UNIVERSITY OF SOUTHERN QUEENSLAND

PROCESS STUDIES OF ODOUR EMISSIONS FROM EFFLUENT PONDS USING MACHINE-BASED ODOUR MEASUREMENT

A Dissertation Submitted by

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FOR THE AWARD OF
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To my wife with love

JI YOUN

Thanks Mate.

ABSTRACT

Odours caused by intensive piggery operations have become a major environmental issue in the piggery industry in Australia. Effluent ponds are the major source of odours in typical piggeries. It is assumed that the odour emissions from ponds are mainly driven by pond loading rate. However, there are few data to corroborate this concept.

Allied to this is the need for a convenient and low cost method of odour measurement, which can be used as an alternative method for current olfactometry. The present odour measurement methods using olfactometry is time-consuming, expensive and often impractical because of its fundamental problem of using subjective human panels.

In addition, one of the major problems in odour measurement lies in the air sampling method. Wind tunnels have been accepted as a preferred method for the sampling of odour from area sources. However, current wind tunnels do not consider meteorological factors, which directly affect the odour emission rates.

A machine-based odour quantification method and a novel wind tunnel were developed and evaluated in this Ph D study. These methods were then used in a demonstration trial to investigate the effects of pond loading rate on odour emissions.

The AromaScan A32S electronic nose, and an artificial neural network were used to develop the machine based odour quantification method. The sensor data analysed by the AromaScan were used to train an ANN, to correlate the responses to the actual odour concentration provided by a human olfactometry panel. Preprocessing techniques and different network architectures were evaluated through network simulation to find an optimal artificial neural network model. The simulation results showed that the two-layer back-propagation neural network can be trained to predict piggery odour concentrations correctly with a low mean squared error. The trained ANN was able to predict the odour concentration of nine unknown air samples with a value for the coefficient of correlation, r^2 of 0.59.

A novel wind tunnel was developed for odour sampling. The USQ wind tunnel was designed to have a capability to control wind speed and airflow rate. The tunnel was

evaluated in terms of the aerodynamics of the airflow inside the tunnel, and the gas recovery efficiency rate, in order to further improve the performance of the wind tunnel

The USQ wind tunnel showed that sample recovery efficiencies ranging from 61.7 to 106.8%, while the average result from the entire trial was 81.1%. The optimal sample recovery efficiency of the tunnel was observed to be 88.9% from statistical analysis. Consequently, it can be suggested that the tunnel will give estimates of the odour emission rate with significant level of precision. However, the tunnel needs to be calibrated to compensate for the error caused by different airflow rates and odour emission rates. In addition, the installation of a perforated baffle upstream of the sampling section was suggested to improve its performance.

To investigate the relationship between the pond loading rate and odour emission rate, replicable experimental studies were conducted using a novel experimental facility and the machine based odour quantification method. The experimental facility consisted of reactor vessels to simulate the operation of effluent ponds and the USQ wind tunnel for odour sampling.

A strong relationship between organic loading rate (OLR) and physical and chemical parameters was observed except pH and NH_3-N. The pH was not affected by OLR due to the buffering capacity of piggery effluent. EC and COD were suggested as indicators to estimate the operating condition of the piggery effluent ponds because the regression results show that these two parameters can be predicted accurately by OLR. The time averaged odour emission rates from the reactor vessels showed a strong relationship with OLR. Consequently, it can be concluded that heavily loaded effluent ponds would produce more odours.

The effect of hydraulic retention time (HRT) was examined. The HRT was increased from 30 days to 60 days, resulting in a significant decrease in odour emission rates from the reactor vessels. This decrease ranged from 59.1% to 54.9%, with an average of 57.1%. Therefore, it can be concluded that the increasing HRT will decrease the odour emission rate.

This trial confirmed the value of the project methodology in obtaining unambiguous data on odour emission processes. However, more data are required for a wider range of OLR, HRT and other pertained variables before a usable model can be formulated.

CERTIFICATION OF DISSERTATION

I certify that the ideas, experimental work, results, analyses and conclusions reported in this dissertation are entirely my own effort, except where otherwise acknowledged. I also certify that the work is original and has not been previously submitted for any other award, except where otherwise acknowledged.

Signature of Candidate Date

Endorsement:

Signature of Supervisor/s Date

Signature of Supervisor/s Date

ASSOCIATED PUBLICATIONS

Sohn J H; Smith R; Yoong E; Hudson N; Kim T I (2004) Evaluation of a novel wind tunnel for the measurement of the kinetics of odour emissions from piggery effluent, Water Science and Technology, Vol 50 (4)

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Sohn, Jae Ho
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NOTATION

A	area covered by the wind tunnel, m^2
a	wind profile exponent which in a function of stability
A_{exp}	experimental area covered by the tunnel, m^2
A_i	inlet area of the wind tunnel, m^2
A_o	outlet area of the wind tunnel, m^2
A_s	surface area covered by the tunnel, m^2
A_t	cross sectional area of the tunnel, m^2
C	odour concentration, OU/m^3
C_i	measured odour emission rate, OU/m^2s
C_m	measured average concentration in the measurement section, kg/m^3
C_o	concentration of odorant at the detection threshold
C_s	odour concentration in the bag, OU/m^3
C_z	measured odour concentration at the selected sampling location
$\overline{C}$	mean odour concentration, OU/m^3
c'	fluctuating components of odour concentration, OU/m^3
D	duct diameter, m
e	vector of network errors
$EVOL_P$	effective or useful liquid volume of pond
F_g	vertical flux of odour that is transferred by turbulence from the surface to the atmosphere, OU/m^2
v'	fluctuating components of wind speed, m/s
HRT_T	theoretical mean hydraulic retention time, days
I	odour intensity (perceived strength), dimensionless
J	Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases turbulence intensity; is the
k	temperature factor according to piggery location, g/m^3day
K_g	turbulent diffusivities for odour, m^2/s
K_m	turbulent diffusivities for momentum, m^2/s
k_w	Weber-Fechner constant
L_P	pond life, year

$\overline{VC}$	mean component of horizontal flux of odour, OU/m^{2}s
$\overline{C_i}$	mean odour concentration averaged over the inlet area, OU/m^3
$\overline{C_o}$	mean odour concentration averaged over the outlet area, OU/m^3
$\overline{C}$	mean odour concentration, OU/m^3
$\overline{Q_s}$	mean volume airflow rate through the tunnel, m^3/s
$\overline{Q}$	mean volumetric airflow rate through the tunnel, m^3/s
$\overline{Q_E}$	average flowrate of the piggery effluent entering the pond
$\overline{Q}_{R,0}$	volume airflow rate at standard conditions (0 $^\circ$C and 101.3kPa), m^3/s
n	number of areas
OER	odour emission rate, OU/m^{2}s
OER_1	odour emission rate corresponding to wind speed 1m/s, OU/m^{2}s
OER_2	odour emission rate corresponding to actual ground level wind speed, OU/m^{2}s
OER_A	actual odour emission rate measured by olfactometry, OU/ m^{2}s
OER_a	calculated odour emission rate, OU/ m^{2}s
OER_P	predicted odour emission rate by the AromaScan, OU/m^{2}s
OER_V	odour emission rate corresponding to wind speed V, OU/m^{2}s
p	absolute pressure inside the vent, kPa
P_s	absolute pressure in the tunnel, kPa
Q	flow rate through the wind tunnel, m^3/s
Q_m	volume flow rate measured inside the vent, m^3/s
Re	Reynolds number
SAR	sludge accumulation rate in pond, m^3/kg
t	air temperature inside the vent, $^\circ$C
TS_L	total solid loading rate, kg/year
$V_{0.125}$	wind speeds (m/s) at 0.125m heights
V_1	wind speed inside wind tunnel for sample collection
V_{10}	wind speeds (m/s) at 10m heights
V_2	actual ground level wind speed
V_i	wind speed in area i (m/s)
VOL_A	active volume of effluent pond, m^3
VOL_O	volume of effluent pond for odour control, m^3

VOL_P	total liquid volume of pond
VOL_s	sludge volume in effluent pond, m^3
V_{ref}	wind speed at the wind measurement height Z_{ref}, m/s
VS_O	standard VS loading rate for odour control, 61 g VS/m^3day
VS_L	volatile solid loading rate, g/day
V_t	wind speed inside the tunnel, m/s
V_z	wind speed at height Z above the ground, m/s
$\breve{V}$	wind speed at a height of 1m based on 1m/s at half tunnel height based on Urwin Rural coefficients for the stability classes
$\overline{V}$	mean horizontal wind speed, m/s
$\langle V \rangle$	bulk wind speed in the duct of the wind tunnel, m/s
z	height above the surface, m
Z_{ITE}	panellists' individual threshold estimate
α	recovery rate of the sampling system
ρ_a	air bulk density, kg/m^3
τ_0	momentum flux or shear stress, kg/ms^2
υ	dynamic viscosity of the air, kg/ms
Φ_{exp}	CO emission rate emitted from the ground of testing section, kg/m^2s
Φ_i	odour mass flux through the inlet area, OU/m^2s
Φ_o	odour mass flux through the outlet area, OU/m^2s
Ψ_z	non dimensional coefficient at the sampling height

CHAPTER 1
INTRODUCTION

1.1 Background

The pork industry in Australia is important to the nation's economic well being, producing $855 million per year in farm revenue that contributes to the vitality of rural communities. It has played an important role in the agricultural export market through the export of $195 million of pig meat to about 47 countries in 2001 (APL, 2002).

In the meantime, odours, in particular those caused by intensive piggery units, have become a major environmental issue at Australian piggeries. Regulatory authorities wish to ensure that neighbours do not experience odour nuisance. Nuisance occurs when the frequency, intensity, duration and offensiveness of the odours cause unreasonable interference with a neighbour's lifestyle.

Often regulatory authorities require the use of air dispersion modelling to prove that odour nuisance will not occur too often. Alternatively, regulatory authorities use standard guidelines to determine allowable separation distances. These guidelines for planning and licensing are aimed at maintaining adequate buffer zones between piggery operations and residents. However, the nature of pig production has changed and these guidelines and regulations are outdated and they are no longer applicable to present pig production practices (Watts, 1999b).

Other environmental impacts of pig production have also become a major consideration. Nutrient recycling and disposal, ammonia emissions, greenhouse gas emissions and odours are now significant issues that concern the sustainability of the industry.

In the piggery industry, odour emissions from effluent treatment ponds are identified as the main cause of the nuisance to neighbours. Effluent ponds are the major source of odours in typical Australian piggeries, contributing about 75% of all odour emissions (Smith *et al*, 1999). In order to solve this problem, the first step is to accurately quantify the emission rates of odour from effluent ponds. Current methods for estimating odour nuisance use standard emission rates that do not take into account the effect of loading rates and effluent characteristics. Consequently, there is considerable difference between the estimated and measured values.

Appropriately designed and well-managed ponds are observed to produce a lower odour than overloaded and undersized ponds, but there are few data to corroborate this observation. A more complete data set of gross odour emission rates and effluent characteristics is required from a range of piggery effluent treatment ponds. Such data will assist in the planning of new and expanding piggery developments. Also required are easy-to-measure indicators of pond conditions and the likelihood of odour emissions. Allied to this is the need for a convenient and low cost method of odour measurement, which is able to be used as an alternative method for current olfactometry.

