cold regions. Therefore, leachate recirculation rate has to be selected such that the desired moisture content levels, moisture movement, and supplements distribution are provided, and at the same time, the pre-mentioned issues are monitored and incorporated in the decision-making process. It should be noted that there are other technical limitations, associated with the movement of large quantities of leachate and the rapid degradation of waste, which can be avoided before operation, i.e. at the design stage (Reinhart *et al.*, 2002). These critical issues include: (1) failure of leachate and gas piping systems due to the rapid settlement resulting from waste decomposition, (2) potential clogging and biological growth in the leachate collection and recirculation systems, which can impede the drainage of trenches, and (3) potential breaks/cracks in the BL liners as a result of the increased weight of the waste matrix and high pore water pressure, associated with the higher moisture content of waste.

As water percolates downward through landfills, organic and inorganic constituents are dissolved. The ***quality*** of leachate is highly dependent on waste composition and operational phase (El-Fadel *et al.*, 1997). Leachate has been reported to contain a wide range of toxic organic compounds, including aliphatic and aromatic hydrocarbons, halogenated organics and other classes (Lisk, 1991). Typically, the concentration of constituents, including pollutants, in leachate decreases with the waste age. The large variation in the biochemical characteristics of the leachate as produced makes it an unsteady solution for the recirculation process. For example, the concentrations of dissolved organic substances in young leachate are usually much higher than in older leachate. Continuous recirculation of young leachate in early phases of operation will increase the concentration of short chain fatty acids inside the BL which either inhibits methanogenesis directly or indirectly by lowering the pH of the system. Recently, researchers examined the use of different leachate (mature leachate) for recirculation (Erses and Onay, 2003; Jianguo *et al.*, 2007; Filipkowska, 2008; Benbelkacem *et al.*, 2010). Sanphoti *et al.* (2006) demonstrated that addition of supplemental water to the recirculated leachate in early operational phases promotes dilution of inhibitory substances and reduces leachate strength resulting in favourable conditions for methanogens. In the SMART system, supplemental water is used in combination with other leachate manipulation techniques to correct certain process deviations, reduce the impact of detrimental substances, and/or enrich the concentration of other beneficial compounds.

The general effect of increasing salt concentration in anaerobic systems was first demonstrated by McCarty (1964) as in Figure 4-2. The same trend was also used to express the effects of essential and non-essential, both toxic and nontoxic metals on anaerobic systems (Oleszkiewics and Sharma, 1990). Figure 4-2 shows that a substance which is essential to a biological process can stimulate the bacterial growth at low concentrations. However, as concentrations increase above optimal, the rate of microbial activity decreases until the process is inhibited. Similarly, this trend can be adapted to describe the effects of adding leachate and other amendments on the BL performance. This may explain the different, and sometimes contradicting, results reported in many studies since the same substance can be useful or harmful depending on its dose. While most studies reported process improvements, other studies found the contrary, such as toxicity and souring conditions. Other factors that may affect the results include: (1) case-specific operational factors, such as the types and characteristics of the amendments, and (2) operational phase and progressive evolution of the BL.

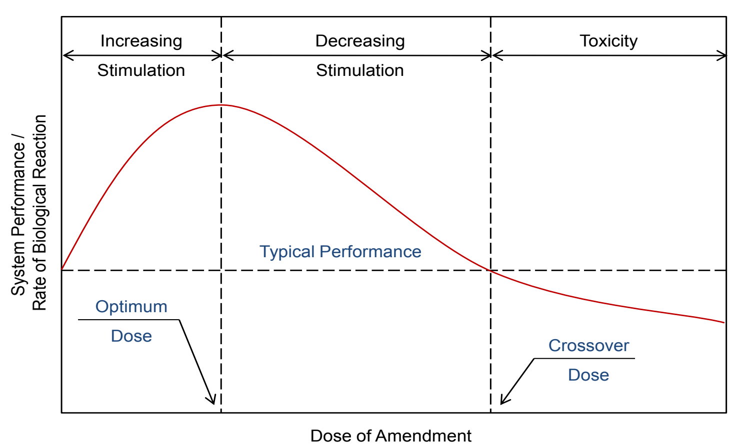

Figure 4-2 Effect of adding amendments on BL performance (modified from McCarthy, 1964)

Compiling optimal methodologies for the recirculation and manipulation processes is not straightforward. Direct usage of the quantities of amendments reported in the BL literature is impractical because those quantities are rarely, if ever, correlated to an established reference (for example, volume per unit weight of viable biomass).

4.3. Expert System

The Main Controller Unit (MCU), the decision-making component of the SMART control system, includes the control guidelines that address all of the above issues and difficulties. The MCU unit features two interacting software components: the monitoring interface, as well as the control program. The control program receives the measured data (inputs), processes them within the expert system, makes the control decision, and sends it to the Primary Driving Controller in the form of quantified commands. This section discusses the SMART control program and components of the expert system in detail.

The expert system is designed to determine the required volumes of leachate, make-up water as well as bioaugmentation and nutritional amendments necessary to provide the BL microbial consortia with their optimum growth requirements. Two basic assumptions were made for the development of the control program:

1) The BL is an attached growth fixed-bed reactor in which the degradable and non-degradable fractions of the waste act as the biomass and packing media, respectively. Given that leachate is recirculated cyclically, the BL operates in a semi-batch mode whereby recirculated solution is the input, and leachate produced is the main output.

2) The chemical/biochemical characteristics of the effluent leachate are representative of the conditions within the whole BL waste matrix. Regulating the characteristics of the recirculated leachate alters the characteristics of the waste matrix through which it percolates, in a gradual stepwise manner, over a number of *cycle times*. This assumption was also made by Jiang *et al.* (2007) who used the analyses of leachate parameters to characterize the corresponding solid waste properties.

The data flow diagram and hierarchy of the developed control program are shown in Figure 4-3. The structure of the program is composed of multiple cascading logic controllers (LCs 1-5) and mathematical calculations (MCs 1-5) where the outputs of the first layer serve as the inputs to the next, and so on. The control sequence in Figure 4-3 is repeated every operational cycle. *Cycle time* is the time interval between solution input and collection of generated leachate and is dependent on the hydraulic conductivity of the waste matrix.

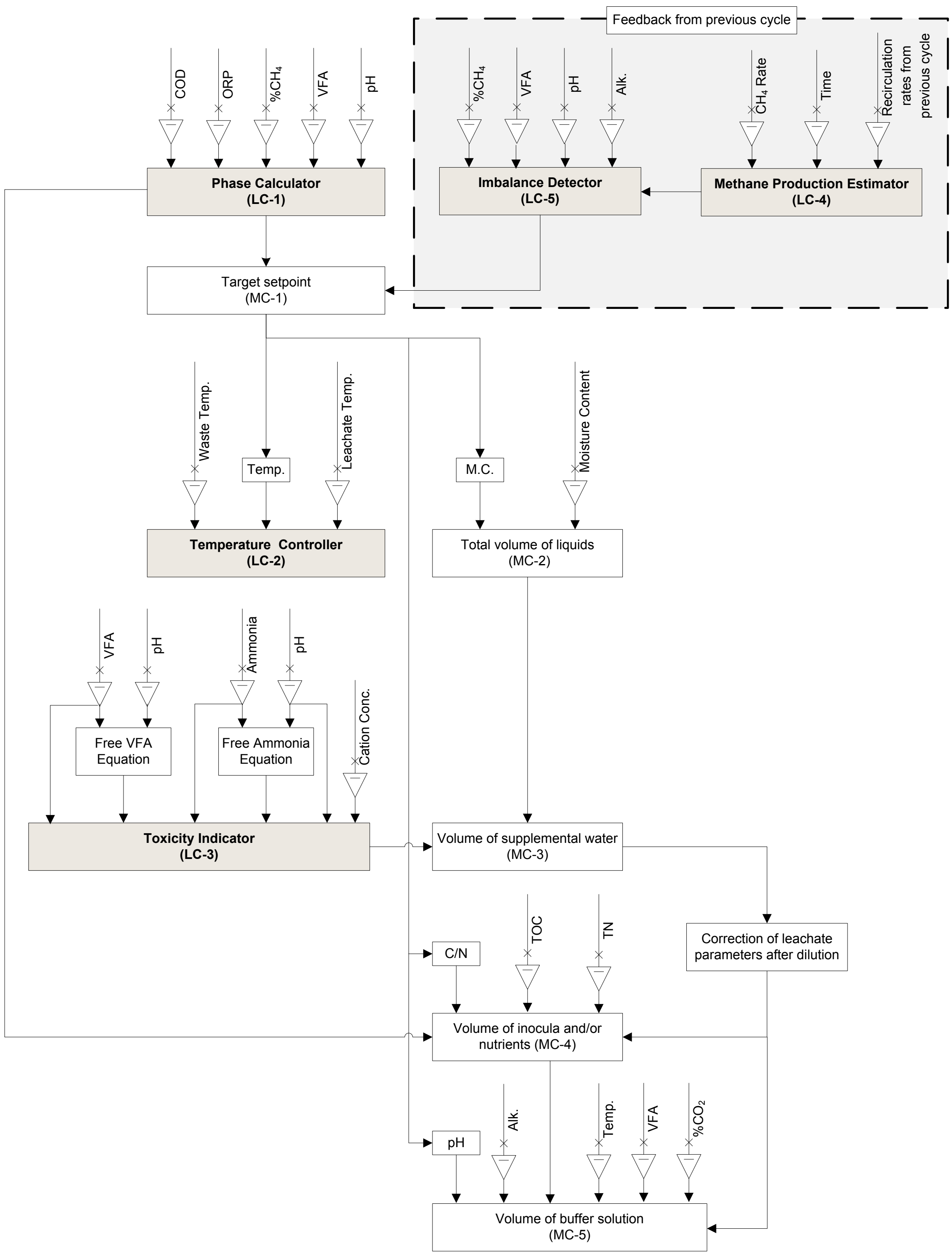

Figure 4-3 Dataflow diagram of the control program

4.3.1. Control Program

As shown in Figure 4-3, the program sequence starts with the *Phase Calculator* (LC-1). LC-1 is a fuzzy logic controller which identifies the current operational phase of the BL based on quantifiable characteristics of the generated leachate and biogas. Input parameters include leachate COD, VFA, pH, ORP, and methane content in the landfill gas. The output of LC-1 is a real number in the interval [0, 3] that expresses the BL operational phase, where 0 is the aerobic phase and 3 is the methanogenic phase. A comprehensive discussion of LC-1 is presented in chapter 5.

The output from LC-1 is the input to the first mathematical step (MC-1). In MC-1, setpoints of pH (leachate), C/N ratio (leachate), temperature (waste matrix), and moisture content (waste matrix) are computed based on the BL operational phase determined from LC-1. Table 4-1 shows default setpoints for the two main BL operational phases. It should be noted that these setpoints can be adjusted according to the process feedback (discussed later in LC-4 & LC-5), and may basically vary depending on several site-specific factors such as holding capacity of waste matrix, degree of compaction, and waste composition. However, in general, leachate recirculation rates during the early acidogenic phase should initially be low and then gradually increase as methanogenesis becomes established. Also, the required C/N ratio, pH, and temperature for the optimum growth of acidogens are lower than that for the methanogens.

Table 4-1 Setpoints of process parameters at the acidogenic and methanogenic phases

Parameter	Medium	Phase 2 Acidogenic	Phase 3 Methanogenic
pH	Leachate	5.5-6.5	6.8-7.2
C/N ratio	Leachate	10	15
Temperature, °C	Waste Matrix	20-25	30-35
Moisture content, %	Waste Matrix	50	60

MC-1 applies linear interpolation between the predefined parameter values (shown in Table 4-1). The parameter setpoint *(S)* at a given phase *(P)* can be calculated as follows:

$$S_P = S_i + [(S_{i+1} - S_i) \times (P - i)] \tag{4-1}$$

where P is the computed phase from LC-1, i is the integer part from the computed phase P, S_i is the setpoint at phase i, and S_{i+1} is the setpoint at phase $i+1$.

Next, the calculated setpoint for waste temperature (from MC-1) is used by the temperature controller (LC-2). LC-2 is a cascade controller where by the waste temperature is controlled by manipulating the temperature of the recirculated solution. The inputs include the actual temperatures of the waste matrix and generated leachate, as well as the setpoint for waste temperature. The output is the temperature up to which the solution should be heated in order to achieve the desired waste temperature setpoint. In addition, LC-2 has a conditional statement that circumvents rapid changes in waste temperature which should not exceed 2-3°C per cycle time. Sudden fluctuations in temperature can have a negative effect on the dominant fermentative bacteria that produce the substrates for the methane-forming bacteria (Gerardi, 2006). It is worth mentioning that temperature control is most relevant in cold regions where recirculating cold leachate would cool down the internal temperature of a BL, and consequently inhibit bacterial activity. This effect is exacerbated by the differential changes in microbial activity with temperature of the acidogenic and methanogenic consortia. Methanogens have much greater decreases in specific activity at lower temperatures compared to acidogens. This differential change can lead to accumulation of VFA's and potential souring of the landfill (Speece, 2008).

In parallel, MC-2 computes the total required volume of recirculated liquids to bring the moisture content of the landfill up to its calculated setpoint (from MC-1). Two key variables are used to quantify the moisture content of the waste: (1) field capacity, which is the maximum moisture content that the waste can retain while subjected to drainage under gravity; and (2) absorptive capacity, which is the difference between the actual moisture content and field capacity of the waste. Typically, field capacity decreases with time as a result of degradation of the organic matter which has a high water absorptive capacity compared to other waste fractions, as well as concomitant increases in field density. It should be noted that beyond field capacity, the absorptive capacity of the waste is negligible. However, liquid recirculation should continue in order to provide better moisture distribution and transport of essential amendments, dilute high concentrations of inhibitory substances, and make up for possible water losses. When the net water balance is zero (i.e., the volume of recirculated liquid is equal to the volume of leachate produced), the required recirculation volume is equal to the liquid volume needed to raise the water content of the waste matrix from its current level to the desired setpoint value (established by MC-1). The liquid volume is calculated as follows:

$$V_{liquid} = (S_{mc} - \omega) \times \frac{w}{\rho_{water}} \tag{4-2}$$

Where V_{liquid} is the total required volume of liquids to be added in a given cycle, S_{mc} is the setpoint for the gravimetric water content (calculated in MC-1), ω is the actual measured gravimetric moisture content, ρ_{water} is the water density, and w is the bulk weight of the waste. It should be noted that since all moisture sensors presently available measure the volumetric water content (θ), equation (4-2) is rewritten in terms of θ using equation (4-3):

$$\omega = \frac{\theta}{\gamma} = \frac{\theta \times \rho_{water}}{\rho_{bulk}} = \frac{\theta \times \rho_{water} \times V_{waste}}{w} \tag{4-3}$$

$$V_{liquid} = \left(\frac{S_{mc} \times w}{\rho_{water}} \right) - \left(\theta \times V_{waste} \right) \tag{4-4}$$

Where γ is the specific gravity (relative density) of waste, θ is the measured volumetric water content, and V_{waste} is the volume of the waste matrix.

One of the main benefits of supplemental water addition is to dilute and reduce elevated concentrations of pollutants in the leachate to be recirculated which may inhibit the microbial consortia in the waste matrix. The *Toxicity Indicator* (LC-3) is a fuzzy logic controller that evaluates the toxicological status of the leachate based on certain parameters that directly contribute to or indirectly indicates bacterial inhibition. The primary inhibitors, incorporated in LC-3, included ammonia-nitrogen (TAN), VFA, and their free unionized/ undissociated fractions (UAN and UVFA, respectively), as well as alkali cations. UAN and UVFA concentrations are highly dependent on the temperature and pH of the leachate, and are calculated as follows:

$$UAN = \frac{TAN}{(1 + 10^{(pK_{AN} - pH)})} \tag{4-5}$$

Where TAN is the concentration of total ammonia-nitrogen, and K_{AN} is the dissociation constant of ammonia in water at temperature T,

$$UVFA = \sum_{i=1}^{n} \frac{VFA_i \times 10^{(pK_{VFA_i} - pH)}}{(1 + 10^{(pK_{VFA_i} - pH)})} \tag{4-6}$$

Where VFA_i is the concentration of an individual volatile fatty acid, K_{VFAi} is the dissociation constant of VFA_i in water, and n is the number of VFAs measured.

Based on the selected toxicity parameters, LC-3 generates a dilution factor (D) that is used in MC-3 to determine the volume of supplemental water to be added. The supplemental water volume is the greater of: (1) required water volume for dilution purposes (equation 4-7), or (2) water volume required to make up for shortage of produced leachate (equation 4-8).

$$V_{water \cdot 1} = D \times V_{liquid} = \left(\frac{D}{(1-D)} \right) \times V_{leachate} \tag{4-7}$$

$$V_{water \cdot 2} = V_{liquid} - V_{leachate} \tag{4-8}$$

Where V_{water} is the required volume of supplemental water to be added, D is the dilution factor generated from LC-3, V_{liquid} is the total required volume of liquids from MC-2, and $V_{leachate}$ is the available volume of leachate (i.e., that produced in the previous operational cycle). If $V_{water\ 1}$ is greatest, the volume of leachate used must be reduced to be equal to the difference between V_{liquid} and $V_{water\ 1}$. The resulting mixture of supplementary water and produced leachate is called hereafter the diluted leachate (DL). The fuzzy logic controller design of LC-3 is presented in chapter 5.

Next, MC-4 determines additional nutrient requirements using the setpoints for C/N ratio, TOC, and TN of the generated leachate. The addition of a nitrogen source to the BL is controlled according to the C/N ratio since a high ratio indicates a rapid consumption of nitrogen by the methanogens, and a lower ratio indicates ammonia accumulation within the system. It should be noted that the operational phase *(P)* is also used in MC-4 to determine whether to use anaerobic sludge as a bioaugmentation supplement and source of nutrients instead of applying a nutrient/mineral salts enriched media. Anaerobic sludge is a beneficial supplement for early phase BLs since it provides an active bacterial population, high buffering capacity, nitrogen, phosphorous, as well as other nutrients and micronutrients.

Nutrient/mineral salts enriched media are more useful in later BL phases when bio-available nutrients may become limiting. Anaerobic sludge is used up to the onset of the methanogenic phase at which point nutrient/mineral salts enriched media, will be used if required. Equation (4-9) is used to calculate the volume of nutritional source:

$$V_{nutrients} = \frac{\left(\frac{TOC}{S_{C/N}}\right) - TN}{TN_{nutrients}} \times V_{liquid} \tag{4-9}$$

Where $V_{nutrients}$ is the required volume of the nutritional source, $S_{C/N}$ is the setpoint calculated for the C/N ratio, V_{liquid} is the volume of liquid calculated in MC-2, and *TN*, *TOC and TN* $_{nutrients}$ are the concentrations of total nitrogen for DL, total organic carbon for DL, and total nitrogen of the nutritional source to be used, respectively. The TOC concentration in the nutritional source is assumed to be negligible with respect to that of the DL or produced leachate. It is expected that nutrient addition in the early phases (P1-P2) will be negligible since there will be an excess of readily degradable organics. However due to the other benefits discussed above, it is suggested that the anaerobic sludge is added at a constant percentage of the recirculated solution. It should be noted that instead of the COD, TOC can be used to express the organic matter because leachate typically contains high concentrations of inorganic substances that may alter the results of the COD test significantly. Kylefors *et al.* (2003) found that up to one-third of leachate COD may be due to the inorganic components of leachate.

Next, the required amount of buffer solution is calculated in MC-5. The buffering salt, which is used to adjust the pH and provide external source of alkalinity to the system, is composed of an anion and cation. In anaerobic systems, buffer solutions that release bicarbonate alkalinity directly are preferred. Also, of all the cations released by alkali chemicals, sodium (Na^+) and potassium (K^+) are the least toxic to the bacterial population (Gerardi, 2003). Jun *et al.* (2009) examined the effect of adding alkalinity on the stabilization of MSW using sodium carbonate (Na_2CO_3), sodium bicarbonate ($NaHCO_3$), and sodium hydroxide (NaOH). The buffering capacity of the carbonate (CO_3^{2-}) was proven to be the highest, bicarbonate (HCO_3^-) and hydroxide (OH^-) followed. On the other hand, HCO_3^- was easily consumed by microorganisms, while OH^- was least. Therefore, sodium bicarbonate ($NaHCO_3$) is selected as the optimum buffer solution in SMART. In case sodium toxicity occurs, an antagonist, namely potassium, can be used instead. Antagonism and synergism in anaerobic digestion have been widely observed in relation to alkali and alkaline earth metals (Barnes and Fitzgerald, 1987). The toxic effect of a particular cation present in waste can be reduced or eliminated by the addition of an antagonist ion. Conversely, toxicity may be increased by adding a synergist ion. The sodium antagonists include potassium, magnesium, as well as potassium and calcium.

At the near-neutral pH in anaerobic systems, the major chemical system controlling pH is the carbon dioxide-bicarbonate system (McCarty, 1964). Typically, a buffer solution is added in order to neutralize the leachate before being recirculated to the reactor. In practice, this neutralization process is never precise, mainly due to the stripping of carbon dioxide (CO_2) from the leachate which tends to decrease H^+ (raises pH) and to consume HCO_3^- (reduces alkalinity). This effect can be explained by the reactions below,

$$CO_2(aq) + H_2O \Leftrightarrow H_2CO_3 \quad (4\text{-}10)$$

$$H_2CO_3 + H_2O \Leftrightarrow H_3O^+ + HCO_3^- \quad (4\text{-}11)$$

$$HCO_3^- + H_2O \Leftrightarrow H_3O^+ + CO_3^{2-} \quad (4\text{-}12)$$

In reaction (4-10), CO_2 combines with water to form carbonic acid (H_2CO_3). The H_2CO_3 can then dissociate in water (reaction 4-11) to form hydronium ion (H_3O^+) and bicarbonate (HCO_3^-). It should be noted that at a pH below 7, the dominant species is HCO_3^- and H_2CO_3, and the contribution of CO_3^{2-} from the reverse of reaction (4-12) is considered negligible (Sawyer *et al.*, 2003). Therefore, adding the buffer solution at low pH values, i.e., high concentration bicarbonate ion and hydrogen ion, results in a shift in the chemical equilibrium, according to Le Châtelier's principle, towards the production of H_2CO_3 and subsequently CO_2. This process often results in the consumption of an excessive amount of buffer solution. Therefore, MC-5 calculates the required bicarbonate alkalinity to be added to the leachate regardless of the resultant pH. In the developed control program, alkalinity is added to provide the difference between the required alkalinity (CO_2/water buffering system) and the available alkalinity in the system. The available bicarbonate alkalinity can be calculated as:

$$BA = ALK - 0.83 \times f \times VFA \quad (4\text{-}13)$$

Where BA is the bicarbonate alkalinity (mg $CaCO_3$/L), ALK is the total alkalinity (mg $CaCO_3$/L), VFA is the concentration of the volatile fatty acids (mg-AA/L), 0.833 is a unit conversion factor (Equivalent weight of $CaCO_3$/Equivalent weight of AA), and f is a factor for the percentage of VFA titrated at the pH endpoint of the alkalinity test. The f factor can be determined analytically by dividing the concentration of VFA in the leachate sample after alkalinity titration by the concentration of VFA in the original sample.

On the other hand, the required alkalinity (RA) for the CO_2/water buffering system can be calculated as:

$$RA = [HCO_3^-] = \frac{K_1 \times K_H \times P_{CO_2} \times 50 \times 1000}{[H^+]} \tag{4-14}$$

Where $[HCO_3^-]$ is the required concentration of bicarbonate ion for CO_2 neutralization (mg $CaCO_3$/L), K_1 is the ionization constant for carbonic acid, K_H is the hydration equilibrium constant, P_{CO2} is the partial pressure of CO_2 in the system (fraction of CO_2 in the composition of air), $[H^+]$ is the concentration of hydrogen ion at the pH setpoint calculated in MC-1, and 50 is the equivalent weight of $CaCO_3$. The added alkalinity is the difference between the required and available alkalinity in the system. The volume of buffer solution to provide the required alkalinity can be calculated as:

$$V_{buffer} = \frac{\left([HCO_3^-] - BA \right) \times EW_{buffer} \times V_{liquid}}{50 \times C_{buffer}} \tag{4-15}$$

Where V_{buffer} is the required volume of buffer solution, EW_{buffer} is the equivalent weight of the buffer salt, C_{buffer} is the concentration of buffer salt in the solution, and V_{liquid} is the volume of recirculated liquid. The amount of buffer solution to be added should be equal or greater than the amount required to bring the pH up to the setpoint calculated from MC-1.

The feedback control scheme in the control program is realized in the *Methane Production Estimator* (LC-4) and the *Imbalance Detector* (LC-5). LC-4 incorporates a FL model that estimates methane production from BLs (discussed in chapter 5) based on the operational phase of the BL (time) as well as the recirculation rates of leachate and sludge. The BL site operator compares the actual methane production with LC-4 output (i.e., predicted methane generation), and in case of less-than-expected production, the operator indicates the possible causes and remediation actions. In SMART, a new method was developed to assist the BL site operator in tracking the factors affecting the methane generation process, and hence indicating possible negative/positive parameters that need to be addressed/augmented to enhance the process. It is suggested that the BL operator uses Fuzzy Cognitive Maps (FCM) which are fuzzy graphical structures that are capable of modeling complex dynamic systems (Kandasamy and Smarandache, 2003). A typical FCM is a cognitive map within which the relationships between the elements (e.g. system parameters and processes) can be used to determine the weighted impact of particular elements. Based on the compiled literature, a cognitive map was developed to incorporate the interconnecting relations between the main operational parameters and processes for a BL. As shown in Figure 4-4, the map includes multiple parameters that affect the methane generation in a typical BL. The solid lines show a proportional relationship, whereas, dashed lines show an inverse correlation between the two elements. This map can also be effectively employed to track the net effect of each leachate manipulation variable on the methane production. For example, in the highlighted path of the FCM shown in Figure 4-4, the basic buffering may cause accumulation of the alkali cation, which would lead to potential toxicity that affect the methanogenic activity and consequently, reduce the methane generation.

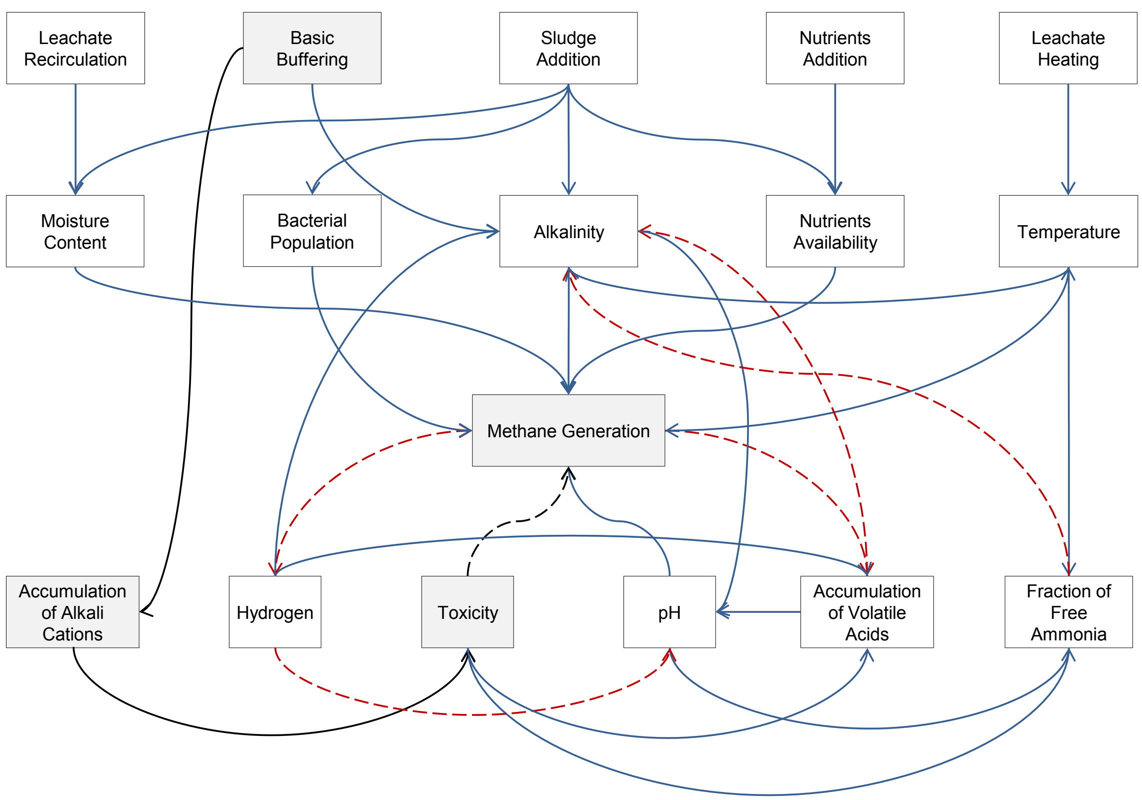

Figure 4-4 Cognitive map of the bioreactor landfill process

Additionally, LC-5 provides a detection, diagnosis, and correction unit that employs feedback from previous cycles to handle any long or short term process trends or deviations affecting BL performance. LC-5 monitors and evaluates 5 specific process parameters in order to detect common phase specific operational problems. These parameters include VFA, total alkalinity (TA), VFA/TA ratio, pH, rate of change of pH (dpH/dt), and methane production (MP). LC-5 uses the operational fault descriptors presented in Table 4-2 as the base for detection, diagnosis, and correction. These operational scenarios were compiled from pilot and full-scale experiences with anaerobic digesters. As shown in Figure 4-3, the output from LC-4 can override the target setpoints of the manipulated parameters, after authorization from site operator, to deal with chronic or acute descriptors that are having a negative effect on BL performance. For example, when the VFA/TA ratio increases (descriptor is +) and the pH is concurrently decreasing (descriptor is -), then the BL is diagnosed to have high acidification and the control action suggested by LC-5 is to increase buffer and anaerobic sludge addition.

Table 4-2 Operational imbalance scenarios in terms of LC-5 input parameters *

VFA	TA	VFA/TA	pH	dpH/d t	MP	Diagnosis	Recommended control action	
							Decrease	Increase
		+				Acidification		Buffer
		+	−			High acidification		Buffer & sludge
			−	+		Souring		Buffer & sludge
+	+					Washout	Total liquid	
+	+				−	Bacterial washout	Total liquid	

* *The positive sign (+) means an increase of the parameter, whereas, the negative sign refers to a decrease.*

4.4. Conclusions

The hierarchy and data flow of SMART's control program were discussed. The structure of the program is composed of cascading logic controllers (LCs 1-5) and mathematical calculations (MCs 1-5) that: (1) identify current operational phase of BL (LC-1), (2) compute setpoints of key system parameters (MC-1), (3) compute total volume of recirculated liquids (MC-2), (4) calculate leachate heating requirements (LC-2), (5) evaluate toxicological status of BL (LC-3), (6) determine volume of supplemental water (MC-3), (7) determine type and quantity of nutritional source (MC-4), (8) determine required amount of buffering solution (MC-5), and (9) evaluate and correct the control decisions made by the program (LC-4 & LC-5). The application, assessment, and potential improvements of SMART are studied in the next phase of this research project (chapter 6).

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CHAPTER 5

IMPLEMENTATION OF FUZZY LOGIC CONTROL IN SMART

This chapter is a combination of the following publications:

(1) *Abdallah, M., Kennedy, K., Narbaitz, R. Warith, M., Petriu, E. (2011)* ***Sensor-based Monitoring and Remote-control Technology (SMART) for bioreactor landfills: II) control program****. Submitted to the Journal of Environmental Management.*

(2) *Abdallah, M., Petriu, E., Kennedy, K., Narbaitz, R. Warith, M. (2011)* ***Application of fuzzy logic in modern landfills****. Proceedings of the IEEE International Conference on Computational Intelligence for Measurement Systems and Applications.*

(3) *Abdallah, M., Fernandes, L., Warith, M., Rendra, S. (2009)* ***A fuzzy logic model for biogas generation in bioreactor landfills****. Journal of Environmental Engineering and Science, 36(4), 701-708.*

(4) *Abdallah, M., Fernandes, L., Warith, M. (2008)* ***Modeling of biogas generation in bioreactor landfills using neuro-fuzzy system****. Proceedings of the International Conference of Modeling and Simulation, Quebec, QC.*

5.1. Abstract

The heterogeneity of solid waste as well as the complexities of bioreactor landfill (BL) processes have led to the implementation of soft computing modeling techniques such as fuzzy logic (FL). FL is considered a powerful tool that implements the concept of partial truth or uncertainty, and has been successfully applied in a variety of ecological and environmental applications including modeling, control, and prediction tasks. FL has many advantages over traditional techniques, because of their ability to model nonlinear multi-parameter systems such as the BL. In the SMART control system, FL was used to solve the complex control issues by facilitating the process analysis. This chapter is divided into three parts that discuss the three FL controllers incorporated in the control program of SMART. The specific objectives of the developed FLCs are: (1) determination of the current

operational phase of BL (LC-1), (2) identification of the toxicological status of leachate (LC-3), and (3) estimation of the methane production from BL (LC-4).

5.2. Determination of Operational Phase

The *Phase Calculator* FLC was developed to identify the current operational phase of the BL based on quantifiable parameters of the leachate generated and biogas produced.

5.2.1. Problem Identification

Bioreactor landfills undergo the typical waste decomposition phases of sanitary landfills but in a shorter time frame (Reinhart and Townsend, 1998). The main features of those phases in terms of gas (volume & composition) and leachate (quality parameters) were discussed in chapter 2. Naturally, the anaerobic degradation process takes place in four dependent and consecutive steps. It begins with bacterial hydrolysis of the organic materials to break down complex organic matter, such as cellulose and carbohydrates, and make them available for other bacteria. Acidogenic bacteria then convert the sugars and amino acids into acetic acid, CO_2, H_2, NH_3, and organic acids. Acetogenic bacteria then convert organic acids into acetic acid, along with additional NH_3, H_2, and CO_2. Finally, acetoclastic and hydrogenotrophic methanogens convert the intermediate products (acetic acid, CO_2, and H_2) to CO_2 and CH_4.

The determination of the current operational phase of the BL is vital because the bacterial consortia change significantly throughout the BL lifetime, and accordingly so do the conditions for their optimal growth. In order to stimulate the decomposition process and consequently biogas generation, those requirements have to be adequately provided. Practically, the identification of the dominant operational phase of the BL at a given time is challenging especially because of factors such as the heterogeneity of the waste which may cause system parameters not to follow their normal expected trends. Moreover, since landfills receive waste continually over several years, these progressive phases occur simultaneously, but in different neighbouring locales. The temporal and spatial dimensions of each phase depends on many factors such as waste characteristics, landfill design, operational strategy, and environmental conditions, that can be characterized by changes in various physical and biochemical indicator parameters.

It is worth mentioning there was a previous attempt in the literature to identify the different periods of the life of a traditional landfill by Jiang *et al.* (2009). The researchers developed an integrated evaluation index to divide the landfill lifespan into five phases based on leachate's COD, BOD, BOD/COD, NH_3-N, percentage of CH_4 in the landfill gas, and the solid waste's biological methane potential (BMP), VS, and the ratio of cellulose-hemicellulose and lignin. However, this index had some limitations: (1) the index was based only on the pilot-scale experiment conducted by researchers, and was not verified against external data, (2) the number of selected evaluation parameters is large, (3) some of the index parameters are not easy to be determined analytically, and (4) the method used to develop the index does not account for the expected uncertainty in the measured parameters due to heterogeneity of waste in the BL. Therefore, the objective of the present work is to employ the modeling capabilities of FL in developing a knowledge-based controller that achieves the same objective taking uncertainty issues into consideration, and with fewer and easy to determine input parameters.

5.2.2. Rationale of Input Selection

The input variables selected in the *Phase Calculator* included the leachate's COD, total volatile acids (TVA), pH, ORP, and methane content of the landfill gas (%CH_4). These parameters are among the standard tests for the monitoring plan of BLs recommended by the Interstate Technology & Regulatory Council (ITRC, 2005) and the National Risk Management Research Laboratory (U.S. EPA, 2003). The pH, ORP, and %CH_4 can be easily measured onsite, while COD and TVA can be determined in the lab based on simple, fast, and reliable analytical methods. It should be noted that CH_4 was selected over other individual landfill gases as it can give a more acceptable projection of the overall gas composition.

5.2.3. Model Development

The *Phase Calculator* is a FL model designed to identify the current operational phase of a BL based on certain quantitative characteristics of the generated leachate and biogas. The model is designed according to a static multi-input-single-output (MISO) structure using the PID and Fuzzy Logic Toolkit in LabVIEW™. The input variables include the leachate's

COD, VOA, pH, ORP, and $\%CH_4$ in biogas, whereas, the single output variable is an index that defines the current operational phase of the BL, hereafter named the *Phase Index*.

The first step in the design of FL models is to build the *data base* which contains the membership functions defined for each input and output variable. Each variable is expressed by linguistic terms (fuzzy sets) within its predefined range (universe of discourse). The degree of truth of a fuzzy set A is defined by a membership function μ_A, which is represented by a real number in the interval [0, 1] depending on the degree at which it belongs to the set. This is different from conventional numerical sets where an element either belongs or does not belong to a particular set (membership = 0 or 1). This distinctive feature is advantageous for controlling biological ecosystems, like the BL, where the change in input variable does not cause the controlled process to shift abruptly from one state to another. Instead, as the variable changes, it loses its membership in one fuzzy set while gaining membership in the next. This is a logical approach to account for the fact that a part of the BL may be in a particular operational phase, while adjacent parts may be in other phases.

Membership functions (MFs) can have different shapes such as triangular, trapezoidal, bell-shaped (Gaussian), or wave-shaped (Sigmoid). In the *Phase Calculator*, the fuzzy sets were defined mainly by trapezoidal and/or triangular (special case of the trapezoidal shape) MFs where the uncertainty in each variable is represented by the most likely interval (i.e., the range at membership degree = 1.0) and the largest likely interval (i.e., the range at membership degree = 0.0) as shown in Figure 5-1. These intervals facilitate the interpretation of overlapping and disagreement in the compiled data ranges. The membership value is constant in the most likely interval [b, c], and increasing linearly from 0 to 1 between (a & b) and decreasing linearly from 1 to 0 between (c & d), thus providing the trapezoidal shape.