As the human nose has been the only satisfactory device for odour measurement, olfactometry, in which a human odour panel evaluates the odours, has been accepted as the most precise odour measurement technique for odour quantification. Human assessment, however, can be time-consuming and expensive. In addition, odour samples may degrade rapidly with time so human panels have to perform evaluations shortly after sample collection for accurate

assessment. Since piggery odour research is being conducted all around the nation on a 24-hour basis, odour testing with human panels is often impractical. Therefore, a rapid, accurate, cost-effective technique to measure and evaluate odour emissions is vitally important to the piggery industry.

1.2 Research development

Initial proposals for this dissertation concerned research into the development of a model to describe the relationship between pond loading or condition and odour emission rate so as to enable the quantitative prediction of odour emission and dispersion from effluent ponds. It was expected that this model would be used for the sizing of ponds for odour control (Sohn, 2001). This need had been identified from the comprehensive literature review as a key issue in the sustainability of the piggery industry. It was believed that the development of appropriate odour minimisation strategies for effluent ponds through an odour prediction model would assure the further development of intensive piggery units.

However, it soon became apparent that this was not the true state of affairs. A number of problems were encountered which altered the focus of the research work. It became apparent that before the issue of odour modelling could be addressed it would be necessary to develop a range of more appropriate odour sampling and quantification techniques.

While there existed a number of air sampling methods used for odour research, it was found that none of these sampling methods truly addressed the effect of meteorological factors such as wind speed on odour emissions. As will be discussed in later section of this dissertation, the odour emission rate from the effluent pond is known to depend on volatile organic loading rate, the characteristics of the effluent (volatile solids, pH, and temperature) and meteorological factors. It was also found that despite various air sampling methods currently used, these methods do not offer the reliable and confident data set required for regulatory or practical implementation of the odour assessment work.

Furthermore, there was the urgent need for a convenient and low cost method of odour measurement that is able to be used as an alternative method to current

olfactometry. Thus, the decision was made to shift the focus of the research to develop a novel odour measurement and sampling methodology and to evaluate it through a series of experiments using effluent pond simulating reactor vessels.

1.3 Overview of research

1.3.1 Hypothesis of research

The hypothesis underlying this Ph. D study is outlined as:

"It is possible to develop novel odour measurement methodologies involving wind tunnels and electronic nose technology. The relationship between pond loading condition and odour emission rate enables the quantitative prediction of odour emission. Such a model can be used for sizing ponds for odour control."

1.3.2 Key issues identified for investigation

In addressing the effects of pond loading rate on odour emissions in the piggery industry, three key areas of odour measurement technology have been identified and addressed in this dissertation. These are:

- Development and experimental verification of a novel wind tunnel for odour sampling;
- Application of the electronic nose and artificial neural network for odour quantification; and
- Investigation of the effects of pond loading rate on odour emissions.

Development and experimental verification of a novel wind tunnel for odour sampling

One of the major challenges in quantifying odours in intensive piggery operations lies in the air sampling method. To develop an appropriate air sampling method, it is necessary to consider meteorological factors because they directly affect the odour emission rate.

There are two different methods for collecting air samples from point or area odour sources:

- Flux hoods; and
- Wind tunnels.

However, the flux hood is not considered an accurate method for measuring odour emission (Smith & Dalton, 1999a; Smith & Watts, 1994a). Therefore, the wind tunnel was adopted for this research.

The flux hood (isolation chamber) is not designed to take into account convective mass transfer caused by air movement above an emitting surface. The aerodynamics of the device does not guarantee the repeatability and reproducibility of the emission rates measured. Generally, the flux hood records much lower emission rates than the results from wind tunnel techniques and indirect estimation using mathematical modelling (Smith & Dalton, 1999a).

Smith and Watts (1994a) indicated several factors affecting the rate of emissions as sampled by a flux hood:

- The pressure inside the chamber (which should be identical to that outside);
- The relatively small area of emitting surface enclosed by the hood;
- The suppression of the turbulent transport mechanism which under ambient conditions transports the emissions away from the emitting surface; and
- Imperfect mixing of the emissions and the sweep air.

Wind tunnels are portable, open-bottomed enclosures that are placed over the emitting surface. Ambient or filtered air is drawn or blown through the tunnel to mix with and transport the emissions away from the emitting surface. This simulates the convective mixing and transport process present above the emitting surface (Watts, 1999a).

Wind tunnels have been accepted as an accurate method for the sampling of odour. However, there is no standard for their design. Variations in tunnel geometry include differences in the material used in the construction of the tunnel, the length/width ratio, the surface area sampled and the height. Consequently there are substantial effects on the aerodynamics over the emitting surface. A further complication is the variation in wind speed from one device to another (Smith & Watts, 1994a).

The development of a novel wind tunnel, which has capabilities to control the meteorological factor such as air flow rate, is essential for the accurate odour measurement because the wind tunnel allows for the emission of odours and other volatiles under an atmospheric transport system similar to ambient conditions.

Application of the electronic nose and artificial neural network for odour quantification

An accurate, rapid and cost effective technique for odour measurement is required. At present, olfactometry in which human panels are employed as the odour sensor, has been regarded as the industry standard method. However, olfactometry has a considerable disadvantage in terms of cost and labour requirements (Nimmermark, 2001). In addition, olfactometry is often thought to be an unreliable measurement technique because of its dependence on subjective human responses. Recent developments in the electronic nose technology and artificial neural networks provide an opportunity to extend the scope of odour measurement.

Since the raw data from the electronic noses is a fingerprint for each specific gas or odour, pattern recognition techniques can be used to analyse the raw response generated by the sensors. A variety of pattern recognition techniques have been utilised such as graphical analyses, multivariate analyses and artificial

neural network analyses. Although graphical and multivariate analyses are an effective means of comparing samples and of reducing the high dimensionality in multivariate problems, they may not always be suitable methods for the analysis of piggery odours. This is because of noise in the sensor responses caused by the complex odour background.

An artificial neural network (ANN) is able to provide a better alternative to traditional statistical methods because of its computational efficiency and generalization ability. It has proved more adaptable to events occurring in real analytical situations because it is much more resistant to random error, and drift in sensor signal magnitudes.

Investigation of the effects of pond loading rate on odour emissions

Appropriately designed and well-managed ponds produce less odour than overloaded and undersized ponds, but there are few data to corroborate this. A more complete data set of gross odour emission rates and effluent characteristics is required for a range of piggery effluent treatment ponds to assist in the planning process of new and expanding piggery developments. Also required are easy-to-measure indicators of pond condition and the likelihood of odour emissions.

In order to address this issue, it is proposed that the development of a novel experimental facility consisting of reactor vessels to simulate the operation of effluent ponds and a wind tunnel for emissions sampling. Allied to this, there is the need to apply a convenient and low cost method of odour measurement, using the electronic nose. By replicable experimental studies using this facility, the relationship between the pond loading rate and odour emission rate can be developed and easy-to-measure indicators of pond condition identified.

1.3.3 Specific objectives of research

Within the broad aim of this project and the key issues outlined above, the following specific objectives have been identified for this dissertation:

- To examine the current status of research concerned with the odour emission processes at piggery industries focused on the emission of odours from effluent ponds;
- To design and construct a novel wind tunnel for odour sampling method;
- To evaluate the air sampling and wind simulation performance of the wind tunnel through gas recovery rate calibration trials and wind profile experiments;
- To develop an odour quantification technique using an electronic nose and artificial neural network so as to get an accurate, rapid and cost effective technique for odour measurement;
- To perform experiments to quantify the effect of pond loading rate on odour emission rates using the pond simulating reactor vessels and the wind tunnel; and
- To investigate the relationship between pond condition and odour emission rate.

1.4 Structure of the dissertation

This dissertation consists of ten chapters addressing the nature of odour, odour measurement methods, the electronic nose, the wind tunnel and the process experiments on pond effluent. The first five chapters provide the background to the research.

Chapter 2 presents an overview of odour science. It shows the distinction between odour and specific gases. It assesses the scientific aspects of odours and provides the basis for further discussion in later chapters of the dissertation.

Chapter 3 discusses the detailed issues of odour sampling methodology. It focuses on odour sampling from area sources to provide fundamentals for the development of a novel wind tunnel. A discussion of wind tunnel theory is provided at the end of this Chapter.

Chapter 4 reviews the currently available odour measurement methods. The methods using gas chromatography and olfactometry are briefly discussed. It then addresses machine-based odour measurement methods using electronic nose technologies. More detailed topics such as sensor selection, pattern recognition analysis, and application of electronic nose to intensive livestock operations up to this point, are also presented.

Chapter 5 addresses the subject of piggery pond odour emissions. It includes factors affecting pond odour emissions, easy-to-measure indicators for monitoring pond condition, and pond odour emission data from Australia and other countries.

Chapter 6 shifts focus to the first major issue identified for this work, namely the development of an odour quantification technique using an electronic nose and artificial neural network. After reviewing the AromaScan A32S system, an

electronic nose, this chapter discusses artificial neural network technology, which is used as the interface for the sensor data from the AromaScan.

Chapter 7 presents the experimental evaluation of the odour quantification technique using the electronic nose and artificial neural network. The sensor data of the AromaScan was used to train an artificial neural network, and to correlate the responses to the actual odour concentration provided by olfactometry.

Chapter 8 addresses the second major issue, odour sampling using a novel wind tunnel. This chapter firstly presents the design and development of the USQ wind tunnel. It then addresses the experimental evaluation of the tunnel. The results of wind profiles, turbulence intensity profiles, and gas recovery efficiency rate are discussed to verify the air sampling performance of the tunnel.

Chapter 9 presents the third major issue, which is the practical application of the developed odour quantification and sampling methodologies to investigate the practical issues in piggery effluent ponds. The pond simulating reactor vessels are suggested for the experiments to investigate the effects of pond loading rate on odour emission rates. The results of replicable experiments to quantify effects of pond loading rates on offensive odour emission are discussed in the end of this Chapter.

Chapter 10 draws together the results of the previous chapters, presenting a summary of key findings and conclusions. A number of key areas are also presented for further research and development in ongoing programs.

CHAPTER 2
ODOUR

2.1 Introduction

Recent studies have suggested that the odours emitted from intensive piggery operations may well have adverse health effects (Schiffman *et al.*, 2000). Odour appears to play a significant role in the recognition of and concern over symptoms in neighbours of hazardous waste sites (Shusterman, 1992; Shusterman *et al.*, 1999). It has been reported that indicators of altered mood, assessed using validated scales, are significantly worse in subjects who live in the vicinity of intensive piggery operations compared with control subjects (ISU Odor Group, 2002; Schiffman, 1995).

With regard to the effect of odours on workers in piggeries, Donham *et al*. (1977) first reported that workers in piggery confinement facilities described significantly more respiratory symptoms than unexposed workers (ISU Odor Group, 2002). Studies describing the adverse respiratory effects on piggery workers have been published in the United States, Sweden, Canada, the Netherlands and Denmark (Reynolds, 1996). Results of these studies concur that approximately 50 percent of these workers experience one or more of the following health outcomes: bronchitis, toxic organic dust syndrome (TODS), hyper-reactive airway disease, chronic mucous membrane irritation, occupational asthma and hydrogen sulfide intoxication (Reynolds, 1996; Chapin *et al*., 1998).

In addition to this, odours not only affect human health but also influence local economies, property values and community dynamics. Property values have been shown to be adversely affected due to the release of offensive odours from intensive piggery operations. A study assessing house sales surrounding eight large hog operations in Michigan, USA revealed that house values decreased by 43 cents for each additional pig within a 5 mile radius of the house (Abeles-Allison & Conner, 1990). These results also indicated that the magnitude of adverse effects on property values can vary with respect to both the size of a nearby piggery operation and the distance between the facility and a private residence (Palmquist, 1997).