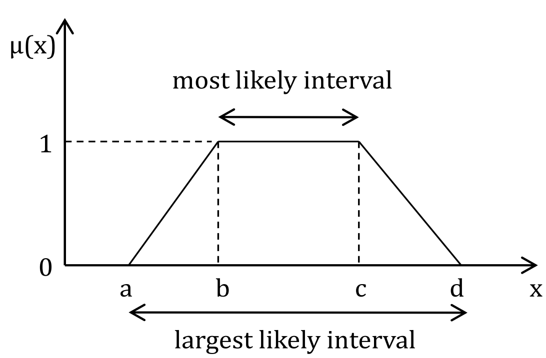


Figure 5-1 Typical trapezoidal membership function

For the special case of the triangular MF, the only difference to the trapezoidal MF is that the most likely interval [b, c] is a single point. The membership value of an element x in a trapezoidal fuzzy set can then be described as:

$$\mu_A(x) = \begin{cases} \dfrac{(x-a)}{(b-a)}, a \le x \le b \\ 1, b \le x \le c \\ \dfrac{(x-d)}{(c-d)}, c \le x \le d \\ 0, x \rangle d \ or \ x \langle a \end{cases} \tag{5-1}$$

Figure 5-2 shows the MFs defined for a sample input (ORP) and the single output (Phase Index). The linguistic labels (fuzzy sets) used to describe the ORP values are *positive* (P), *zero* (Z), *negative* (N), and *very negative* (VN). The 'Phase Index' variable was defined by the basic phases that typically characterize the BL life span; initial/ *aerobic* (A), *transition* (T), *acid formation* (AF), and *methane generation* (MG).

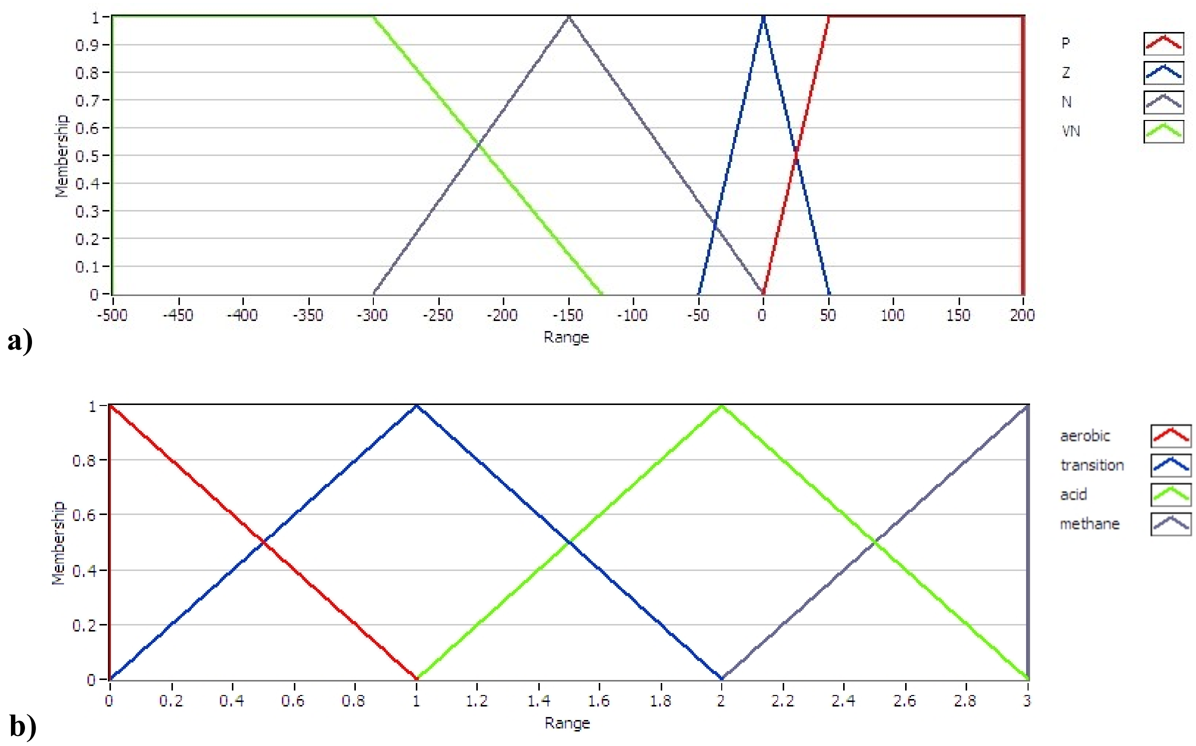


Figure 5-2 Membership functions for: a) ORP, and b) phase index

The next step in the design of FLC is developing the *rule base* for the controlled process. The *rule base* consists of fuzzy rules which are stated as IF–THEN statements that define the system behaviour and predict the output variable. A typical fuzzy rule can include several variables in the antecedent (IF part) and consequent (THEN part) of the rule. If a rule has more than one antecedent, a fuzzy operator such as AND, OR, or NOT, is used to connect them, and to determine how to calculate the truth value of the aggregated rule antecedent. In the *Phase Calculator*, five basic statements (rules) were created to define the expected operational phase based on different quantifiable parameters. The probabilistic-type of the OR operator, which uses the probabilistic sum of the degrees of membership of the antecedents, was applied in the formulated rules. The following is an example of the developed rule base statements:

*IF ' **ORP**' is 'VN' OR ' **pH**' is ' HN' OR ' **COD**' is ' H' OR ' **TVA**' is ' I' OR '**%CH$_4$**' is ' H' THEN ' P**hase Index**' is ' MG'*

In the above rule, VN, HN, H, I, H, and MF are fuzzy sets that denote *very negative*, *high neutral*, *high, intermediate*, *high*, and *methane generation*, respectively. The complete fuzzy rules as well as parameters of membership functions defined in the *Phase Calculator* are presented in Appendix B.

Example: Based on the compiled knowledge base, when the ORP of the leachate is -250 mV, it has a 0.3 membership in the "*negative*" fuzzy set, and a 0.7 membership in the "*very negative*" fuzzy set (see Figure 5-2a). This allows the single input (-250 mV) to be processed with multiple rules, i.e., the fuzzy rules that include "*negative*" and "*very negative*" ORP in their antecedents. Although all the invoked rules influence the output, the rules with higher truth values ("*very negative*" in this case) have the greatest effect. This weighing system helps in dealing with the uncertainties in the landfill ecosystem, as well as simplifying the complexity of the controlled process.

The *data base* and *rule base* represent the knowledge components based on which the FLC makes the decision. The knowledge of the *Phase Calculator* was compiled from information presented by Barlaz *et al.* (1989), Reinhart and Townsend (1998), Pohland and Kim (1999), and Gerardi (2003). Table 5-1 shows the reported ranges of the input system parameters in the compiled studies.

Table 5-1 Ranges of selected system parameters at the main operational phases*

Parameter	Study	Phase II Transition	Phase III Acid Formation	Phase IV Methane Formation	Phase V Maturation
COD	A	20 - 20,000	11,600 - 34,550	1,800 - 17,000	770 - 1,000
mg/l	B	-	15,000 - 41,000	1,000 - 41,000	-
TVA	A	200 - 2,700	1 - 30,730	0 - 3,900	0
mg/l	B	-	7,000 - 15,000	10,000	0
	A	5.4 - 8.1	5.7 - 7.4	5.9 - 8.6	7.4 - 8.3
pH	B	-	5 - 6	5.6 - 7.1	-
	C	-	5.8 - 6	6 - 7.8	7.1
$\%CH_4$	B	-	0	0 - 50	40
	C	-	-	23 - 62	-
ORP	B		50 - 0	0 - (-125)	-
mV	D	50 - (-50)	(-100)	(-300)	-

* *A: Reinhart and Townsend (1998), B: Pohland and Kim (1999), C: Barlaz et al. (1989), and D: Gerardi (2003).*

The knowledge bases are incorporated in the typical FLC structure, shown formerly in Figure 2-3, which includes: (1) *fuzzification unit*, (2) *inference engine*, and (3) *defuzzification unit*. The *fuzzification unit* converts the input variables into fuzzy sets using the predefined membership functions. The *inference engine* then processes the fuzzy inputs based on their relevant fuzzy rules, and determines the fuzzy output(s). As mentioned above, the *inference engine* invokes more than one rule, which results in having different memberships in multiple output fuzzy sets. In the *Phase Calculator*, the *inference engine* uses the *product* implication method in which each output MF is scaled down at the truth value of the corresponding aggregated rule antecedent. The output from this step is an irregular area under the scaled-down membership functions. Finally, the *defuzzification unit* incorporates a number of fuzzy sets in a calculation that gives a single numeric value for each output. In the

Phase Calculator, the defuzzification method used is the *Center of Gravity* of the resultant area after implication. In this method, the defuzzified value, O, can be calculated as:

$$O = \sum_{i=1}^{r} \mu_{Ci} . C_i \Bigg/ \sum_{i=1}^{r} \mu_{Ci} \qquad (5\text{-}2)$$

Where r is the total number of rules, μ_{Ci} is the degree of membership of the output fuzzy set i, and C_i is the value associated with the peak of output fuzzy set i. FLC output is a function of all the input variables, and in order to help visualize the non-linear characteristics of the Phase Index, surface plots were generated by varying two variables while the other variables remained constant. This can generate an infinite number of response surface, however if grouped for each pair of inputs, the number of possible groups of response surfaces becomes equal to the combination $C(n, 2) = n! / 2! (n - 2)!$ where n is the number of input variables. In the *Phase Calculator*, 10 groups of response surfaces can be established for the 10 possible pairs of input variables. It is worth mentioning that adding more variables (such as VFA/TA or BOD/COD ratios) to the input matrix would generate five more groups of response surfaces per added variable. Figure 5-3 shows the response of the output variable 'Phase Index' to changes in two pairs of the input variables, namely ORP and COD as well as TVA and pH, at the average defined value for the other input variables. The non-linear variation of the response intensity for the different values of input variables is considered one of the main advantages of the fuzzy logic system. Moreover, SMART's numeric representation for the operational phase offers a unique feature being able to obtain the transitional stage of the controlled BL. For example, when the 'Phase Index' is equal to 2.7, this means that the bioreactor is transitioning from the acid formation phase (2.0) to the methane generation phase (3.0). The value (2.7) indicates also that the BL microbial ecosystem is closer to the methanogenic stage.

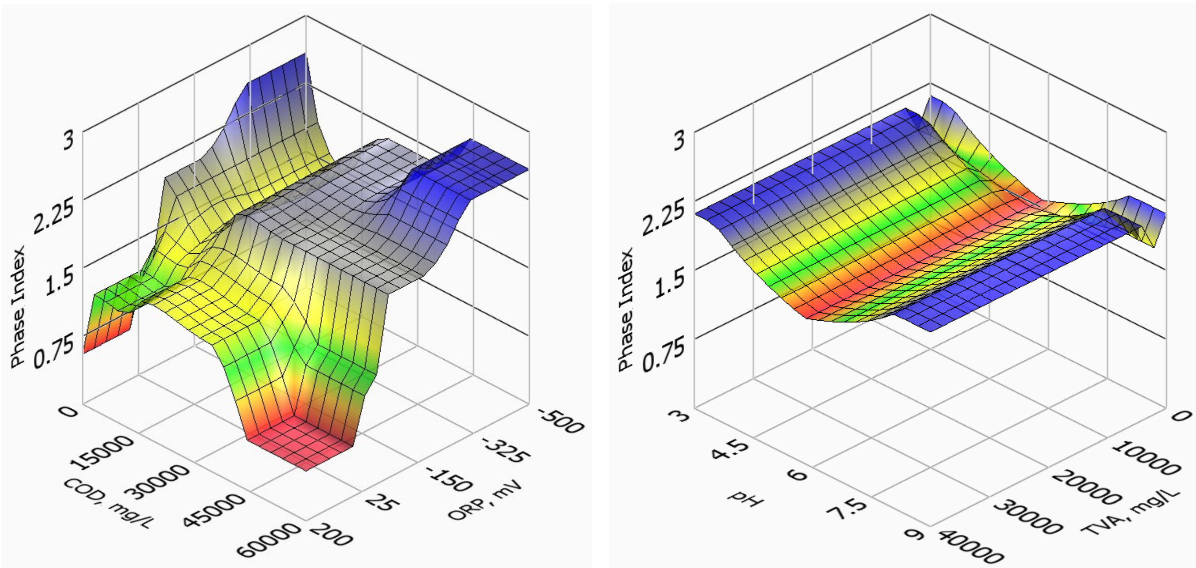
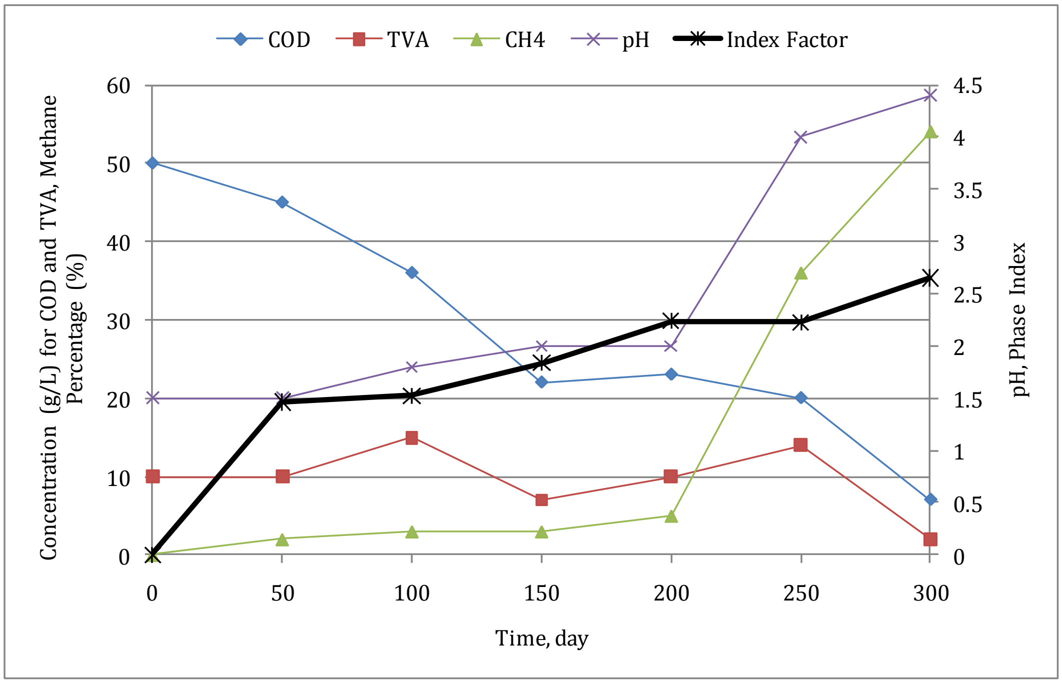


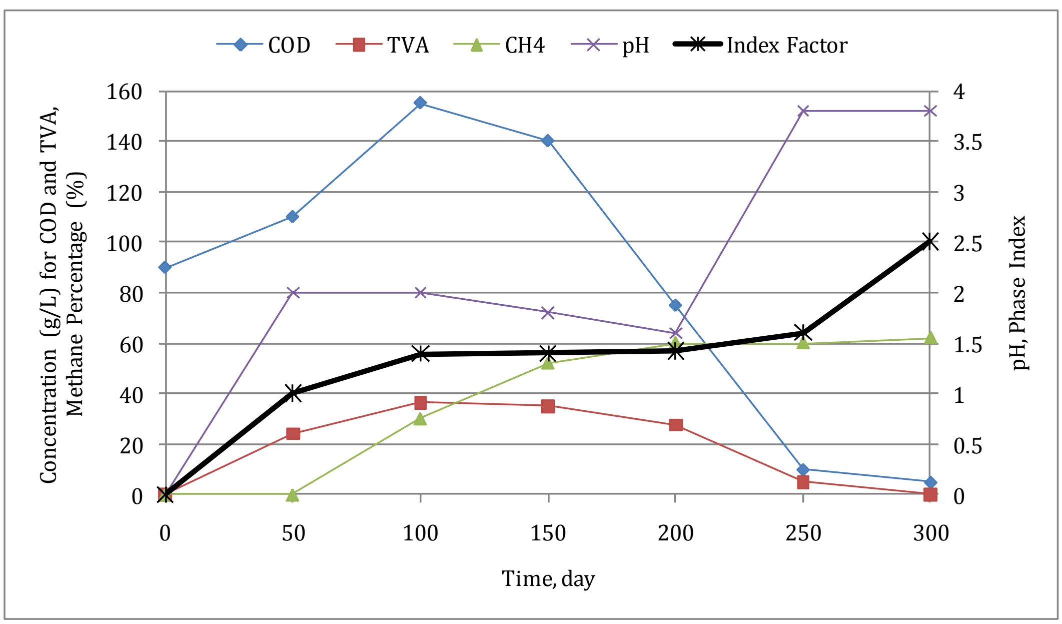
Figure 5-3 Response surfaces for two pairs of input variables: 1. COD and ORP (left), and 2. TVA and pH (right)

5.2.4. Model Validation

The *Phase Calculator* was verified using data compiled from two previous studies in the literature. It should be noted that due to the lack of studies reporting the five input parameters selected for the *Phase Calculator*, the model was modified by removing ORP from its structure. Two studies, Sanphoti *et al.* (2006) and Bae *et al.* (1998), were subsequently used for model validation of the *Phase Calculator*. Figures 5-4 show the input variables as well as the computed Phase Index from the simulation conduced for both experiments. The results showed a reasonable progressive trend for the Phase Index, with a different evolution between the two studies. It is also clear that while consideration of multiple inputs will provide a much more accurate determination of the operational phase, if left to human interpretation, the exercise becomes very complicated and inaccurate as seen by the complexity of the experimental data in Figure 5-4. However, the *Phase Calculator* was able to evaluate the phase condition and identify the transition regions between phases based on multiple input parameters. The *Phase Calculator* model indicated that the BL in Sanphoti *et al.* (2006) evolved from the transition phase to the acidogenic phase in the period between day 30 and day 170 after which it started transitioning to the methanogenic phase. On the other hand, the same evolution took about 220 days in Bae *et al.* (1998). At the end of the examined periods, the Phase Index reached its maximum at 2.48 for Bae *et al.* (1998) and 2.59 for Sanphoti *et al.* (2006). Overall, this validation shows that FL can be an effective tool in solving the multi-parameter nonlinear problem of determining the current operational phase of a BL.



a)



b)

Figure 5-4 Progress of input parameters and phase index with time for a) Sanphoti *et al.* (2006), and b) Bae *et al.* (1998) [* zero point of the pH scale = pH 4]

5.2.5. Conclusions

A FLC was developed to identify the operational phase of a BL at any given time based on up to 5 quantifiable parameters of the leachate generated and biogas produced. The output phase index is expressed as a real number that shows the exact transitional phase of the BL. This feature offers a great advantage because the in-situ growth requirements for the bacterial population inside the BL can be easily interpolated. As a result, safe and smooth transition from one operational phase to another can be achieved.

5.3. Determination of Toxicological Status

The *Toxicity Indicator* FLC was also developed to evaluate the toxicological status of the leachate produced from a BL based on certain parameters that directly contribute to or indirectly indicates toxicity. The main objective of this controller is to make a decision about the suitability of the leachate, in terms of its toxicological condition, for recirculation to the BL. In SMART, dilution of the recirculated leachate is the adapted strategy for the remediation of leachate toxicity. Therefore, the *Toxicity Indicator* determines the dilution required for leachate recirculated so as to prevent introducing inhibitory constituents to BL.

5.3.1. Problem Identification

Leachate has been reported to contain a wide range of toxic organic compounds, such as aliphatic and aromatic hydrocarbons, as well as inorganic compounds such as heavy metals (Lisk, 1991). Typically, the concentrations of pollutants in leachate vary significantly with time causing leachate to be, sometimes, not suitable for direct recirculation. Alternatively, researchers replaced young leachate with mature leachate for recirculation either throughout the operation (Jianguo *et al.*, 2007; Filipkowska, 2008; Benbelkacem *et al.*, 2010), or during the early operational phases (Erses and Onay, 2003). Furthermore, adding supplemental water to BLs had been a common practice in BL studies as simulated rain (San and Onay, 2001; Sponza and Agdag, 2004). However, with the new top liner regulations, the penetration of rain water in new landfills becomes minimal, and introducing water to the landfill is to be practiced on purpose. Sanphoti *et al.* (2006) demonstrated that the addition of supplemental water to the recirculated leachate in early operational phases promotes dilution of inhibitory substances and reduces leachate strength resulting in favourable conditions for methanogens. However, these researchers examined the addition of a constant volume of supplemental water that was not based on any measured system parameter. Alternatively in SMART, process monitoring plays a major role in determining the control actions of leachate manipulation and recirculation processes to further optimize methane generation. Therefore, it was suggested that supplemental water should be added in response to the toxicological status of the leachate.

5.3.2. Rational of Input Selection

The primary inhibitors, incorporated in the *Toxicity Indicator*, included the free unionized fraction of ammonia (UAN), free undissociated volatile fatty acids (UVFA), and the alkali cation (CAT) used in the buffer (e.g., Na^+ if the buffer salt is $NaHCO_3$). In addition, ammonium ion itself (TAN) can be inhibitory beyond concentrations exceeding toxicity threshold levels of the anaerobic microbial consortia, and may cause substrate toxicity (McCarty, 1964). Also, high concentrations of VFAs, which are vital metabolic intermediates in anaerobic biodegradation, are indicative of disequilibrium in the anaerobic degradation chain, and may result in an organic shock. Therefore, both VFA and TAN are also considered as inhibitors of concern and are incorporated in the *Toxicity Indicator*.

5.3.3. Model Development

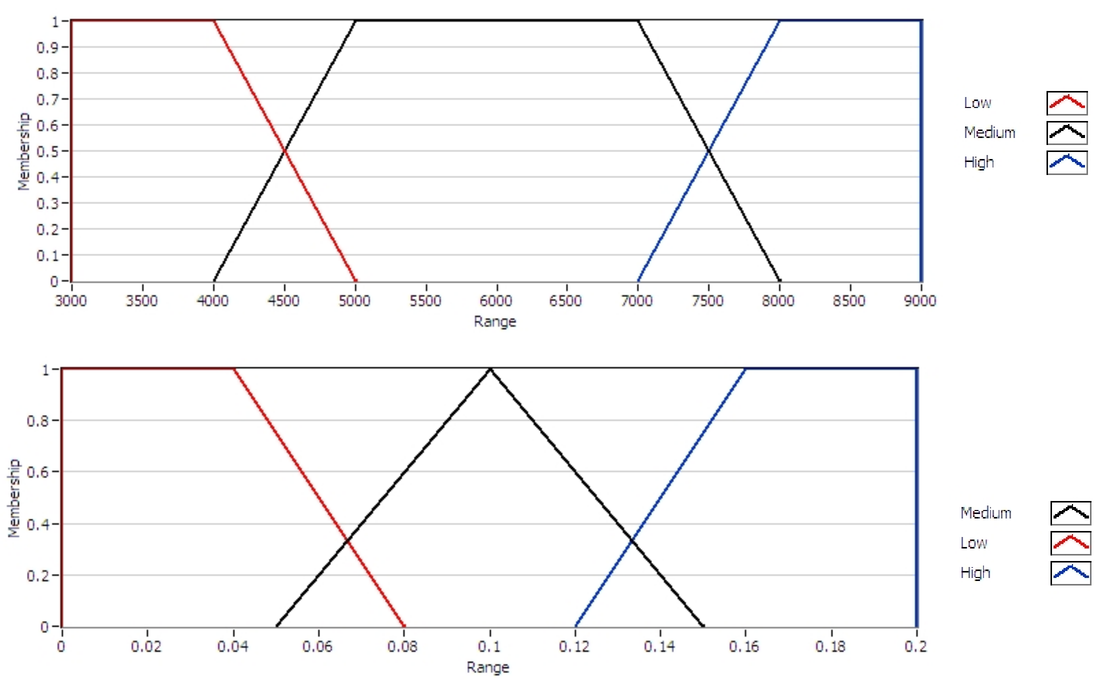
The *Toxicity Indicator* was designed according to a static MISO structure using the PID and Fuzzy Logic Toolkit in LabVIEW™. The input variables include the leachate's UAN, UVFA, CAT, VFA, and TAN, while the single output generated is a leachate/water dilution factor (*D*) which is used in MC-3 to determine the volume of supplemental water to be added. The knowledge-base on which the fuzzy rules of *Toxicity Indicator* were formulated is presented in Table 5-2. The table divides the effect level of the selected inhibitors into: stimulatory, with no adverse effect, and inhibitory.

In the *Toxicity Indicator*, the fuzzy sets of inputs and output were defined by trapezoidal and triangular MFs. Figure 5-5 shows the MFs defined for a sample input (TAN) and the single output (Dilution Factor). The linguistic labels used to describe the model variables are *low*, *medium*, and *high*.

Table 5-2 Stimulatory and inhibitory concentrations of the potential inhibitors of anaerobic processes*

Potential Inhibitors	Effect Level			Comments
	Stimulatory	No adverse	Inhibitory	
UVFA (mg-AA/L)	–	–	1,000 – 2,000 [1]	Propionic acid is more toxic than acetic acid [1]
TAN (mg-N/L)	50 – 200 [4]	200 – 1,000 [4]	1,900 – 2,000 [2] 1,500 [3] 3,000 [4]	5,000 – 8,000 can be tolerated at low pH [1] 1,500 – 3,000 can be inhibitory at high pH [4]
UAN (mg-N/L)	–	–	100 – 200 [1] 50 [3]	–
CAT (mg/L)	100 – 400 [3] 100 – 200 [4]	–	1,500 [3] 3,500 – 5,500 [4]	strongly inhibitory at 8,000 [4]

** [1]: Henze and Harremoes (1982), [2]: Koster (1986), [3]: Gerardi (2003), and [4]: McCarthy (1964).*



a)

b)

Figure 5-5 Membership functions for: a) TAN, and b) dilution factor

In the present model, seven fuzzy rules were formulated to define the required dilution factor based on different quantifiable inhibitors. The probabilistic-type of the OR operator as well as the minimum-type of the AND operator were applied in the created rules. The following is an example of the developed rule base statements:

$$IF\ '\mathbf{TAN}'\ is\ 'low'\ \ AND\ '\mathbf{UAN}'\ is\ 'high'\ THEN\ '\mathbf{DilutionFactor}'\ is\ 'high'$$

The complete fuzzy rules and membership functions defined in the *Toxicity Indicator* are presented in Appendix B. The defuzzification method used is the *Center of Gravity* of the resultant area after implication. Figures 5-6 show the response of the output variable ‘Dilution Factor’ to changes in two pairs of the input variables, namely TAN and UAN as well as VFA and CAT.

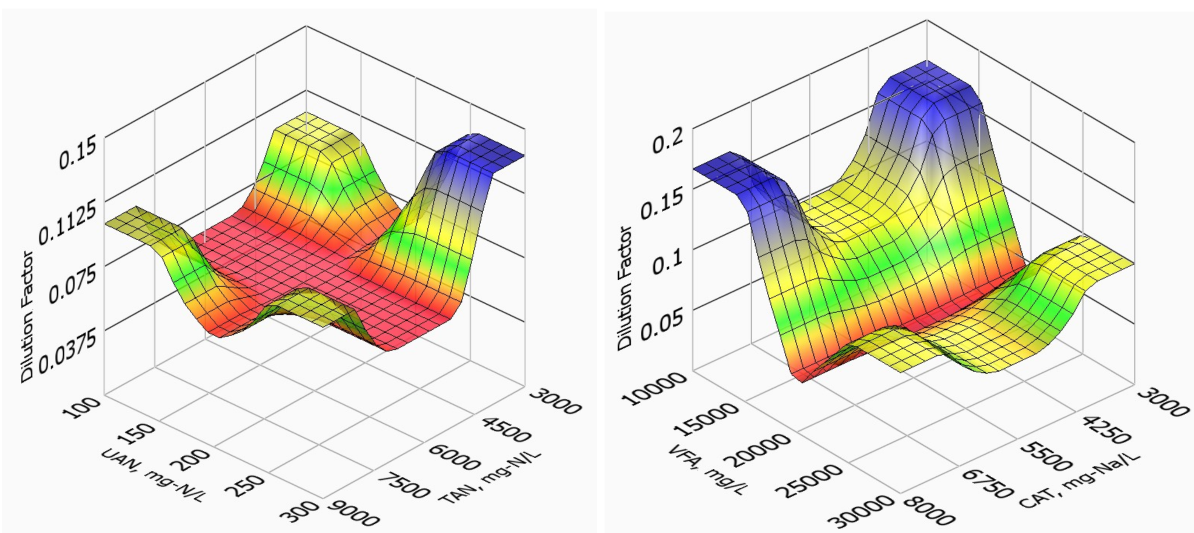


Figure 5-6 Response surfaces for two pairs of input variables: 1. TAN and UAN (left), and 2. VFA and CAT (right)

5.3.4. Conclusions

A FLC was developed to determine the dilution required for leachate recirculated in order not to introduce inhibitory constituents to the BL ecosystem. The controller utilizes certain leachate chemical parameters that directly contribute to or indirectly indicates toxicity.

5.4. Modeling Methane Production

As part of the feedback control scheme of SMART, a FL model was developed to simulate and predict the methane production in a BL at a given operational phase based on key operational parameters, namely leachate recirculation and sludge addition. The knowledge-based FL model was typically developed by describing the process qualitatively, and then was manually calibrated. Alternatively, the learning algorithm of artificial neural networks (ANN) was employed to adjust the FL model parameters, resulting in a hybrid neuro-fuzzy (ANN-FL) model. The developed models, FL and ANN-FL, were thoroughly evaluated and compared based on multiple statistical indices.

5.4.1. Problem Identification

An accurate landfill gas generation model is very helpful as it can be used to: (1) design gas recovery systems, (2) analyze economic viability of gas recovery projects, (3) evaluate biogas productivity, (4) detect deficiencies in the biogas generation process, and (5) assess potential environmental impacts and landfill gas explosion hazards. In the last few decades, biogas generation in landfills was modeled using several techniques that focused mainly on describing the physical, chemical and biological processes within the system. Various mechanistic mathematical models were developed to simulate landfill gas production such as in Peer *et al.* (1992), El-Fadel *et al.* (1996), and White *el al.* (2004). Thus far, most of these models are practically inapplicable as they are complicated and require extensive data inputs. Furthermore, the heterogeneity in waste characteristics as well as the complex processes taking place within the landfill add difficulty in assessing the individual and coupled effect of various parameters in the system. Alternatively, unconventional modeling techniques were applied such as: stochastic modeling (Copty *et al.*, 2004; Zacharof and Butler, 2004), neural networks (Ozkaya *et al.*, 2007; Ozcan *et al.*, 2006), and fuzzy logic systems (Garg *et al.*, 2007). In the later study, an index for potential gas production from a landfill was generated based on several climatological, geological, and landfill parameters. However, their developed model was only able to estimate the total gas production, but not the progressive trend for biogas generation which is of a great importance to gas recovery projects, and real-time decision making control systems such as SMART.

5.4.2. Rationale of Input Selection

The biogas generation from waste biodegradation in BLs is highly affected by specific environmental conditions, such as moisture and temperature. Other factors that affect waste biodegradation include climate-related conditions, site-specific settings, and waste characteristics. However, moisture content remains the main factor that affects the decomposition processes and consequently the biogas production. Leachate recirculation is considered the principal operational practice in BLs, and has been proven repeatedly to stimulate the microbial activity in BLs by providing adequate moisture levels (Reinhart and Townsend, 1998). Therefore, leachate recirculation is employed as the main process parameter (input variable) in the models developed in this work together with the BL operational phase with which the biogas quantity and quality are highly connected. Also, anaerobic sludge addition is included in the input variables since it has a direct effect on the methane generation process. Sludge addition enriches the inventory of anaerobic microorganisms in the BL, and serves as a source of alkalinity and nutrients.

5.4.3. Experimental Datasets

The datasets used for model development were compiled from lab-scale experiments that involved various operating scenarios. Table 5-3 summarizes the main characteristics and operational conditions of the compiled experimental datasets. Datasets from Rendra (2007) were divided into two groups: (1) datasets (A1, A2, and A3) which were used to formulate the fuzzy rules, calibrate the FL-model, and train the hybrid FL-ANN model; and (2) datasets (B1 and B2) which were additional data from the same experiment, used to validate the models. Also, external experimental studies (C1, C2, and C3) were compiled to validate model predictions against actual observations. It should be noted that the first group of experiments (A1, A2, and A3) is hereafter named the *development dataset*. The main characteristics of the compiled studies are presented in Appendix A.

Table 5-3 Main features and operating conditions of the compiled experimental studies*

Study	Dataset notation	Dataset usage	Sludge Addition l/kg/d	Recirculation rate, %/d
Rendra (2007)	A1	Calibration of FL-model and training ANFIS-model	0.5	11.2
	A2		0.5	31.6
	A3		1	22.4
	B1	Internal validation within the same experiment	1.5	13.3
	B2		1.5	33.7
Chugh *et al.* (1998)	C1	Validation with external experiment	N/A	30
Sanphoti *et al.* (2006)	C2		N/A	5-12
Bae *et al.* (1998)	C3		0.25-1.1	0.1-1.8

* *In Rendra (2007), bioreactors ANA-1, ANA-2, ANA-5, ANA-3, and ANA-4 were used in datasets A1, A2, A3, B1, and B2, respectively. In Chugh et al. (1998), experimental data was compiled from the bioreactor running at 30% recirculation ratio. Reactors (R1) and (L-Sludge) were used from Sanphoti et al. (2006) and Bae et al. (1998), respectively.*

5.4.4. Development of Fuzzy Logic Model

A static FLC was developed to model the methane production in BLs. As shown in the architecture in Figure 5-7, the inputs included *time* (or operational phase), *sludge addition*, and *leachate recirculation* rate. The *time* variable is normalized by dividing the raw input time (t) by total lifetime (T), where T is the time until waste is stabilized, i.e., low organic matter in leachate and/or minimal biogas production. The *Lag time factor* is incorporated to account for the time required by the bacterial population to adapt to the new growth environment, and is equal to (λ/T), where λ is the lag phase time. It should be noted that lag time is more significant in lab-scale applications where the waste is homogeneous and loaded all at once. In contrast, in full-scale application, the waste is placed in lifts throughout a long period and the gas collection system is installed after a relatively long period of operation, during which landfill gas is already being produced. The *Potential production factor* incorporates site-specific parameters (such as recirculation patterns and distribution networks) which may affect the potential gas production from a landfill.

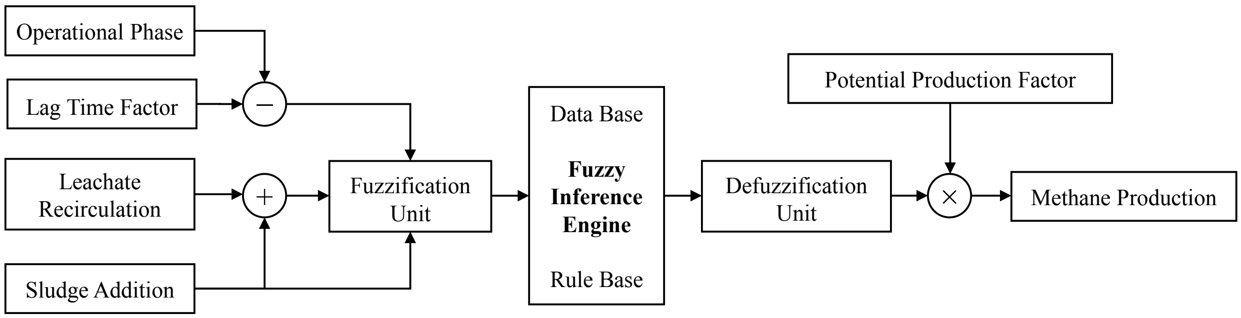


Figure 5-7 Modified structure of the fuzzy logic controller in the FL model

In order to generalize the model, *leachate* volume is normalized with respect to the volume of the waste matrix (as percentage of waste volume per day, %/d). Additionally, the liquid fraction of *sludge* is added to the *leachate* volume (as %/d), while the mass of *sludge* is introduced to the model separately (as litres per mass of waste per day, l/kg/d). Figures 5-8 show the MFs defined for the three inputs and single output of the FL model. The linguistic labels used to describe the input rates are *low rate* (LR), *medium rate* (MR), and *high rate* (HR). Time (or operational phase) was defined by the five main phases that typically characterize the BL lifespan; *initial* (I), *transition* (T), *acid formation* (AF), *methane generation* (MG), and *final maturation* (FM). Being the longest operational phase in a microbiologically active landfill, the MG phase was further divided into three sub-phases: *accelerating* (AMG), *constant* (CMG), and *decelerating* (DMG).