As a first step to solve these significant odour issues, this chapter aims to provide a source of fundamental information on odour issues, focused on the piggery industry. The following topics are discussed in this chapter:

- Distinction between odours and gases: the difference between the two terms, odours and gases, their definition and role in air quality issues;
- Odour science: the various attributes used to characterise odours, and their interactions to be perceived as our sense of smell; the definitions of odour concentration and intensity and their relationship; odour nuisance generating mechanisms; and
- Odours in the piggery industry: odour creation mechanisms in piggery operations, odour sources including piggery housing, waste storage and treatment processes, land application, and carcass disposal.

2.2 Distinction between odours and gases

It is important to recognise the distinction between odours and specific gases because they not only are measured and regulated separately, but also have different effects on human and environmental health. Although many people refer to odours and gases interchangeably, there is a difference between these two terms. Moreover, there is no known correlation between odour and the specific gases emitted from piggery operations. The term 'odour' refers to the complex mixture of gases, vapours and dust that result from the anaerobic decomposition of piggery manure (Chapin *et al*., 1998).

There are 168 odourous compounds that have been identified in piggery waste (Veenhuizen, 1996). All of these compounds are metabolic end products of anaerobic bacteria. These substances include fatty acids, organic acids, alcohols, aldehydes, carbonyls, sulphides, esters, mercaptans, amines and nitrogenous compounds, which often contribute far more offensive odours than ammonia or hydrogen sulphide (Swine Odor Task Force, 1995). Four methylphenol, also called paracresol, is a predominant metabolite which gives piggery slurry its characteristic creosote or disinfectant type odour (Yokoyama, 1994).

Odourous compounds from piggery manure are often divided into 4 chemical classes (Mackie, 1994):

1. Volatile fatty acids (including acetic acid, isobutyric, 2-methylbutyric, isovaleric, valeric, caproic, and capric acids);
2. Indoles and phenols (including indole, skatole, cresol, and 4-ethylphenol);
3. Ammonia and volatile amines (including putrescine, cadaverine, and aliphatic amines such as methylamine and ethylamine);
4. Volatile sulphur-containing compounds (*e.g.*, sulphide, methyl- and ethyl-mercaptans).

Many of these odorous compounds are carried by piggery dust and other airborne particulates, including pig dander, bedding dust and manure dust, which

also contribute to an odour plume. In addition, these particles are capable of carrying bacteria and other microorganisms that may originate in an intensive piggery. Thus, piggery odours are quite complex, making it difficult to determine the specific substances that are contributing to the offensive smell. On the other hand, the term 'gases' refers solely to the specific gaseous compounds that are emitted from piggery operations. Some of these gases may be constituents of an odour plume; however, unlike odours, these compounds are neither combinations of compounds nor carriers of microorganisms and other particulates. Contrary to odours, many gases are also odourless and tasteless, making them seem benign since they are difficult to detect with the human nose (Chapin *et al*., 1998).

Furthermore, it is also necessary to describe the differences between the actual odour intensity of specific gases and their respective gas concentrations. Odour intensity is a measure of gas detection by the human nose, while gas concentration measurements denote the actual concentration of the gas in the atmosphere (Schmidt & Jacobson, 1995). The relationship between these two parameters varies among different gases. For instance, odour intensity and concentrations of ammonia are positively correlated, yet do not follow a 1:1 correlation ratio. Thus, reductions in gas concentrations do not translate into the same reductions in odour intensity (Chapin *et al*., 1998).

2.3 Odour science

The effects of odour are directly related to the subjective response of the individual exposed and their tolerance to the presence of a particular odour. When odour exceeds the annoyance tolerance of an exposed population, nuisance occurs. The annoyance reaction of a person whose nose senses an unpleasant odour is determined by non-sensory variables such as personality traits, attitude to the source, and environmental circumstance. To completely describe an odour, four different dimensions to the sensory perception of odorants are often considered (NZWWA, 2000):

- Detectability: The odour detection threshold refers to the minimum concentration of an odorous substance that can produce an odour sensation in 50% of a panel of observers. It is important to note that these values are not fixed physiological facts or physical constants, but statistically represent the best estimate value from a group of individual responses.
- Concentration: The concentration of odour emissions is described using odour units (OU/m^3), *i.e.,* the number of times the odorous air must be diluted with odour-free air until the concentration of the odorous substance reaches the detection threshold. 'Concentration' refers to the perceived strength of the odour sensation. The concentration is normally expressed as odour units per cubic metre (OU/m^3) of the original odorous sample.
- Quality: Odour quality is a qualitative measure, not quantitative. It describes the general character of the odour, or what the substance smells like. Odour quality is highly dependent on receptors and sensory neurons in the nasal cavity and the brain. The specific details of how the brain determines odour quality are complex and yet to be fully understood.
- Hedonic Tone: Like odour quality, the hedonic tone is a qualitative judgment of the pleasantness or offensiveness of the odour. For example, odours from perfumes and flowers are generally considered to be pleasant, whereas the odours from sewers and tanning factories are considered offensive.

Odour complaints occur when individuals consider the odour to be unacceptable and are sufficiently annoyed by the odour to take action. The New Zealand Ministry for the Environment (1995) suggests five factors that influence odour complaints:

- Frequency of the odour occurrence;
- Intensity of the odour;
- Duration of the exposure to the odour;
- Offensiveness of the odour; and
- Location of the odour.

Frequency, intensity, duration and location are quantifiable and may be used for a regulatory purpose. However, odour offensiveness is subjective and difficult to quantify (WA DEP, 2002).

2.3.1 Odour concentration

There are as yet no instrument-based methods that can measure an odour response in the same way as the human nose except in some trials at the level of laboratory research. Therefore, dynamic olfactometry is typically used as the basis of odour management. Dynamic olfactometry is the measurement of odour by presenting a sample of odourous air to a panel of people at a range of dilutions and seeking responses from the panellists on whether they can detect the odour. The correlations between the known dilution ratios and the panellists' responses are then used to calculate the number of dilutions of the original sample required to achieve the odour detection threshold (WA DEP, 2002).

Odour concentration measured by olfactometry is expressed as odour units per cubic meter (OU/m^3). Odour units were defined as the volume of diluent required to dilute a unit volume of odour until the detection threshold of the odour is obtained (Schmidt, 2002). Alternatively, odour units per cubic meter are defined as the concentration of odour in one cubic meter of air at the panel

detection threshold of the odour (NCMAWM, 2001; CEN, 1999). In the field of air pollution control, the pollutant concentration is commonly expressed as mass per unit volume (g/m^3). Therefore, the unit OU/m^3 seems logical to use for expressing odour concentration, but OU is not a mass measurement (Zhang *et al.*, 2002).

The European standard (CEN, 1999) defines a European Reference Odour Mass (EROM), which is equivalent to 123 µg n-butanol evaporated into 1 m^3 of neutral gas air. This leads to a definition of the European odour unit, denoted as OU_E by some researchers, which is the amount of odorant that, when evaporated into 1 m^3 of gas air at standard conditions, elicits a physiological response from a panel (detection threshold) equivalent to that of one EROM. Therefore, the odour concentration is expressed as OU_E/m^3, or simply OU/m^3.

However, it is important to note that the different methods of dynamic olfactometry provide different results for the odour concentration in odour assessment studies. It is vital that any use of published odour concentrations should be thoroughly checked for the method used and appropriate adjustment factors, prior to use in current assessments (WA DEP, 2002). For instance, the Dutch NVN 2820 method gives an odour concentration of approximately twice as many odour units as when the Victorian EPA B2 method is performed at the Victorian EPA laboratories (Bardsley & Demetriou, 1997)

2.3.2 Odour intensity

Odour intensity is another measure of the strength of an odour (Zhang *et al*., 2002). However, unlike odour concentration, it is a measure of the human response to an undiluted odour (Hamilton & Arogo, 1999). A common way of measuring odour intensity is to compare the intensity of an odour to the intensities of different but known concentrations of a reference odorant. It is recommended

that successive concentrations of the reference odorant are greater than the preceding levels by a step factor of two (ASTM, 1999).

Odour intensity is obtained when a match is found between the intensity of the odour and the intensity of one of the concentrations of the reference odorant. It is often difficult to match the intensity of an odour to the intensity of only one concentration of the reference odorant. In such cases, the odour intensity is considered as the intensity corresponding to the geometric mean of adjoining concentrations of the reference odorant (ASTM, 1999). In addition to this, there is no reported matching of odour intensity between the odours in piggeries and n-butanol gas which is used for olfactometry analysis as a reference gas. The two odours are quite different from each other (Zhang *et al*., 2002).

In odour intensity measurement, it is usually accepted that a 'distinct' odour may just be able to be recognised (*i.e.* has an odour concentration equivalent to its recognition threshold). An odour described as "distinct" under highly controlled laboratory conditions is likely to be harder to detect in the environment (WA DEP, 2002).

At present, various methodologies for odour intensity measurement are used. They are summarised in following sections.

The German standard VDI 3882 Part 1: Olfactometry determination of odour intensity

The German standard VDI 3882 provides qualitative descriptions of odour intensity with a numerical scale that may be used in back-calculating the corresponding odour concentration. These descriptions are shown in **Table 2.1** (VDI, 1992). Like odour threshold determination, assessment of odour intensity is undertaken in the laboratory by odour panels and dynamic olfactometry equipment. Panel members are presented with odour at concentrations greater

than the odour threshold (by definition 1 OU/m^3) and asked to rate the odour strength on the scale in **Table 2.1** (WA DEP, 2002).

Table 2.1 Odour intensity categories.

Odour strength	*Intensity level*
Extremely strong	6
Very strong	5
Strong	4
Distinct	3
Weak	2
Very weak	1
Not perceptible	0

Odour intensity referencing scale (OIRS)

A common OIRS uses n-butanol as a standard reference odorant (Kephart & Mikesell, 2000; Schmidt, 2002; ASTM, 1999). ASTM (1999) describes two standard procedures for measuring odour intensity using n-butanol references. These include the "dynamic-scale" and "static-scale" methods.

In the dynamic-scale, an olfactometer, also referred to as n-butanol olfactometer (NCMAWM, 2001; Watts, 2000), may be used to obtain different concentrations of n-butanol by passing a diluent across the surface of a glass container of liquefied pure (99 + mol%) n-butanol (ASTM, 1999). Panellists compare the intensity of odours to different intensities of n-butanol presented using the olfactometer. With each presentation, the panellists decide if the intensity of the odour is less, similar or greater than the intensity of the diluted n-butanol sample (NCMAWM, 2001; Watts, 2000; ASTM, 1999).

In the static scale, different n-butanol concentrations are obtained by mixing liquefied pure (99+ mol%) n-butanol with distilled, odourless water. The different n-butanol mixtures are stored in glass containers and presented to panellists. Panellists shake the glass containers before sniffing the n-butanol vapour in the container headspace. Reference is made to the concentration of n-butanol in water (BIW) (NCMAWM, 2001; ASTM, 1999) or, n-butanol in air (BIA) (St. Croix Sensory, 2000). The concentration of the vapour in the headspace is less than the BIW by a factor of ten (St. Croix Sensory, 2000).