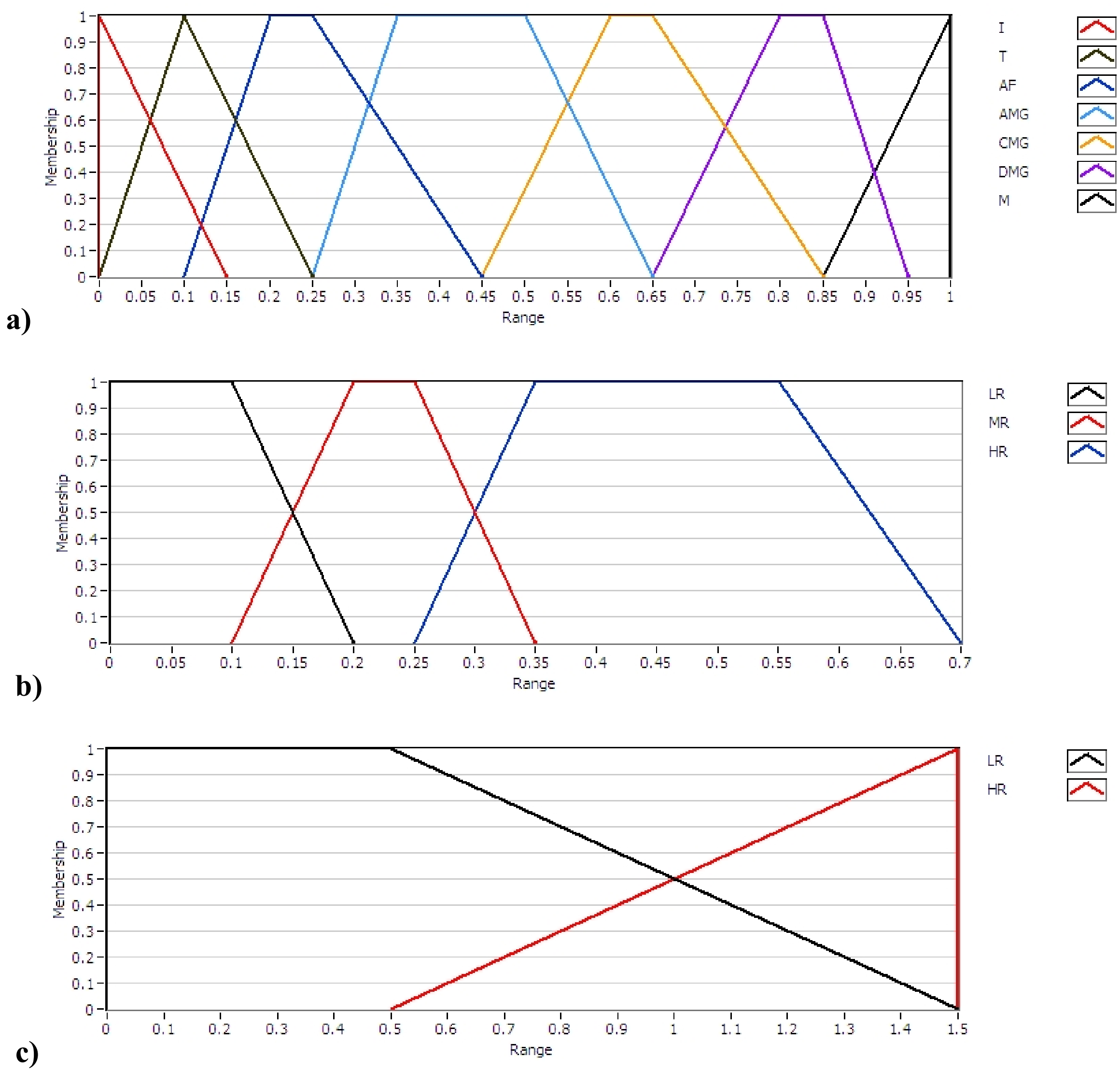


Figure 5-8 Membership functions defined for the input variables of FL model: a) time, b) leachate recirculation rate, and c) sludge addition rate

5.4.4.1. Fuzzy Inference System

A group of 21 fuzzy rules was created to describe the methane generation trend under various operating conditions. Table 5-4 shows the formulated fuzzy rules in the FL model. The defuzzification method used in this model was the *Center of Gravity* method. The FL model was developed using the Fuzzy Logic Toolbox 2.0 in MATLAB™ R2009b, and the simulation was designed and run at discrete variable steps using Simulink™.

Table 5-4 Fuzzy rules defined for the FL-model *

Time	Leachate Recirculation, Sludge Addition		
	LR, LR	LR, HR	MR, MR
I	XL	XL	XL
T	VL	L	VL
AF	L	M	VH
AMG	M	H	H
CMG	VH	M	M
DMG	H	L	L
FM	M	L	VL

** The rules read such that for the first cell: "IF **time** is I and **leachate recirculation** is LR and **sludge addition** is LR THEN **methane generation** is XL", where I, LR, and XL stand for initial, low rate, and extra low, respectively.*

5.4.5. Development of Neuro-Fuzzy Model

The implementation of ANN as a learning technique in FL systems is referred to as ANFIS (Adaptive Neuro-Fuzzy Inference System). In ANFIS, the learning algorithm of ANN is employed to optimize the parameters of a FL model. Hence, the merits of both systems could be merged, and the limitations of both systems, such as the black box behaviour of ANN and the tuning of FL model parameters, could be avoided (Jang, 1993). ANFIS optimizes the parameters associated with the FL membership functions throughout a learning process. The computation of these parameters (or their adjustment) is facilitated by a gradient vector which provides a measure of the adequacy of the inference system in modeling the input/output data. The gradient vector is optimized by any of a number of multiple optimization routines which tune the parameters so that the error between actual and simulated outputs is minimized (Jang and Gulley, 1995). ANFIS is starting to gain significant attention in modeling complex systems; however, its application in modeling biological systems is still limited (Yordanova, *et al.*, 2005; Cakmakci, 2007).

5.4.5.1. ANFIS Inference System

The ANFIS model applies the Takagi-Sugeno method for the fuzzy inference system. This method is similar to the widely used Mamdani method in many aspects, especially the fuzzification of inputs and applying the fuzzy operator. However, the Takagi-Sugeno output MFs can only be either linear or constant. The Takagi-Sugeno system is compatible with adaptive techniques, such as ANN, being more compact and computationally efficient than the Mamdani system. The developed ANFIS model is comprised of three input variables (time, leachate recirculation, and sludge addition), 13 input MFs, 63 output MFs, and 63 fuzzy rules. The *Weighted Average* method was used for defuzzification, and is obtained by weighing the average of each output of the set of fuzzy rules. This method is computationally faster, easier, and gives fairly accurate results. The output is computed as;

$$O = \sum_{i=1}^{n} \mu^{i} w_i \Big/ \sum_{i=1}^{n} \mu^{i} \tag{5-3}$$

Where O is the defuzzified output, μ^{i} is the membership of the output of each rule, and w_i is the weight associated with each rule.

Figure 5-9 shows the complete structure of the ANFIS model as generated by MATLAB. To discuss the computations made in ANFIS, the architecture is simplified in Figure 5-10.

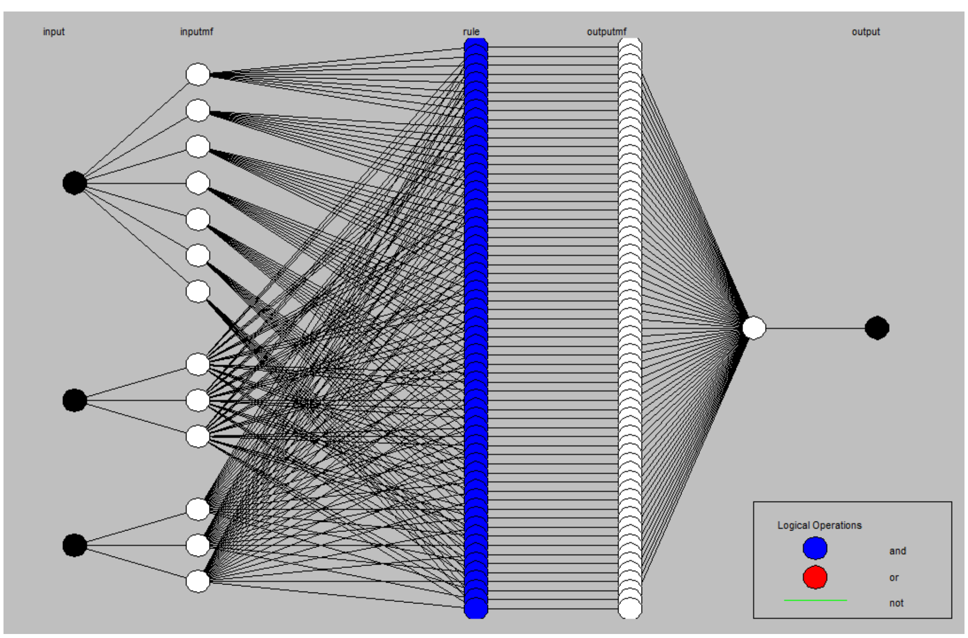


Figure 5-9 Complete structure of ANFIS model

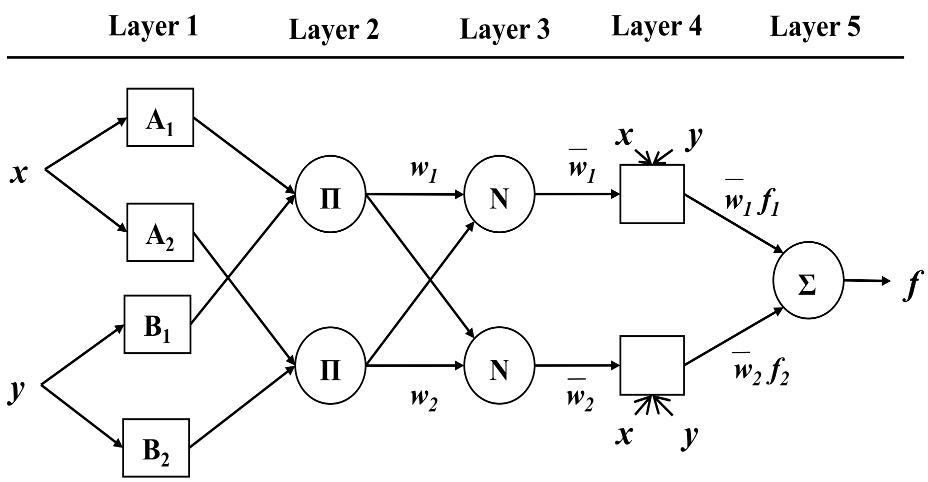


Figure 5-10 Simplified architecture of ANFIS

In Figure 5-10, there are two inputs (x) and (y), and a single output (f). The rule base contains two fuzzy rules of the Takagi-Sugeno type:

Rule 1: If x is A_1 and y is B_1, THEN $f_1 = p_1 \cdot x + q_1 \cdot y + r_1$

Rule 2: If x is A_2 and y is B_2, THEN $f_2 = p_2 \cdot x + q_2 \cdot y + r_2$

Based on the methodology of Jang (1993), the architecture includes five layers:

Layer 1: Every node in this layer is an adaptive node with a node function that can be computed as:

$$O_i^1 = \mu_{Ai}(x) \tag{5-4}$$

Where x is the input to node i, and A_i is the linguistic label set associated with this node.

Layer 2: Every node in this layer is a fixed node, labeled (Π), that represents the firing strength (w) of a fuzzy rule. The output of each node is the product of the incoming signals:

$$O_i^2 = w_i = \mu_{Ai}(x) \cdot \mu_{Bi}(y) \quad ,i=1,2 \tag{5-5}$$

Layer 3: Every node in this layer is a fixed node (N) which calculates the ratio between the firing strength of each rule and the sum of firing strengths of all rules. The outputs of this layer are called normalized firing strengths and can be computed as:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad ,i=1,2 \tag{5-6}$$

Layer 4: Every node in this layer is an adaptive node with a node function (i.e., linear combination of input variables). If $\{p_i, q_i, r_i\}$ is the parameter set, then:

$$O_i^4 = \overline{w_i} \cdot f_i = \overline{w_i}(p_i x + q_i y + r_i) \tag{5-7}$$

Layer 5: The single node in this layer is a fixed node that computes the overall output as the summation of all incoming signals:

$$O_i^5 = \sum_i \overline{w_i} \cdot f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5-8}$$

5.4.5.2. Implementation of ANFIS Model

The ANFIS model was implemented using the ANFIS Editor in the Fuzzy Logic Toolbox 2.0 of MATLAB™ R2009b. Certain conditions restrain the implementation of ANFIS including: (1) inference system must be Takagi-Sugeno type, (2) modeled system must have a single output obtained using the *weighted average* defuzzification technique, (3) all output membership functions must be of the same type (either *linear* or *constant*), and (4) there should be no rule sharing or weighing. The optimization method used in the ANFIS model to adjust the parameters to reduce error is *back propagation*, and the output membership function type was *linear*. The initial FL structure was generated based on *grid partitioning* of the training datasets at a maximum of 10 training epochs (iterations).

The flowchart of the training algorithm of ANFIS is shown in Figure 5-11. The process starts by loading the training and checking datasets, including inputs/output data vectors. Each vector contained three inputs (time, sludge addition, and leachate recirculation) and one output (methane generation). An error tolerance (ET) value is defined for the maximum acceptable difference between the actual and simulated output. The model starts the training process with the initial parameters of the membership functions, and the error for each data pair is calculated. If this error is larger than the ET value, the membership parameters are adjusted through an optimization step, otherwise, the process ends. Simultaneously, the error of the checking dataset, which typically decreases to a certain point and then increases, is calculated. This overturn represents the point of model over-fitting. The program chooses the model parameters associated with the minimum checking error. In the present ANFIS model, the training process was terminated when a 10% error between simulations and actual data was reached.

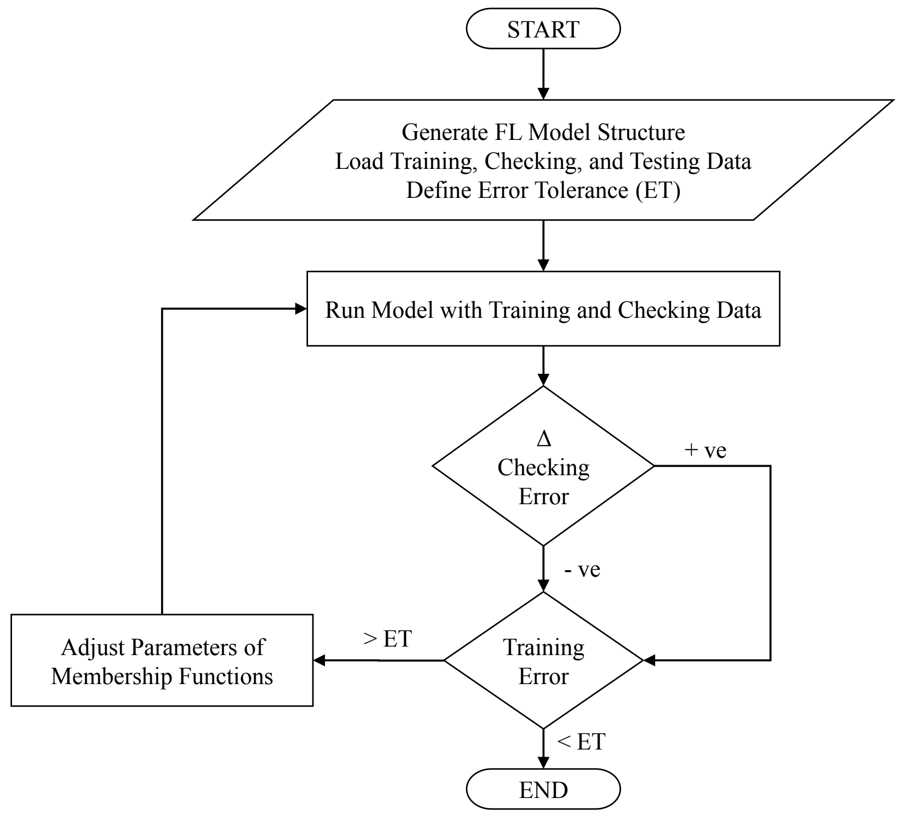


Figure 5-11 Flowchart for the learning algorithm of ANFIS

5.4.6. Results and Discussion

5.4.6.1. Model Verification

The developed FL and ANFIS models are verified by fitting adequacy of their predictions to the *development dataset* on which they were based, i.e., used in creating the fuzzy rules, calibrating the membership functions in FL model, and training the ANFIS model. The progress of the predicted versus observed methane production rates is plotted for the BL cells of (A1, A2, and A3) in Figures 5-12 (a, b. and c), respectively. The general pattern of methane production in the three cells followed the typical trend; starting with an increasing rate to a peak value, followed by a declining phase. As shown in Figures 5-12, the actual production trend was largely reproduced by the predictions of the FL model, given the fact that the model was calibrated on these datasets. The FL model overestimated the generation rates in experiments A1 and A2, but agreed excellently with the observed data in A3. The differences between observed and predicted daily production rates were approximately 0.5 % of total production per kg of waste on average.

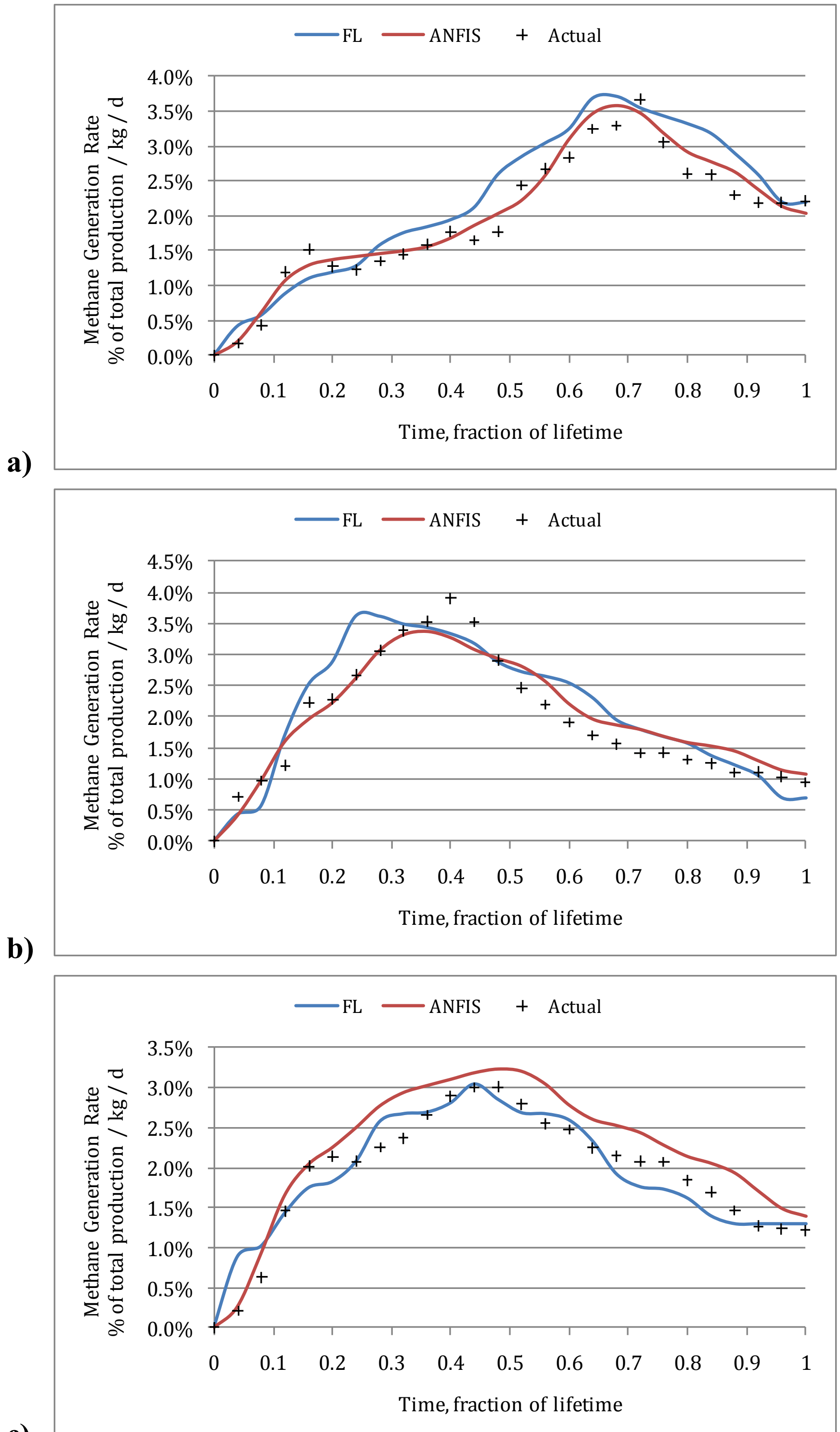


Figure 5-12 Modeled and actual methane generation of FL-model and ANFIS-model for datasets: (a) A1, (b) A2, and (c) A3

The simulations of ANFIS reproduced the experimental data slightly better than FL due to the fact that the model was trained on this data. It should be noted that the developed ANFIS model was first trained on data for 100 training epochs (iterations) resulting in an identical reproduction of the observed data. However, the ANFIS model also reproduced the noise in the experimental data which occur due to measuring inaccuracy and/or operating problems. This means that the ANFIS system works well only if the data used for training its membership function parameters is of high quality and fully representative of the features of the modeled system. In practice, the measured data usually suffers from various sources of noise which may result in model distortion. Such situations can be observed during the validation of the model, and can be minimized by: (1) using replicated training data, and (2) optimizing the number of training epochs in order to avoid *over-training* of the model. The *over-training* issue, which related to ANFIS training algorithms, is discussed thoroughly in Appendix C. Based on the above findings, the number of training epochs for the present ANFIS model was reduced to a maximum of 10 epochs, resulting in a better overall quality and smoothness of model predictions, as shown in Figures 5-12.

5.4.6.2. Model Validation

Once trained and calibrated, the models were validated in order to examine their applicability under a wider range of operational conditions. The models were validated using new datasets from the *basic experiment* used in their development (B1 and B2) as well as external datasets (C1, C2, and C3). The validation datasets were selected so as to be representative of the data on which the models were based, yet sufficiently distinct from it, otherwise the validation process becomes meaningless. As shown previously in Table 5-3, the external validation datasets were selected to strongly test both models; experiment (C1) had a constant recirculation rate of leachate with no sludge addition, experiment (C2) was conducted at variable recirculation rates of leachate (unlike the *development datasets*) with no sludge addition, and experiment (C3) had variable rates of leachate recirculation and sludge addition, both extending to ranges that were not considered in the models' inference systems. The rates of leachate and sludge additions in the validation experiments were introduced as a function of time to the developed FL and ANFIS models, and the output methane generation rates are plotted against the actual datasets in Figures 5-13 and 5-14.

a)

b)

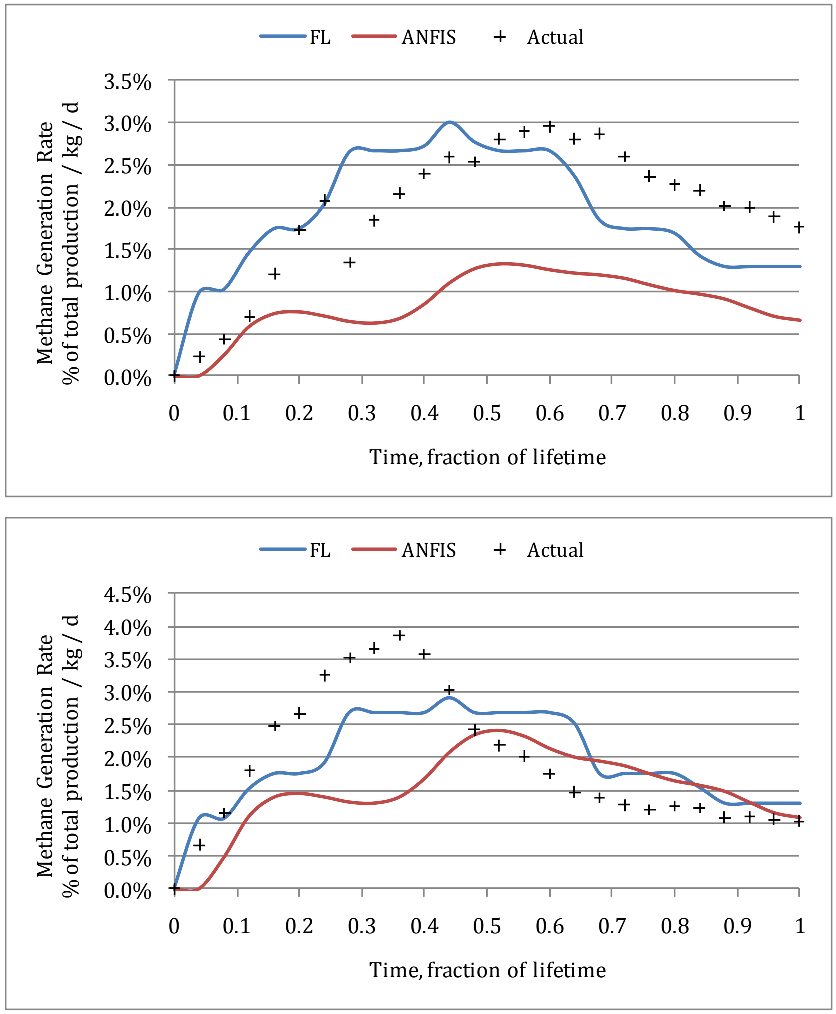


Figure 5-13 Modeled and actual methane generation of FL-model and ANFIS-model for datasets (a) B1, and (b) B2

In experiments (B1) and (B2), the rate at which sludge was added was higher than the maximum introduced in the model calibration data. Since these rates were not expressed in the fuzzy rules, the FL model applied the maximum defined recycling rate scenario constantly during that experiment, i.e., the trend of experiment A3. This resulted in poor agreement in the first half-lifespan of cell B1, which improved in the second half, and also, an overall fair agreement with cell B2. However, the FL model accurately predicted the mean actual methane production in both experiments (mean of predictions was 98.5% the mean of actual production rates). On the other hand, the performance of ANFIS was not acceptable as it consistently and significantly underestimated the methane generation rates in the two experiments.

In the external validation datasets shown in Figures 5-14, the ANFIS model predicted the general production trend fairly well despite the fact that it underestimated the generation rate during most of the lifespan of C2 and C3. The simulations of the FL model were in much better agreement with the observed data compared to ANFIS.

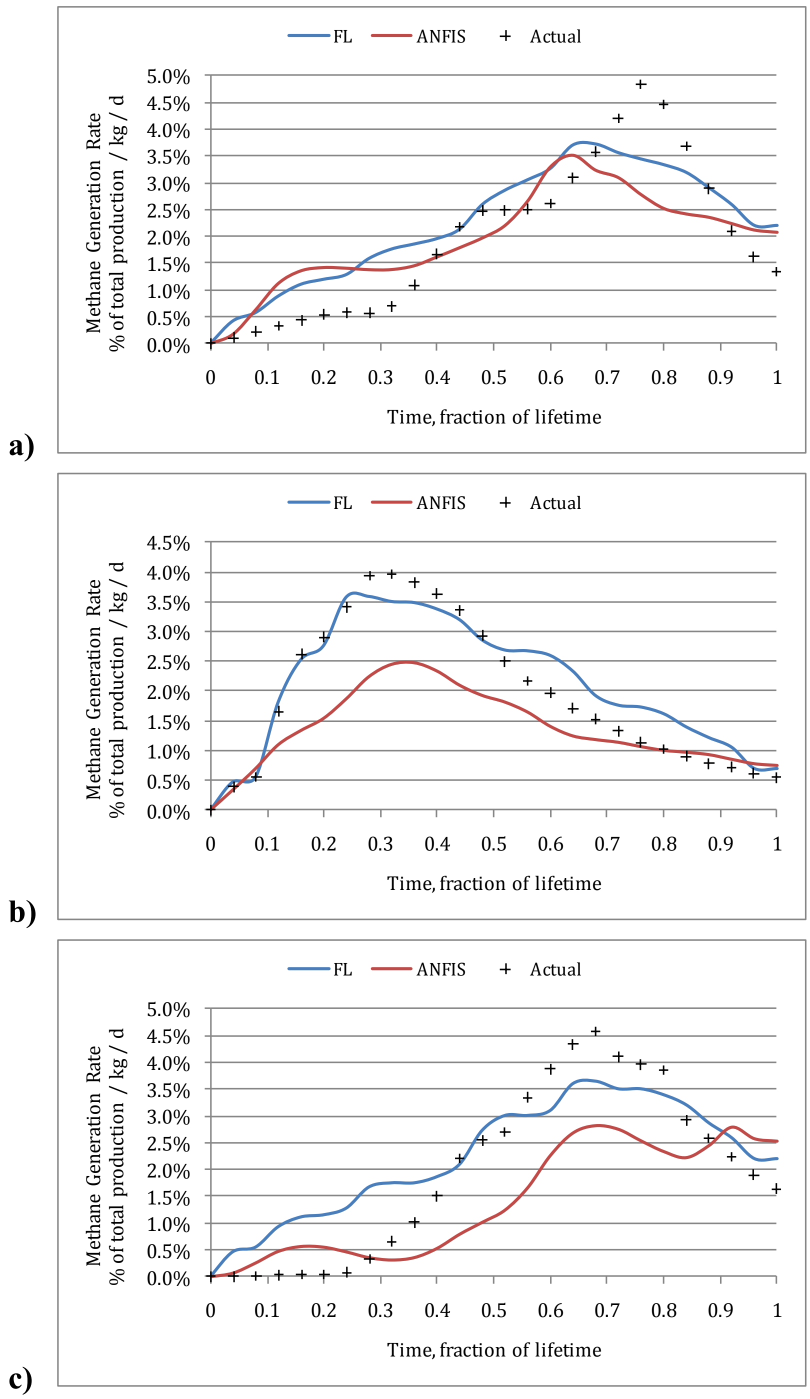


Figure 5-14 Modeled and actual methane generation of FL-model and ANFIS-model for datasets (a) C1, (b) C2, and (c) C3

It is clear from Figures 5-14 that the FL model responded well to the variable recirculation rates introduced in C2 and C3. On the other hand, the ANFIS model continued to be highly affected by the type of data used in its training; ANFIS performed well in experiment C1 (where recirculation rate was constant), while it poorly reacted to the variable recirculation rates in C2 and C3. Moreover, ANFIS unpredictably generated small peaks at the beginning and end of the lifespan of C3.

5.4.6.3. Statistical Analysis

In order to quantify model performance, predicted and observed data were evaluated with a group of statistical measures including: correlation coefficient (R), coefficient of determination (R^2), mean bias error (MBE), mean absolute error (MAE), percentage error (PE), fractional bias (FB), mean squared error (MSE), normalized mean squared error (NMSE), root mean squared error (RMSE), systematic root mean squared error ($RMSE_S$), unsystematic root mean squared error ($RMSE_U$), index of agreement (IA), as well as the intercept (a) and slope (b) of the regression line between observed and predicted data. The calculations and interpretation of these indices are presented in Appendix D, and the results are shown in Table 5-5.

From an overall view of the highlighted data in Table 5-5, it is statistically evident that ANFIS performed better in predicting methane generation in the *development datasets*, while FL was better in predicting the validation experiments. The predictions of the FL and ANFIS models achieved high correlation with the *development datasets* (R=0.95 and 0.98 on average, respectively). ANFIS model achieved a slightly better performance in datasets (A1) and (A2) in terms of all statistical indices compared to the FL model which performed a little better in dataset A3, as shown by the majority of statistical measures.

Table 5-5 Statistical indices of the FL-model and the ANFIS-model for the experimental datasets

Dataset	a	b	R	R^2	MBE	MAE	PE	FB	MSE	NMSE	RMSE	$RMSE_S$	$RMSE_U$	IA
A1	0.00043	1.10817	0.96527	0.93175	0.00254	0.00325	0.46903	0.122058	1.5E-05	0.00097	0.00389	0.00273	0.002775	0.961916
	0.00032	1.01912	0.98388	0.96802	0.0007	0.00163	0.31276	0.035074	3.5E-06	0.00027	0.00186	0.00072	0.001714	0.990207
A2	0.00141	1.01274	0.93741	0.87873	0.00166	0.00343	0.44914	0.082898	1.7E-05	0.00118	0.0041	0.00166	0.003746	0.960016
	0.00341	0.863	0.9661	0.93336	0.00078	0.00229	0.37782	0.040057	7.7E-06	0.00062	0.00278	0.00157	0.002296	0.977879
A3	0.00198	0.89253	0.95223	0.90674	-8E-05	0.00184	0.46934	-0.00415	5.8E-06	0.00053	0.00241	0.00085	0.002251	0.974612
	0.00162	1.06836	0.98685	0.97388	0.00292	0.00292	0.41065	0.141903	1.1E-05	0.00074	0.00328	0.00297	0.001376	0.961092
B1	0.00715	0.61299	0.69506	0.48311	-0.0004	0.00528	0.66904	-0.02039	3.8E-05	0.00347	0.00613	0.00321	0.005222	0.829673
	0.00034	0.41404	0.94234	0.888	-0.0111	0.01107	0.73835	-0.79393	0.00015	0.06761	0.01214	0.01208	0.001211	0.590962
B2	0.0088	0.53312	0.77422	0.59941	-0.0002	0.00549	0.53662	-0.01039	4.3E-05	0.004	0.00656	0.0048	0.004477	0.845041
	0.01075	0.21669	0.36102	0.13034	-0.0044	0.00801	0.61169	-0.25431	0.00012	0.0172	0.0108	0.00915	0.00575	0.587624
C1	0.0087	0.68975	0.92429	0.85432	0.0027	0.00557	0.81753	0.130322	4.3E-05	0.00278	0.00658	0.00518	0.004055	0.928696
	0.00908	0.5297	0.84559	0.71502	-2E-05	0.00649	0.79606	-0.00112	6.8E-05	0.00573	0.00822	0.0067	0.004761	0.864925
C2	0.00457	0.84236	0.96996	0.94082	0.00153	0.00298	0.4612	0.076413	1.3E-05	0.0009	0.00358	0.00247	0.002594	0.975446
	0.00389	0.50309	0.96497	0.93117	-0.0057	0.00637	0.51756	-0.34647	7.2E-05	0.01236	0.00851	0.00835	0.00168	0.814848
C3	0.00955	0.63984	0.9548	0.91164	0.00256	0.00597	3.37549	0.123456	4.8E-05	0.00314	0.00696	0.00622	0.003133	0.929075
	0.00336	0.55274	0.84167	0.7084	-0.0053	0.00866	1.96554	-0.31811	0.00011	0.01373	0.01044	0.00883	0.005578	0.841218

* the successful model is highlighted in each of the statistical indices. Where FL model is successful, its statistical index is highlighted in yellow, and where ANFIS is better, its index is highlighted in turquoise.

In the external validation datasets (C1, C2, and C3), the FL model simulations were in an excellent agreement with the actual data at (*R*) of 0.92, 0.97, and 0.95 and (*IA*) of 0.92, 0.98, and 0.93, respectively. In general, the descriptive statistical indices, shown in Table 5-5, revealed that the FL model produced smaller deviation and exhibited a superior predictive performance on forecasting methane production rates compared to ANFIS model. For example, in experiment (C3), an (R^2) coefficient of 0.91 indicated that only 8.9% of the total variations were not explained by the FL model in predicting methane production rates. On the other hand, in ANFIS model, about 29.2% of total variations did not fit the experimental data. In terms of the RMSE fractions, the FL model proved to be more accurate as its systematic errors were mostly smaller than unsystematic errors. On the other hand, ANFIS frequently produced systematic errors in its predictions, which indicates that the model itself or the training datasets need refinement.

As mentioned before, the validation datasets were selected to test the developed models under operational scenarios that were quite different from what they were calibrated to. Results showed that ANFIS did not yield satisfactory predictions of methane production rates in the validation datasets as good as the FL model. ANFIS continually and highly underestimated the validation experiments, and failed to estimate methane generation in untrained situations indicating the significant effect of the training datasets on the performance of ANFIS model. It should be noted that this critical issue is thoroughly discussed in Appendix C.

Figures 5-15 show the scatter plots of the linear regression between model predictions and observed data for all the compiled experimental datasets, with the (a), (b), and (R^2) coefficients shown on graphs. The plots indicated that the predictions of FL model were more accurate compared to ANFIS model, as shown by the slope of regression lines being closer to unity in the FL model. In contrast with ANFIS model, the FL model's simulation points were generally less scattered around the regression lines, which attests the higher precision of FL. It was also observed that the intercepts of regression lines of both models were always positive which shows that the models tended to underestimate the methane generation rates.

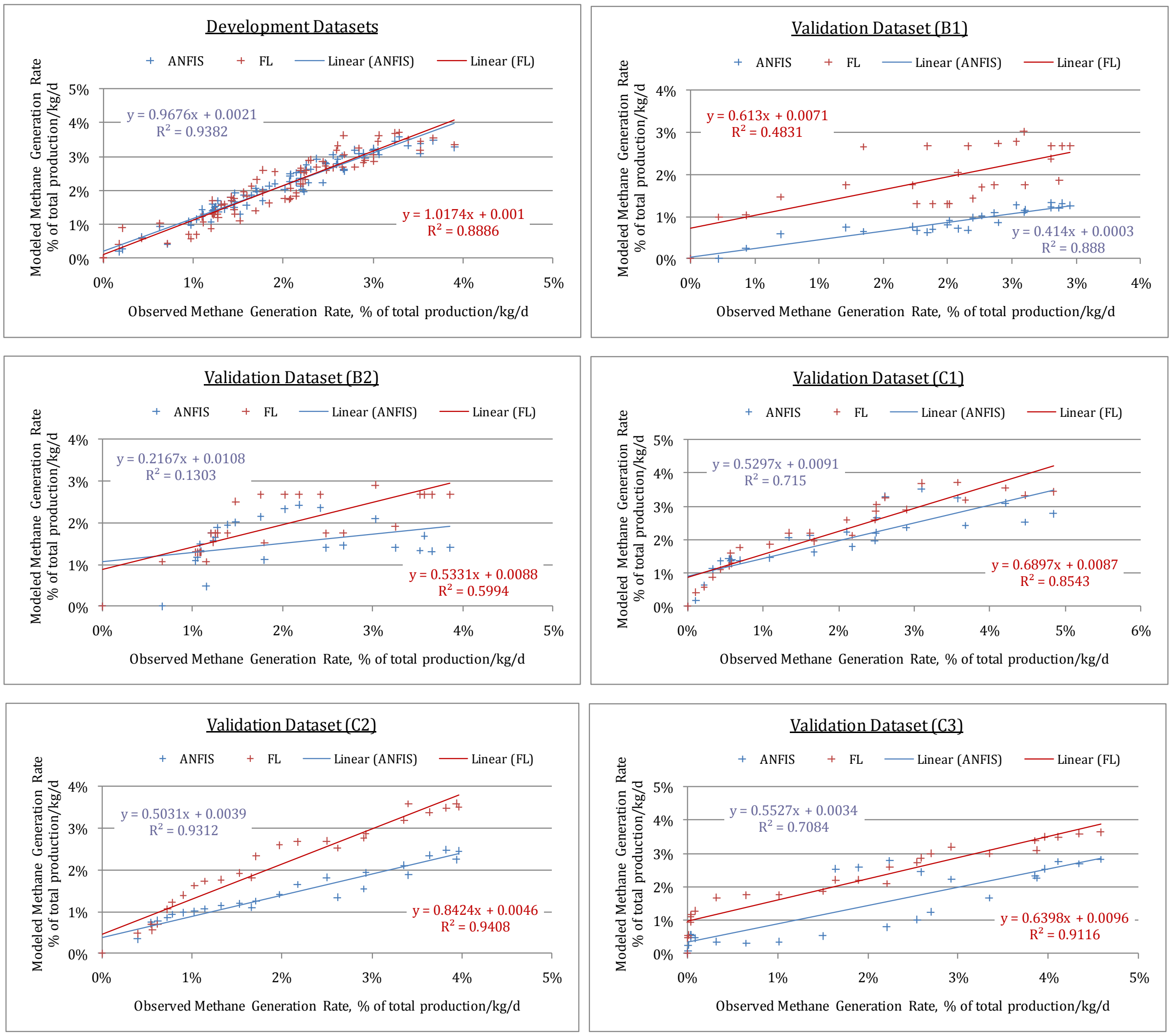


Figure 5-15 Linear regression between modeled and actual methane generation data for the compiled development and validation datasets

5.4.7. Conclusions

The main objective of the work presented in this chapter was to develop FL- and ANFIS-based models that predict the methane generation in a BL. Evaluation of the statistical indices and the external validation simulations indicated that the FL model was far more robust and flexible than the ANFIS model in simulation of experimental data outside of their calibration and training ranges. While ANFIS simulated its training datasets slightly more accurate than FL, it was unable to simulate conditions on which it was not trained. On the other hand, the FL model had a much better ability to simulate a variety of atypical operating scenarios, as evidenced by its response to the operational scenarios of the validation datasets.

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CHAPTER 6

APPLICATION, ASSESSMENT, AND IMPROVEMENT OF SMART

This chapter is a combination of the following publications:

1- *Abdallah, M., Warith, M., Petriu, E., Kennedy, K., Narbaitz, R. (2011)* ***Sensor-based Monitoring and Remote-control Technology (SMART) for bioreactor landfills: III) system application****. To be submitted to the Journal of Environmental Management.*

2- *Abdallah, M., Narbaitz, R., Warith, M., Kennedy, K. (2011)* ***Temperature control in bioreactor landfills****. Submitted to the Journal of Waste Management & Research.*

6.1. Abstract

The main objectives of this phase of the research were to: (1) design, build, and instrument a pilot-scale prototype BL, (2) develop and apply the software and hardware components of SMART on the prototype, (3) evaluate and study possible improvements of the SMART system, and (4) investigate the feasibility of temperature control. The experimental work was conducted on two BL setups over a 13-month period divided into two phases (I and II). Phase I extended from start-up until pseudo steady state methane production was achieved, and was targeting the evaluation and calibration/improvement of the system as well as the investigation of temperature control via recirculation of heated leachate. In phase II, an improved version of SMART was implemented in one cell, while a conventional open-loop control scheme was applied in the other (constant predefined rate of leachate recirculation). Throughout the monitoring period, the measured parameters included COD, VFA, TOC, TN, TA, pH, and ORP of the leachate, biogas production and composition, as well as waste temperature and moisture content. The present chapter begins with a thorough discussion of the materials and methods used to build, develop, and operate the prototype controlled by SMART, including: experimental configuration, instrumentation, software development, data processing, and communication. Then, the decision making process and control actions made by SMART are illustrated, and finally, the overall performance of SMART is assessed by studying its effect on the evolution of various system parameters throughout the operation period.

6.2. Rational of Temperature Control

The biodegradation rate of MSW is highly affected by temperature; the specific growth rate, decay, biomass yield, and microbial reaction kinetics are temperature dependant (Speece, 1996). The optimum temperatures for methane production in mesophilic MSW decomposition are in the 30 to 40˚C range (Barlaz *et al.*, 1990). Reduced gas generation rates are expected at temperatures below 20°C as a result of lower conversion rates of organic acids to methane and carbon dioxide (Tchobanoglous *et al.*, 1993). The specific effect of temperature on landfill ecosystems has not been widely studied compared to other parameters, such as moisture. This is probably due to the consensus that temperatures in the mesophilic range are typically attained in MSW landfills, especially in deep and well-insulated sites (Townsend *et al.*, 1996; McBean *et al.*, 2007). In the majority of lab-scale BL studies, experimental setups were operated in temperature-controlled environments where temperatures above 30˚C were maintained (see Appendix A). However, due to the fact that MSW decomposition rates increase with temperature, the reported results from those studies could be affected if the actual temperatures were lower than the optimum.

Bacterial populations within the landfill ecosystem are incapable of controlling their internal temperature (El-Fadel *et al.*, 1996), and therefore, microbial growth primarily depends on external air temperatures and operational conditions (Hanson *et al.*, 2010). Waste temperatures at shallow depths and near the landfill edges conform to seasonal air temperature variations, whereas elevated temperatures can be reached at deep and central zones (Yesiller *et al.*, 2005). Therefore, temperature control can be considered vital in landfill sites where optimal temperatures are unlikely to be achieved such as in cold regions, smaller/ shallower/ inadequately insulated landfills, and/or leachate recirculating sites in which introducing cold leachate to the landfill body is expected to cool down the landfill internal temperatures. However, to date, potential means for temperature control in BLs have not been thoroughly explored. Temperature control through the recirculation of heated leachate was among the control tools proposed to be incorporated in the SMART control system. Hence, one of the objectives of the first phase of the present experimental work was to evaluate the feasibility of conducting temperature control in SMART, and also to provide a comprehensive analysis of the effect of introducing heated leachate on the internal temperatures of the BL as well as on the overall performance of the system. In addition, a dynamic assessment was conducted in order to determine the short-term temporal and spatial effects of recirculating heated and unheated leachate on the waste temperature.

6.3. Materials and Methods

6.3.1. Solid Waste

The solid waste used in this experiment was obtained from waste collection trucks arriving at a sanitary landfill located in Eastern Ontario, Canada. The waste was a mix of two waste streams: residential waste and food waste. Before using the residential waste, large objects were screened, then plastic and paper materials were cut into smaller size pieces (less than 150 mm). About 500 kg of residential waste was processed in this manner, and was then sampled by the quartering method. The main constituents of the residential waste stream were food & yard trimmings (38.8%), plastics (14.8%), paper & cardboard (18.2%), and others (textile, metal, glass, etc.). Residential waste contained about 39% organics, while food waste was completely organic. The initial moisture content (by weight) of residential and food wastes was 25.7% and 65.3%, respectively. The major chemical and biochemical parameters of the food waste used are presented in Appendix E.

6.3.2. Experimental Setup

Experimental work was conducted on two bioreactor setups; Cell-1 and Cell-2. Figure 6-1 shows the configuration of a single bioreactor cell with its leachate collection and recycling tanks. The bioreactor cell was 675 litres volume, 1060 mm internal diameter, and 750 mm height, while the leachate tank volume was 114 litres. The two setups were identical in all components, except that a heating device was attached to the leachate tank in Cell-2. Both cells were covered with vinyl-protected high-density fibreglass insulation sheets, and operated in a temperature-controlled room (20±2°C) to isolate external temporal effects, and to simulate the insulating effect of surrounding waste in larger landfills. Actual pictures of the experimental setup and the instrumentation of SMART are presented in Appendix F.

Residential and food wastes were thoroughly mixed while loaded to the bioreactor cells. Each reactor was uniformly filled with waste and manually compacted to reach an average specific weight of 600 kg/m^3, which is comparable to what is achieved in many BL sites. The average total organic fraction and water content of the mixed waste was about 73%, and 48%, respectively. It should be noted that the actual ratios between residential and food waste streams as well as the organic fraction and initial moisture contents of the mixed waste in both cells are presented in Appendix E.

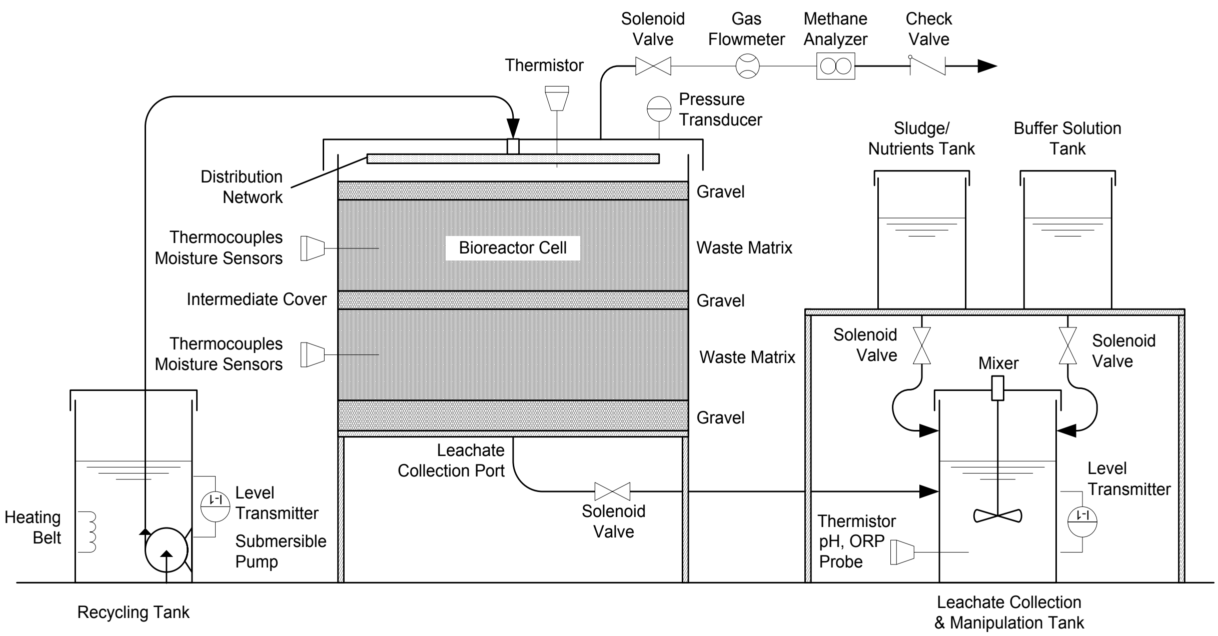

Figure 6-1 Configuration and instrumentation of the prototype bioreactor cell

In each bioreactor cell, mixed waste was placed in two lifts separated by an intermediate 100-mm thick gravel layer. A 100-mm thick layer of gravel was placed at the bottom of each cell to simulate a leachate collection system, and to prevent clogging of the leachate withdrawal outlet. A 15-mm thick gravel layer was placed on top of waste to achieve uniform spreading of leachate over surface. A plastic mesh with 25-mm openings was placed in all contact surfaces between waste and gravel in order to avoid movement of solid particles with leachate which may clog the leachate collection system. In the headspace, a leachate distribution network was attached to the bioreactor lid, and consisting of a main pipe from which four laterals (two at each side) extend to cover the surface area. The laterals were 13-mm diameter PVC pipes perforated such that the holes' diameters increased towards the end of the capped lateral pipe. Finally, the cells were covered, gas-tightened using silicon sealant, and then flushed with pure nitrogen to ensure anaerobic conditions.

6.3.3. Instrumentation

Each bioreactor cell was equipped with three type-T thermocouples measuring temperature in different radial positions at three equidistant vertical levels in the waste matrix. In addition, three (5EC, Decagon Devices, Inc., USA) moisture sensors, placed at the same monitoring spots, measured the volumetric water content (VWC) using frequency domain technology. The moisture sensors used a 70 MHz frequency to measure dielectric permittivity, which was correlated to VWC through calibration curves generated specifically for the type of waste used. The conducted calibration procedures as well as a novel method used for the insertion of moisture sensors are discussed in Appendix G.

Biogas exited the system from an upper outlet port in the lid which was connected to the gas measuring setup. The biogas generated went through a disposable nylon inline microfiber gas filter filled with silica gel to absorb moisture, followed by a micro-turbine wheel flow meter (Model-100, McMillan, Inc., USA) that measured volumetric flows between 20 and 100 mL/min. The flow meter was factory-calibrated for measuring the flow of air; therefore, a correction factor was applied to the sensor readings, and was updated cyclically according to the variable gas fractions in the produced biogas (see Appendix G). Next, the biogas entered the inline infrared methane analyzer (BCP-CH4, BlueSens, Inc., Germany) which measured the methane content from 0 to 100 Vol. % in biogas. The BCP-CH4 sensor was used because its readings are pressure-compensated and independent of gas flow. In order to prevent backflow of the ambient air, a check valve was installed after the methane analyzer (see Figure 6-1). It should be noted that the methane analyzer was calibrated monthly according to the procedures presented in Appendix G. Biogas temperature was measured in the headspace of the bioreactor cell using a thermistor probe, while the internal pressure was monitored with a mechanical pressure gauge (Xmitr, Ashcroft, Inc., USA) in the range of 0 to 2 bars. Leachate was collected by gravity from a lower outlet port connected to the collection tank. This tank also received the flow from the amendments' tanks through tube lines with actuated solenoid valves (see Figure 6-1). A mechanical mixer was installed in the tank in order to blend leachate with the amendments added. The tank was designed to provide continuous measurements for pH, ORP, and temperature of leachate throughout operation. Therefore, the probes were kept submerged in an always-full container with the most recently produced leachate, and the leachate withdrawal port in the bioreactor cell was fully controlled through a two-way normally-closed pinch solenoid valve. This procedure had another benefit as it prevented ambient air from entering the cell from its lower port.

After being mixed with amendments, leachate was manually transferred to the recycling tank where it was ready for recirculation. Leachate was recirculated in a cyclic batch mode using a submersible pump. Total volume of leachate to be recirculated per cycle was divided into smaller equal volumes that were pumped sequentially (in 8 to 12 hours intervals) in order to promote absorption of liquid, avoid excess pore pressure within the waste matrix, and/or prevent leachate escape from the edges of waste surface. Short circuiting was monitored by comparing the volumes produced to the volumes recirculated. The recycling tank of Cell-2 incorporated a flexible drum heater made of reinforced fibreglass silicon rubber in order to adjust the leachate temperature prior to being pumped. It should be noted that the volumes of leachate produced, amendments added, and leachate recycled were measured by ultrasonic level transmitters (EchoPod DL10, Flowline, Inc., USA) installed inside their tanks.

6.3.4. Data Processing

Online process parameters were measured by analog sensors controlled by the Primary Sensory Data Processor (PSDP) unit. The sensors' outputs ranged from 4 to 20 mA (in current mode) or 0 to 10 volts (in voltage mode). As shown in Figure 6-2, the PSDP unit incorporated two interacting modules: (1) input modules that acquire sensor data, and (2) processor module that multiplexes the acquired data into a combined data frame. On the control side of the system, the Primary Driving Controller (PDC) unit was composed of two modules: (1) processor module that de-multiplexes the received data frame carrying the commands (control actions) from the computer to the final control elements, and (2) output modules that transmit the commands to each control device in the form of digital signals (0 or 1). These digital signals were transmitted to AC/DC solid state relays (Opto22, Inc., USA) that switched the electrically actuated solenoid valves, mixers, heating elements, and pumps.

As shown in Figure 6-2, the hardware part of SMART included a network of data acquisition (input) and control (output) modules (NuDAM, ADLINK Technology, Inc., Taiwan). Analog input voltage and current signals were acquired by a (ND-6017, ADLINK Technology, Inc., Taiwan) module, while thermocouple readings were measured by a (ND-6018, ADLINK

Technology, Inc., Taiwan) module which has a built-in reference temperature sensor. Both modules had a sampling rate of 10 samples per second, and 16 bits resolution. Input/output (I/O) digital signals were acquired/generated by a (ND-6050, ADLINK Technology, Inc., Taiwan). The network used a standard RS-485 interface for transmitting and receiving data at high rates and over long distances (able to reach over 4000 feet without repeaters). Each I/O module was connected to the RS-485 multi-drop network via twisted pair wires, and had a unique address ID through which it was identified by the PSDP/PDC units. The host computer was connected to the PSDP/PDC units by Universal Serial Bus (USB) standard connections. The conversion from RS-485 to USB was achieved by a (ND-6530, ADLINK Technology, Inc., Taiwan) converter module. It should be noted that the signals generated from some probes, specifically thermistors and pH/ORP probes, had to pre-processed in signal conditioning and transmitting units before the analog input modules. Thermistors were connected to transmitters that linearized their outputs over the temperature range. The (αlpha 500, Eutech Instruments, Ltd, Singapore) transmitters were used to scale the PH/ORP probes' outputs to 4-20 mA signals with automatic temperature compensation (ATC) for pH and dual-line LCD display.

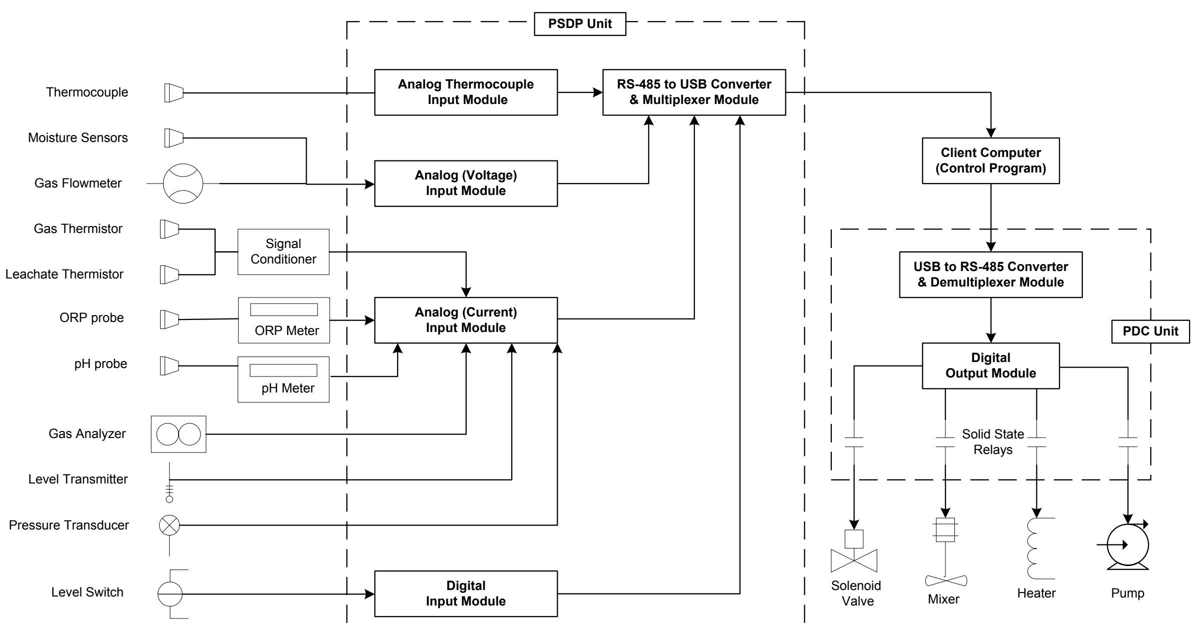

Figure 6-2 Dataflow diagram of the experimental setup

6.3.5. Software

The software part of SMART was programmed on the LabVIEW™ 2009 Professional Development System with the *PID and Fuzzy Logic Toolkit* (National Instruments, Inc. USA). LabVIEW is a graphical programming platform for developing measurement, test, and control systems with advanced tools for data visualization, user interface design, data management, and software connectivity. A LabVIEW program, called Virtual Instrument (VI), is composed of two main interconnected components: a user interface called the front panel (FP), and a programming interface called the block diagram (BD). Within LabVIEW environment, data flows from data sources (such as controllers in FP or outputs of functions in BD) to data sinks (such as indicators in the FP or inputs of functions in the BD) through connecting wires that direct the dataflow throughout the program, i.e., determine the execution order of the functions/loops/structures in the BD. The architecture of LabVIEW enables execution of multiple in-parallel operations as well as sequential operations offered in traditional text-based programming languages. The graphical user interface (GUI) of SMART, shown in Figure 6-3, was used for data visualization, process monitoring, and interaction with the control program.

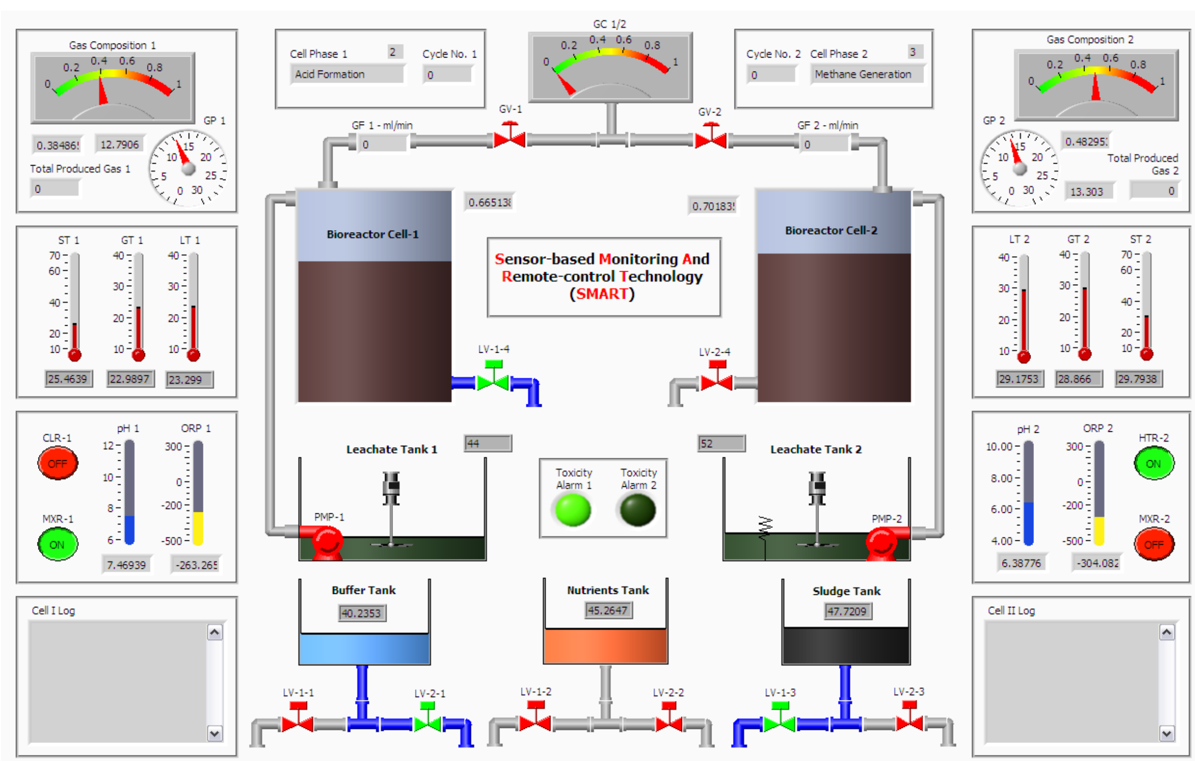

Figure 6-3 Diagram of the graphical user interface of SMART (version 1.0)

The control program was created from numerous inter-wired array/string/Boolean functions in addition to other major LabVIEW tools described in Table 6-1.

Table 6-1 Description and usage of major features employed in LabVIEW

Group	Feature	Description / Usage
Structures	Sequence Structure	- Consist of one or more sub-diagrams, or frames, that execute sequentially. - Used when the input of one frame depends on the output of another, i.e., to ensure that a sub-diagram executes before or after another sub-diagram.
	Case Structure	- Include one or more sub-diagrams, or cases, only one of which executes when the structure executes. - Used to select the executed case based on Boolean, string or numeric value.
Loops	For Loop	- Execute its sub-diagram n times.
	While Loop	- Repeat the sub-diagram inside it until its conditional terminal receives a particular Boolean value.
Advanced Tools	Dialog User Interface	- Display a standard dialog box. - Used to prompt user to enter information and/or show instructions.
	Web Publishing Tool	- Create HTML documents, and embed static/animated images of front panel. - Used to view and control applications remotely using a web browser on client computer.
	Report Generation	- Convert 1D or 2D array of strings or numbers to a text string, and write the string to a new spreadsheet file or append it to an existing file. - Used to create and manipulate reports of LabVIEW applications.

The SMART program generated three types of measurement reports: daily, cyclic, and dynamic. The daily report included measurements of the biogas (flow, total production, pressure, temperature, and methane content), the leachate (volume, temperature, ORP, and pH), and the waste (top/center/bottom moisture contents and top/center/bottom temperatures). The dynamic report was used to record the spatial and temporal changes in waste moisture content and temperature corresponding to leachate recirculation episodes. This report included the cycle number, episode count, recirculated leachate temperature and volume per episode, as well as the waste temperature and moisture content at the monitoring spots described before. A cyclic report was generated at the end of each weekly recirculation cycle, and consisted of online measurements, manually inserted data by the operator, and results from the programmed cycle calculations. The report included: date, cycle number, leachate parameters (TOC, COD, TN, VFA, ammonia, undissociated VFA, free ammonia, alkalinity, pH before and after each amendment, ORP, and temperature before and after heating), waste's (moisture content and temperature), biogas parameters (methane and carbon dioxide percent), current BL operational phase, leachate dilution factor, computed and actual volume of leachate, water, and other amendments recirculated, leachate produced and absorbed, and the selected setpoints for waste moisture content, leachate's pH, C/N ratio, and temperature. The control sequence that was executed cyclically in SMART is shown in Figure 6-4. The sequence illustrates the steps performed by SMART to deliver the calculated amounts of leachate and other amendments.

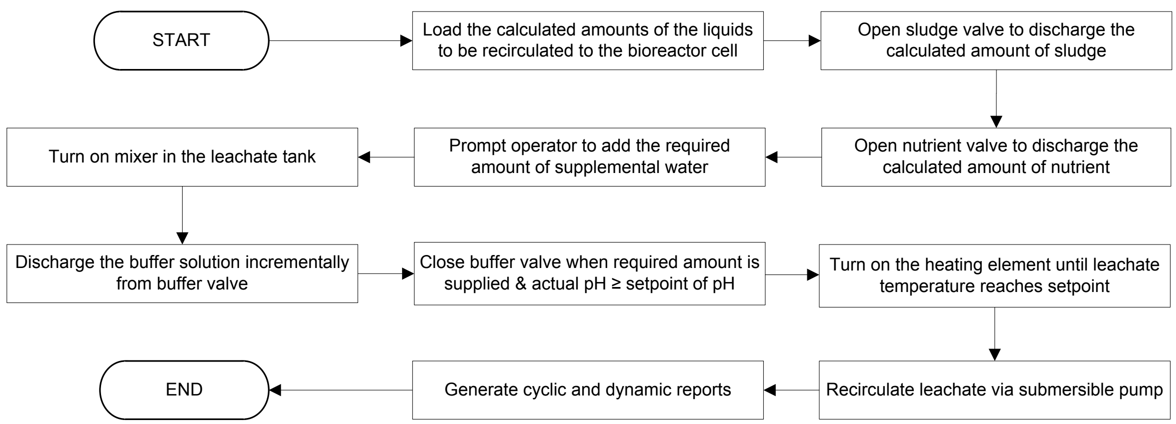

Figure 6-4 Control sequence programmed in LabVIEW

It should be noted that the control system was programmed to continuously ensure multiple operational conditions including: (1) recirculation pump must be fully submerged, i.e., pump is stopped when the water level is just above it; (2) gas valves were to be opened to release biogas build-up when internal pressure is critical; (3) level switches served as alarms to refill the amendments' tanks; and (4) leachate collection valves were to be opened intermittently to prevent liquid build-up in the BL cells. In version 2.0 of SMART software, the program was upgraded to a project library that contained four interacting VIs that share data via the Shared Variable Engine in LabVIEW™ 2009. The program upgrade offered more versatility and improved overall execution performance. The four VIs included: (1) a VI that acquires signals (through data sockets), converts them into engineering units (via calibration curves and equations), and generates the measurements' reports, (2) two VIs, each combining an improved GUI, an automated controller, an emergency manual controller, for each bioreactor cell (see Figure 6-5), and (3) a master VI that calls and synchronizes the other VIs.

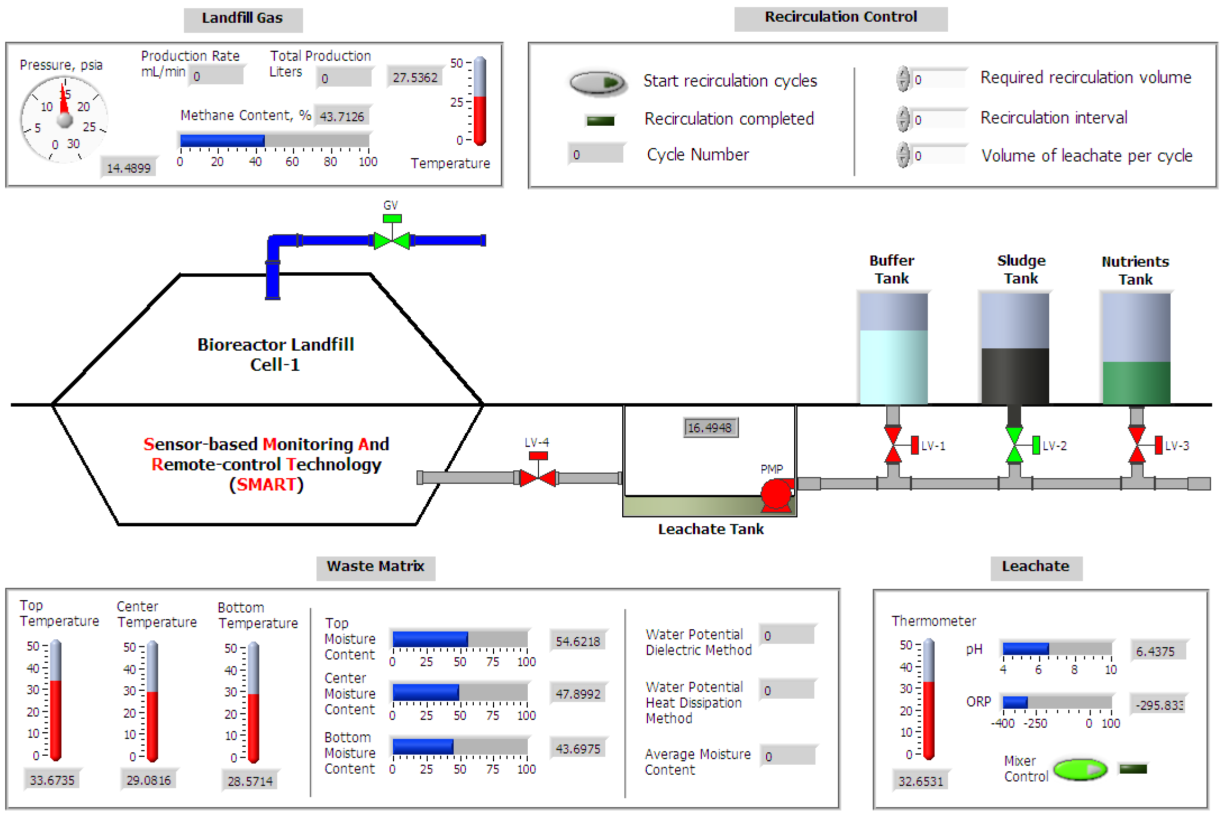

Figure 6-5 Diagram of the graphical user interface of SMART (version 2.0)

6.3.6. Communication Interface

Data exchange between software and hardware components of SMART was based on an OPC (Object Linking and Embedding for Process Control) standard interface. OPC is a set of standard interfaces that allow any computer program containing an OPC client protocol to access any OPC-compatible devices through a standard Microsoft COM interface. This interface was developed to alleviate duplication of effort in developing device drivers, eliminate inconsistencies between drivers, and avoid access conflicts in industrial control systems (NI, 2008). In SMART, the LabVIEW was employed as an OPC client by connected to the OPC server through *DataSocket* connections. An OPC Data Access specification 2.0

compliant Server (NDS-OPC™, ADLINK Technology, Inc., Taiwan) was used in the data exchange between the control software and the PSDP/PDC units.

6.3.7. Analytical Methods

Leachate was sampled from the collection tanks, and lab analyses were carried out at least in duplicate to ensure the validity of results. Samples were analyzed for pH, ORP, COD, TOC, TN, TS, VS, NH_3-N, TA, and VFA. The methods used for these measurements are shown in Table 6-2. Gas samples were collected weekly, and analyzed for: methane, carbon dioxide, nitrogen, and oxygen via a thermal conductivity gas chromatograph (series 400, Gow-Mac Instrument Co., USA). The detector, injection port and column temperatures were 130, 130, and 120°C, respectively, and the carrier gas was helium at inflow rate of 30 mL/min. Actual pictures of the instruments and methods used in the lab analyses are presented in Appendix H.

Table 6-2 Leachate sampling program and analytical methods

Parameter	Type	Frequency	Method/ Instrument
COD	lab	weekly	Closed reflux, colorimetric method (5220-D, APHA, 2005)
TOC/TN	lab	weekly	High-temperature combustion method (5310-B, APHA, 2005) using a catalytic combustion analyzer (Apollo 9000 with TN module, Teledyne Technologies, Inc., USA)
VFA*	lab	weekly	Gas chromatographic method (5560-D, APHA, 2005) using a gas chromatograph (Agilent 6890 GC, Agilent Technologies, Inc., USA) with a flame ionization detector
TA*	lab	weekly	Titration, endpoint at pH = 4.50 (2320-B, APHA, 2005)
TS/VS	lab	biweekly	Drying/ ignition method (2540-B / 2540-E, APHA, 2005)
N-NH_3	lab	weekly	Ammonia-selective electrode method, (4500-NH_3-D, APHA, 2005)
pH/ORP	online	continuous	Tuff-tip double-junction pH/ORP electrode (Cole-Parmer Instrument, USA)
Temperature	online	continuous	Thermistor probe (400-Series, Oakton, Australia)

** Samples were vacuum filtered through a membrane filter with a pore size of 0.45 µm.*

6.3.8. Control Amendments

The manipulation of recirculated leachate was achieved by adding various amendments such as inoculum, nutritional source, buffer solution, and supplemental water. The inoculum used was collected from the sampling port of an anaerobic digester at the Robert O. Pickard Environmental Center (ROPEC) wastewater treatment plant in Ottawa. The average physical, chemical, and biochemical characteristics of the used anaerobic sludge are shown in Table 6-3. The selected sludge provided an active bacterial population, high buffering capacity, nitrogen, phosphorous, as well as other nutrients and micronutrients. Sludge was kept at 4°C for a maximum period of 2 months, as the characteristics of sludge were found not to change significantly (less than 5% on average) during this time. Sludge was allowed to reach room temperature before being added. On the other hand, the nutrient enriched source was in the form of a liquid plant fertilizer with total nitrogen and phosphorus contents of 18 and 3%, respectively. The solution was diluted fivefold resulting in TN and phosphoric acid concentrations of 36 and 6 g/L, respectively. The pH and alkalinity of leachate were manipulated by adding sodium bicarbonate ($NaHCO_3$) as a buffering solution. The concentration of the buffer solution used was 42 g/L.

Table 6-3 Average characteristics of the anaerobic sludge used

pH	Alkalinity	TVA	COD	NH_3	TN	TP	SO_4	TS	VS
-	mg/L as $CaCO_3$	mg/L	mg/L	mg/L	mg/L	mg/L	mg/L	%	%
7.35	4250	234	26500	990	1050	915	30	2.1	56

6.3.9. Operation Plan

After loading the BL cells, the waste was kept in an initial static state for thirty days prior to starting weekly cyclic recirculation. This period was used to test the communication and synchronization between SMART's components: sensory instrumentation, I/O data modules, PSDP/PDC units, and control software. Both cells were already at field capacity due to the high initial moisture content of the waste. The experimental setup was operated for one year according to the operation schedule, shown in Figure 6-6, which was divided into two phases.

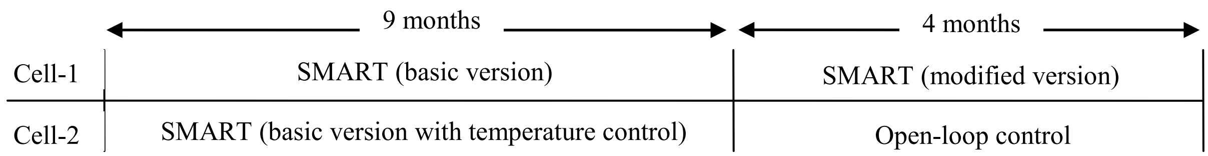

Figure 6-6 Operation plan of the experimental setup

Phase I: the two bioreactor cells were operated for nine months with SMART in order to evaluate the system and investigate possible modifications. During this phase, addition of supplemental water was not practiced, and temperature control via recirculation of heated leachate was examined in Cell-2, while Cell-1 was running with the basic system. After 150 days of operation, recirculation was stopped, and both cells were allowed to drain for 120 days until leachate production ceased completely.

Phase II: the modified version of SMART, which primarily includes the feedback scheme as well as the addition of supplemental water to the recirculated solution, was applied in Cell-1 for four months so as to test it. During this phase, Cell-2 was running, according to a conventional open-loop control scheme, at a constant rate of leachate recirculation equal to a predetermined percentage (8%) of the initial volume of waste matrix.

6.4. Results and Discussion

The present discussion aims to provide a comprehensive assessment of the SMART control system, and is presented in two main sections: (1) illustration of the decision making process leading to the control actions made by SMART, and (2) evaluation of the performance of SMART by studying its effect on various leachate, biogas, and waste parameters.

6.4.1. Implementation of SMART

The sequential calculations made by the SMART control program to determine the required amounts of leachate and other amendments to be recirculated, are shown in Figure 6-7. It should be noted that the highlighted blocks shown in the figure are the controllers added in version 2.0 of the software program (applied in phase II). These controllers were developed in response to the high concentrations of organic and inorganic compounds that accumulated in the recirculated leachate during phase I (discussed in detail in *Section 6.4.2*). It is worth mentioning that the complete cyclic control sequence of SMART can be pictured by combining Figure 6-4 and Figure 6-7.