Category estimation technique

In this technique, human assessors estimate the intensity of an odour by ranking it according to their perception of its strength. Odour intensity is then determined from the geometric mean of the different levels (intervals) of the category scales as perceived by each panellist. The following is an example of the category intensity scale (NCMAWM, 2001; St. Croix Sensory, 2000; Misselbrook *et al*., 1993):

- No odour
- Very faint odour
- Faint odour
- Distinct odour
- Strong odour
- Very strong odour
- Extremely strong odour

2.3.3 Relationship between odour concentration and odour intensity

Odour intensity is a useful dimension to quantify because some odours are perceived as being stronger than others. In other words, all odours will be just detectable at a concentration of 1 OU/m^3, however, at twice the concentration, or 2 OU/m^3, some odours may be perceived as very weak while others may be

perceived as distinct. At ten times the concentration, or 10 OU/m^3, one odour may be perceived as distinct while another odour at 10 OU/m^3 concentration may be very strong. This means that defining an odour criterion based on odour concentration, as has historically been done for the purposes of managing odour impact on the community, will result in different perceived odour strengths. The only time this will not occur is when the odour criterion is equal to the detection threshold (*i.e.* 1 odour unit), which effectively becomes a "no impact" criterion (WA DEP, 2002).

Once the odour intensity and concentration data are available, the Weber-Fechner law (Eqn 2.1) is useful to develop the mathematical relationship between intensity and concentration. This relationship may then be solved for the odorant concentration, which corresponds to an appropriate criterion (WA DEP, 2002).

$$I = k_w \log(C / C_o) + Const \qquad (2.1)$$

where, I is the Intensity (perceived strength), dimensionless; k_w is the Weber-Fechner constant; C is the concentration of odorant; C_o is the concentration of odorant at the detection threshold (by definition equals 1 when using odour units) and *Const* is a constant which relates to the use of mean intensity levels. This constant is calculated from the line of best fit for each odorant.

2.3.4 Odour nuisance

The mechanism that leads from an emission of odorants to the atmosphere to actual odour nuisance is quite complex. It involves the following main factors (Power & Stafford, 2001):

- The characteristics of the odour that is released (detectability, intensity, hedonic tone, annoyance potential);
- Variable dilution in the atmosphere through turbulent dispersion (turbulence or stability of the boundary layer, wind direction, wind speed, *etc*.);

- Exposure of the receptors in the population (location of residence, movement of people, time spent outdoors, *etc.*);
- Characteristics of emission of the odour (farm activities, industrial activities, *etc*);
- Context of perception (*i.e.* other odours, background of odours, activity and state of mind within the perception context);
- Receptor characteristics (exposure history, association with risks, activity during exposure episodes, psychological factors such as coping behaviour, perceived health and perceived threats to health).

The factors that play a role are more diverse and mutually interactive. This process can be summarised as: odour generation → emission → dispersion → detection → appraisal → annoyance → nuisance. Hence, the following conceptual model from odour generation to reception for piggery industry is suggested (modified from Power & Stafford, 2001; Smith, 1995). The model is presented in *Fig 2.1*.

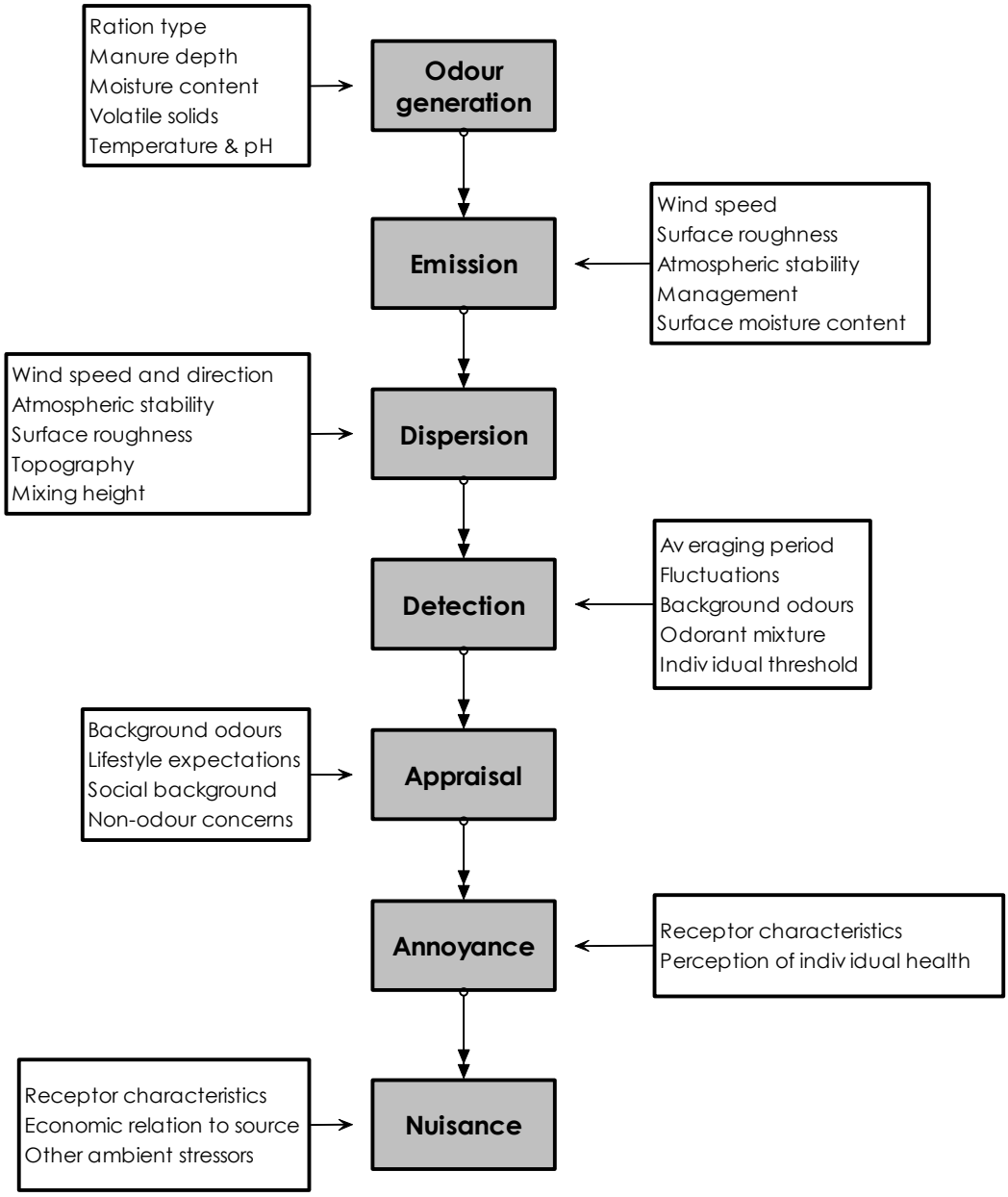


Fig 2.1 The conceptional model of odour nuisance generating mechanism in piggery industry (modified from Power & Stafford, 2001; Smith, 1995)

2.4 Odours in the piggery industry

2.4.1 Odour generation

Odours from piggeries are generally the by-products of the anaerobic breakdown of organic matter, the exception being volatilisation of ammonia. The organic matter being decomposed is primarily manure (urine and faeces) but can also include spilt feed, afterbirth, carcasses and any other organic matter on-site (FSA Environmental, 2000).

Anaerobic breakdown occurs when organic matter is combined with water in the absence of oxygen. It is a two-stage process. The first acid-forming stage converts complex carbohydrates to simpler organic acids like volatile fatty acids (VFA). In the second stage, these acids are converted to methane and carbon dioxide. The offensive odours associated with the anaerobic breakdown are the VFA and associated minor, yet offensive, by-products. These gases are most often released when anaerobic breakdown is incomplete and second stage (methane formation) does not occur or is incomplete. The most offensive compounds are nitrogen and sulphur based (FSA Environmental, 2000). The major substrates and products from anaerobic biological reactions are depicted in *Fig 2.2.*

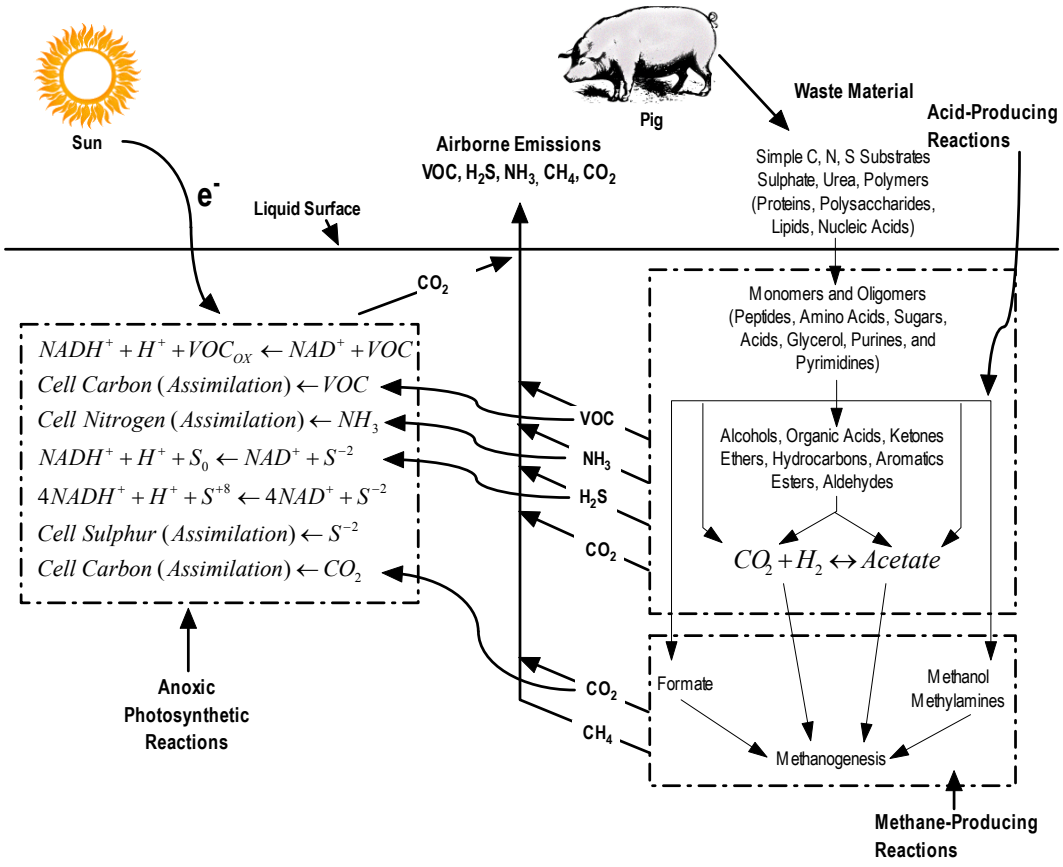


Fig 2.2 Model for the biotransformation of piggery manure (reproduced from Zahn et al., 2000)

2.4.2 Odour sources

Odour can be generated at various sites around a piggery. These include piggery sheds, waste storage and treatment processes, land applications, and carcass disposal areas.

Piggery shed

In comparison to traditional piggery sheds on smaller scale farms, piggery sheds used in intensive piggery operations are more enclosed and tightly constructed. These sheds also house a higher density of animals.