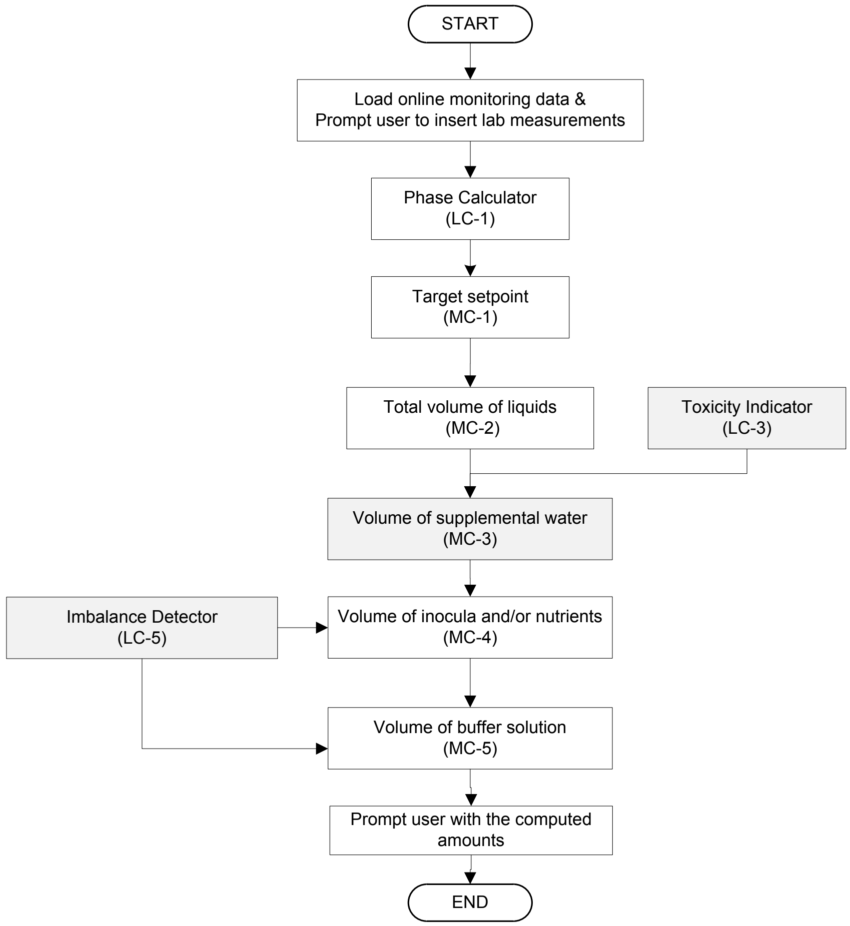

Figure 6-7 Computational steps of SMART programmed in LabVIEW

6.4.1.1. Demonstration Cycle by SMART

In the following section, an example of an actual cycle (the 18th cycle in Cell-1) controlled by SMART is presented, showing the input data acquired from online sensors and lab analysis, as well as the FL and mathematical computations.

According to Figure 6-7, the program sequence of the example cycle started with the *Phase Calculator*. The input values of leachate's COD, VFA, pH, ORP, and CH_4 content in the biogas were **89,561** mg/L, **12,179** mg-AA/L, **6.53**, **-469** mV, and **56.6**%, respectively. Based on these inputs, the *Phase Calculator* identified the index of the current operational phase in Cell-1 as **2.51**, i.e., halfway through the methanogenic phase. Next, based on the calculated Phase Index as well as the setpoints predefined in Table 4-1, the setpoint for the C/N ratio of the leachate was computed as follows:

$$S_{C/N} = S_i + [(S_{i+1} - S_i) \times (P - i)] = 10 + [(15 - 10) \times (2.61 - 2)] = 12.55$$

The setpoints for pH (leachate) and moisture content (waste matrix) were calculated using the analogous equation to be **6.75** and **55.1%**, respectively. It should be noted that the moisture sensors in Cell-2 measured approximately 20% higher waste moisture contents than in Cell-1, which might be a result of being placed in an over-compacted zone with less water holding capacity. Therefore, the predefined moisture contents for Cell-2 were increased to 70 and 80% for acidogenic and methanogenic phases, respectively. This modification shows that the SMART system can be tailored (customized) to be compatible with the site-specific conditions of the controlled BL.

Next, the total required volume of recirculated liquids was calculated based on the average VWC measured by the moisture sensors in Cell-1 (**37.29** %**)**, as follows:

$$V_{liquid} = \left(\frac{S_{mc} \times w}{\rho_{water}} \right) - (\theta \times V_{waste}) = (0.551 \times 354.9) - (0.3729 \times 460) = 24 Liters$$

Next, concentrations of inhibitory parameters, required as inputs for the *Toxicity Indicator*, including UAN, UVFA, TAN, VFA, and CAT were **6.84** mg-N/l, **229** mg-AA/L, **3,888** mg-N/L, **12,179** mg-AA/L, and **3,340** mg-Na/L, respectively. Na was the selected alkali cation in view of the fact that its concentrations were substantially higher than other cations as a result of using $NaHCO_3$ buffer throughout operation. Based on the above concentrations, the *Toxicity Indicator* computed the dilution factor (*D*) to be **0.08**. The required volume of supplemental water was then calculated as follows:

$$V_{water} = D \times V_{liquid} = 0.08 \times 24 = 1.7 Liters$$

As a result of the dilution of supplemental water, leachate parameters were recalculated. The concentrations of TOC and TN in the diluted leachate became **23,533** mg/L and **3,577** mg-

N/L, respectively. Next, the additional nutrient requirements were calculated using the setpoint of the C/N ratio, TOC and TN of leachate, as well as TN of anaerobic sludge (**1,100** mg-N/L). The volume of nutritional source was calculated as:

$$V_{nutrients} = \frac{\left(\frac{TOC}{S_{C/N}}\right) - TN}{TN_{nutrients}} \times V_{water} = \frac{\left(\frac{23533}{12.55}\right) - 3577}{1100} \times 24 = -ve \approx zero$$

It should be noted that the negative value of V $_{nutrients}$ shows that the nutrients required at this stage were already available within the BL. It is worth mentioning that, except for the first month when the TN concentration in leachate was low, the nutritional requirements of the BL was always met by the leachate, and no external source of nutrients was needed. This was expected in a pilot-scale application where the effect of waste heterogeneity is minimal and the efficiency of leachate recirculation is high. On the other hand, in full-scale applications, while nutrients are typically available in the waste, they may not reach all of the waste because the recirculated leachate cannot flow evenly through the entire waste mass. It should be noted that anaerobic sludge was used as a bioaugmentation supplement due to its rich and active methanogenic population. Therefore, anaerobic sludge was added as a constant percentage (5%) of the liquid recirculated, and the volume added in the current cycle was **1.2** Litres.

Next, the required volume of buffer solution was calculated as the difference between the available alkalinity in the system and required alkalinity to maintain the pH setpoint (**6.75**). The concentration of TA of the leachate produced in the previous cycle was **15,900** mg $CaCO_3$/L, and the fraction of CO_2 gas in the BL cell was **41.42**%.

$$BA = ALK - 0.83 \times f \times VFA = 15900 - 0.83 \times 0.8 \times 12179 = 7813 mgCaCO_3 / L$$

$$RA = \frac{K_1 \times K_H \times P_{CO_2} \times 50 \times 1000}{[H^+]} = \frac{1.78 \times 10^{-6} \times 0.032 \times 0.4142 \times 50 \times 1000}{10^{-6.75}} = 8114 mgCaCO_3 / L$$

$$V_{buffer} = \frac{(RA - BA) \times EW_{buffer} \times V_{liquid}}{50 \times C_{buffer}} = \frac{(8114 - 7813) \times 84 \times 24}{50 \times 42000} = 0.3 Liter$$

Finally, the feedback from previous cycle (the 17th cycle) was evaluated to check if user intervention was needed. The cyclic change in the imbalance descriptors, defined in LC-5, was negative for VFA and VFA/TA ratio, and positive for TA, *dpH/dt*, and methane production. Hence, the current state did not match any of the faulty operational scenarios defined in Table 4-2, and therefore, the feedback intervention status from LC-5 was **False**. It should be noted that the intermitting trend of methane production from the BL cells hindered proper cyclic evaluation of gas generation (in LC-4), and therefore, it is proposed that the evaluation of the system performance should be conducted based on the methane content of the biogas produced rather than the production rate.

At this point, the computational steps of SMART are complete, and the calculated amounts are sent to the final control elements (electrically actuated valves and pumps). It should be noted that the above control sequence was repeated every operational cycle throughout the operation period, and the volumes of leachate and other amendments were varying according to the ongoing conditions inside the BL cells.

6.4.1.2. Evaluation of SMART Control Decisions

<u>Leachate Recirculation</u>

There has been no consensus in the literature on the optimal leachate recirculation rates in BLs, and the reported rates are extremely diverse to over 400 fold (Benbelkacem *et al.*, 2010). It was also found that higher recirculation rates do not necessarily achieve better performance of the BL (Sponza and Agdag, 2004; Warith, 2002). Alternatively, in SMART, recirculation rates vary based on the site-specific and real-time conditions of the BL. Figure 6-8 shows the different recirculated volumes of leachate as determined by SMART for both cells throughout their operation period (except phase II of Cell-2). It can be observed that the calculated volumes of leachate did not follow a predictable trend, and they varied significantly over time (the maximum volume was almost double the minimum).

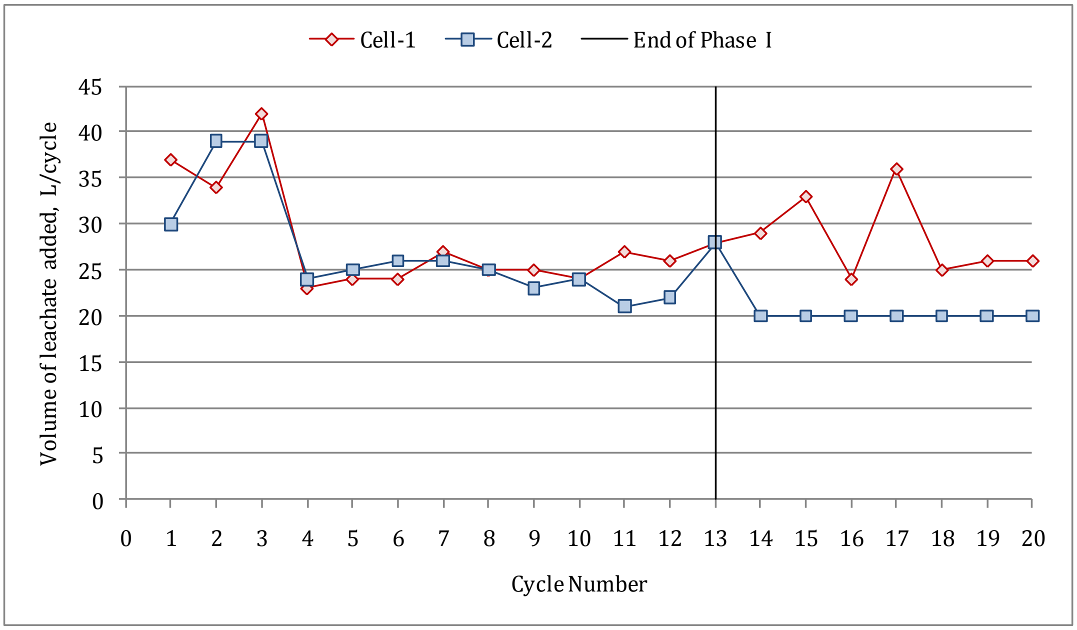

Figure 6-8 Cyclic recirculated liquid volumes in Cell-1 and Cell-2

<u>Leachate Manipulation</u>

The various fractions of leachate, water, buffer, and sludge in the total recirculated solution in each cycle are shown for both cells in Figures 6-9. It can be observed that, similar to leachate volumes shown above, the progress of different fractions did not follow a specific trend that can be predicted. Moreover, the calculated amounts of amendments in the two cells were different from each other despite the fact that most of their process variables, such as waste composition and cell configuration, were actually similar. This shows that there are numerous direct and indirect factors affecting the processes inside the BL, and that as a result of this, developing generic operational guidelines can be very complicated. Instead, SMART takes a quite different path in which site-specific guidelines are established for system parameters rather than operational practices, and therefore every BL is controlled according to its own evolution.

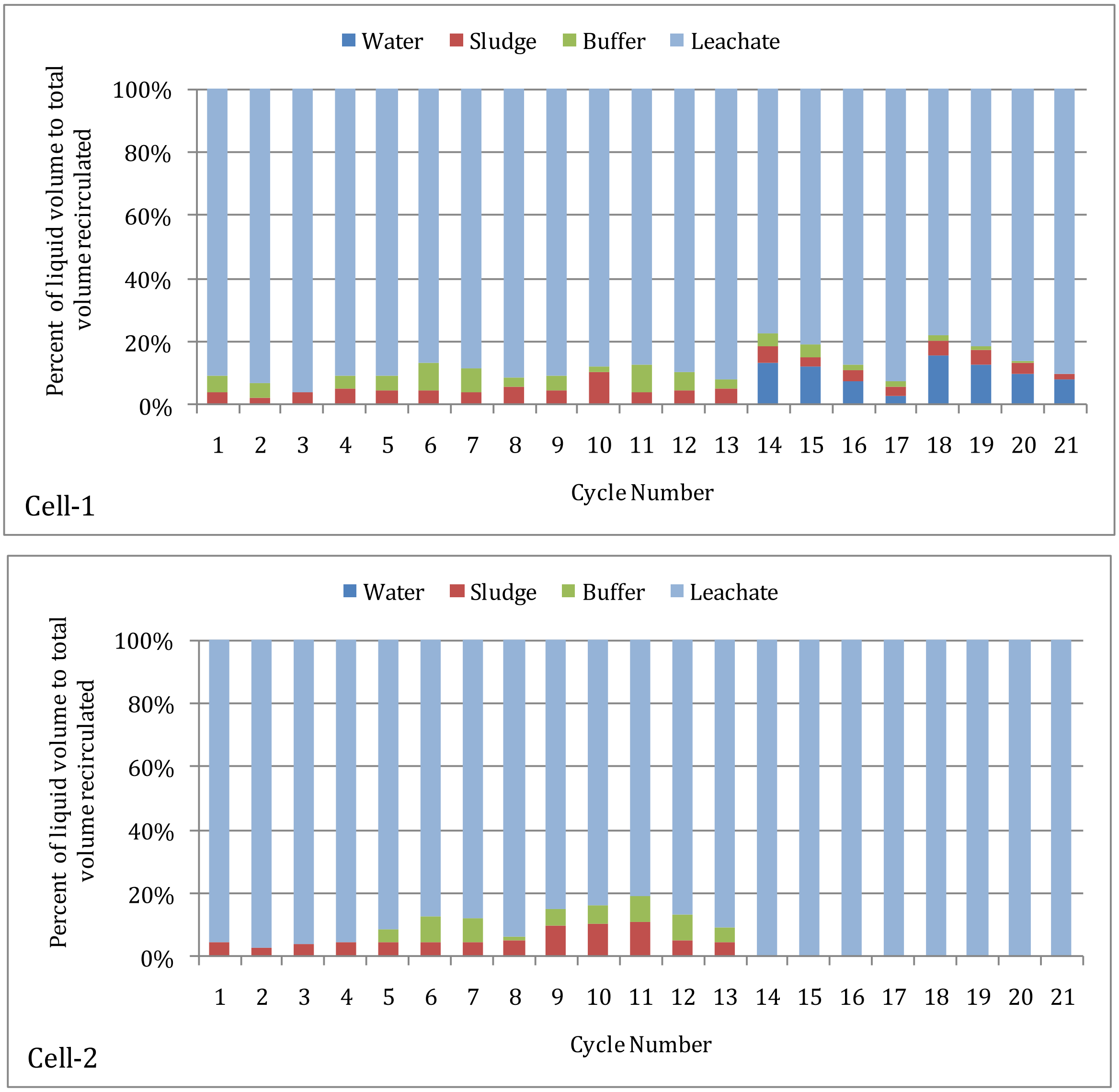

Figure 6-9 Fractions of leachate, water, sludge, and buffer in the total recirculated liquid

Leachate Buffering

In the BL studies that involved leachate buffering such as, San and Onay (2001), Warith (2002), Erses and Onay (2003), Sanphoti *et al.* (2006), and Jianguo *et al.* (2007), the target was always to neutralize the leachate, i.e., add buffer until pH of leachate is 7. However, this practice can be misleading due to the inevitable errors in pH measurements. If the leachate sample is exposed to air for a short period of time, CO_2 will escape causing the pH to rise (Speece, 1996). Moreover, the standard method used to determine pH involves stirring the sample until the pH measurement is stabilized, which increase the stripping of CO_2 even faster. Alternatively in SMART, buffer is pre-calculated based on the difference between the actual and required buffering capacity of the BL cell. Between the 15th and 19th cycles of the present experiment, the amount of buffer required to neutralize the leachate was analyzed in the lab in order to estimate the amount of buffer that can be conserved by applying SMART (see Figure 6-10). In order to minimize CO_2 escaping, the analysis was conducted by titration of the leachate sample with buffer in an airtight beaker with two openings precisely fitted for the burette tip as well as the pH probe (see Appendix H for the modified apparatus). It was observed that while the modified apparatus helped in minimizing the imprecision of the test, the pH kept on increasing when the leachate was left for more few minutes after titration. As shown in Figure 6-10, the amounts applied by SMART were significantly less than those required to neutralize the leachate. On average, SMART required about 55% less buffer solution than the common leachate buffering practice (titration to neutrality), which shows that SMART aims to achieve proper control of the BL system with minimum resources used. It is worth mentioning that in addition to the monetary savings that can be achieved from conservation of buffer, another advantage can be realized by have potentially less alkali cation toxicity which can typically occur from the addition of buffer.

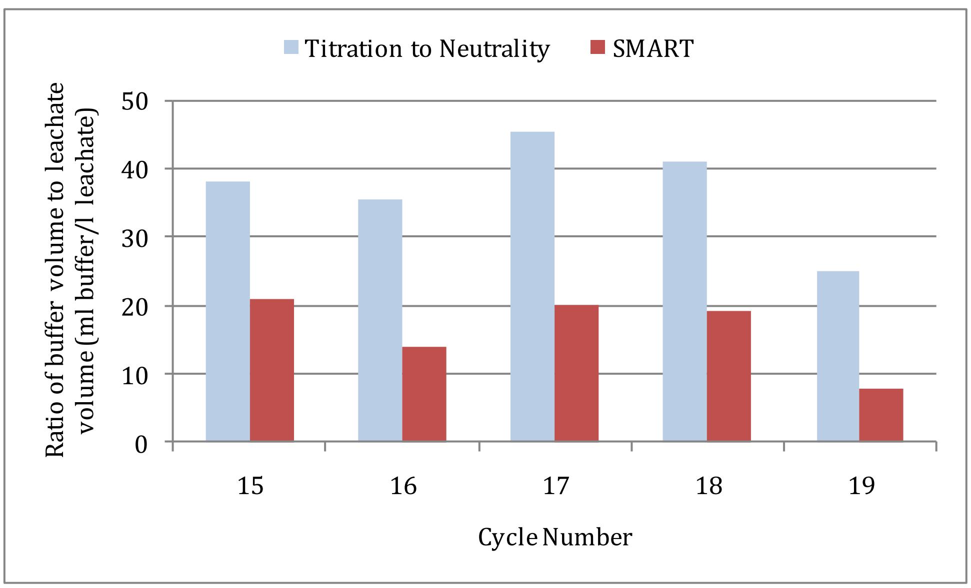

Figure 6-10 Comparison of buffer volumes determined by SMART and by neutralization

System Evolution

The Phase Index, determined by the *Phase Calculator*, for the two cells is shown in Figure 6-11. Upon startup, both cells scored almost the same Phase Index, however three months later in phase I, Cell-2 (the heated cell) started evolving more rapidly than Cell-1. It can be observed that leachate recirculation seemed to prolong the acidogenic phase in both cells, which conforms to the findings of Lay *et al.* (1998a). The recirculation practices caused the concentrations of different pollutants to increase dramatically (as shown later) which resulted in an unfavourable growth environment for methanogens. Therefore, in phase II, the SMART system was modified in order to address the toxicity problem caused by leachate recirculation, especially in early operational stages, and the modified version was only applied to Cell-1. As a result, the progress of Cell-1 surpassed that of Cell-2 which was also evolving but at slower rate. It is clear that since Cell-2 was running with an open-loop control scheme with no leachate heating, the improvement in the evolution pattern of Cell-1 can be mostly attributed to the implementation of SMART.

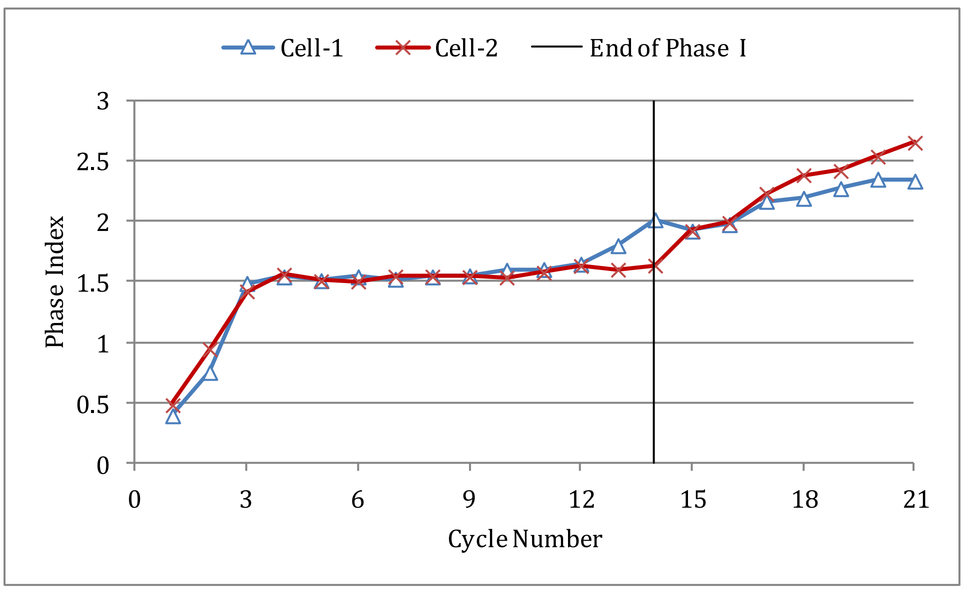

Figure 6-11 Progress of the Phase Index of Cell-1 and Cell-2

Control Strategy

During the operation period, the operator had to interfere occasionally so as to insure the control actions address all potential problems. This man-computer interaction was crucial due to: (1) the instability and unexpected behaviour of the BL system, in part due to its complexity and nonlinear responses, and (2) the fact that the reasoning of the FLC is limited to its knowledge base. Therefore, applying a semi-automated control strategy, rather than a fully automated one, was found to achieve more stable performance of the system. In this control strategy, SMART collects and analyzes the data, performs the computational effort to determine the optimum operational strategy, and then aids the site operator to apply the final operational decision through the computer interface.

Feedback Control Scheme

The control actions determined by SMART were based on multiple leachate and biogas parameters acquired from previous cycles. The response time of the BL ecosystem, i.e., time from changing a system parameter to when its effect (feedback) on system performance is detected, was found to be sufficient to facilitate the application of the feedback control scheme. As shown in phase II, the BL performance was significantly improved with the application of closed-loop control (in Cell-1) as opposed to an open-loop strategy (in Cell-2).

6.4.2. Evaluation of Process Parameters

The following section of discussion focuses on the evaluation of SMART based on the progress of various system parameters throughout the operational phases (I and II). It should be noted that the assessment was conducted in each phase separately since the operating scenario of the two BL cells was different in each phases. In phase I, both cells were controlled by SMART, and the only difference was the heat introduced to Cell-2. Therefore, when the same observation was noted in the two cells, it was attributed to the implementation of SMART, while any variation in performance was returned to the temperature control. On the other hand, in phase II, Cell-1 was controlled with the modified version of SMART, while Cell-2 was operated with fixed leachate recirculation. Consequently, any improvement in performance in Cell-1 compared to Cell-2 was attributed to SMART. Moreover, since Cell-1 was always controlled by SMART, but with different versions (version 2 in phase II), any unanticipated enhancement in Cell-1 after the beginning of phase II was attributed to the modifications performed on SMART. It should be noted that supplemental results and discussions are presented in Appendix I.

6.4.2.1. Organic Matter and Volatile Fatty Acids

The development of organic concentration in the leachate produced is plotted in terms of COD and TOC in Figure 6-12. In phase I, the general trend was similar in both cells, with Cell-2 leachate always having lower COD. Since both COD generation and conversion were occurring simultaneously in both cells, this data suggests that generation of COD in both cells was similar, while consumption of COD (i.e., conversion to methane) was higher in the heated cell. This observation can be explained by the known differential changes in metabolism rates with temperature being lower for acidogens (COD producers) and higher for methanogens (COD converters) (Speece, 2008). The concentrations of COD in leachate reached their peaks in similar time frames (about 4 months) in both cells, after which the concentration started to decrease dramatically in Cell-2 compared to Cell-1. The last recorded COD concentration in phase I from Cell-2 was 25% lower than of Cell-1, and the rate of COD degradation (days 125-275) was 233 mg/L·d which was 3 fold higher than that of Cell-1 which was 86 mg/L·d. It is clear that the degradation rate of organic matter increased significantly with temperature because higher temperatures result in greater methanogenic activity, faster waste stabilization rates, and concomitant reduced leachate pollution loads, as soluble carbon compounds are metabolized to biogas. The positive effect of introducing temperature was observed in later stages of phase I even after leachate heating was stopped which is likely associated with a larger methanogenic bacterial inventory in Cell-2 compared to Cell-1.

It should be noted that the insulation sheets covering both BL cells were removed two months before the beginning of phase II at so as to minimize the residual effect of leachate heating on the waste temperatures from phase I. As shown in Figure 6-12, the degradation rate of COD in Cell-1 (controlled by SMART) was 416 mg/L·d along the duration of phase II, while COD concentrations in leachate from Cell-2 were fluctuating, and finished the phase at approximately the same starting concentration (104 g/L). After 60 days in phase II, COD concentration in leachate from Cell-1 became constantly less than that of Cell-2 which shows that the implementation of SMART had a positive effect on the degradation of organic matter. It should be noted that the enhanced COD reduction achieved in Cell-1 was confirmed not to be a result of the dilution with supplemental water that was conducted occasionally by SMART in Cell-1, due to the following facts: (1) the cyclic change in COD reduction and water addition did not follow the same pattern, (2) the COD concentration in the leachate of Cell-2 was 5 to 24% higher than that of Cell-1, while the dilution ratio was always less than 15%, and (3) the differential change between Cell-1 and Cell-2 was not reproduced in the other leachate parameters.

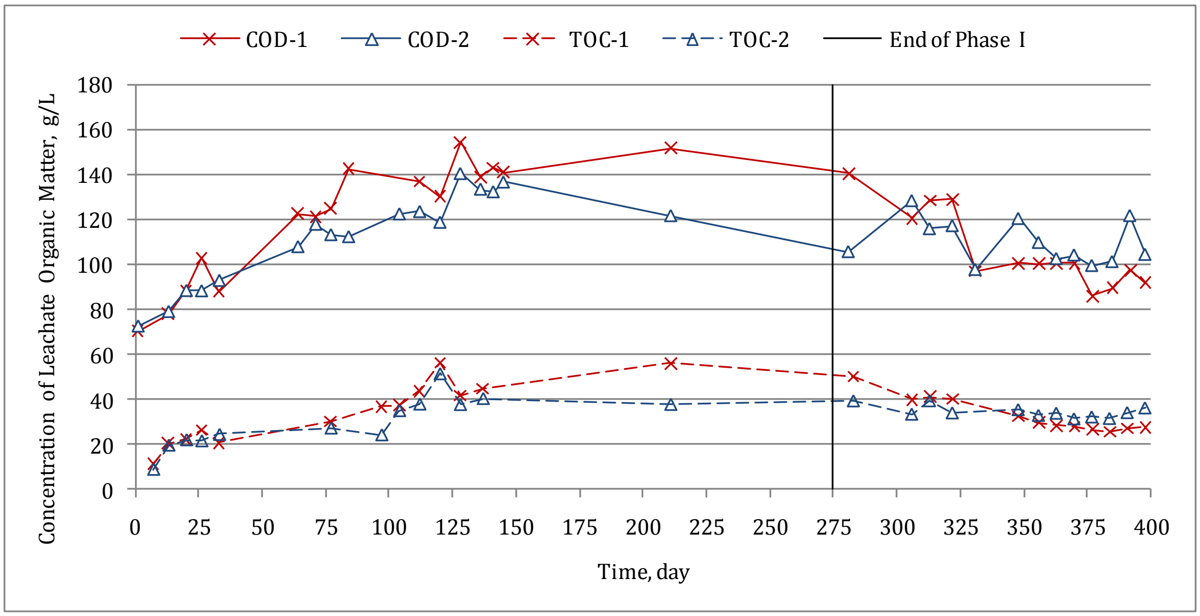

Figure 6-12 Evolution of organic concentration of leachate from Cell-1 and Cell-2

It should be noted that the leachate COD concentrations in both cells were generally very high compared to the literature, possibly due to the high organic load in waste (initial leachate COD was about 70,000 mg/L). These high concentrations may also be explained by the findings of Kylefors *et al.* (2003) who proved that the high concentrations of inorganic substances and volatile organic compounds in leachate can alter the results of the COD test significantly. The results of their study showed that up to one-third of COD may be due to the inorganic components of leachate.

In the present study, the concentration of organic matter in leachate was also determined in terms of TOC. As shown in Figure 6-12, the TOC concentrations followed exactly the same trend as COD including the peaks in phase I and the inflection point between Cell-1 and Cell-2 in phase II. However, TOC measurements showed more consistency than COD, probably due to the machine-based analysis of TOC compared to the analytical method used to determine COD, which may have involved more random human errors. It is worth mentioning that by the end of phase II, the TOC concentration in leachate from Cell-1 was 45% less than its initial concentration in the same phase, whereas in Cell-2, it only decreased by 8% during the same period. The above analysis shows the great improvement achieved by SMART especially that Cell-1 was already behind Cell-2 at the beginning of phase II.

As shown in Figure 6-13, shortly after start-up, VFAs accumulated due to rapid fermentation of the readily degradable fraction. The concentration of VFAs in Cell-1 reached its peak in phase I after 110 days when it started to decrease, while the peak was reached after 130 days in Cell-2, and then it continued to slowly accumulate. The significant drops that occurred at day 210 in Cell-1 and in day 280 in Cell-2 were associated with increased rates of methane production in both cells. However, as shown later, the methanogenic activity in Cell-1 was not robust at this phase, and was not able to consume the produced VFAs which consequently started to increase again. According to Wang *et al.* (2009), accumulation of VFAs as well as the high COD can be attributed to the conversion of soluble organic carbon by syntrophic activity of acetogenic and methanogenic bacteria which limits methane production. The temporal VFA acid concentrations in both cells concurred with the COD results, which supports the importance of differential temperature activity of the methanogenic bacteria discussed before.

The conversion of VFAs to methane continued to increase in phase II resulting in lower and mostly similar concentrations of VFA in leachate from both cells throughout the phase. However, in day 375, the VFA concentration in Cell-1 started to drop rapidly, leading to an overall conversion rate of 120 mg-AA/L.d along phase II compared to 50 mg-AA/L.d in Cell-2. The last recorded concentration of VFAs was less than 10,000 mg-AA/L in leachate from Cell-1, while it reached about 13,900 mg-AA/L in Cell-2. It is therefore clear that the modifications on SMART in phase II stimulated the methanogenic activity which rapidly consumed the produced VFAs.

Figure 6-13 Development of total volatile fatty acids with time

As shown in Figure 6-14, the VFAs measured were mostly composed of butyric and acetic acids (each about 40% on average). The concentrations of various fractions of VFAs were almost constant throughout phase I which indicates that methane was produced from all acid-methane conversion pathways; otherwise there would have been accumulation of a certain VFA over the others. At the end of phase I, the acetic acid fraction in Cell-2 dropped indicating that, after 200 days, methane was mostly generated by acetoclastic methanogens.

It was found that the acetic acid fraction was always lower in the heated cell in phase I, which conforms to the findings of Cokgor *et al.* (2009) who reported, that temperature affects the VFA composition such that a higher temperature results in a lower acetic acid fraction. Propionic acid was the only relative VFA fraction in which the heated cell remained higher than the control cell. This may be due to the temporal sensitivity of the propionate degradation process at relatively high temperatures. It was reported that, in the mesophilic temperature range, higher temperatures increase the propionate fraction in total VFAs (Speece, 1996). The higher propionic fraction in Cell-2 tends to indicate that higher temperatures had a greater positive impact on acetoclastic methanogens compared to hydrogenotrophic methanogens. It should be noted that the high concentration of butyric acid (about 10,000 mg/L on average) may have inhibited the onset of methanogenesis in phase I, and this may have been exacerbated by the high concentration of sodium in the recirculated leachate (about 4,000 mg/L on average) in both cells. However, it seems that the bacterial population in Cell-2 was better able to acclimatize to these concentrations. It is worth mentioning that because of the inhibitory conditions that occurred in phase I, the SMART control program was amended by multiple controllers that aimed at detecting and addressing the toxicity of the recirculated leachate as well as utilizing feedback from previous cycles.

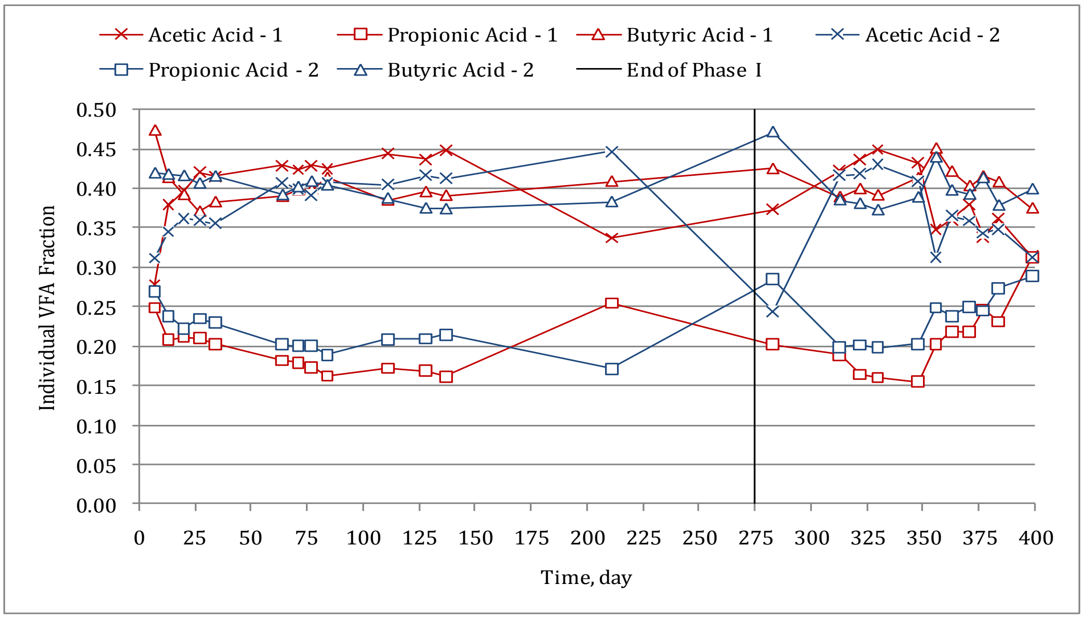

Figure 6-14 Fractions of volatile fatty acids including: acetic, propionic, and butyric acids

In the last two months of phase II, the acetic acid fraction started to decrease from 45% (in Cell-1) and 43% (in Cell-2) to 32% in both cells, while the propionic acid increased in Cell-1 and Cell-2 from 15% and 20% to 32% and 28%, respectively. This shows that in both cells, methane was mostly produced by acetoclastic methanogens, and therefore, it is clear that SMART did not have an effect on the distribution of microbial consortia producing methane.

6.4.2.2. Effects on Methanogenesis

The CH_4 and CO_2 fractions of the biogas produced from both cells are shown in Figure 6-15. In the first four months, CH_4 fraction was almost the same in the two cells; CH_4 production started in 6 weeks, soon after ORP became negative, and was likely due to the degradation of readily decomposable organic fraction of the waste. After about 140 days, the heated cell started producing significantly greater CH_4 than the control cell, until it reached about 40% methane at which time Cell-1 was still at 10%. It should be noted that the delayed improvement in Cell-2 may be attributed to the effect of temperature on the hydrolysis rate upon the bioreactor startup. Hydrolysis is considered the first and main rate-limiting step in the anaerobic digestion of organic material. El-Fadel *et al.* (1996) reported that hydrolysis rate constants increase with increasing temperature, and that temperature has a greater effect on the system during early operational phases, but after steady state conditions prevails, temperature impacts are minimal.

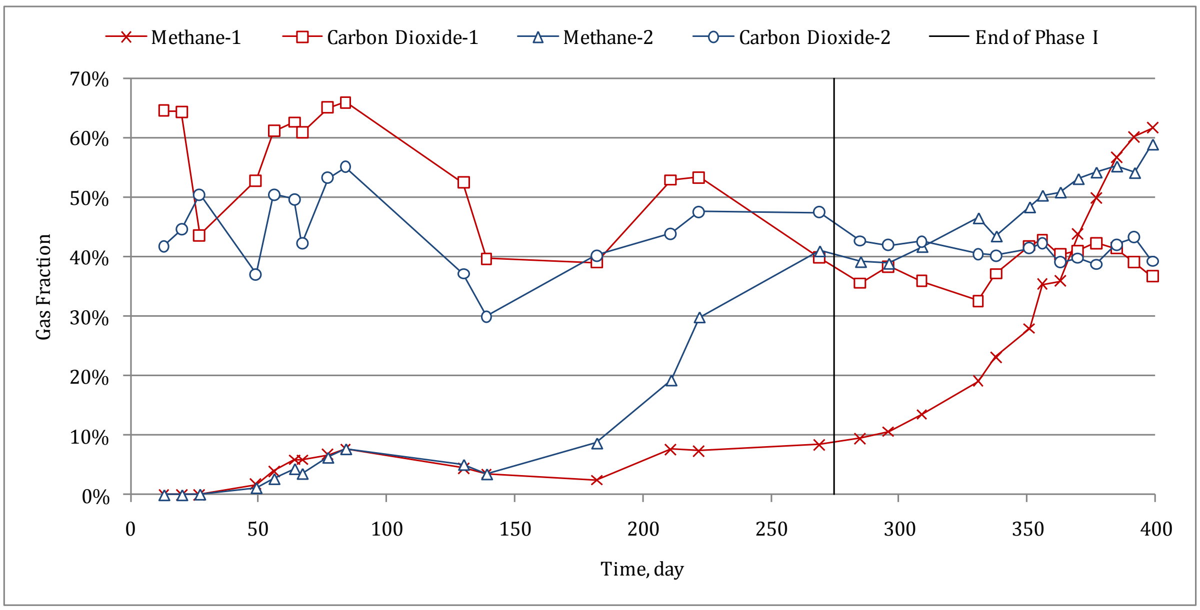

Figure 6-15 Development of methane and carbon dioxide fractions in the biogas produced

By applying the modified SMART control program in phase II, the performance of Cell-1 in terms of the rate of increase of the CH_4 fraction was improved. SMART was successful in leading the cell through the transitional stage from acid formation to methane generation. The percentage of CH_4 increased from 10% to 62% in Cell-1 within four months period, while Cell-2 continued to increase but at slower rate going from 40 to 58% during the same period. It should be noted that the continuous progress in the methanogenic activity in Cell-2 shows that applying SMART with temperature control in phase I helped to establish a balanced methanogenic consortia that continued to flourish, even after temperature control and adding amendments (other than leachate) were stopped. On the other hand, as shown in Figure 6-15, fraction of CO_2 in biogas produced was between 35 and 65% with an average 8% less in the heated cell in phase I, while it stabilized at 40% for the most part of phase II.