There are two main sources of odours within these sheds: the actual pigs, and the manure and urine, which are excreted at two to four times the daily rate of a

70-kilogram man. In the tight confines of these sheds, pigs become soiled with manure, urine and feed dust and their body heat radiate the odour of the culmination of these substances (Chapin *et al*., 1998). In most large-scale facilities, the manure and urine that do not collect on the pig pass through slatted floors into a holding area beneath the shed, where they remain until the next removal occurs. These holding areas often generate a large portion of the odours associated with housing facilities, especially when ventilation devices are utilised, pumping the odorous by-products of decomposition outdoors. In addition, when dust from dander, feed and manure is neglected, nearly every surface of the facility, including coating walls and ventilation systems, releases odours. Odours are emitted from piggery sheds in a concentrated dose (Swine Odor Task Force, 1995).

Odour emission rates from piggery sheds are dependent on a number of factors, such as the type of operation (gestation, nursery, finishing, *etc.*), management practice, manure handling and storage, and ventilation (Zhang *et al*., 2002). Several studies have also suggested that odour emission rates from animal facilities vary over the course of the day, and over the year (Zhu, 2000; Schauberger *et al*., 1999). As well, indoor and outdoor temperatures seem to play a role in odour emission (Heber, 2002). Generally, the operation type, manure storage method and ventilation are considered the most influential factors concerning odour emission. As a result, most researchers have grouped odour emission rates according to these characteristics, while primarily grouping results by the shed type (Zhang *et al*., 2002).

Waste storage and treatment processes

In most cases, piggery wastes are washed, pumped or scraped from beneath housing structures and stored in outdoor effluent ponds. During the start-up phase of a new pond, several offensive odours are produced until decomposition processes reach an equilibrium status. Mature, well-managed ponds are capable of

releasing minimal odours; however, if a mature pond is mismanaged, with excessive amounts of new raw waste being added too rapidly, a relatively severe odour problem may develop (Chapin *et al*., 1998; Swine Odor Task Force, 1995).

Land application

Due to the rich nutrients present in piggery excreta, manure wastes are often utilised as fertilisers for pastures, crops and woodlands. In this process, liquid manure is drawn from the surface of ponds and distributed across the area of destination. This process is often performed during the summer months with heat and humidity promoting the release of odorous compounds (Chapin *et al*., 1998). Liquid manure drawn from the surface of ponds generally does not create a severe odour problem when used for land application. However, if the deeper anaerobic sludge of effluent ponds is spread across land, highly volatile compounds rapidly rise into the air, creating offensive odours for downwind receptors. In addition, the odour problem associated with land application is oftentimes aggravated when the application process is poorly managed. For example, even if surface pond manure is spread across land, the odour can become severe if too much manure is spread on one occasion (Chapin *et al*., 1998; Swine Odor Task Force, 1995).

Carcass disposal areas

Due to disease, crowding, and other mass production techniques utilised by intensive piggery operations, thousands of pigs die each month before they are finished and ready for slaughter. It makes the problem of carcass disposal. For example, a farrow-to-finish operation supporting 1000 sows produces nearly 18200 kilograms of dead swine each year (Chapin *et al*., 1998). Pig carcasses are disposed of in the following ways: landfills, mass on-farm burial sites, incineration or rendering for future use (Swine Odor Task Force, 1995). Decomposing carcasses have possibilities to emit strong offensive odours in the storage and transport processes that precede these disposal methods. Furthermore,

the risk of disease transmission is inherent if pigs that died from infections are not disposed of properly (Chapin *et al*., 1998).

While reports have been made that inadequate incineration or other improper mortality disposal may cause 'bad' or 'unpleasant' odours, no quantifiable data has been given (AAFRD, 2002). Little scientific research was found with regard to odour concentrations or emissions from carcass disposal sites. The reasons behind this can be explained in a number of ways. Generally, it is required that carcasses be properly disposed of within 24-72 hours (Fulhage, 1994; MBAH, 1996). This does not commonly provide enough time for a carcass to decay significantly and produce offensive odours. Secondly, carcasses are rarely generated in significant quantities and thus are easily dealt with. Thirdly, unlike manure, carcasses are dealt with well within farm property boundaries (Zhang *et al*., 2002).

2.5 Chapter summary

In this chapter, foundational information on odour issues in the piggery industry have been investigated in detail. It firstly covers the distinction between odours and gas. The general odour science and odour emitting sources in piggery industry are also discussed.

Although it is often seen that many people refer to odours and gases interchangeably, there is a difference between these two terms. There is no known correlation between odour and the specific gases emitted from piggery operations. Odours are the mixture of odorous materials including gases, piggery dust and other airborne particulates. In addition, these particles are capable of carrying bacteria and other microorganisms. On the other hand, the gases refers solely to the specific gaseous compounds that are emitted from piggery operations

Odour concentration and odour intensity are used to measure of the strength of an odour. The nuisance leading mechanism of odour is presented. It can be summarised as: odour generation → emission → dispersion → detection → appraisal → annoyance → nuisance.

Odour can be generated at various sites around a piggery. These include piggery sheds, waste storage and treatment processes, land applications, and carcass disposal areas. Among these sources, piggery sheds and effluent ponds are indicated as major odour sources. In piggery sheds, the operation type, manure storage method and ventilation are considered the most influential factors concerning odour emission. With regarding to the effluent ponds, it is known that mature, well-managed ponds are capable of releasing minimal odours. However, if a mature pond is mismanaged, with excessive amounts of new raw waste being added too rapidly, a severe odour problem will develop.

CHAPTER 3
ODOUR SAMPLING

3.1 Introduction

The odour emission rate (OER) has units of 'odour unit per unit area per time' (*e.g.* OU/m^2s or OU/m^2hr). It is used to quantify the rate of odour discharge from odour sources. The measurement of the odour emission rate involves the sampling of odorous air from the source, the laboratory analysis of that air sample, *i.e.* odour measurement, and calculation of the emission rate (Freeman *et al*., 2000). The procedures for sampling and analysis of the odorous air sample are quite separate activities, each with their own issues and problems. Therefore, these topics are addressed separately in Chapters 3 and 4, respectively.

Unless appropriate odour sampling and measurement techniques are followed, errors are incurred in the process of measuring an OER. It may be accumulated so that the final calculated emission rate carries a large uncertainty. The most likely sources of error include (Freeman *et al.*, 2000):

- Contamination of air samples by the sampling equipment used;
- Instability of odour concentration in the air sample;
- Erroneous measurement of air flow rates in stacks and sampling hoods;
- Additional problems with area source sampling relating to whether the type of sample hood used reflects actual ambient emission conditions; and
- Uncertainties in odour concentration determined by olfactometry procedure.

For the reasons mentioned above, the potential for these errors to have occurred should be considered in any odour study. Furthermore, it is required to develop a robust, reliable and appropriate odour sampling technique.

In this chapter, firstly, an overview of odour sampling is presented. Odour sampling methods are then described in detail. It is then focused on the odour sampling from an area source without mass outward flows. Finally, the theoretical background of wind tunnel method is addressed.

3.2 Overview of odour sampling

3.2.1 Considerations required for odour sampling

It is important that the equipment used to collect an odour sample does not contaminate the sample or cause minimal changes to the odour in the sample. Therefore, specialised equipment and materials are required. Samples are collected into special purpose plastic bags made of Tedlar^{TM}, nalophane or polytetrafluoroethylene (PTFE) to minimise adsorption of the odour onto the bag surface (Freeman *et al.*, 2000). However, significant background odour emission from Tedlar^{TM} bags have been reported by a number of laboratories (CASANZ, 1998).

The plastic bags used to collect the samples have to be filled only once because some types of odour or very strong odours might be able to adsorb to material surfaces in either the sampling equipment or the olfactometer even with the precautions for use of specialised equipment and materials. These odours can then contaminate other odour samples passing through the same equipment. Therefore, operators should be alert to the potential contamination problem, and carry out routine and frequent equipment calibration and quality control testing. Further problems can occur if the original sample is influenced by condensation, chemical reaction, sample instability, or particles which contribute to or absorb the odour.

3.2.2 Definition of source type

Odorous emissions may arise from a number of different sources within an industrial process or livestock operation. These are listed below, along with their basic information requirements.

- *Point source*: Discharges from a small opening such as a stack (chimneys) or vent. For piggery operation units, point sources could be stacks or mechanically-ventilated fan outlets.
- *Area source*s: A source with a large surface area such as a landfill surface, a pile of solid material, or a liquid surface. Typical examples of area sources include effluent ponds and areas of exposed, disturbed soil. For such sources, the basic information required includes its location, height above ground level, surface area, dimensions and a brief description of the nature of the source. If an estimate of the emissions is to made, more detailed information will probably be required. For example, for a piggery effluent pond, data on the organic loading rates discharged from sheds and chemical constituent of the effluents would be required to enable an estimation of the potential odour emission rate (Woodward-Clyde Ltd., 2002).
- *Volume sources:* A bulky, diffuse source. Typical examples of volume sources include fugitive emissions from buildings or a bag-house which discharges via louvered vents rather than a stack.
- *Line source:* A long, narrow source such as a roadway or roofline vent along a long, narrow building.

A typical area source, a piggery effluent pond, is presented in *Fig 3.1*. It shows the odour sampling work using the wind tunnel, which is placed over the effluent pond.

Fig 3.1 Sampling odours from an effluent pond, an area source

3.2.3 Odour sampling at area source

Sampling of odours from area sources is more complicated than for point sources due to the diffuse nature of the emissions and, in many cases, the sheer size of the odour source (Woodward-Clyde Ltd., 2002). A number of sampling methodologies including the static flux hood and the wind tunnel, have been developed for odour testing of area sources. These methodologies can be classified into two different methods according to the presence of outward flows on emission sources or not.

3.2.3.1 Sampling from an area source without outward flows

For passively venting area sources such as a piggery effluent pond, sampling may be carried out using use of some form of sampling chamber such as a wind tunnel. These devices are used to create a specific cross-flow velocity across the

emission surface enclosed by the sampling chamber section of the wind tunnel, which may be chosen to correspond to a typical ground level wind speed. The air sample is drawn from the outlet of the wind tunnel using an air sampling pump. The emission rate can be calculated by the equation (modified from Jiang & Kaye, 2001):

$$OER = \frac{QC}{A} \tag{3.1}$$

where, OER is odour emission rate, OU/m^{2}s; Q is flow rate through the wind tunnel, m^3/s; C is odour concentration, OU/m^3; and A is area covered by the wind tunnel, m^2.

Most of the wind tunnels have an internal sweep velocity of 1.0 - 3.0 m/s. Hence, OER data needs to be corrected to a surface wind speed that is compatible with actual surface wind speeds. The reason of this correction is that the surface wind speed, which prevails under the worst case meteorological condition, tends to give rise to odour complaints.

A standardised surface wind speed of 0.05 m/s is often used. This value corresponds approximately to the wind speed at a height of 100mm above the surface (one half of sampling hood height) for a recorded wind speed of 0.5 m/s. This correction is made using the following equation (Freeman *et al.*, 2000):

$$OER_2 = OER_1 \left[\frac{V_2}{V_1} \right]^{0.5} \tag{3.2}$$

where, OER_1 is odour emission rate measured using the wind tunnel, OU/m^{2}s; OER_2 is odour emission rate corresponding to actual ground level wind speed, OU/m^{2}s; V_1 is wind speed inside wind tunnel for sample collection; and V_2 is actual ground level wind speed.