The cumulative CH_4 production from both cells is shown in Figure 6-16. The trend of CH_4 production agreed with the progress in CH_4 fraction shown before. Based on the equations of the trend lines fitted to the actual data of cumulative production, the rate of increase in methane production was similar in both cells for the first five months, and then became fourfold higher in Cell-2 until the end of phase I. In phase II, the progress of methane production in Cell-2 remained unchanged at the same rate, while the rate in Cell-1 became 1.7 fold higher than that of Cell-2, and sevenfold higher than before the modified version of SMART. This shows that the modifications made significantly enhanced the performance of SMART. By the end of phase II, the cumulative methane production reached 34 and 32 m^3 in Cell-1 and Cell-2, respectively. It is worth mentioning that 80% of total production in Cell-1 was achieved in the last four months, while the same percentage of total production in Cell-2 needed almost double the time (230 days). By the end of the monitoring period, the methane yield of Cell-1 and Cell-2 was 84.4 and 79.1 L/kg of waste, respectively.

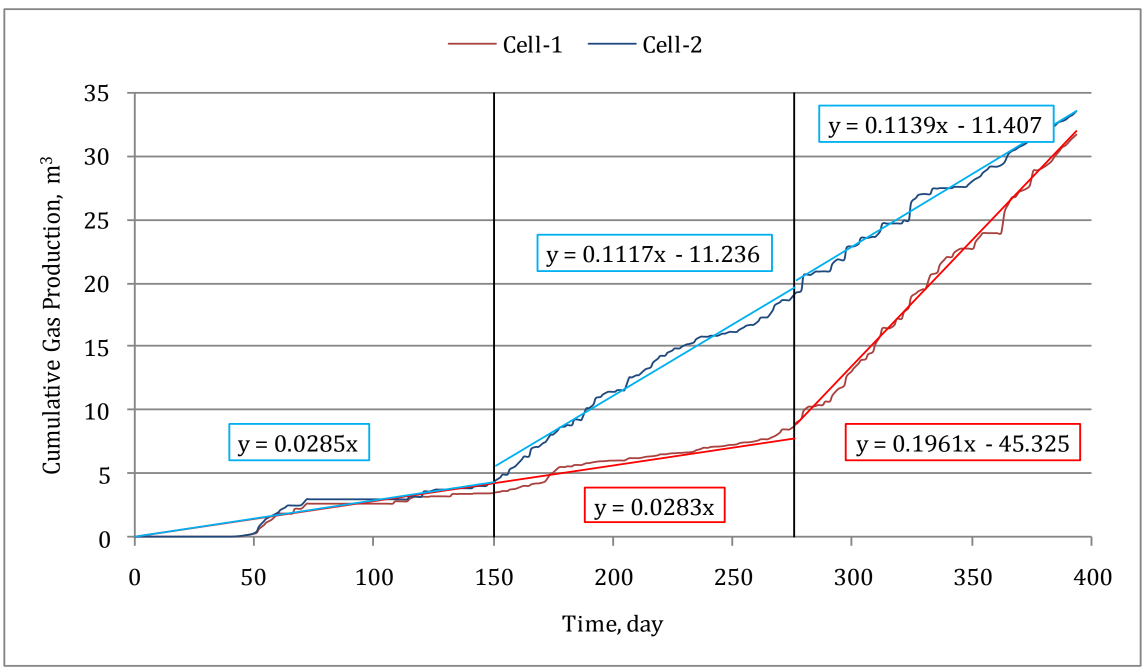

Figure 6-16 Cumulative biogas production from Cell-1 and Cell-2

6.4.2.3. Effects on Alkalinity, pH, and ORP

As shown in Figure 6-17, in phase I, alkalinity of leachate increased initially and then stabilized, similarly to the VFAs' development trend in both reactors, which shows that the buffer added by SMART in both reactors provided a sufficient buffering capacity in response to VFA production. The buffering capacity maintained the pH around 6 throughout phase I. Leachate from Cell-2 had less alkalinity than from Cell-1 probably due to the temperature effect on the equilibrium constants of the bicarbonate system, which increase with temperature causing the system to exert more alkalinity for neutralization. This effect overcame the higher vapour pressure of water (associated with temperature increase) which lowers the solubility of carbon dioxide in water leading to less alkalinity requirements.

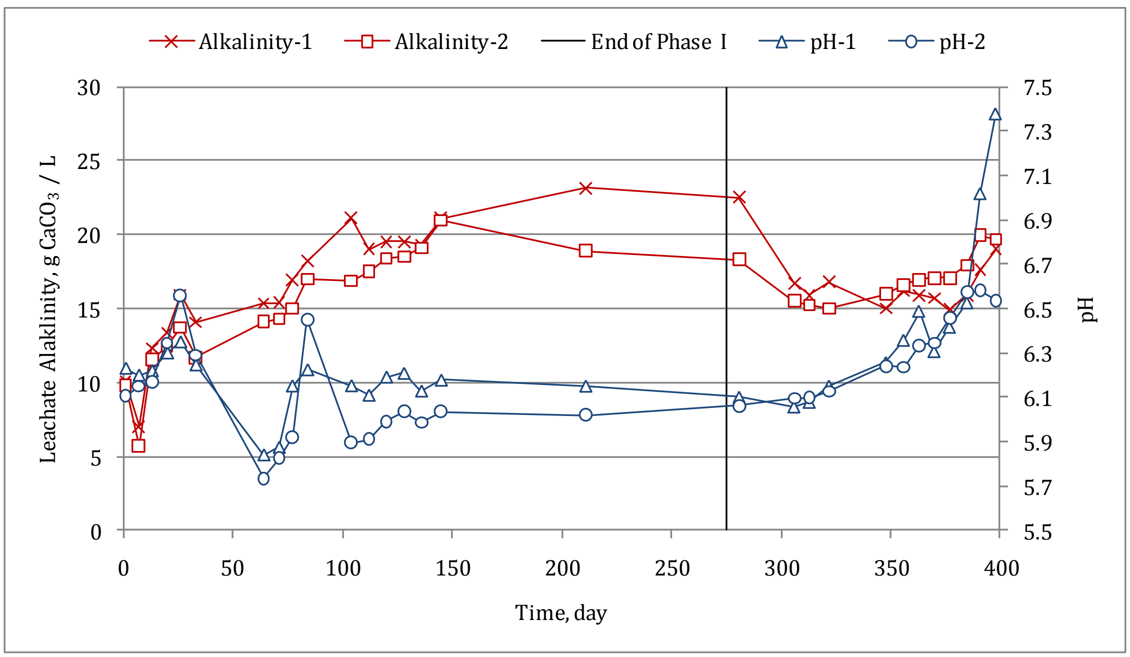

Figure 6-17 Evolution of alkalinity and pH in Cell-1 and Cell-2

In phase II, the alkalinity was very similar in both cells, and it actually started to decrease following the decrease in VFAs, and then increased with the utilization of VFAs by the methanogens in both cells. However, since the concentration of VFAs in Cell-1 was less than in Cell-2, the buffering capacity was sufficient for the neutralization, and consequently pH started to increase in the last three weeks of operation.

During the operation of both cells, pH remained in the range between 5.8 and 6.5 except late in Cell-1. This low pH, while not preferred for methanogens, did not prevent methanogenesis from being established. It has been reported in some BL studies that methane production was established and maintained at pHs below 6.5 (Chugh *et al.*, 1998; San and Onay, 2001; Sponza and Agdag, 2004). It should be noted that the low pH in both cells may have affected the VFA composition as higher pH has been reported to decrease acetic acid and increase propionic acid fractions which is consistent with the present results (Cokgor *et al.*, 2009). In addition, the low pH in both cells helped positively to reduce the free fractions of ammonia and VFAs resulting in less toxicity to microorganisms. Furthermore, during phase I, the lower pH in Cell-2 than in Cell-1 may have reduced the inhibitory levels of the contaminants in leachate, and helped the methanogens to acclimatize faster, which was seen by the earlier production of methane in Cell-2.

In phase II, the effect of operating with and without SMART was clear in the progress of pH. The leachate pH of the both cells were low at around 6.1, however, by the end of phase II, the pH of Cell-1 reached over 7.3 resulting in optimal growth conditions for the methanogens. The increase of pH in Cell-1 was due to the optimized addition of buffer by SMART, which was stopped in the 19th cycle when pH was in the optimum range of 6.8 to 7.2. On the other hand, pH in the leachate of Cell-2 increased slowly and reached 6.5 at the end of operation.

The ORP of leachate from both cells was monitored online as shown in Figure 6-18. The ORP of the bacterial environment is important as it determines the sequence of order of the final electron carrier molecules utilized in the respiration process, and consequently the reduced product by anaerobic bacteria (Gerardi, 2003). In both cells, ORP was initially above zero indicating a short aerobic phase, and as soon as oxygen was depleted, ORP decreased. The ORP in Cell-2 dropped at a faster rate in phase I reaching about -500 mV after 270 days, and thus providing the methanogenic bacteria with their suitable reducing environment. The ORP trend line in Cell-1 was mostly in the -200 to -300 mV range indicating that the dominant cellular activity is mixed-acid fermentation which could be another potential reason for higher concentrations of VFAs in Cell-1.

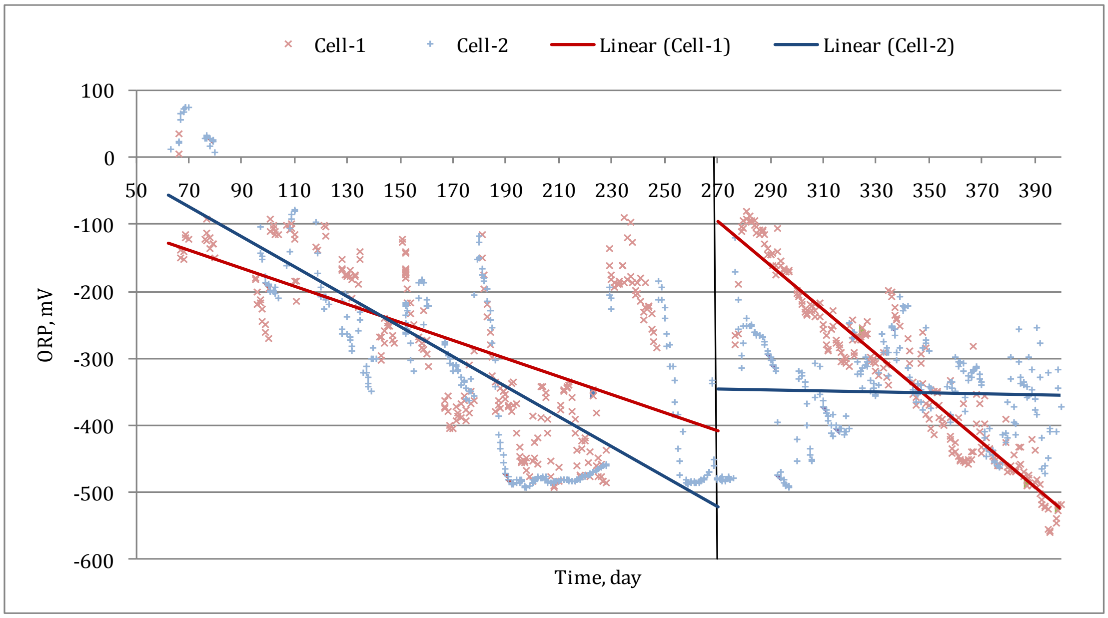

Figure 6-18 Progress of ORP with time in Cell-1 and Cell-2

Based on the ORP trend line in phase II, it is clear that there was a significant improvement in Cell-1 as seen by the high declining rate of change of ORP, reaching ORP below -550 mV. Cell-2 did not show any improvement in phase II, and was fluctuating around an average value of -350 mV, which shows that the open loop control scheme resulted in unstable consortia of microorganisms. It should be noted that the sudden increases in ORP, such as in days 120, 170, and 270, were due to maintenance performed at the leachate collection port.

6.4.2.4. Effects on Total Nitrogen

In this study, the common Total Kjeldahl Nitrogen (TKN) was replaced by TN which detects inorganic N (mostly NH_3) and organic bound N (excluding N_2) in sample. TN represents a good approximation of TKN, while being faster and easier to measure. Also, since the NH_3-N measurements were not stable in late stages of experiment, NH_3-N was replaced by TN since both parameters were highly correlated and NH_3-N accounted for about 90±5% of TN.

As shown in Figure 6-19, the concentrations of TN increased initially from 1,000 to over 4,000 mg-N/L in less than three weeks as a result of decomposition of nitrogenous organic matter, such as protein and amino acids. The TN concentration was then stabilized at around 5,000 mg-N/L in both cells with Cell-1 always slightly higher than Cell-2. It can be observed that the recirculation practice provided the opportunity for reintroducing nitrogen to the system, and consequently its accumulation. However, after 340 days, the TN concentration in Cell-1 started to significantly decrease, while being stable in Cell-2, indicating that nitrogen released by waste solubilisation or decomposition decreased, and that part of the nitrogen in the recirculated leachate was presumably consumed through biological assimilation of microorganisms, especially methanogens in the active methanogenic phase.

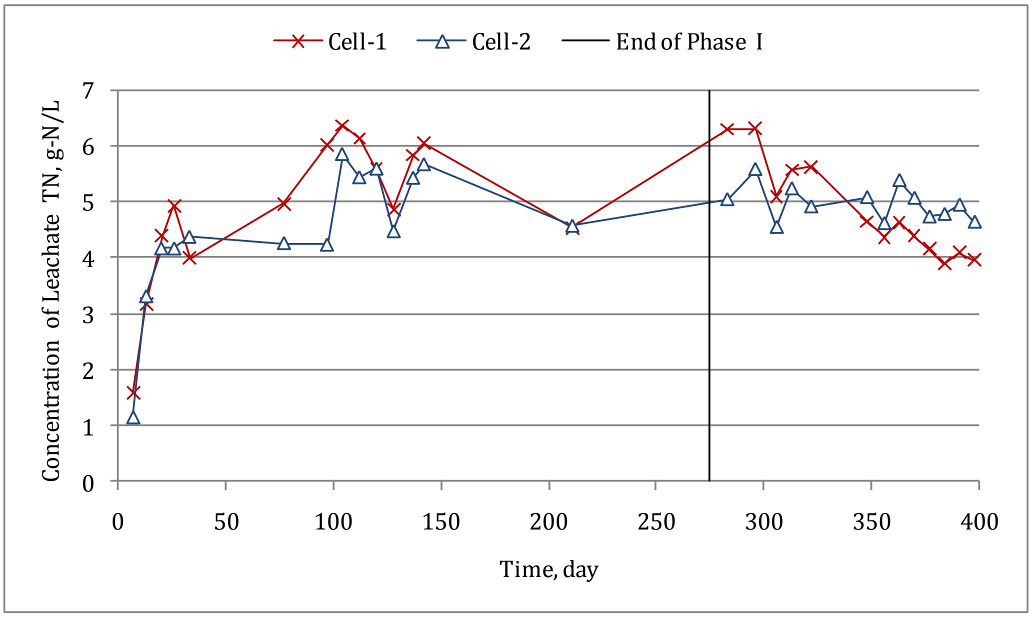

Figure 6-19 Concentration of TN in leachate from Cell-1 and Cell-2

6.4.2.5. Effects on Concentrations of Dissolved Elements

Inductively coupled plasma atomic emission spectrometry (ICP- AES) was used to determine the concentrations of multiple dissolved elements in the leachate during the operation period. The analyzed elements included alkali metals (Na, K), alkaline earth metal (Mg, Ca), transition metals (Mn, Fe, Co, Ni, Cu, Zn, Cd), post-transition metals (Pb, Al), metalloids (As, B, Si), and non-metals (S, P). Except for the Ca and P in the initial leachate sample, the concentrations of dissolved elements were considered within the typical ranges for leachate, as reported by El-Fadel *et al.* (1997). Since this was essentially a closed batch system and only CH_4, CO_2 and H_2S gases could exit the process, all elements tested, except S, must be either sorbed to waste or leached from waste to leachate. The analysis shown in Appendix E indicated that, as might be expected, the concentrations of various metals in the leachate varied widely, with a trend towards decreasing concentrations in the leachate for 12 of the 18 elements tested. Higher concentrations of sodium in the leachate are attributed to the use of $NaHCO_3$ as a buffer, while the increase in silicon likely resulted from using it as a sealant in the experimental setup. In phase I, Cell-2 achieved higher sorption efficiencies for elements such as in K, S, Mg and lower leaching rates, hence lower accumulations for Na, and Ni in the leachate than Cell-1. It seems that the higher differential temperature increase in Cell-2 had little effect on increasing the dissolution of metal elements from the waste matrix. However, in phase II, the leachate from Cell-1 had generally less concentrations of dissolved elements as a direct result of the supplemental water dilution. Figures 6-20 show the concentrations of the six highest concentrated elements in the leachate collected from both cells (Na, K, Ca, S, Mg, and P). It can be observed that the concentrations of these elements were constantly decreasing in Cell-1 (controlled by SMART throughout operation), while only significant in phase I of Cell-2 when SMART was applied and heating was introduced.

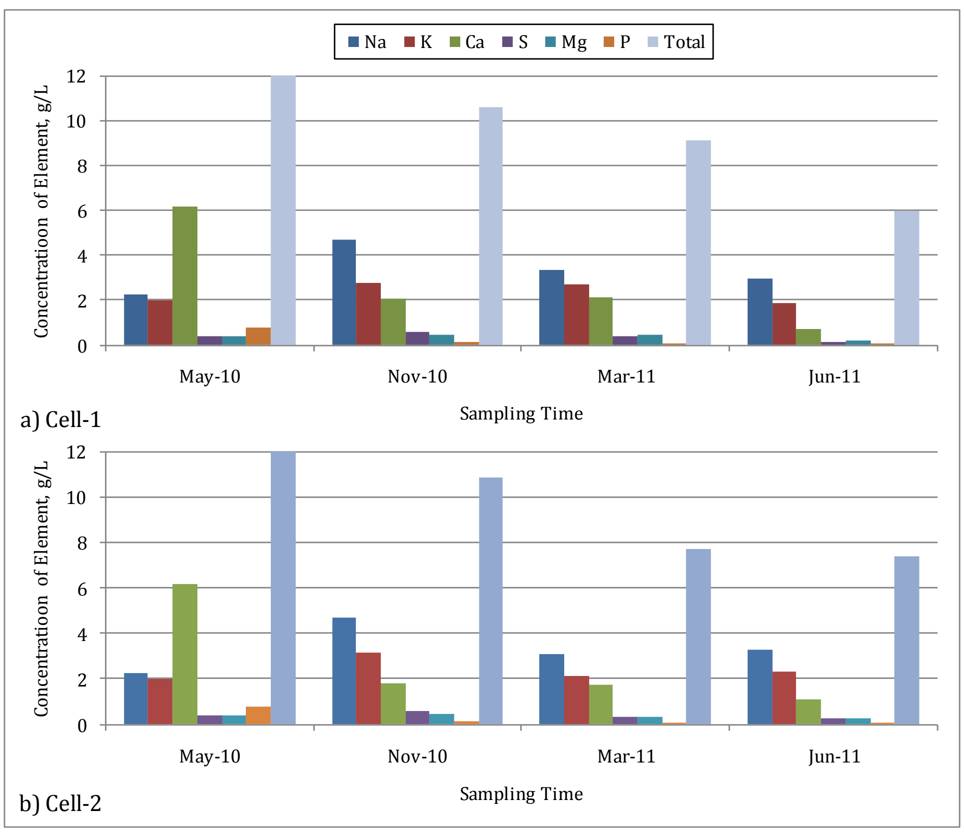

Figure 6-20 Concentrations of selected dissolved elements in leachate during operation

6.5. Conclusions

A comprehensive discussion of the application of the SMART control system in a pilot-scale prototype was presented. Overall, the present implementation of SMART confirmed the applicability and validity of the system to control the BL. The software developer used (LabVIEW), communication interfaces (RS-485/USB), and data exchange protocol (OPC) achieved robust performance based on the type and quality of data acquired from the BL. The evaluation of SMART showed that recirculating variable calculation-based amounts of leachate and other amendments resulted in a positive influence on the overall performance of the BL system. Moreover, it was proven that, with minimum amendments used, SMART optimized the leachate recirculation and manipulation techniques as seen in terms of methane generation and leachate stabilization. It was clear that the modifications made on SMART, including the addition of supplemental water to reduce the impact of detrimental substances in leachate, enhanced the system performance significantly, and assisted in a proper transitioning to the methane generation phase.

The analysis of leachate and biogas parameters showed that, within the temperature range studied, temperature control via recirculation of heated leachate can achieve: (1) higher degradation rate of organic matter as well as conversion rates of acids to methane, (2) greater positive impact on acetoclastic methanogens compared to hydrogenotrophic methanogens, and (3) improved methanogenic activity leading to significantly greater methane production. Additionally, it was proven that raising the leachate temperature by 10°C increased the waste temperature slightly (average of 1.56°C) due to the high specific heat capacity of waste. The rate of increase in waste temperature at early phases was tenfold the increase in later phases. However, it is expected that additional improvements may be achieved if a more aggressive temperature control strategy is implemented.

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CHAPTER 7

CONCLUSIONS & RECOMMENDATIONS

7.1. Conclusions

The present work developed a control framework in which an expert system, referred to as SMART, is responsible for the operation of BLs. The main control objective of the SMART system was to optimize the performance of the BL by manipulating the quantity and quality of leachate recirculated so as to supply the microbial consortia inside the BL with their optimal growth requirements. In this manuscript, the proposed conceptual framework of the system as well as the expert system and control guidelines were described in detail, and a comprehensive assessment was conducted for a SMART-controlled pilot-scale BL in order to examine the applicability, feasibility, and effectiveness of the technology. Based on the development and demonstration of the SMART system, the following categorized conclusions were drawn:

Control System

1. SMART successfully determined the quantity and quality of the recirculated liquid based on the BL operational stage and multiple process leachate and biogas parameters. The FL-based control program was able to accommodate the uncertainties and complexities of the nonlinear multi-parameter BL processes. Thus, hypothesis #1 is correct.

2. The pilot-scale implementation of SMART demonstrated the feasibility of the system. Since all the incorporated hardware components are commercially available, the system can be readily scaled-up to a larger scale application.

3. The performance of the BL was significantly improved with the application of closed-loop control as opposed to an open-loop strategy. Accordingly, the second hypothesis is accepted.

4. As the reasoning of the FL controller is limited to its knowledge base, operator-computer interaction is critical to insure the control actions address all potential

problems. Therefore, applying a semi-automated control strategy, rather than a fully automated one, can achieve stable performance of the BL.

Experimental Observations

1. Despite the fact that most of the process variables of the two BL cells were similar, the SMART-calculated amounts of amendments for the two cells were different. This showed that there are numerous direct and indirect factors affecting the processes inside the BL, and therefore, a site-specific control strategy is required for optimal performance (hypothesis #3 is correct).
2. The response time of the BL ecosystem, i.e., time from changing a system parameter to when its effect (feedback) on system performance is detected, was found to be sufficient to facilitate the application of the feedback control scheme.
3. Early-phase recirculation of leachate, as produced, appeared to prolong the acidogenic phase by reintroducing various organic and inorganic compounds to the BL resulting in unfavourable growth conditions for the methanogenic bacteria.
4. Using the biogas production rate to evaluate the performance of the SMART control system was not feasible due to its intermittent nature (abrupt short-term fluctuations).

Fuzzy Logic Controllers

1. The FLC was able to successfully identify the operational phase of a BL at any given time based on multiple parameters of the leachate and biogas. The computed phase index described the transitioning progress between the main phases of the BL, which enabled the interpolation of the evolving growth requirements for the bacterial population inside the BL, and led to successful transition from one phase to another.
2. The FLC managed to evaluate the potential toxicity of the leachate based on key indicators, and effectively determined the amount of supplemental water required to minimize the inhibitory concentrations in the leachate.

3. The FL model was far more robust and flexible than the ANFIS model in simulation of experimental data outside of their calibration and training ranges. FL had a much better ability to simulate a variety of atypical and untrained operating scenarios.

Leachate Management

1. Leachate manipulation techniques, such as buffering, bioaugmentation, supplemental water addition, and heating, were proven to be potentially effective control tools that are able to adjust/optimize the leachate characteristics. Thus, hypothesis #4 is correct.

2. The optimal volumes and fractions of leachate, water, buffer, and sludge in the final recirculation solution, as determined by SMART, did not follow a specific trend that can be predicted.

3. The calculation-based approach of SMART determined the optimal amounts of buffer needed which was found to be significantly less than typically used to neutralize leachate.

4. Supplemental water addition was shown to be an effective control method to address leachate toxicity issues, as it significantly enhanced the BL performance.

5. Temperature control via recirculation of heated leachate achieved: (1) higher degradation rates of organic matter as well as conversion rates of acids to methane, (2) greater positive impact on acetoclastic methanogens compared to hydrogenotrophic methanogens, and (3) improved methanogenic activity leading to greater methane production.

7.2. Contributions

1. This research is leading edge in the field of unconventional knowledge-based control of the BL.

2. This work has established the basis for a comprehensive sensor-based and semi-automated control system to optimize the operation of the BL process.

3. This work is among the first efforts in studying BL management using a controlled leachate recirculation strategy.

4. The proposed control guidelines are the first to employ the leachate manipulation techniques to adjust the quality of the recirculation solution.
5. This research is among the very first studies exploring the temperature control of BLs.
6. Applying advanced process control theories has unveiled a novel field of BL research that targets the management of the real-time state and behaviour of the BL system in an optimized fashion.

7.3. Recommendations for Future Research

Due to the new concepts of the present research, multiple pathways can be proposed for future work. The recommended future research can be divided into SMART-based topics, as well as general topics, as follows:

SMART-based Future Research

1. Investigate the evaluation of system performance based on the quality of the biogas, rather than the quantity of gas produced which can be used for long-term evaluations.
2. Study the relationship between the chemical/biochemical characteristics of the solid waste matrix and those of the leachate produced.
3. Extend the use of fuzzy cognitive maps in modeling the BL system by employing weighted interconnections to show the degree of influence between the map elements.
4. Implement alternate unconventional techniques in modeling/controlling the BL process, e.g., genetic algorithms.
5. Upgrade to a demonstration-scale application of SMART under field conditions.
6. Apply SMART to other BL configurations, such as aerobic and facultative BLs.
7. Develop specialized instrumentation that suits the aggressive environment of the BL.

General Future Research

1. Study the effects of applying variable rates of different supplements to the BL.

2. Explore the addition of unconventional supplements, such as lignase, cellulose, and pectinase enzymes, to the BL.
3. Assess the effectiveness of leachate heating under a wider range of temperatures (mesophilic and thermophilic), as well as its economical aspects.

Appendix A

Summary of Recent Lab Studies Pertaining to Bioreactor Landfills

Study	Volume, Litre	Temperature, °C	Mass, kg.	Bioaugmentation	Buffer Addition	Recirculation Rates	Comments
Bae *et al.* (1998)	163	35	114	0.08-0.15 L/d of anaerobic digester effluent	-	0.15 L/d of simulated rain	leachate was treated in an anaerobic digester whose effluent was used for recirculation
Benbelkacem *et al.* (2010)	800	35 ± 2	412	-	-	4.25 and 17 L weekly	Used mature leachate for recirculation 17 L reactor performed better
Chugh, *et al.* (1998)	200	38	100	-	-	2 , 10, and 30 % of initial waste volume	Used young and mature leachate alternatively 30% reactor was the best
Erses and Onay (2003)	96	32	13	Anaerobic digested sludge (1 L. total)	1N KOH from day 56 to 84 & 100 g/L Na_2CO_3afterwards	1 to 3 L/week leachate plus 0.5 L/week water	KOH buffer was replaced by Na_2CO_3 as accumulation of K reached inhibitory levels. Used mature leachate in early phase only
Filipkowska (2008)	44	20	-	-	-	2.15 to 4.30 mm/d	Used mature leachate for recirculation 4.3mm/d recirculation was better

Study	Volume, Litre	Temperature, °C	Mass, kg.	Bioaugmentation	Buffer Addition	Recirculation Rates	Comments
Francois *et al.* (2007)	113	38	50	Sewage sludge (6.2-6.6% of waste mass)	-	0.541 L/d leachate plus 0.11 L/d water	Reactors were initially saturated with tap water mixed with inocula
Jianguo *et al.* (2007)	30,000		28,000	10 kg sewage sludge added once upon startup	$Ca(OH)_2$ to neutral or mildly alkaline when necessary	5.3, 2.7, and 0.7% of waste volume weekly	Used mature leachate for recirculation
Rendra (2007)	7	22±2	2.5	Anaerobic sludge (1, 2, and 3% of waste volume /d)	$NaHCO_3$ to neutrality	10, 20, and 30% of waste volume / d)	Best performance was at the highest rates for leachate recirculation and sludge addition
San and Onay (2001)	73	34	13	-	buffer applied in the last operational phase	1 to 8 L/week leachate plus 1 L/week water	The frequency of recirculation varied from 1 to 4 times/week 4 times/week frequency was best
Sanphoti *et al.* (2006)	64	N/A	38	-	$NaHCO_3$ (total amount of 0.86 kg)	Initially 5% of waste volume and increased up to 15%	Buffer was added to adjust TVA/Alkalinity ratio not to exceed 0.8
Sponza and Agdag (2004)	54	35	27	1 L initial of anaerobic sludge	-	13 and 30% of the reactor volume	13% achieved better performance
Warith (2002)	80	25	20	Municipal sewage sludge (5% of recirculated leachate volume)	NaOH to neutrality	6, 12, 25 % of the reactor volume weekly	Nutrients added as plant food at N and P contents of 20% each. Optimum efficiency at 12% rate.

APPENDIX B

PARAMETERS OF FUZZY LOGIC CONTROLLERS IN SMART

Membership functions and fuzzy rules defined for the FL models in SMART are presented.

B.1. Phase Calculator

B.1.1. Variables

Name	**Type**	**Range**	**Number of membership functions**
ORP, mV	Input	-500 to 200	4
pH	Input	3 to 9	3
COD, mg/L	Input	0 to 60000	3
TVA, mg/L	Input	0 to 40000	3
CH_4, %	Input	0 to 65	2
Phase Index	Output	0 to 3	4

B.1.2. Defuzzification Method

Center of Area

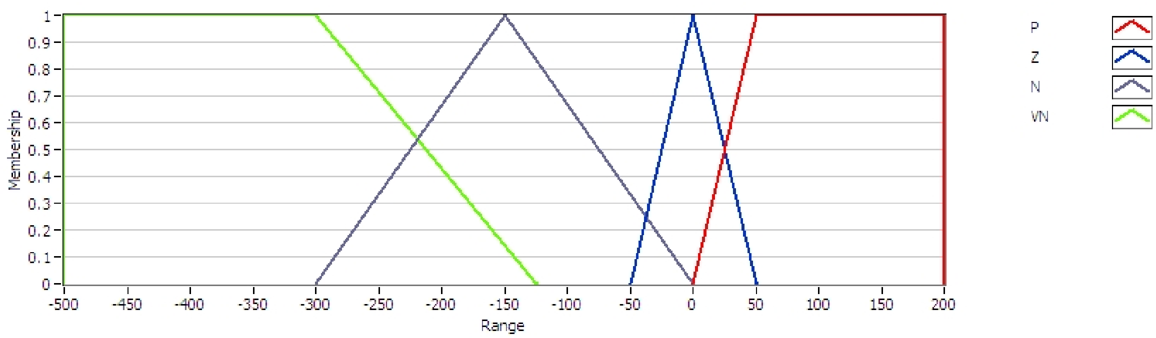
B.1.3. Input Membership Functions

The values of the ***parameters*** shown in the following tables represent the following:

For the Trapezoidal MF (***a***; ***b***; ***c***; ***d***): parameters ***a*** and ***d*** locate the "feet" of the trapezoid, whereas parameters ***b*** and ***c*** locate the "shoulders." For the Triangular MF, parameters ***a*** and ***c*** locate the "feet" of the triangle and parameter ***b*** locates the peak.

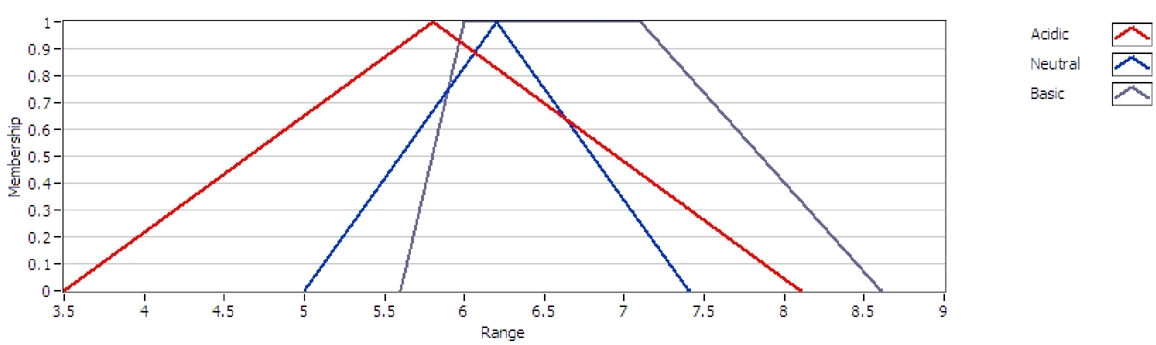
B.1.3.1. ORP, mV

Membership function	Shape	Parameters
P	Trapezoid	0 ; 50 ; 200 ; 200
Z	Triangle	-50 ; 0 ; 50
N	Triangle	-300 ; -150 ; 0
VN	Trapezoid	-500 ; -500 ; -300 ; -125



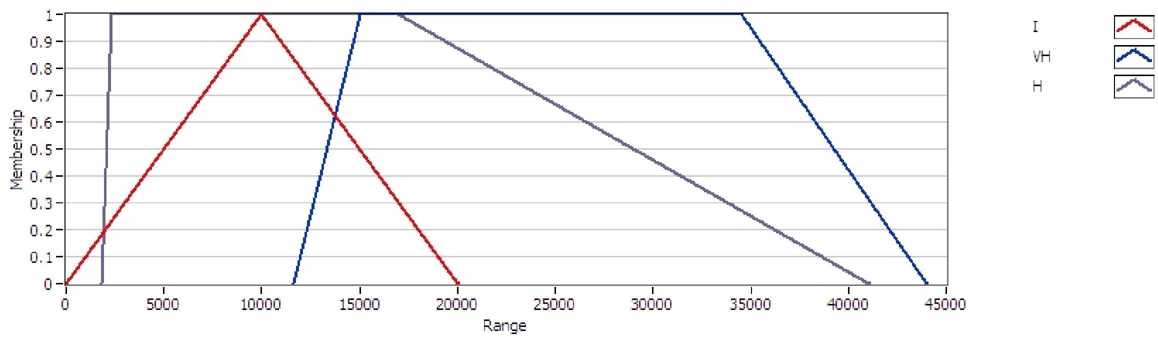
B.1.3.2. pH

Membership function	Shape	Points
Acidic	Triangle	3.5 ; 5.8 ; 8.1
Neutral	Triangle	5 ; 6.2 ; 7.4
Basic	Trapezoid	5.6 ; 6 ; 7.1 ; 8.6



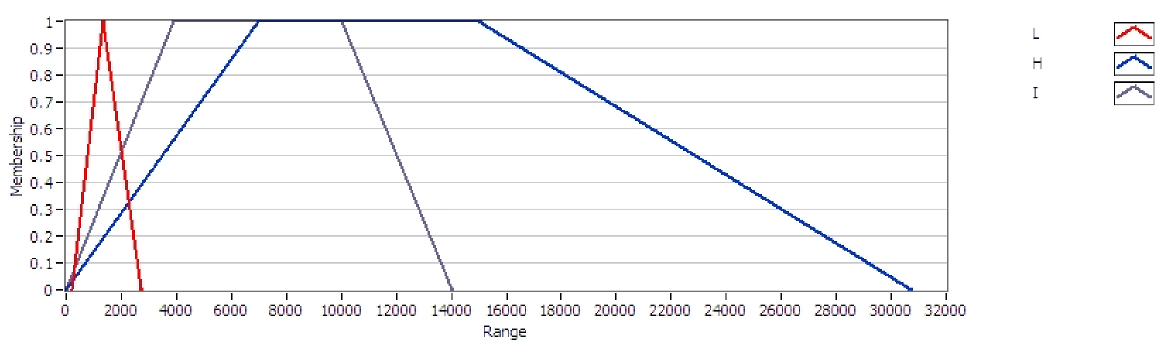
B.1.3.3. COD, mg/L

Membership function	Shape	Points
I	Triangle	20 ; 10000 ; 20000
VH	Trapezoid	11600 ; 15000 ; 34550 ; 44000
H	Trapezoid	1800 ; 2300 ; 17000 ; 41000



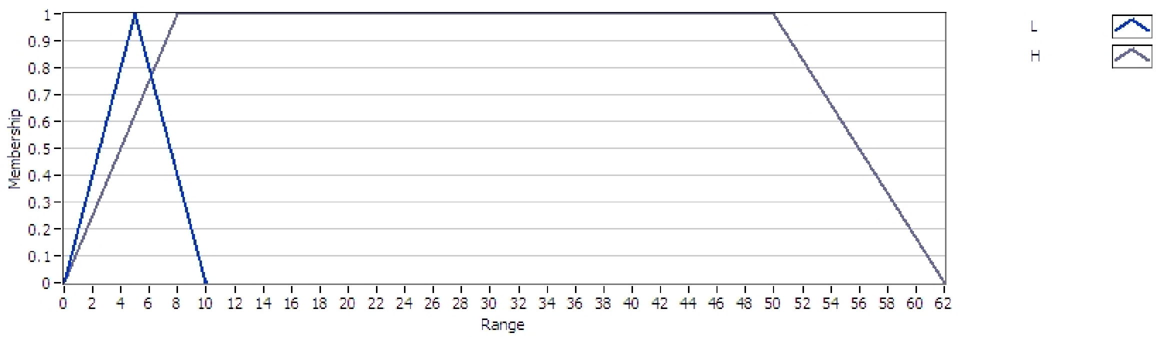
B.1.3.4. TVA, mg-AA/L

Membership function	Shape	Points
L	Triangle	200 ; 1350 ; 2700
H	Trapezoid	1 ; 7000 ; 15000 ; 30730
I	Trapezoid	0 ; 3900 ; 10000 ; 14000