This relationship between emission rates and wind speeds is derived from boundary layer theory and has been verified experimentally (Schulz *et al.*, 1995a). This formula can also be used to calculate OER values at other wind speeds, which can then be used in a dispersion model to simulate changes in OER with changing wind speed (Freeman *et al.*, 2000).

Bouwmeester & Vlek (1981) determined the appropriate tunnel wind speed by determining a relationship between bulk wind speed in the tunnel, V_t, and wind speed at 8 m above a rice paddy, V_8, using surface shear stress theory. The relationship for their wind tunnel was:

$$V_8 = 0.53V_t^{1.5} \tag{3.3}$$

From the experiments on odour emission from spread pig slurry, Pain *et al.* (1987) suggested a relationship of the following form:

$$OER_V = OER_1 V^{1.2} \tag{3.4}$$

where, OER_V is the odour emission rate corresponding to wind speed V, OU/m^{2}s: OER_1 is the odour emission rate corresponding to wind speed of 1 m/s, OU/m^{2}s.

For wind speeds less than 1 m/s, the exponent on the velocity term in Eqn (3.4) would be 0.4. Jiang & Kaye (1996) suggested 0.5 for the exponent of the velocity term in Eqn (3.4) for their portable wind tunnel.

On-site meteorological wind sensors are usually affixed to a 10 m mast. Consequently, the ground level wind speeds at half wind tunnel height (0.125 m) may be calculated from the 10 m height wind speeds using the following equation (modified from Jiang & Kaye, 2001):

$$V_{0.125} = V_{10}\left[\frac{0.125}{10}\right]^{n} \quad (3.5)$$

where, $V_{0.125}$, V_{10} = wind speeds (m/s) at 0.125 m and 10 m heights, respectively.

The wind profile exponent, *n* is assigned on the basis of the Pasquill stability class. In a recent Australian study (Kaye & Jiang, 2000), median values for each of the 6 Ausplume default wind categories together with the exponent for the corresponding stability classes were used, such that for each area1 emission source a 6×6 matrix of emission rates was generated (36 values for each area1 source). Irwin Urban exponents of 0.15, 0.15, 0.2. 0.25. 0.4. and 0.6 were used respectively for stability classes A, B, C, D, E, and F (Jiang & Kaye, 2001).

3.2.3.2 Sampling from an area source with outward flow

With regard to sources where there is a measurable outward flow, such as a biofilter or mechanically-ventilated compost windrow, flow rates should be measured using an anemometer at a number of points across the surface to determine whether the flow is even (Woodward-Clyde Ltd., 2002).

Based on the results of this preliminary assessment, the size of the source and the expected degree of uniformity of the emission rate over the surface area, the emission source should be divided into a number of sub-areas with an appropriate grid size. Then, the concentration should be measured in the sub-areas using the wind tunnel, with a cross-flow wind speed corresponding to the outward flow measured previously. This enables sampling to occur without restricting or artificially enhancing the outward flow. The emission rate is then calculated using equation 3.6 (Woodward-Clyde Ltd., 2002):

$$OER = \frac{\sum_{1}^{n} C_i V_i}{n} \tag{3.6}$$

where, OER is odour emission rate, OU/m^{2}s; C_i is measured odour emission rate, OU/m^{2}s; V_i is wind speed in area i (m/s); and n is number of areas.

For the samples from sources where temperature and pressures are significantly different from ambient conditions, the gas flow rate is calculated and adjusted to NTP (Normal Temperature and Pressure *i.e.*, 20°C and 101.3 kPa) conditions using the following equation (Jiang & Kaye, 2001):

$$Q = Q_m \frac{(273+20)}{(273+t)} \frac{p}{101.3} \tag{3.7}$$

where, Q is the volume flow rate at NTP conditions, m^3/s; Q_m is the volume flow rate measured inside the vent, m^3/s; t is air temperature inside the vent, °C; and p is the absolute pressure inside the vent, kPa.

3.3 Odour sampling methods

3.3.1 Overview

Methods currently used for sampling odours from area sources include (EPA NSW, 2001):

- Static (isolation) flux hood;
- Wind tunnel;
- Equipment enclosure ('tent'); and
- Witch's hat.

Table 3.1 is an attempt to classify the appropriateness of area source sampling methods according to source type. The classification process considered practical sampling issues and the methods likely to best estimate the actual odour source emission rate. It is important to note that (CASANZ, 1998):

- No one method is currently considered universally applicable; and
- The information contained in Table 3.1 is a first attempt at categorising area source sampling methods.

Through the extensive research about odour sampling issues in Australian intensive livestock operations (Smith & Hancock, 1992; Smith, 1993; Smith & Watts, 1994a & 1994b; Smith, 1995; Smith & Kelly, 1996; Bliss *et al*., 1995; Jiang *et al*., 1995b), the following sampling techniques are revealed to be available for piggery effluent ponds or piggery waste spreading areas (Watts, 1999a). They include:

- Physical surface sampling methods (static flux hoods and wind tunnels)
- Downwind sampling methods (the TPS method and the STINK method)

Table 3.1

Diffuse source sampling methods, according to source type

(from EPA NSW, 2001)

	Diffuse source sampling method				
Source type	*Back calculation*	*Wind tunnel*	*Flux Hood*	*Tent*	*Witch's hat*
Waste water treatment sources					
Aerated	×	√	×	×	√
Still	×	√	√	×	√
Inlet works	×	√	√	√	×
Anaerobic pond	√	√	√	×	×
*Trickling filter (top)**	×	×	√	√	×
Other sources					
Cattle feed lot	√	×	×	×	×
Compost wind rows (static)	×	√	√	×	√
Compost wind rows (aerated)	×	×	×	×	√
Soil bed filters/Biofilters	×	×	×	√	√
Landfills	√	×	√	TBD	TBD

√ applicable sampling method for this source type
× sampling method not applicable for this source type
TBD applicability to be determined
* trickling filter base vents should be sampled concurrently as point sources.

3.3.2 Isolation flux hood

The isolation flux hood (chamber) method was developed by the USEPA in 1983 (Klenbusch, 1986). The emission assessment using the isolation flux hood in the dairy industry is illustrated in *Fig 3.2* (Schmidt, 2001). The flux hood system has been used for nitrous oxide emissions from farmland (Denmead, 1979), measurement of gaseous emission rate from land surface (Klenbusch, 1986) and sampling emissions from hazardous waste dumps (Clark *et al*., 1988).

The flux hood is a sealed chamber open at the base. It is placed on the odour emitting surface for the purpose of sampling the emissions. During operation, clean dry air is forced under pressure into the hood. This air is mixed with the emitted odours by the physical layout of the hood. The sample is drawn from the

chamber, when required, at a slow rate (Watts, 1999a). The critical design parameters are the mixing characteristics of the chemicals and the selection of the carrier gas (Gholson *et al*., 1991).

The design of static flux hoods is based on the two-film model that is frequently used to explain the experimental phenomenon of the volatilisation of organic compounds from water in the laboratory. For gas-phase-controlled VOC emissions, the volatilisation process will be influenced by wind-induced gas-phase turbulence. Static techniques do not simulate wind turbulence (UNSW, 2003). The US EPA evaluation study for the flux hood did not consider gas-phase controlled processes (Gholson *et al*., 1989).

There are number of factors which may limit the application of the flux hood in the determination of odour emission rates. Denmead (1979) demonstrated the dependence of the measured emission rate on the pressure deficit (or surplus) in the chamber. A deficit of 0.01 m head resulted in a twelve fold increase in the emission rate. Furthermore, several other uncertainties have been reported (UNSW, 2003):

- It was reported by the original authors that complete mixing only occurred at a zone of 2 - 9.5 cm above the air and water interface (Gholson *et al*., 1989). This stratification is dependent on the temperature of the carrier gas, surface temperature and ambient air temperature. The variations in the stratification layer thickness under different sampling conditions could significantly affect the repeatability and reproducibility of the testing results;
- The selection of the sweep air (carrier gas) rate has been found not to be fully satisfactory (Reihart *et al*., 1992). By increasing the sweep air rate it was found that the chemical concentration inside the isolation chamber did not alter (Hwang, 1985); and

- The measured emission rates depend largely on the configuration of the enclosure and operating procedures (Reihart *et al*., 1992). It has also been shown that the isolation chamber could not easily be used for aerated liquid surfaces (Gholson *et al*., 1989).

Smith & Watts (1994) indicated several factors affecting the rate of emissions as sampled by a flux hood:

- The pressure inside the chamber relative to that outside;
- The relatively small area of emitting surface enclosed by the hood;
- The suppression of the turbulent transport mechanism which under ambient conditions transports the emissions away from the emitting surface; and
- Imperfect mixing of the emissions and the sweep air.

Generally, the flux hood records much lower emission rates than the results from wind tunnel techniques and indirect estimation using mathematical modelling (Smith & Dalton, 1999a). Under field conditions, measured odour emission rates between the isolation flux hood and the wind tunnel have been observed to differ by up to 300 times in some cases (Jiang & Kaye, 1996).

In summary, the isolation flux hood method is not recommend for odour sampling purposes especially for area sources (Watts, 1999a; Sohn, 2000; Jiang & Kaye, 2001) because it is not designed to take into account convective mass transfer caused by air movement above an emitting surface. As well the aerodynamics of the device does not guarantee the repeatability and reproducibility of the emission rates measured.

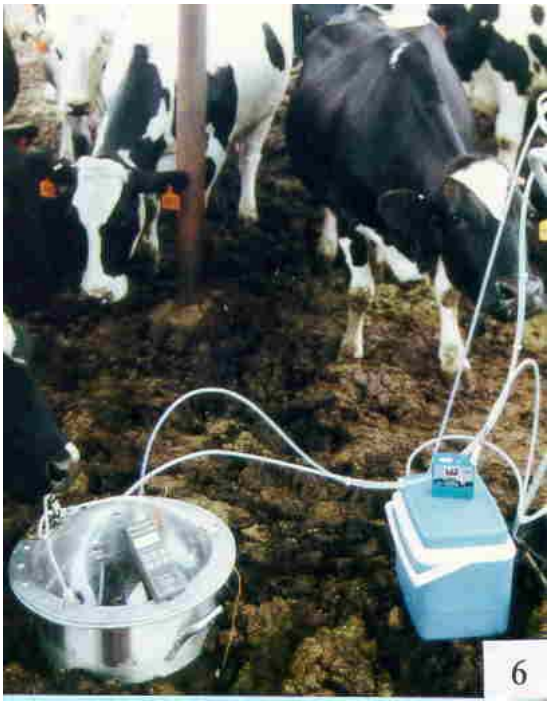


Fig 3. 2 The emission assessment using the isolation flux hood in dairy industry (reproduced from http://www.ceschmidt.com)

3.3.3 Wind tunnel

Wind tunnels are portable, open-bottomed enclosures that are placed over the emitting surface. Ambient or filtered air is drawn or blown through the tunnel to mix with and transport the emissions away from the emitting surface. This simulates the convective mixing and transport process present above the emitting surface (Watts, 1999a).

Wind tunnels have been used for estimating ammonia emissions from dairy cow collecting yards (Misselbrook *et al*., 1998) and arable land (Loubet *et al*., 1999b); estimating odour emissions from piggeries (Smith & Dalton, 1999a), from feedlots (Smith & Watts, 1994b; Watts *et al*., 1994) and poultry manure (Jiang & Sands, 2000).