B.1.3.5. CH_4, %

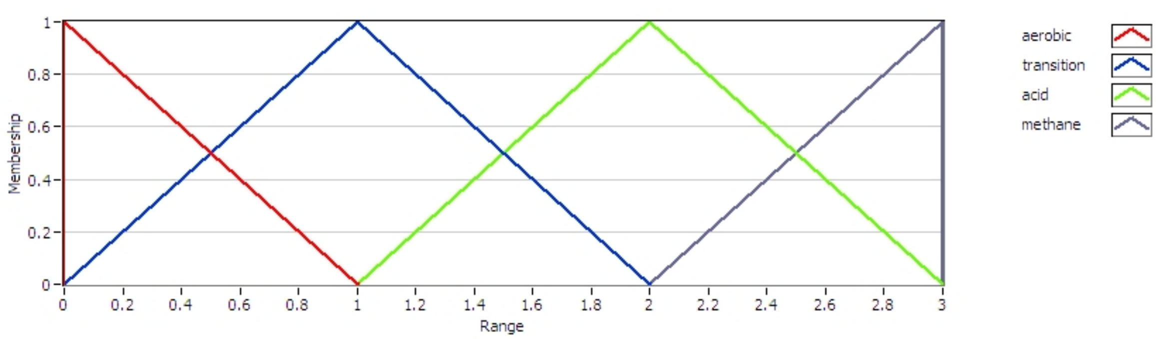
Membership function	Shape	Points
L	Triangle	0 ; 5 ; 10
H	Trapezoid	0 ; 8 ; 50 ; 62



B.1.4. Output Membership Functions

B.1.4.1. Phase Index

Membership function	Shape	Points
initial	Triangle	0 ; 0 ; 1
transition	Triangle	0 ; 1 ; 2
acid formation	Triangle	1 ; 2 ; 3
methane formation	Triangle	2 ; 3 ; 3



B.1.5. Fuzzy Rules

1. IF 'ORP, mV' IS 'P' THEN 'Phase Index' IS 'aerobic'
   connective: AND (Minimum); implication: Product; degree of support: 1.00
2. IF 'ORP, mV' IS 'Z' OR 'pH' IS 'Acidic' OR 'COD, mg/L' IS 'I' OR 'TVA, mg/L' IS 'L' THEN 'Phase Index' IS 'transition'
   connective: OR (Probabilistic); implication: Product; degree of support: 1.00
3. IF 'ORP, mV' IS 'N' OR 'pH' IS 'Neutral' OR 'COD, mg/L' IS 'VH' OR 'TVA, mg/L' IS 'H' OR 'CH4, %' IS 'L' THEN 'Phase Index' IS 'acid formation'
   connective: OR (Probabilistic); implication: Product; degree of support: 1.00
4. IF 'ORP, mV' IS 'VN' OR 'pH' IS 'Basic' OR 'COD, mg/L' IS 'H' OR 'TVA, mg/L' IS 'I' OR 'CH4, %' IS 'H' THEN 'Phase Index' IS 'methane formation'
   connective: OR (Probabilistic); implication: Product ; degree of support: 1.00

B.2. Toxicity Indicator

B.2.1. Variables

Name	Type	Range	Number of membership functions
VFA, mg/L	Input	10000 to 30000	3
TAN, mg-N/L	Input	3000 to 9000	3
UAN, mg-N/L	Input	100 to 300	3
UVFA, mg/L	Input	100 to 400	2
CAT, mg-Na/L	Input	3000 to 8000	3
Dilution Factor	Output	0 to 0.2	3

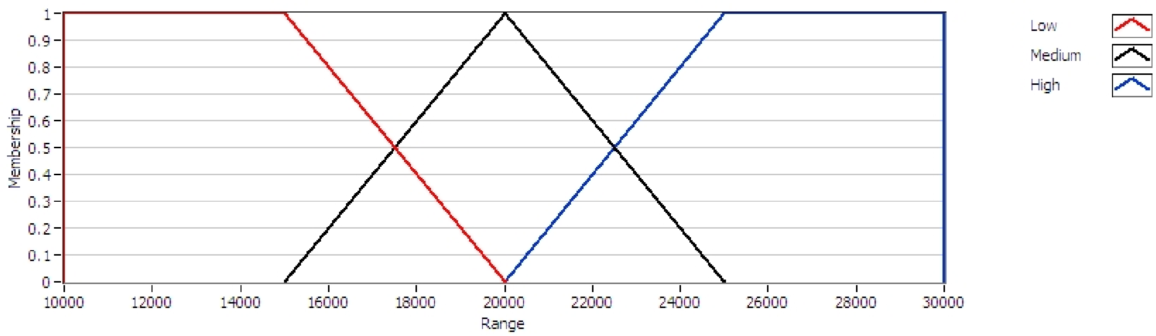
B.2.2. Defuzzification Method

Modified Center of Area

B.2.3. Input Membership Functions

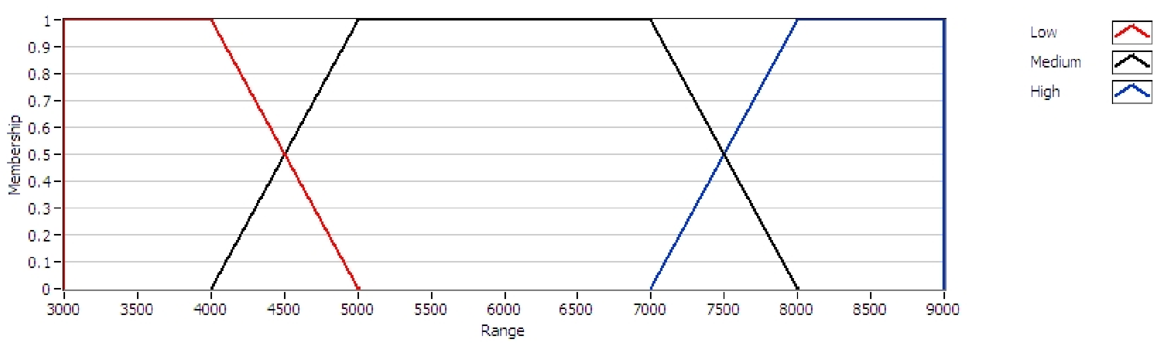
B.2.3.1. VFA, mg-AA/L

Membership function	Shape	Points
Low	Trapezoid	10000 ; 10000 ; 15000 ; 20000
Medium	Triangle	15000 ; 20000 ; 25000
High	Trapezoid	20000 ; 25000 ; 30000 ; 30000



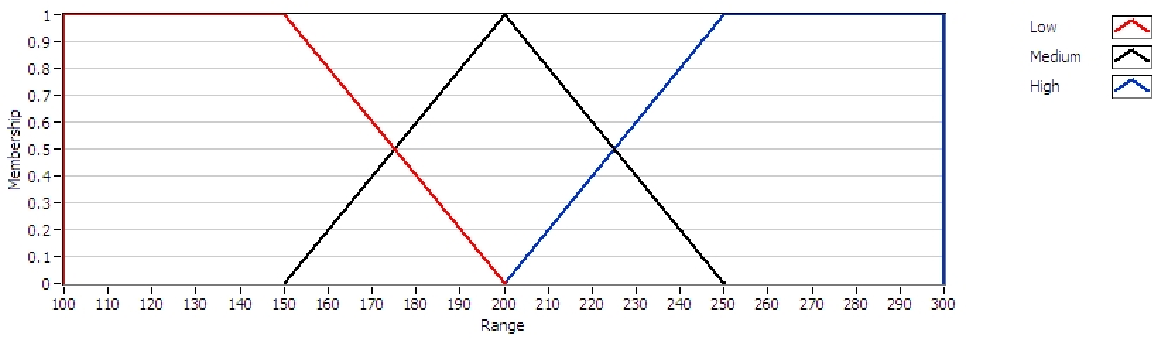
B.2.3.2. TAN, mg-N/L

Membership function	Shape	Points
Low	Trapezoid	3000 ; 3000 ; 4000 ; 5000
Medium	Trapezoid	4000 ; 5000 ; 7000 ; 8000
High	Trapezoid	7000 ; 8000 ; 9000 ; 9000



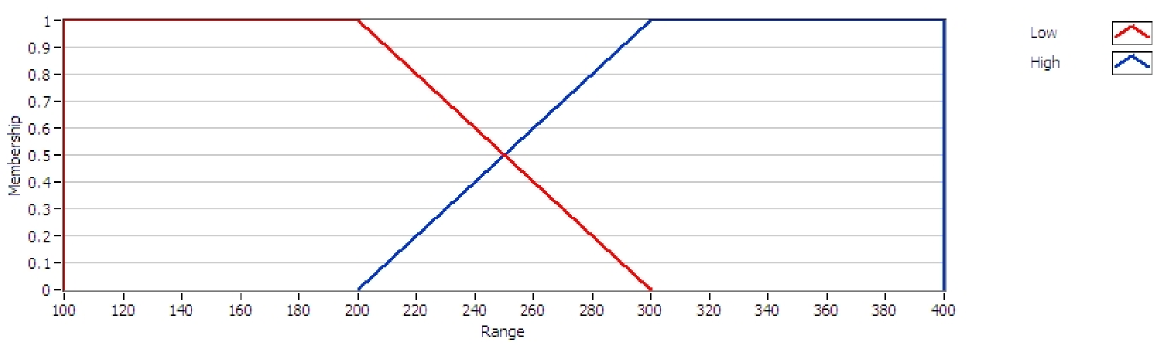
B.2.3.3. UAN, mg-N/L

Membership function	Shape	Points
Low	Trapezoid	100 ; 100 ; 150 ; 200
Medium	Triangle	150 ; 200 ; 250
High	Trapezoid	200 ; 250 ; 300 ; 300



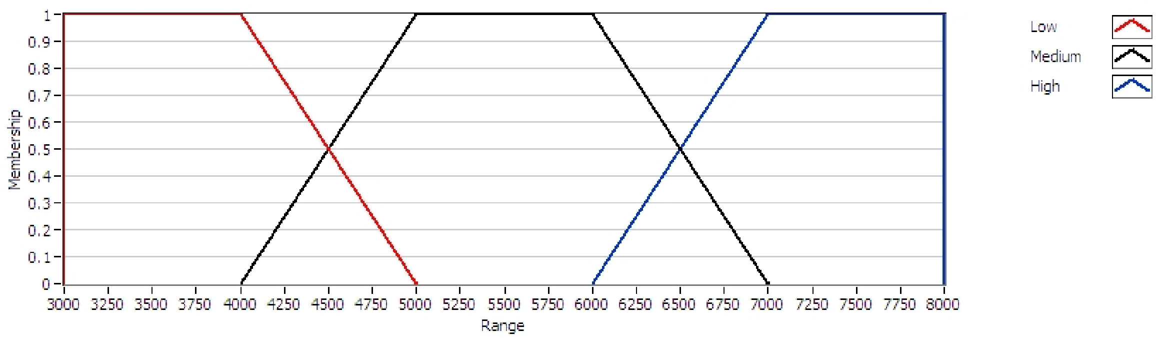
B.2.3.4. UVFA, mg-AA/L

Membership function	Shape	Points
Low	Trapezoid	100 ; 100 ; 200 ; 300
High	Trapezoid	200 ; 300 ; 400 ; 400



B.2.3.5. CAT, mg-Na/L

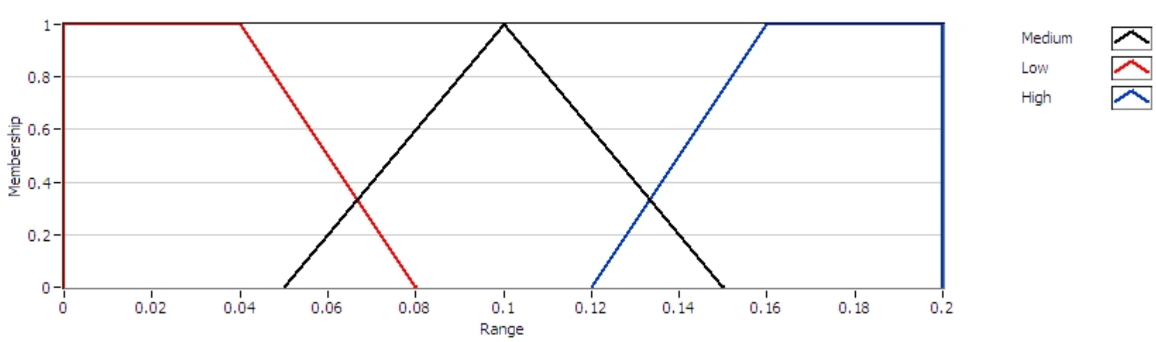
Membership function	Shape	Points
Low	Trapezoid	3000 ; 3000 ; 4000 ; 5000
Medium	Trapezoid	4000 ; 5000 ; 6000 ; 7000
High	Trapezoid	6000 ; 7000 ; 8000 ; 8000



B.2.4. Output Membership Functions

B.2.4.1. Dilution Factor

Membership function	Shape	Points
Medium	Triangle	0.05 ; 0.1 ; 0.15
Low	Trapezoid	0 ; 0 ; 0.04 ; 0.08
High	Trapezoid	0.12 ; 0.16 ; 0.2 ; 0.2



B.2.5. Fuzzy Rules

1. IF 'VFA, mg/L' IS 'Low' AND 'UVFA, mg/L' IS 'High' THEN 'Dilution Factor' IS 'High'
   connective: AND (Minimum); implication: Product; degree of support: 1.00
2. IF 'TAN, mg-N/L' IS 'Low' AND 'UAN, mg-N/L' IS 'High' THEN 'Dilution Factor' IS 'High'
   connective: AND (Minimum); implication: Product; degree of support: 1.00
3. IF 'VFA, mg/L' IS 'High' AND 'UVFA, mg/L' IS 'High' THEN 'Dilution Factor' IS 'Medium'
   connective: AND (Product); implication: Minimum ; degree of support: 1.00
4. IF 'TAN, mg-N/L' IS 'High' AND 'UAN, mg-N/L' IS 'High' THEN 'Dilution Factor' IS 'Medium'
   connective: AND (Product); implication: Minimum ; degree of support: 1.00
5. IF 'UVFA, mg/L' IS 'Low' OR 'UAN, mg-N/L' IS 'Low' OR 'CAT, mg-Na/L' IS 'Low' OR 'VFA, mg/L' IS 'Low' OR 'TAN, mg-N/L' IS 'Low' THEN 'Dilution Factor' IS 'Low'
   connective: OR (Probabilistic); implication: Minimum; degree of support: 1.00
6. IF 'UVFA, mg/L' IS 'Low' OR 'UAN, mg-N/L' IS 'Medium' OR 'CAT, mg-Na/L' IS 'Medium' OR 'VFA, mg/L' IS 'Medium' OR 'TAN, mg-N/L' IS 'Medium' THEN 'Dilution Factor' IS 'Low'
   connective: OR (Probabilistic); implication: Minimum; degree of support: 1.00
7. IF 'UVFA, mg/L' IS 'High' OR 'UAN, mg-N/L' IS 'High' OR 'CAT, mg-Na/L' IS 'High' OR 'VFA, mg/L' IS 'High' OR 'TAN, mg-N/L' IS 'High' THEN 'Dilution Factor' IS 'High'
   connective: OR (Probabilistic); implication: Minimum; degree of support: 0.00

B.3. Methane Estimator

B.3.1. Variables

Name	Type	Range	No. of membership functions
Time Fraction	Input	0 to 1	7
Leachate Recirculation, %/d	Input	0 to 0.5	3
Sludge Addition, l/kg/d	Input	0 to 1.5	2
Methane Generation Fraction	Output	0 to 0.05	7

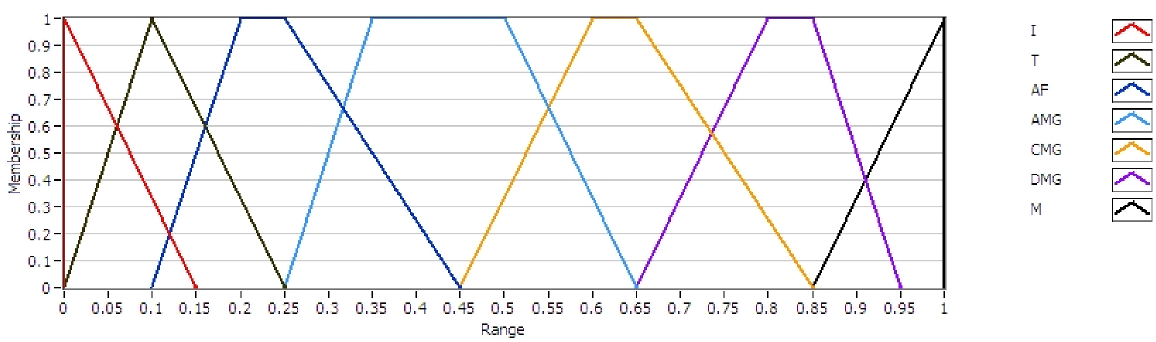
B.3.2. Defuzzification Method

Center of Area

B.3.3. Input Membership Functions

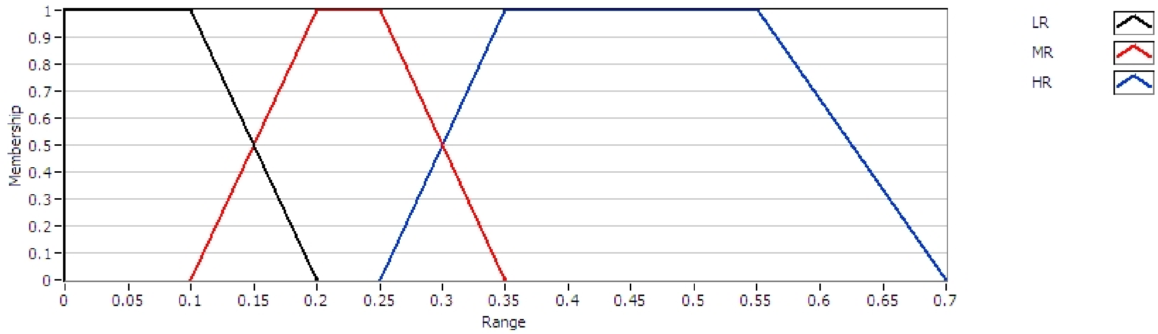
B.3.3.1. Time Fraction

Membership function	Shape	Points
I	Triangle	0 ; 0 ; 0.15
T	Triangle	0 ; 0.1 ; 0.25
AF	Trapezoid	0.1 ; 0.2 ; 0.25 ; 0.45
AMG	Trapezoid	0.25 ; 0.35 ; 0.5 ; 0.65
CMG	Trapezoid	0.45 ; 0.6 ; 0.65 ; 0.85
DMG	Trapezoid	0.65 ; 0.8 ; 0.85 ; 0.95
M	Triangle	0.85 ; 1 ; 1
I	Triangle	0 ; 0 ; 0.15



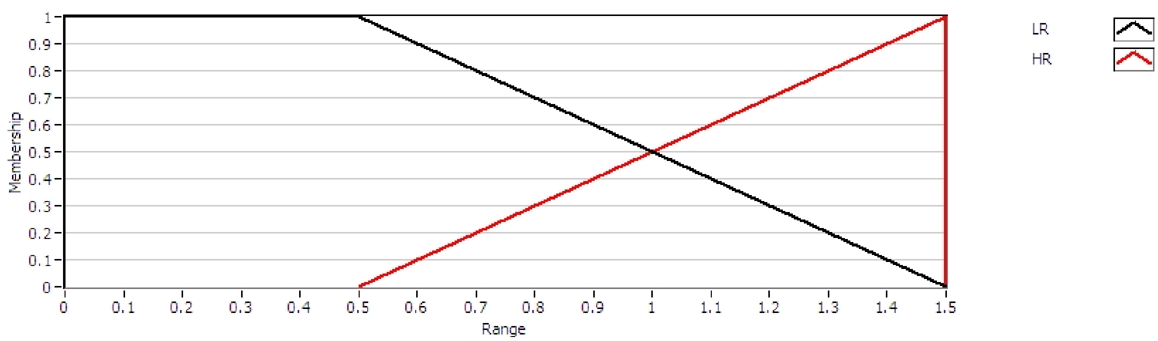
B.3.3.2. Leachate Recirculation, %/d

Membership function	Shape	Points
LR	Trapezoid	0 ; 0 ; 0.1 ; 0.2
MR	Trapezoid	0.1 ; 0.2 ; 0.25 ; 0.35
HR	Trapezoid	0.25 ; 0.35 ; 0.55 ; 0.7



B.3.3.3. Sludge Addition, l/kg/d

Membership function	Shape	Points
LR	Trapezoid	0 ; 0 ; 0.5 ; 1.5
HR	Triangle	0.5 ; 1.5 ; 1.5



B.3.4. Output Membership Functions

B.3.4.1. Methane Generation, % of total production/kg/d

Membership function	Shape	Points
XL	Trapezoid	0 ; 0 ; 0.0015 ; 0.0055
VL	Triangle	0.0015 ; 0.007 ; 0.0125
L	Gaussian	0.0035 ; 0.013
M	Gaussian	0.0035 ; 0.022
H	Gaussian	0.0035 ; 0.0315
VH	Triangle	0.00325 ; 0.04 ; 0.0465
XH	Trapezoid	0.0425 ; 0.047 ; 0.05 ; 0.05

APPENDIX C

CRITICAL ISSUES IN THE PERFORMANCE OF THE NEURO-FUZZY SYSTEM IN CHAPTER 5

C.1. Introduction

A neuro-fuzzy model was presented in chapter 5 to estimate the methane production of a BL. The used technique was the Adaptive Neuro-Fuzzy Inference System (ANFIS). This section discusses two of the critical issues regarding the implementation of ANFIS model: (1) effect of the size of training datasets, and (2) effect of the number of training epochs. The following discussion summarizes a conference paper "***Combining fuzzy logic and neural networks in modeling landfill gas production***" by Abdallah, M., Kennedy, K., Warith, M., Narbaitz, R., and Petriu, E., published in the proceedings of the International Conference of Environmental Engineering and Technology, July 13-15, 2011, Amsterdam, Netherlands.

C.2. Training Datasets

In this section, the effects of the size of training datasets as well as the number of training epochs (iterations) on ANFIS is evaluated statistically via linear regression between actual and predicted data as well as MSE measures. Six independent training datasets of different sizes were compiled from Rendra (2007). The datasets were used to generate six ANFIS sub-models with the same basic structure and input/output variables of ANFIS model discussed in Chapter 5. M-50, M-100, M-150, M-200, M-250, and M-300 are notations for ANFIS sub-models trained with 50, 100, 150, 200, 250, and 300 dataset vectors, respectively.

C.3. Effect of Size of Training Datasets

Figure C-1 shows the linear regression between model predictions and measured data for the six ANFIS sub-models. The slope, intercept, and coefficients of determination for regression lines are shown on figures. It can be observed that, in all sub-models, the slope was close to unity and the intercept was close to zero, indicating model accuracy. The slope did not exceed unity and the intercept was positive in all sub-models, which demonstrates that ANFIS underestimated the measured data in general. Overall, there was not much difference between the performances of ANFIS sub-models, and all the models achieved excellent agreement with the training datasets (average correlation coefficient of 0.98). The best fit was achieved by M-300, the model with the largest training dataset, whereas the least trained model, M-50, scored the lowest fit.

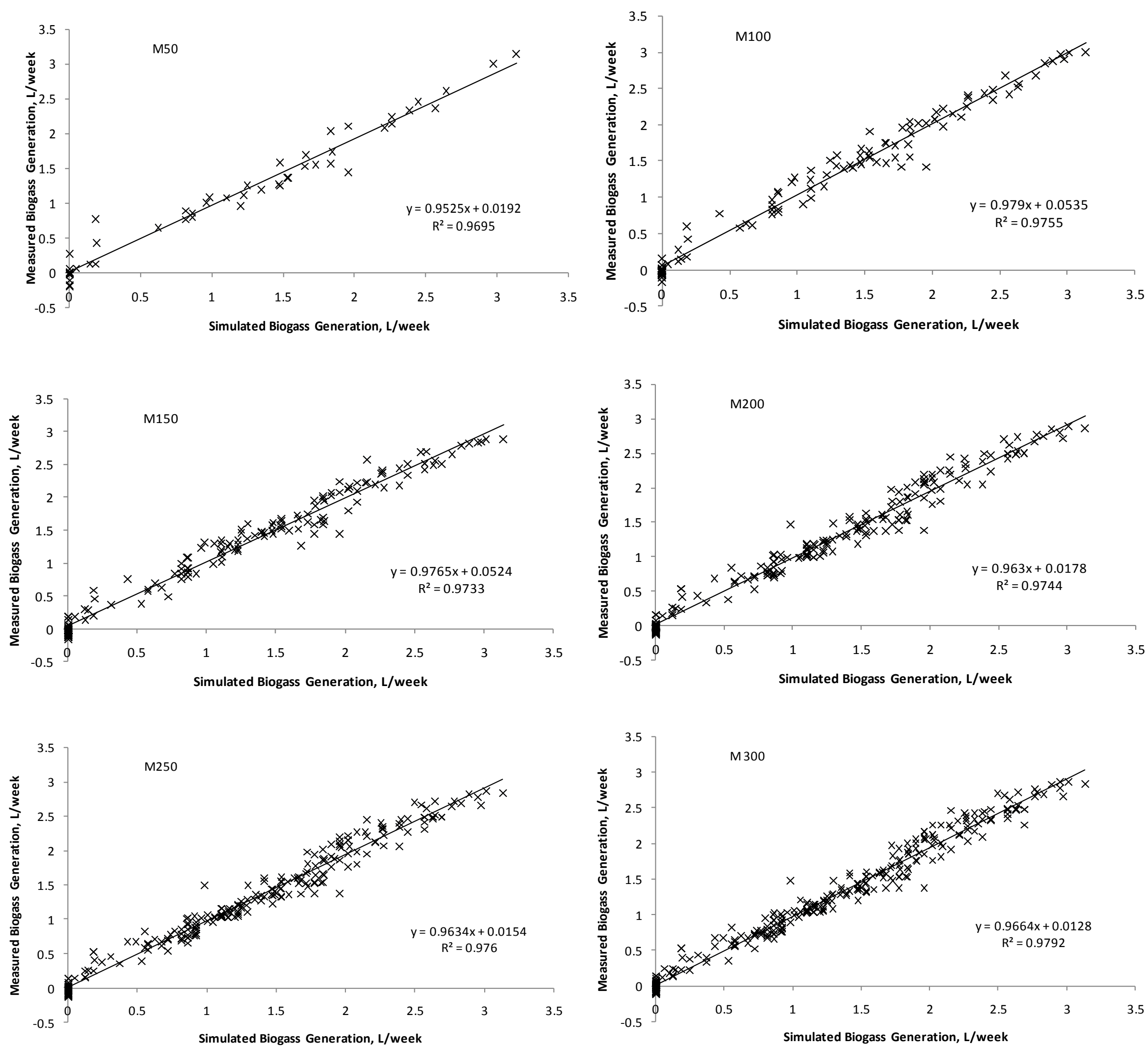


Figure C-1 Linear regression between measured data and simulations of the ANFIS sub-models

As shown in the statistical analyses in Table C-1, ANFIS sub-models achieved an acceptable normalized RMSE that ranged between 11.24% and 14.42%. The number of training vectors highly improved the performance of ANFIS in terms of all statistical measures up until M-150 (see Table C-1). However, beyond M-150, the model did not show significant improvement in response to a larger training dataset.

Table C-1 Statistical indices of the ANFIS sub-models at different training sizes *

Model	MSE	RMSE	N-RMSE
M-50	0.027	0.166	14.423
M-100	0.022	0.147	11.236
M-150	0.022	0.149	11.846
M-200	0.021	0.145	12.290
M-250	0.019	0.138	11.790
M-300	0.017	0.132	11.380

* *MSE: mean square error; RMSE: root mean square error; and N-RMSE: normalized root mean square error (in percent).*

C.4. Effect of Number of Training Epochs

Figure C-2 shows the development of the training error, during the learning process, against the number of training epochs. The training dataset is indicated by the blue stars, whereas, the checking dataset is indicated by the blue circles. It should be noted that the checking dataset is an independent dataset that was used to determine the optimum training effort needed for the system. Usually, the more epochs the system is trained on, the less error will be until a certain point where *overfitting* starts. This point can be observed at iteration#15 of M-50 and at iteration#120 of M-100. It should be noted that the over-fitting problem was not observed in the other sub-models within 300 training epochs.

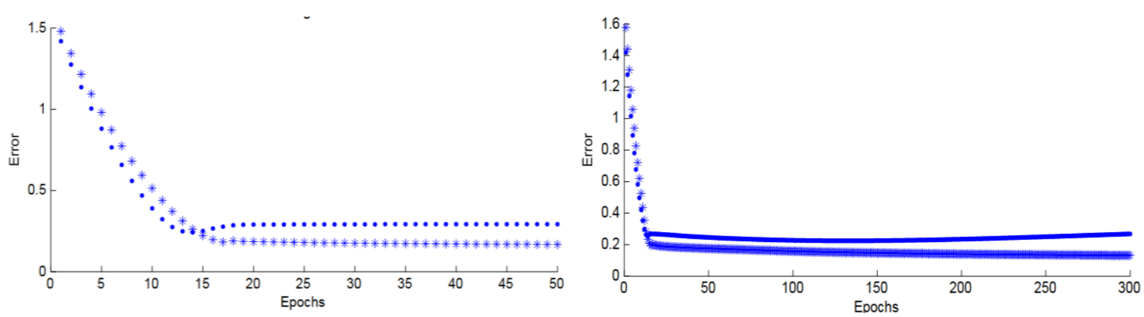


Figure C-2 Training and checking error with training epochs for M-50 (left) and M-100 (right)

The effect of the number of training epochs on the performance of the ANFIS sub-models was also evaluated. To achieve this, each of the sub-models was trained with its assigned training dataset for different numbers of training epochs. Figure C-3 shows the plot for the training error against the number of training epochs for ANFIS sub-models.

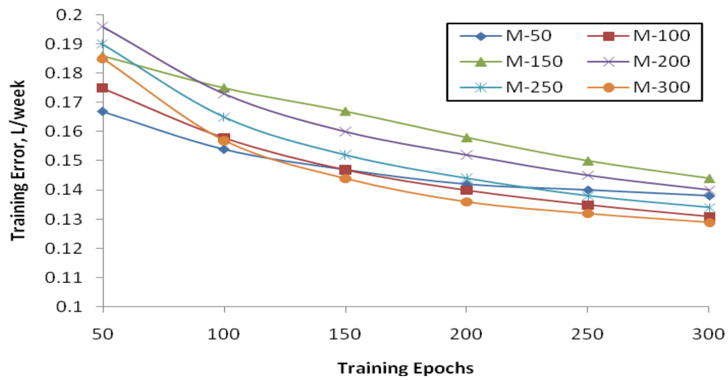


Figure C-3 Progress of training error with training epochs for ANFIS sub-models

Prior to 120 training epochs, M-50 achieved the least training error and M-150 achieved the highest. After 120 training epochs, M-300 had the lowest training error, whereas M-150 scored the highest. After 200 training epochs, the least trained model, M-50, did not show further drop in its training error. More than 40% of the difference between initial and final training error occurred after 50 training iterations. The next 40% took 100 iterations and the last 20% was reached in 150 iterations.

C.5. Conclusion

The effect of the size of training datasets as well as the number of training epochs (iterations) on the modeling efficiency of ANFIS was assessed. It was confirmed that the more epochs the ANFIS system is trained on, the less error occurs until the point where model overfitting begins. It was also shown that the overfitting issue can cause model distortion which results in a poor prediction efficiency.

APPENDIX D

STATISTICAL MEASURES USED IN CHAPTER 5

The soft computational models, presented in chapter 5, were evaluated using a group of statistical measures including: coefficient of determination (R^2), correlation coefficient (R), mean bias error (MBE), mean absolute error (MAE), percentage error (PE), fractional bias (FB), mean squared error (MSE), normalized mean squared error (NMSE), root mean squared error (RMSE), systematic root mean squared error ($RMSE_S$), unsystematic root mean squared error ($RMSE_U$), index of agreement (IA), as well as the intercept (a) and slope (b) of the regression line between observed and predicted data.

D.1. Calculations

The above statistical indices can be calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(O_i - O_m)^2} \tag{D-1}$$

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i) \tag{D-2}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|P_i - O_i\right| \tag{D-3}$$

$$PE = \frac{1}{N}\sum_{i=1}^{N}\frac{\left|P_i - O_i\right|}{O_i} \tag{D-4}$$

$$FB = 2 \times \frac{P_m - O_m}{P_m + O_m} \tag{D-5}$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2 \tag{D-6}$$

$$NMSE = \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(P_i)^2} \quad \text{(D-7)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \quad \text{(D-8)}$$

$$C_i = a + (b \times O_i) \quad \text{(D-9)}$$

$$RMSE_S = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C_i - O_i)^2} \quad \text{(D-10)}$$

$$RMSE_U = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(C_i - P_i)^2} \quad \text{(D-11)}$$

$$IA = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(|P_i - O_m| + |O_i - O_m|)^2} \quad \text{(D-12)}$$

Where O_i and P_i are the observed and predicted values, O_m and P_m represents the mean of observed and predicted values, N is the number of data points.

D.2. Interpretations

- ***R*** coefficient is a good indicator of precision; the higher the ***R***, the higher the precision. ***R*** coefficient represents square root of $\boldsymbol{R^2}$, with perfect agreement at 1.0.
- (***a***) and (***b***) are the least squares regression coefficients, and are good indicators of accuracy; the closer to zero and unity, respectively, the higher the accuracy.
- ***MBE*** is the average unsigned discrepancy between predictions and observations (also called residuals), whereas ***MAE*** is the mean absolute value of these residuals. Lower values of ***MBE*** and ***MAE*** are better, and less than zero values of ***MBE*** indicate underestimation. ***PE*** is the normalized ***MAE*** with respect to observations.

- ***FB*** is a normalized measure of the agreement between the mean of observed values and the mean of predicted values. A model with ***FB***=0 is a model that represents perfectly the measured mean value.

- ***MSE*** is the mean of squared deviations around the regression line. ***NMSE*** is the normalization of ***MSE*** and is calculated by dividing ***MSE*** by the squared predictions. Perfect agreement between observed and predicted values is indicated by ***NMSE*** = 0.

- ***RMSE*** indicates the mean difference between observed and predicted values in their original units. It should be noted that since large errors are weighted heavily in ***RMSE***, large errors in a small sub-region may produce a large ***RMSE*** even though errors may be small elsewhere.

- $\boldsymbol{RMSE_S}$ represents the portion of ***RMSE*** due to systematic model errors, whereas $\boldsymbol{RMSE_U}$ indicates random errors in the model inputs or in the model itself. Therefore, it can indicate if the model or the data acquisition needs refinement. $\boldsymbol{RMSE_U}$ may also result from random process parameters outside the defined range of the model. Ideally, $\boldsymbol{RMSE_S}$ should approach zero and $\boldsymbol{RMSE_U}$ should approach ***RMSE***.

- ***IA*** is a measure of the agreement between the deviation of model predictions from the observed mean, and the deviations of observations from the observed mean. ***IA*** ranges from 0 to 1.0, with the latter score indicating perfect agreement between observed and predicted values, i.e. predictions are free of error.

D.3. Sample Data

A sample data for the spreadsheet developed to calculate the statistical indices is presented below. The complete results of the statistical analysis are shown in Table 5-5.

No.	*P*	*O*	P^2	*C*	*P-O*	$(P-O)^2$	$\lvert P-O \rvert$	$(C-O)^2$	$(C-P)^2$	$\lvert P-O \rvert / O$	$(\lvert P-O_m \rvert + \lvert O-O_m \rvert)^2$
1	0.0000	0.0000	0	0.003	0	0	0	1E-05	1E-05	0	0.002
2	0.0007	0.0000	5E-07	0.003	6E-04	4E-07	6E-04	1E-05	7E-06	16.66804	0.001
3	0.0026	0.0001	7E-06	0.003	0.002	6E-06	0.002	1E-05	7E-07	32.4265	0.001
4	0.0047	0.0003	2E-05	0.004	0.004	2E-05	0.004	1E-05	1E-06	12.91122	0.001
5	0.0057	0.0004	3E-05	0.004	0.005	3E-05	0.005	1E-05	4E-06	13.65182	0.001

No.	*P*	*O*	P^2	*C*	*P-O*	$(P-O)^2$	$\lvert P-O \rvert$	$(C-O)^2$	$(C-P)^2$	$\lvert P-O \rvert / O$	$(\lvert P-O_m \rvert + \lvert O-O_m \rvert)^2$
6	0.0055	0.0004	3E-05	0.004	0.005	3E-05	0.005	1E-05	4E-06	12.23517	0.001
7	0.0047	0.0008	2E-05	0.004	0.004	1E-05	0.004	9E-06	7E-07	4.653196	0.001
8	0.0036	0.0032	1E-05	0.005	3E-04	1E-07	3E-04	4E-06	2E-06	0.104938	0.001
9	0.0031	0.0065	1E-05	0.007	-0.003	1E-05	0.003	2E-07	1E-05	0.520037	0.001
10	0.0036	0.0101	1E-05	0.009	-0.007	4E-05	0.007	1E-06	3E-05	0.646802	0.001
11	0.0053	0.0150	3E-05	0.012	-0.01	9E-05	0.01	1E-05	4E-05	0.647471	0.000
12	0.0079	0.0221	6E-05	0.016	-0.014	2E-04	0.014	4E-05	6E-05	0.640566	0.000
13	0.0102	0.0255	0.0001	0.017	-0.015	2E-04	0.015	6E-05	5E-05	0.600707	0.000
14	0.0124	0.0270	0.0002	0.018	-0.015	2E-04	0.015	8E-05	3E-05	0.538809	0.000
15	0.0166	0.0335	0.0003	0.022	-0.017	3E-04	0.017	0.0001	3E-05	0.503285	0.000
16	0.0226	0.0387	0.0005	0.025	-0.016	3E-04	0.016	0.0002	4E-06	0.415074	0.001
17	0.0269	0.0434	0.0007	0.027	-0.017	3E-04	0.017	0.0003	2E-07	0.381419	0.001
18	0.0282	0.0458	0.0008	0.029	-0.018	3E-04	0.018	0.0003	2E-07	0.383669	0.001
19	0.0275	0.0411	0.0008	0.026	-0.014	2E-04	0.014	0.0002	2E-06	0.329612	0.001
20	0.0254	0.0396	0.0006	0.025	-0.014	2E-04	0.014	0.0002	2E-08	0.358944	0.001
21	0.0234	0.0385	0.0005	0.025	-0.015	2E-04	0.015	0.0002	2E-06	0.392971	0.001
22	0.0223	0.0292	0.0005	0.02	-0.007	5E-05	0.007	9E-05	7E-06	0.239008	0.000
23	0.0245	0.0259	0.0006	0.018	-0.001	2E-06	0.001	7E-05	5E-05	0.051388	0.000
24	0.0279	0.0224	0.0008	0.016	0.006	3E-05	0.006	4E-05	1E-04	0.247131	0.000
25	0.0258	0.0190	0.0007	0.014	0.007	5E-05	0.007	3E-05	1E-04	0.357075	0.000
26	0.0253	0.0164	0.0006	0.012	0.009	8E-05	0.009	2E-05	2E-04	0.542343	0.000
Sum	0.366	0.505	0.01		-0.139	0.003	0.225	0.002	0.0008	100.447	0.0178

Results:

P_m	0.014094	*R*	0.841665	*MSE*	0.000109	*PE*	1.965541
O_m	0.0194251	R^2	0.7084	*MAE*	0.008661	*IA*	0.841218
a	0.003357	*RMSE*	0.010442	*NMSE*	0.013734		
b	0.552742	*RMSE-S*	0.008827	*FB*	-0.318113		
N	26	*RMSE-U*	0.005578	*MBE*	-0.005331		

APPENDIX E

SUPPLEMENTAL DATA FOR EXPERIMENTAL WORK PRESENTED IN CHAPTER 6

E.1. Food Waste Characteristics

Table E-1 shows the major chemical and biochemical parameters of a food waste sample which was obtained from the liquid fraction collected after sequential grinding, homogenizing, and centrifuging of the waste.