Wind tunnels have been accepted as an accurate method for the sampling of odour. However, there is no standard for their design. Variations in tunnel geometry include differences in the material used in the construction of the tunnel, the length/width ratio, the surface area sampled and the height. Consequently there are substantial effects on the aerodynamics over the emitting surface. A further complication is the variation in wind speed from one device to another (Smith & Watts, 1994a). **Table 3.2** gives the dimensions of various wind tunnels reported in the literature.

There are several different wind tunnel designs in Australia. The Intensive Livestock Systems Unit (ILSU) in Queensland Department of Primary Industry/National Centre for Engineering in Agriculture (NCEA) odour research group in University of Southern Queensland has developed and validated several wind tunnels. *Fig 3.3* and *Fig 3.4* illustrate the wind tunnel designs used by the ILSU/NCEA research group. The detailed design specifications of the wind tunnel techniques are addressed in Chapter 8.

Smith & Watts (1994a) reviewed the design and operation of different wind tunnels. The influence of tunnel wind speed was emphasised and a relationship between odour emission rate and tunnel wind speed was proposed. Smith & Watts (1994b) compared odour emission rates measured from cattle feedlot pens using two different-sized wind tunnels. Emission rates were strongly correlated with wind tunnel size. The large wind tunnel gave emission rates consistently lower than those did in the small tunnel by a factor of about 0.8. It was suggested that the different wind velocity profiles in the tunnels might be a reason for the difference (Watts, 1999a).

An isometric drawing and the dimensions of the wind tunnel system developed at the University of New South Wales (UNSW) are shown in *Fig 3.5*. It was used to measure odour and VOCs emission rates from area sources. The system comprises several parts: extension inlet duct, connection duct, expansion

section, main section, contraction section and mixing chamber. The cylindrical floats are used where the odour source is a liquid surface but removed in the cases of solid sources such as broiler litter. The extension inlet duct can be separated from the connection duct to enable cleaning and transport of the hood (Jiang & Kaye, 2001).

It is almost impossible for natural ground-level wind conditions to be duplicated inside a small wind tunnel. Therefore, the wind tunnel is designed to create an environment where the boundary layer is well developed and convective mass transfer occurs. The aerodynamic performance of the wind tunnel is considered a critical parameter (Jiang & Kaye, 2001).

In summary, the wind tunnel technique is accepted as the more appropriate method for the determination of odour and VOCs emissions from area sources as compared with the isolation flux hood because it is able to simulate ambient wind condition.

Table 3.2

Specifications of various wind tunnels (modified from Watts, 1999a)

Type/Material	*L/W ratio*	*Area sampled (m^2)*	*Height (m)*	*Wind speed (m/s)*	*Source*
Semi-cylindrical Transparent polycarbonate	4	1	0.45	0.04 - 3.77 Mean: 1.33	Lockyer, 1984
Semi-cylindrical Transparent polycarbonate	4	1	0.45	1.0	Pain *et al*., 1987
Lindvall box Stainless steel	4	0.32	0.25	0.3	Freeman, 1992 Lindvall *et al*., 1974
Rectangular	1.7	2.05	0.87		Homans, 1987
Rectangular	0.6	0.1	0.2		Homans, 1987
Rectangular Perspex	4	0.5	0.2	0.66	Watts *et al*., 1994
Rectangular Stainless steel	0.6	0.6	0.125	0.2 - 0.4	Schulz & Lim, 1993
Rectangular Stainless steel	4	0.25	0.2	0.2 - 2.0	Smith & Watts, 1994b
Semi-cylindrical Stainless steel	4	1.0	0.45	0.2 - 2.0	Smith & Watts, 1994b
Rectangular	4	0.25	0.2	0.6 - 0.7	Casey *et al*., 1997
Rectangular Stainless steel	2	0.32	0.25		Jiang, 1999
Rectangular Stainless steel		0.76	0.15	1.1	Heber, 2002

Fig 3.3 Wind tunnel design used by ILSU/NCEA

Fig 3.4 Modular designed wind tunnel with variable speed fan developed at USQ

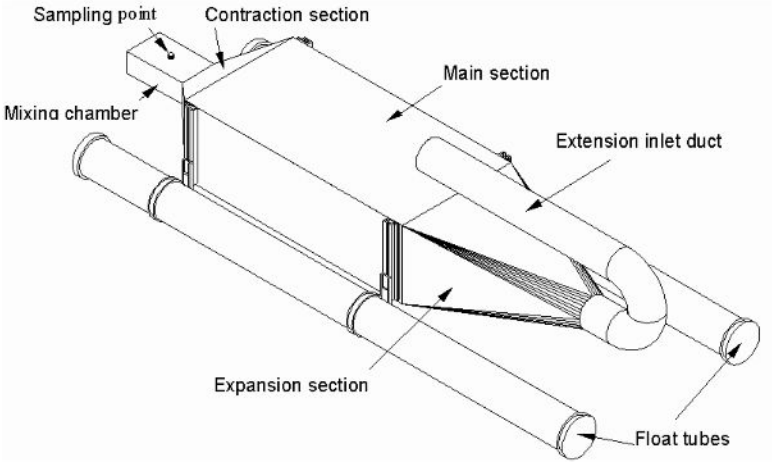


Fig 3.5 An isometric drawing of the UNSW odour wind tunnel (reproduced from Jiang & Kaye, 2001)

3.3.4 Downwind sampling methods

The estimation of emission rates from measurements of concentration taken downwind of the source is a proven approach for which several methods are available (Smith & Watts, 1994a). The preferred method involves the measurement of complete wind speed and concentration profiles at the downwind points. However, this is impractical for odour work because of the cost and difficulty in obtaining a sufficient number of odour concentration measurements (Watts, 1999a). This has resulted in the development of simplified methods (Wilson *et al*., 1981; Smith, 1995), which require the simultaneous measurement of concentration and wind speed at only one height in the profile.

The STINK model was developed by Smith (1995). It employs the Gaussian dispersion model of Smith (1993) to calculate a non-dimensional concentration $\Psi(z)$ at selected receptor locations downwind of the source. Modelling with the STINK model involves taking a number of samples downwind of a source and back calculating an emission rate from the source using the odour concentration from the downwind sample.

The inputs to the STINK model are (Galvin *et al.*, 2002):

- Pond width (X)
- Pond length (Y)
- Wind direction
- Longitudinal and latitudinal distance to the receptor from the centre of the pond (X and Y)
- Averaging time (hours)
- Roughness height
- Monin-Obukhov lengths for stability classes
- Height for calculation of concentration profile (height at which sample was taken)

The model output provides a table of non-dimensional coefficients for increasing sampling heights for different stability classes. A non-dimensional coefficient was then selected according to the stability class at time of sampling and the height at which the sample was taken. The emission rate was then calculated using following equation.

$$OER_a = \frac{C_z \breve{V}}{\Psi_z} \tag{3.8}$$

where, OER_a is a calculated emission rate; C_z is the measured odour concentration at the selected sampling location; $\breve{V}$ is a wind speed at a height of 1m based on 1m/s at half tunnel height based on Urwin Rural coefficients for the stability classes; and Ψ_z is the non dimensional coefficient at the sampling height.

The value for $\breve{V}$ was calculated according to the power law using Irwin Rural coefficients. Equation 3.9 shows the equation used to calculate the wind speed. This equation is essentially the same at equation 3.3.

$$V_z = V_{ref}\left(\frac{Z}{Z_{ref}}\right)^a \tag{3.9}$$

where, V_z is a wind speed at height Z above the ground, m/s; V_{ref} is a wind speed at the wind measurement height Z_{ref}, m/s; and a is a wind profile exponent which in a function of stability.

The important advantages of this model are that (Watts, 1999a):

- It is applicable to sources which may be of irregular shape, of limited lateral extent and with the wind orientation other than perpendicular to edges of the source; and
- Any reasonable location can be used for the measurements providing the location, the size of the source and the wind direction are known.

It should also be noted that the emission rate calculated by this method is a spatially averaged rate for the odour source.

The TPS method of Wilson *et al.* (1981) requires a circular odour emission source. It is applicable for some research situations but is generally not applicable to practical applications.

3.4 Theory of wind tunnel techniques

3.4.1 Principle of wind tunnels

The basic principle of the wind tunnel technique is to assess the difference between the input and the output odour concentration in the wind tunnel. The boundaries for calculating this mass balance are the experimental area covered by wind tunnel, the dimensions of emission chamber of wind tunnel, and the inlet and the outlet cross-sections of the tunnel. Using these boundaries, the mass conservation of the odour emission can then be expressed as (modified from Loubet *et al*., 1999a):

$$A_o \Phi_o = A_i \Phi_i + A_{exp} \Phi_{exp} \tag{3.10}$$

where, A_o is the outlet area of the wind tunnel, m^2; Φ_o is the odour mass flux through the outlet area, kg/m^2s; A_i is the inlet area of the wind tunnel, m^2; Φ_i is the odour mass flux through the inlet area, kg/m^2s; A_{exp} is the experimental area covered by the wind tunnel, m^2; Φ_{exp} is the odour mass flux emitted from the odour source, kg/m^2s.

The contribution of the odour emission from experimental area to air bulk density ρ_a in kg/m^3 is negligible because of its low concentration. And then, the fluxes can be expressed as a function of the wind speed V in m/s and non-dimensional concentration C in m^3/m^3:

$$\Phi_{\exp} = \frac{\rho_a}{A_{\exp}} \left[\int_A \overline{VC} \cdot dA \right]_i^0 \tag{3.11}$$

where, ρ_a is air bulk density, kg/m^3; $\overline{VC}$ is the mean component of horizontal flux of odour, kg/m^2s.

In addition, the symbol $[-]_i^0$ is used for $[x]_i^0 = [x_0 - x_i]$.

In a turbulent flow, both V and C are random variables, and they can be separated into ensemble mean and fluctuating components: $x = X + x'$, where x is a given value at a given time and x' its deviation from the average X over the time interval Δt. Applying that to V and C gives (modified from Loubet *et al*., 1999a):

$$\Phi_{\exp} = \frac{\rho_a}{A_{\exp}} \left[\int_s \overline{VC} \cdot dA + \int_s \overline{v'c'} \cdot dA \right]_i^0 \tag{3.12}$$

where, $\overline{V}$ is mean horizontal wind speed, m/s; $\overline{C}$ is mean odour concentration, m^3/m^3; v' is the fluctuating component of wind speed, m/s; c' is the fluctuating component of odour concentration, m^3/m^3.

Their average over the time step Δt is zero (Loubet *et al*., 1999a). $\overline{v'c'}$ is the turbulent component of the horizontal flux. Considering the field application, a more simplified equation is needed particularly requiring some simplification of turbulent component, $\overline{v'c'}$. If it is assumed that the airflow in the wind tunnel is completely mixed, the odour emission flux can be determined from the following relation.

$$\Phi_{exp} = \rho_a \frac{\overline{Q}}{A_{exp}} \left[\overline{C_o} - \overline{C_i} \right] \tag{3.13}$$

where, $\overline{Q}$ is mean volumetric flow, m^3/s; $\overline{C_o}$ is the mean odour concentration averaged over the outlet area, m^3/m^3; $\overline{C_i}$ is the mean odour concentration averaged over the inlet area, m^3/m^3.

When odour sampling is done using wind tunnel techniques, $\overline{C_i}$ is assumed to be zero because most of wind tunnels use activated carbon filter to introduce odour-free air into its emission testing chamber. Hence, a simple continuity equation applies to odour concentration averaged over the outlet area of the tunnel.