Table E-1 Characteristics of the food waste used

TOCs* mg/L	TN mg/L	COD mg/L	CODs* mg/L	pH -	NH_3 mg/L	Alkalinity mg/L $CaCO_3$	Acetic mg/L	Propionic mg/L	Butyric mg/L	VFA mg/L	TS %	VS %
29682	5839	536317	120289	4.92	779	1600	2731	223	274	3228	32	88

** Soluble fraction was determined by filtering the sample through a filter paper of 0.45 µm pore size.*

E.2. Mixed Waste Characteristics

The actual ratio between residential and food waste streams as well as the organic fraction and initial moisture content of the mixed waste are shown in Table E-2.

Table E-2 Characteristics of the mixed waste in the two bioreactor cells

Cell	Composition fraction, %		Total organic fraction, % (including residential)	Initial water content, % (wet weight)
	Residential waste	Food waste		
1	43.15	56.85	73.70	48.24
2	45.01	54.99	72.46	47.50

E.3. Concentrations of Dissolved Elements in Leachate

Table E-3 shows the concentrations of multiple dissolved elements in the leachate, which were analyzed by the ICP- AES at different times during the monitoring period.

Table E-3 Concentrations (in ppm) of elements in leachate measured using the ICP-AES

Element	Cell-1				Cell-2			
	May 2010	November 2010	March 2011	June 2011	May 2010	November 2010	March 2011	June 2011
Na	2230	4663	3340	2987	2230	4672	3091	3307
K	2002	2732	2714	1857	2002	3171	2107	2335
Ca	6192	2041	2147	708	6192	1823	1713	1106
S	381	583	388	130	381	582	317	232
Mg	369	422	431	192	369	453	340	265
P	745	111	58	54	745	106	55	63
Si	17	54	41	37	17	49	41	64
Fe	86	16	14	5	86	11	42	22
Mn	1.82	2.67	3.11	0.33	1.82	2.53	2.64	0.82
B	0.86	1.46	3.88	2.54	0.86	4.95	1.02	1.04
Ni	0.08	0.81	0.71	0.13	0.08	0.96	0.54	0.18
Al	3.81	0.40	0.06	0.32	3.81	0.05	0.03	0.10
As	1.07	0.32	0.42	0.00	1.07	0.32	0.28	0.05
Zn	1.66	0.28	0.12	0.04	1.66	0.08	0.10	0.16
Cu	0.08	0.26	0.09	0.02	0.08	0.14	0.05	0.04
Co	0.01	0.11	0.12	0.01	0.01	0.11	0.07	0.03
Cd	0.02	0.00	0.00	0.00	0.02	0.00	0.01	0.01
Pb	0.03	0.00	0.00	0.03	0.03	0.00	0.00	0.04
Total	12031	10628	9141	5974	12031	10876	7712	7396

APPENDIX F

PHOTOS OF EXPERIMENTAL SETUP

This section presents the actual pictures of the experimental setup discussed in chapter 6, including the construction, waste placement, and instrumentation stages.

F.1. Sources of Solid Waste

Residential waste was obtained from waste collection trucks at a landfill in Eastern Ontario.

Large objects were screened and plastic and paper materials were cut into smaller pieces.

Residential waste was mixed with the food waste stream while loading the BL cells.

F.2. Experimental Setup

Experimental work was conducted in a temperature-controlled room.

Two pilot-scale BL setups were loaded with the mixed waste.

Residential and food wastes were mixed while loaded to the bioreactor cells.

Mixed waste was placed in two lifts separated by an intermediate gravel layer. A plastic mesh was placed in all contact surfaces between waste and gravel.

A leachate distribution network was installed in each cell.

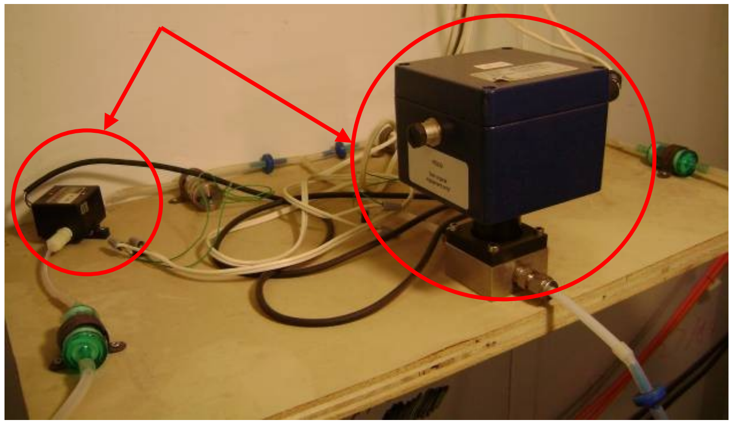
Biogas was collected from an upper port in the lid of each BL cell.

F.3. Instrumentation

Each bioreactor cell was equipped with three type-T thermocouples and moisture sensors.

The internal pressure was monitored with a mechanical pressure gauge, and the biogas temperature was measured in the headspace using a thermistor probe.

Gas production was metered by a micro-turbine flow meter, and analyzed in an online methane analyzer.



Leachate tank was connected to the amendments' tanks via tube lines with solenoid valves.

The pH, ORP, and temperature probes were kept submerged in an always-full container.

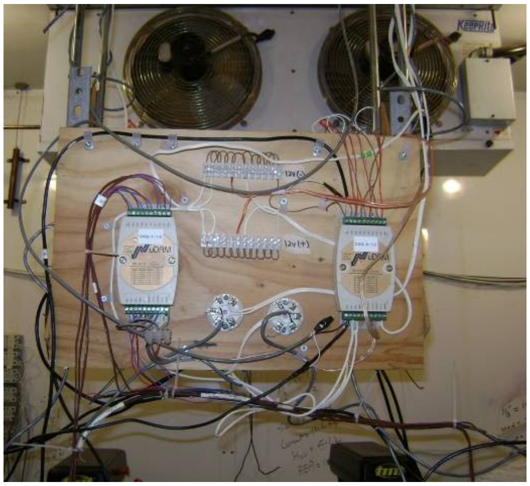
Leachate was recirculated in a cyclic batch mode using a submersible pump.

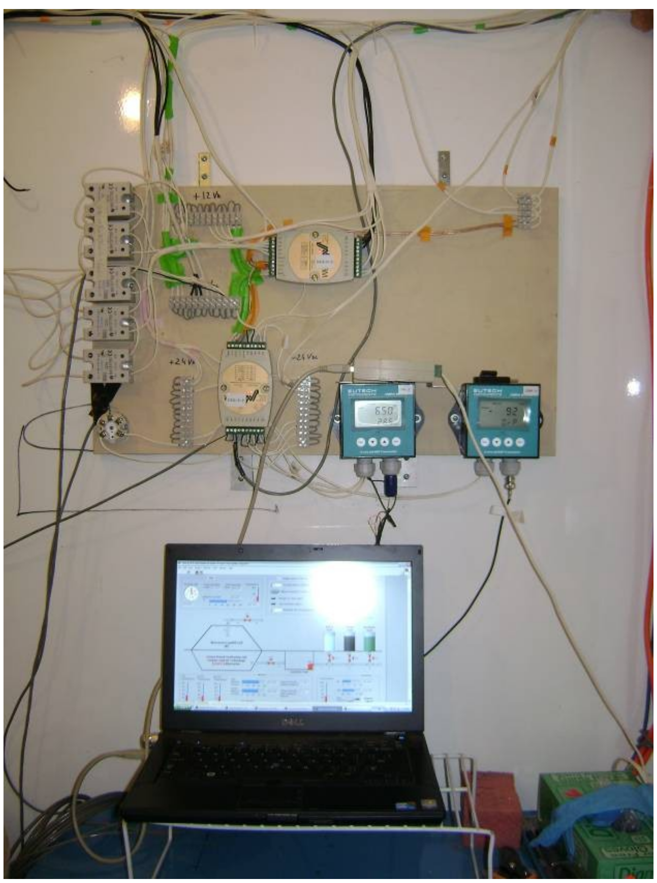
A flexible drum heater was used to heat the leachate in Cell-2.

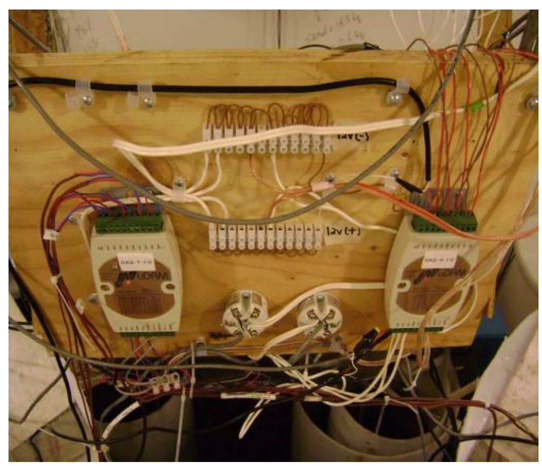
The liquid volume was measured by an ultrasonic level transmitter installed inside tank.

F.4. Communication Hardware

The communication hardware included a network of: analog input modules, thermocouple input modules, Input/output (I/O) digital modules, and RS-485 to USB converter modules. Digital signals were transmitted to DC or AC solid state relays.







APPENDIX G

INSTALLATION AND CALIBRATION OF SENSORS

G.1. Moisture Sensor

G.1.1. Installation Procedures

The moisture sensor used measures the volumetric water content (VWC), and therefore the waste adjacent to the sensor surface has the strongest influence on the sensor reading. Any air gaps or excessive waste compaction around the sensor could significantly influence the readings. Also, the sensor was installed far from large metal objects that may attenuate the sensor's electromagnetic field and adversely affect output readings. Because the EC-5 sensor has prongs, it was also important to consider the size of the media in which it is inserted so that no objects are stuck between prongs. After waste compaction, the sensor prongs were pushed into waste, and buried completely as shown in Figure G-1. The sensor was oriented such that the flat side of sensor was perpendicular to the waste surface, in order to minimize effects on downward water movement.

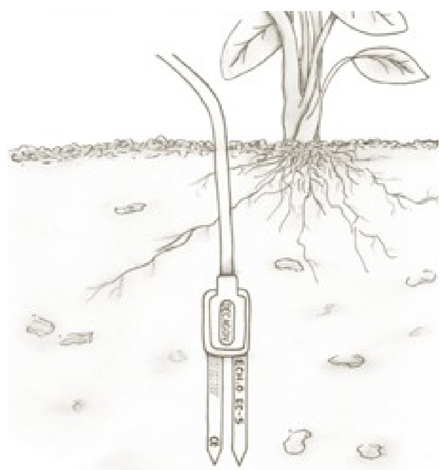


Figure G-1 Installation of the EC-5 sensor (Courtesy of Decagon, Inc.)

During operation, the high overburden pressure of waste damaged the buried sensors and cables. Therefore, new installation procedures were implemented using a new apparatus designed to withstand the pressure, truly represent the waste matrix, and make the sensor accessible for maintenance (see Figure G-2). In the new apparatus, a perforated PVC pipe was cut at a 30° angle from one side, and capped with a plastic cap at the other side. The sensor was placed inside the pipe, and was fixed in a foam stopper so as not to touch the inner surface of pipe which may affect the readings. The pipe was inserted from the side wall of the bioreactor landfill cell through a hole bounded/ sealed by a rubber ring, and so the sensor became planted in waste at the same density.

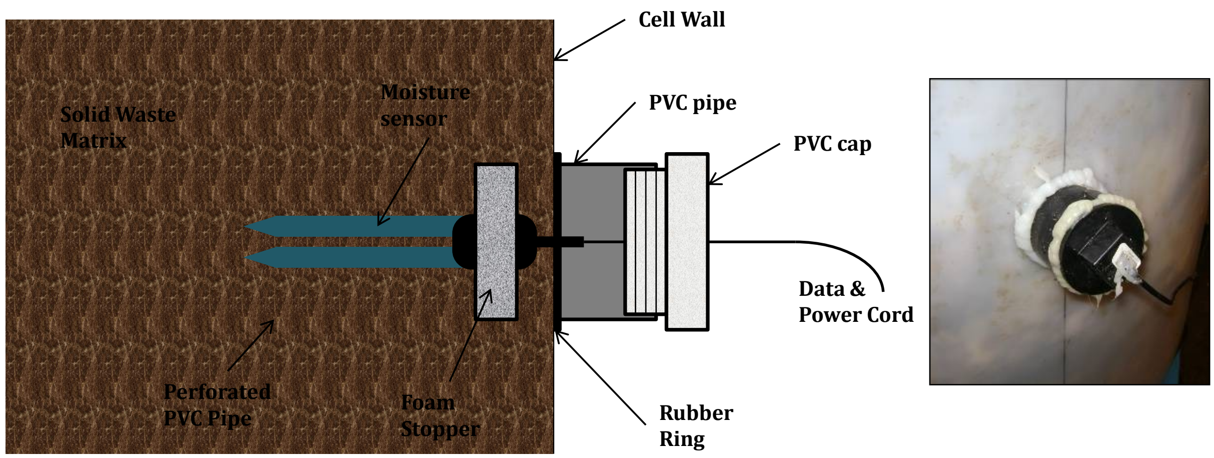


Figure G-2 Installation apparatus for the moisture sensor

G.1.2.Calibration

The manufacturer of the EC-5 sensor (Decagon, Inc., USA) supplies factory calibrations to the sensor output data. The calibration equation for mineral soils was given as:

$$VWC = 1.19 \times V - 0.401 \qquad \text{(G-1)}$$

where V is the output of the sensor when excited at 2.5 Volts.

However, this general calibration equation reaches a maximum at ~60% VWC, and may not be applicable for other soil types. Therefore, a calibration was conducted for the specific type of waste used in the present experiment from which a polynomial equation was derived. The general idea of the calibration procedures is to determine VWC for the waste at various moisture conditions ranging from dry to saturated, and collect the corresponding sensor output readings. The calibration output is a waste-specific plot between different VWCs and sensor readings. The calibration steps were as follows:

1. Compact 4 litres of waste in a container at approximately bulk density. The container had a perforated base to allow air to penetrate and dry the waste.

2. Wet the waste in container evenly until the waste nears saturation, and weigh the container with waste.
3. Insert the sensor vertically into the compacted waste, taking into consideration that the sensor should be surrounded by waste to at least 5 cm radius.
4. Take the sensor reading.
5. Collect a known-volume sample of waste, and weigh it.
6. Oven-dry the waste sample at 60 to 70°C for 48 hours, and weigh the dry waste.
7. From steps (4) and (5), calculate the initial moisture content of waste.
8. Place the container in a fume hood to dry the waste with continuous running air.
9. Collect daily measurements of weight of container with waste, and record the corresponding sensor readings.
10. Repeat steps (5) and (6) to calculate the final moisture content of waste.
11. From measurements in steps (2) and (9), calculate the daily moisture contents of waste sample, and plot them against their corresponding sensor readings.

These calibration procedures were conducted, and the results were mapped in a scatter plot with the sensor output on the X-axis, and the calculated VWC on the Y-axis (see Figure G-3). A trend line was fitted to the data points, and the mathematical relationship was demonstrated by a cubic equation at an excellent correlation coefficient of 0.996. Also, the equation supplied by the manufacturer is plotted in Figure G-3 indicating a significant difference between the output of the specific and general calibration equations.

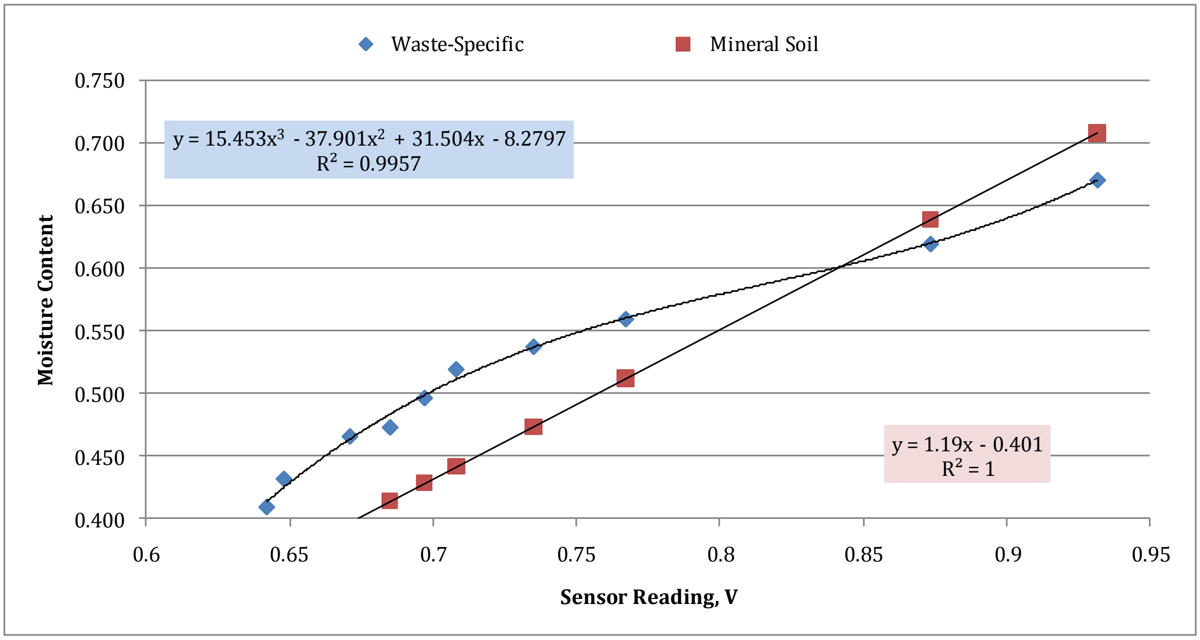


Figure G-3 Calibration curves for waste moisture sensors

G.2. pH and ORP Transmitter

The pH and ORP probes were connected to a specialized display and transmitter (αlpha pH500, Eutech Instruments, Ltd, Singapore) which required a 2-point calibration for the pH and 1-point calibration for ORP readings. The pH calibration was conducted using pH (7.00) and pH (4.01 or 10.1) buffers, whereas ORP calibration used a 215 mV standard solution for Ag/AgCl reference electrodes. The probe was first rinsed with distilled water, then immersed in calibration solution, and stirred gently until the reading was stabilized.

G.3. Methane Gas Analyzer

The methane analyzer (BCP-CH4, BlueSens, Inc., Germany) was calibrated monthly using a 1-point calibration. The zero point of the analyzer was adjusted by exposing it to ambient air (0.00 Vol. % CH_4) for at least 30 minutes.

G.4. Gas Flow Meter

Readings from the gas flow meter had to be corrected when used with a mix of gases such as the case with landfill gas. The correction factor was calculated according to the equation supplied by the manufacturer (McMillan, Inc., USA) as follows:

$$C_f = \left(\frac{\sum_{i=1}^{n} F_i \cdot S_i}{S_{cal}} \right)^{0.3} \qquad \text{(G-2)}$$

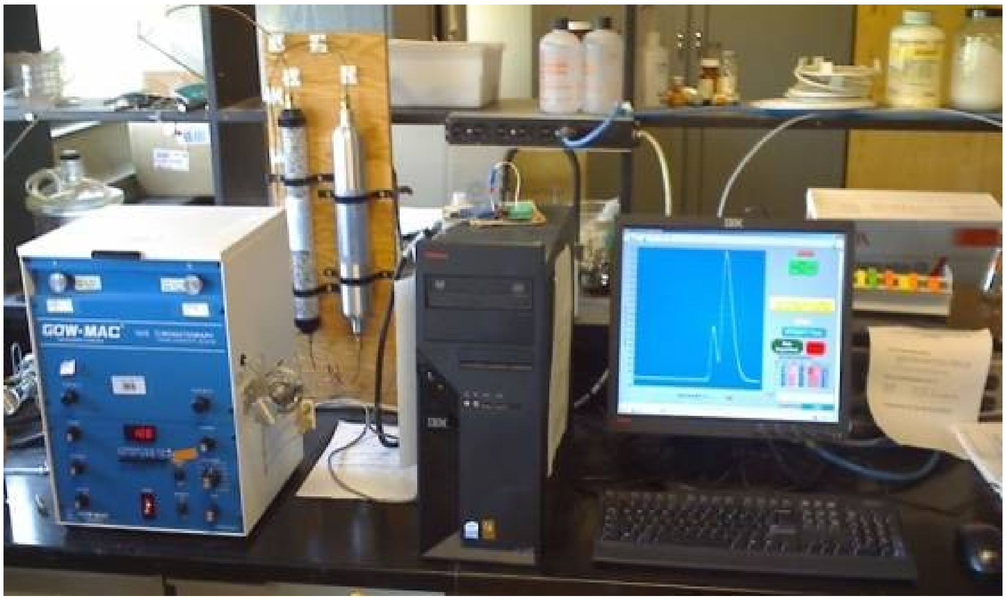
Where C_f = Correction factor, n = number of identified gases in the mix, F_i = fraction of gas i in the mixture, S_i = specific gravity of gas i, and S_{cal} = specific gravity of original calibration gas. The corrected flow reading can be calculated as follows:

$Corrected\ Flow = Flow\ reading \times C_f$

APPENDIX H

INSTRUMENTATION USED IN LAB ANALYSIS

Analyses of different gases (CH_4, O_2 and CO_2) were carried out using a gas chromatograph equipped with thermal conductivity detector (series 400, Gow-Mac Instrument Co., USA).



The biogas samples were pumped using a peristaltic pump into 1 L. Tedlar® gas bags.

Volatile fatty acids were analyzed using a gas chromatograph with a flame ionization detector (Agilent 6890 GC, Agilent Technologies, Inc., USA).

Total organic carbon and total nitrogen were analyzed using a catalytic combustion analyzer (Apollo 9000 with TN module, Teledyne Technologies, Inc., USA).

Sample preparation for alkalinity and ammonia tests included the following:

1. Centrifuge sample for 20 minutes at relative centrifugal force of 9450g in a centrifuge (Sorvall Legend® T plus, Thermo Scientific, Inc., USA).

2. Filter sample using Millipore® 0.45 μm mixed cellulose membrane filter.

3. Conduct test in an air-tight container to minimize gas stripping. The airtight container which was used for titration is shown below.

APPENDIX I

SUPPLEMENTAL RESULTS AND DISCUSSION FOR EXPERIMENTAL WORK PRESENTED IN CHAPTER 6

I.1. Waste Settlement

Waste settlement was monitored quarterly by detecting the waste surface level through the wall of the BL cell using a scanning device. The device uses an internal capacitor plate to detect changes in the dielectric constant of the cell wall while moving over its surface. A significant change in the dielectric constant indicates a dense object behind the wall, showing the waste mass. The percent of settlement with respect to initial volume in both cells are shown in Figure I-1.

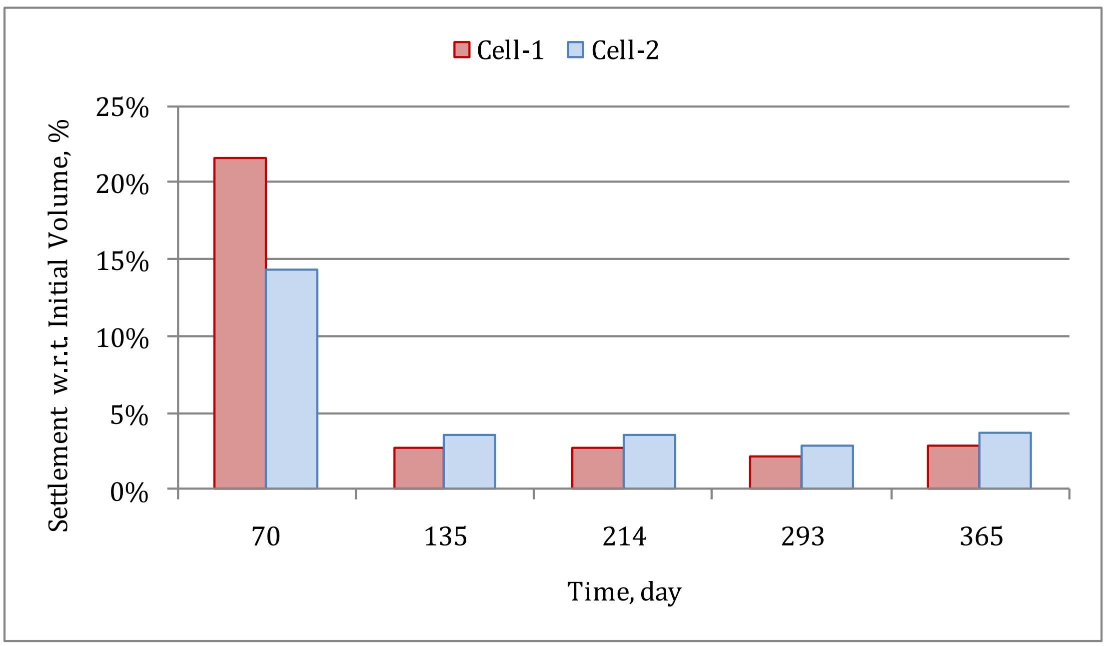


Figure I-1 Waste settlement recorded in both cells

I.2. Waste Moisture Content

Readings of the moisture sensors in both BL cells are shown in Figure I-2. The temporal progress of the moisture content of the waste from the top and bottom sensors of Cell-1 were increasing, while the readings of the middle sensor remained constant (on average at 50%).

In Cell-2, the readings of the moisture sensors did not show any significant change and were constant throughout phase II at around 70%.

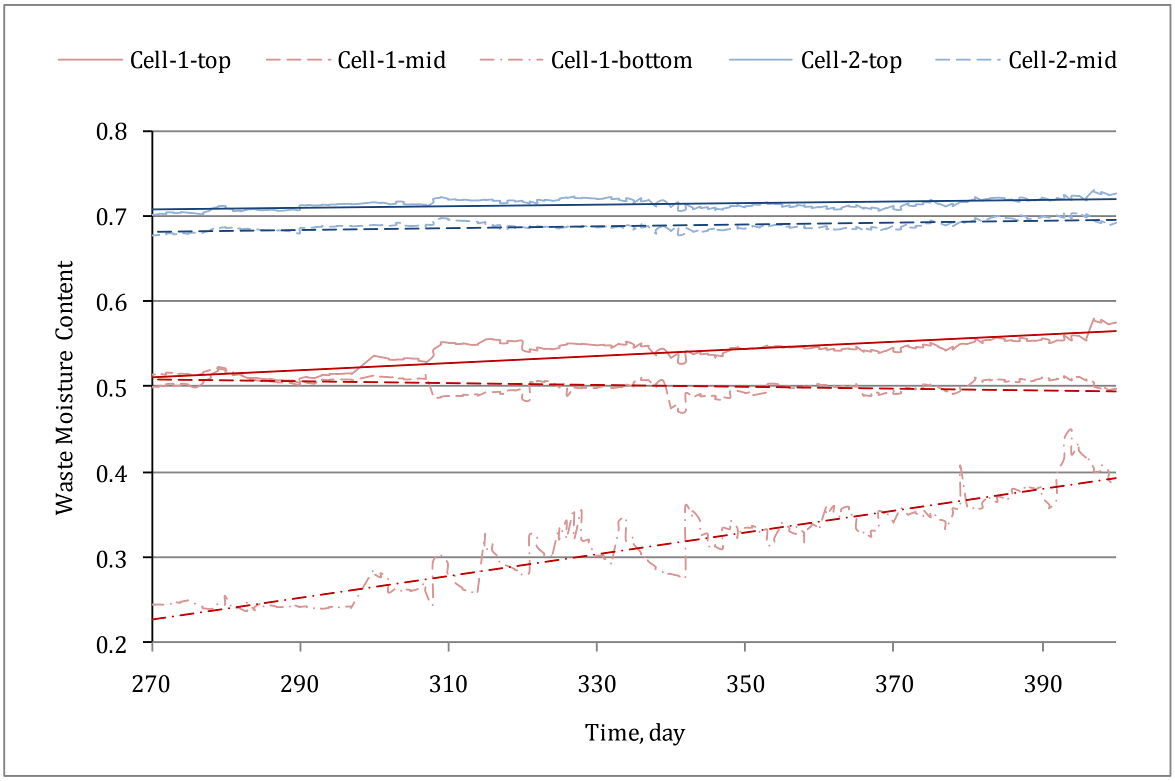


Figure I-2 Readings of the moisture sensors in both BL cells

I.3.Waste Temperature Profile

The temperature profile along the cell depth was recorded dynamically subsequent to leachate recirculation events (Figure I-3). In the 24-hour period shown, the temperature of recirculated leachate in Cell-2 was 5°C higher than the average waste temperature, whereas leachate temperature in Cell-1 was at room temperature (about 5°C lower than the average waste temperature). Waste temperature in the upper surface layer of Cell-2 increased from 24.2 to 24.8°C by the end of the day. However, every time the heated leachate was introduced, an abrupt increase (0.8°C per injection event) was observed in the upper layer, followed by a quick partial restoration of previous temperatures. The net increase in waste temperature was minimal (about 0.2°C per injection). Over the vertical profile of Cell-2, the greatest effect on waste temperature was in the top surface layer, whereas the center and bottom thermocouples recorded minimal changes as leachate heat energy is dissipated as it percolates down through the waste matrix. On the other hand, when leachate at room temperature was introduced to Cell-1, an initial drop (0.5°C) was observed in the upper layer which was partially restored similarly to Cell-2. The bottom thermocouple reported temperatures higher than the center and upper thermocouples, as leachate passed through the waste, it gained heat from the relatively warmer waste.

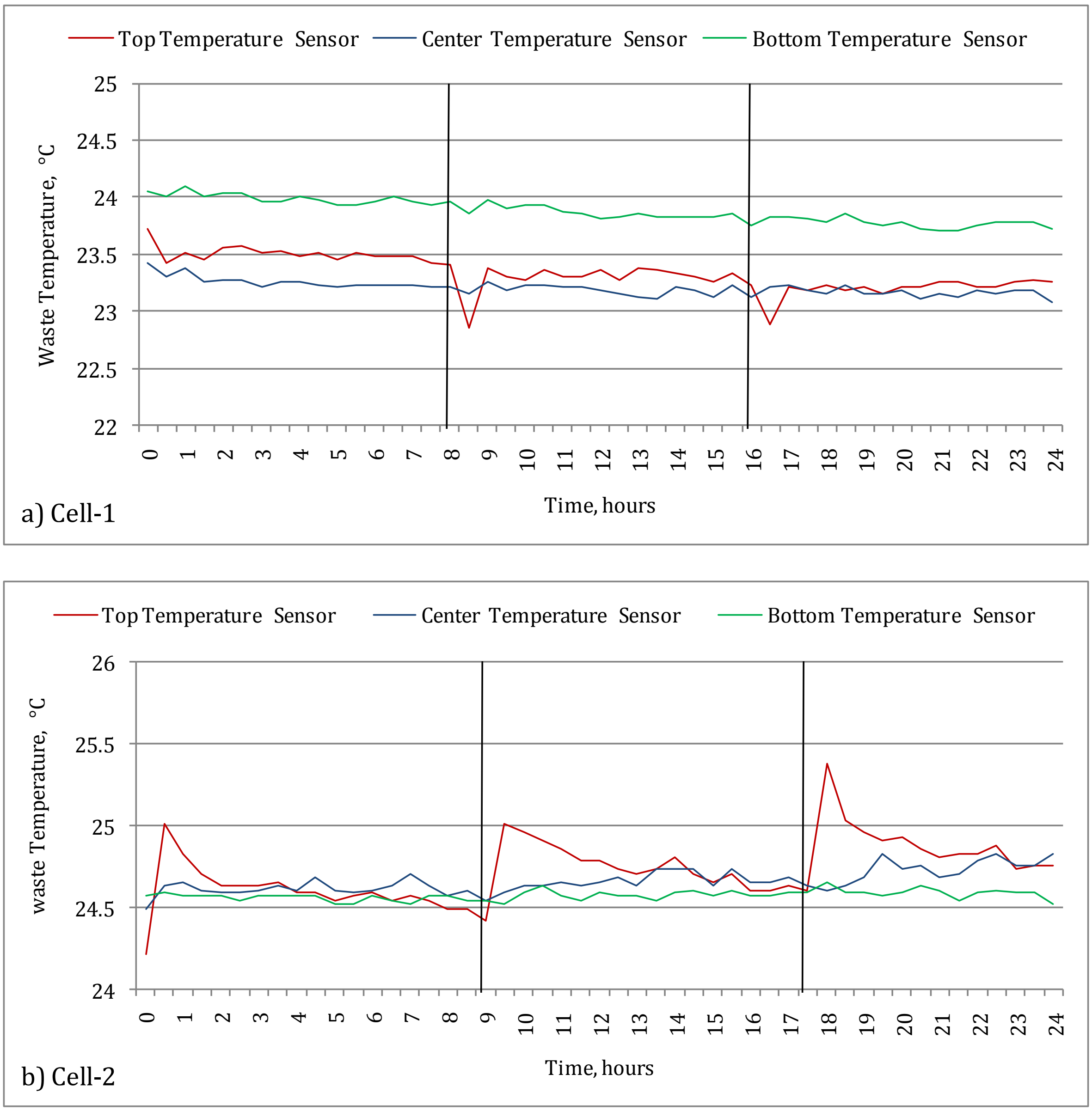


Figure I-3 Dynamic temperature profile in response to leachate recirculation for three recirculation events in a) Cell-1, and b) Cell-2

It is shown that, within the range of temperatures studied, heated leachate did not raise the waste temperature significantly, and that heat was dissipated in the top layers of the cell, causing the effect in lower layers to be minimal. Similarly, in the control cell, recirculating slightly colder leachate has caused the waste temperature to decrease and then return to its normal range. The same localized trends shall be expected in full-scale landfill sites as a result of the insulating nature of surrounding waste. One might note that the waste temperatures in Cell-2 were fairly constant throughout the cell. Conversely, in Cell-1, the lower two thirds of the waste matrix were at a lower temperature than the top section, and all 3 sections were lower in temperature than Cell-2 and concomitantly operating at a lower level of biological activity.

I.4.Solids in Leachate

The progress of solids and organic fraction in leachate is shown in Figure I-4. In phase I and as a result of the recirculation practices, the solids were increasing in both cells with Cell-1 having constantly more solids. However, during the increased methane production in phase II, the total and organic solid fractions began to drop as a result of the degradation of organic matter.

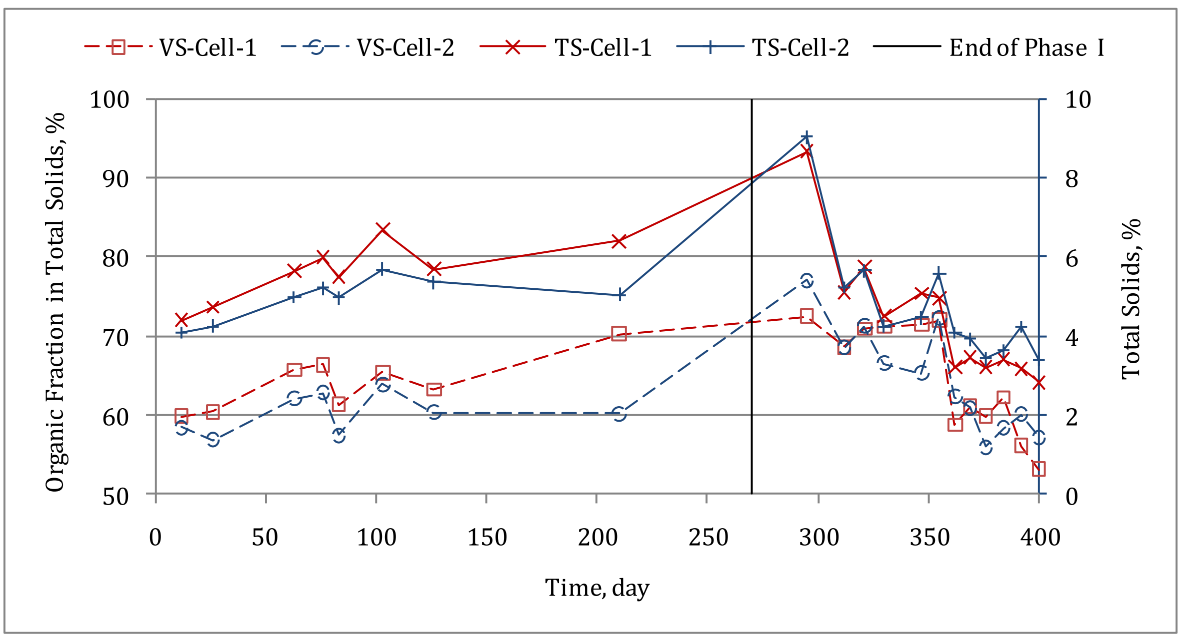


Figure I-4 Progress of total solids and volatile solids in both cells