Φ_{exp} converted to odour emission rate, *OER* (modified from Smith & Watts, 1994a):

$$OER = C_o V_t \frac{A_{exp}}{A_o} \tag{3.14}$$

where, *OER* is odour emission rate, kg/m^{2}s; V_t is the bulk wind speed in the tunnel, m/s.

However, one should be careful in applying this continuity equation because it assumes complete mixing between the emissions and the airflow in the tunnel.

The selection of the appropriate wind speed to use in wind tunnels needs consideration (Smith & Watts, 1994a). Pain *et al.* (1988) indicated that higher wind speeds increase the rate of odour emission shortly after slurry application. This increase appeared to be due to the greater volume of air drawn through the tunnel at the higher speeds rather than due to higher threshold values (*i.e.*, odour concentrations).

3.4.2 Boundary layer effect

3.4.2.1 Mass transfer in the boundary layer

The boundary layer properties are directly related to characteristics of the surface (Oke, 1987). The transfer of gas, momentum and heat between a surface and the airflow depends mainly on the dynamic structure of the flow in the boundary layer (Loubet *et al*., 1999b). This transfer relies heavily on the distribution of the effluvium sources on the surface and the source characteristics. For the majority of sources, the odour strength depends on the concentration gradient and diffusion properties of the odour.

Over natural flat surfaces, the lowest part of the boundary layer displays some special properties. This layer is known as the surface boundary layer or constant flux layer. This causes variability in the dynamic structure of the boundary layer

and consequently affects the diffusion rate. The diffusion rate is a function of wind speed, the roughness height and the latent and sensible heat fluxes. A model that has been proposed to describe a stationary boundary layer is a first order model. This model is depicted by equation 3.15 and 3.16 (Loubet *et al*., 1999b).

$$\tau_0 = -\rho K_m \frac{\delta V}{\delta z} \tag{3.15}$$

$$F_g = -\rho K_g \frac{\delta C}{\delta z} \tag{3.16}$$

where, τ_0 is momentum flux or shear stress, kg/ms^2; F_g is the vertical flux of odour that is transferred by turbulence from the surface to the atmosphere, kg/m^2; K_m is the turbulent diffusivity for momentum, m^2/s; K_g is the turbulent diffusivity for odour, m^2/s; V is mean wind speed, m/s; C is mean odour concentration, m^3/m^3; z is the height above the surface, m.

Generally for a flat surface within the surface boundary layer, the turbulence intensity reaches a maximum near the surface and then decreases with height (Loubet *et al.*, 1999b).

3.4.2.2 Mass transfer in wind tunnels

Boundary layers are very different in enforced and restricted conditions such as the wind tunnel environment due to the size of limiting structures. The turbulent structures are restrained by the pipe-like enclosure. Hence, the structure of the boundary layer may be affected by the flow rate. In non-circular sections of wind tunnels the flows will not have axial or plane symmetry. This could cause flows orthogonal to the mean wind direction. These flows are due to transverse gradients in shear stress along the sides of the tunnel (Loubet *et al*., 1999b). These effects can be expected in an enclosed environment, such as in a wind tunnel. When the flow enters the tunnel, the flow characteristics change. Profiles will vary with distance from the inlet since they depend on surface geometry and the imposed flow rate (Baldo, 2000).

3.5 Chapter summary

In this chapter, odour sampling methods are addressed. The odour emission rates are used to quantify the rate of odour discharge from odour sources. Therefore, appropriate odour sampling methods are required to measure OER without errors. Specialised equipment and materials for the collection of an odour sample are required. These materials must have characteristics which do not contaminate the sample or cause any changes to the odour in the sample. It is also required to choose proper sampling methods depending on the odour source.

Through the extensive research about odour sampling issues in Australian intensive livestock operations, the flux hood and the wind tunnel are revealed to be available odour sampling methods for piggery effluent ponds, the target of this research work. It is revealed that the TPS downwind sampling method is applicable for some research situations but is generally not applicable to practical applications.

However, the isolation flux hood method is not recommended for odour sampling by many researchers because it is not designed to take into account convective mass transfer caused by air movement above an emitting surface. Additionally, the aerodynamics of the device do not guarantee the repeatability and reproducibility of the emission rates measured.

The wind tunnel method is accepted as more appropriate for the determination of odour and VOCs emissions from area sources than the isolation flux hood because it is able to simulate ambient wind condition.

Finally, the theoretical background of the wind tunnel method is addressed. It has been noted that the basic objective of the tunnel is to assess the difference between the input and the output of odour concentration. A series of mathematical equations has then been discussed to explain the influence of turbulent airflow and to show the effects of the boundary layer.

CHAPTER 4
ODOUR MEASUREMENT

4.1 Introduction

With regarding to the measurement of odour, there are two basic approaches: analytical techniques including off-line chemical analysis and direct reading instrumental analysis, and sensory techniques utilising human response.

Analytical techniques (Powell, 2002)

- Off-line chemical analysis: indirect assessment involving the collection of a sample, which is able to give the concentration of the various chemical compounds present in odour samples. This includes substance-specific wet chemistry, gas chromatography (GC) and gas chromatography coupled with mass spectrometry (GC-MS) methods.
- Direct reading instrumental analysis: provides information on the concentration of specific chemical species or their concentrations relative to each other. This includes several portable analysers (including portable GC-MS, flame ionisation detectors (FID), gold leaf analysers and paper tape monitors) and the electronic nose.

Sensory techniques

- Sensory assessment: gives an assessment of the physiological response to a particular mixture like strength, quality, character and provides information on the likely population response. This is obtained by exposing trained individuals to samples of the odorous air, either in the laboratory or in the field. The methods include olfactometry and simplified olfactometric screening like the simple sniff test

In odour measurement, chemical analysis is not regarded as a practical method because there are several difficulties with the method (NZWWA, 2000):

- Odorous air can consist of many odorous compounds. This fact presents a major challenge to the accurate measurement of odour due to the difficulty in identifying all compounds, and the synergistic relationship that may exist between the various compounds.
- The nuisance impact of an odorous compound is often perceived at extremely low concentrations, making instrumental analysis difficult.

In addition, as there are a number of different techniques in use for odour analysis, the selection of a particular method for a specific situation has to be considered depending on (Powell, 2002):

- The purpose of the odour measurement;
- The frequency of monitoring (once-off, periodic, continuous, etc.);
- The location at which the odour is sampled;
- Whether a point source or area (surface) source;
- Source geometry (point or area); and
- The nature and complexity of the emission: a single compound or a complex mixture.

Furthermore, various odour measurement techniques have their advantages and disadvantages with respect to the accuracy of estimation of odour concentration. They have some differences in cost, detection limits and complexity. **Table 4.1** presents the comparison of the characteristics of the various odour measurement techniques.

In this chapter, the gas chromatography, one of the popular methods of chemical analysis, is briefly described. Olfactometry, the sensory evaluation method and the electronic nose are then discussed in detail.

Table 4.1

Characteristics of the odour measurement techniques considered (reproduced from Powell, 2002)

	Subjective Observations	*Specific Chemical tests*	*GC-MS*	*Olfactometry*	*Electronic Nose*
Application	Simplified olfactometry – sniff Test	Source sampling	Source sampling/ Ambient	Source sampling	Source sampling/ Ambient
Analysis	Identifying the presence of odour, offensiveness or identification of source.	Limited to specific compounds	Limited to organic compounds	Fully representative	Fully representative but appropriate sensors must be selected for application
Sampling methodology	Testing protocol required for repeatability	Direct sampling, e.g. colorimetric tubes or instrumental. Indirect, e.g. collection of sample and lab analysis	Various techniques but will require pre-concentration for ambient air samples	Bag sampling	Direct sampling (but portability is limited)
Limit of detection	Typically good, but can vary depending on environment and compounds involved	Depending on test – generally greater than 0.1 ppm	Ca. 1.5 ug/m^3	Ca. 50 dilutions	Not applicable, but detects differences, not absolute concentrations
Uncertainty	High, improved by use of standardised protocol	+/- 5 to 20 %	+/- 10 %[2]	+/- 40 %[1]	Not known
Ease of data interpretation	Reasonable, if protocol is followed	Depends on the technique, e.g. colorimetric tube results easy to interpret	Often poor	Good	Good
Relative unit cost	Low	Low to moderate. Depends on specific tests. Sample collection costs may be moderate to high	Moderate/high. Sample collection costs may be moderate to high	Moderate/high Sample collection costs may be moderate to high	Moderate/high

1. Value given in "Odour control a concise guide" for duplicate samples collected and analysed.
2. Typical uncertainty value for thermal desorption and GC-MS analysis.

4.2 Gas chromatography

Gas chromatography (GC) is a widely used analytical technique for separating the components of an odorous air sample for identification and quantification. Generally, GC using standards of known substances, or gas chromatography coupled with mass spectrometry (GC-MS) when the composition of a gas sample is unknown, is an accurate and very sensitive method of chemical analysis of the nature of the gas (down to 0.1 ppb levels) (NZWWA, 2000).

The basic steps for gas chromatography are (Powell, 2002):

- Sampling: which may involve pre-concentration of a gaseous sample onto a solid adsorbent or absorption in a reagent;
- Thermal desorption or solvent extraction;
- Separation of the components by passing through a GC column; and
- Detection and identification.

In the situation where the odour sample has an unknown composition, a GC-MS has more practical usefulness. Identification of the resulting mass spectrographic pattern is made with reference to a computer based spectrum library, although identification of compounds with similar structures and/or masses can be difficult.

The application of GC and GC-MS to odour measurement can be summarised as follows (Powell, 2002):

- Provides reasonable quantitative analysis for a broad range of aliphatic, aromatic, alcohols and ketones;
- Provides semi-quantitative analysis for certain organic sulphides;
- Does not detect inorganic species, e.g. ammonia, hydrogen sulphide; and
- Poor response to highly reactive species, e.g. amine and certain organic sulphides.

GC and GC-MS only give an indication of the nature and concentration of chemical compounds in the sample, not their contributions to the overall odour of the mixture. Furthermore, odorous compounds often create nuisance at very low concentrations, while non-odorous components of the air sample may be present at much higher concentrations, making interpretation of the chromatogram difficult. A sample may result in literally hundreds of peaks, with only a fraction of them formed by odorous substances. Odour threshold concentrations for most of them are not yet available (NZWWA, 2000).

Powell (2002) summarised the disadvantages of GC and GC-MS in odour measurement as follow:

- Direct calibration for analysing odours is difficult because the composition mixture will often be unknown;
- The concentration in ambient air of individual compounds may be below or close to the lower limit of detection; and
- Longer term samples will average out any peaks, although this may be of secondary importance in source/compound identification.

4.3 Olfactometry

4.3.1 Overview

Olfactometry uses the human nose as the sensor of odours. The human nose can detect thousands of odorous compounds and identify at the parts per billion level of concentration (Jones *et al*., 1994). Gas chromatography is not able to detect many of these compounds at this level (Mackay-Sim, 1992). Compared with other odour measurement methods, olfactometry has number of advantages (Powell, 2002) in that it:

- Provides the only reliable method of accurately quantifying the odour strength for a complex mixture of compounds, especially where identification is difficult and composition variable;
- Provides a measure of the total strength of odour which may be under estimated if just a single component compound is measured using by instrumental method like GC;
- Provides the sensory impact of a mixture of odorants and non-odorants which is rarely predicted from a knowledge of its component parts; and
- Provides a direct link between a particular odour and the human response to it. This is particularly important when considering annoyance issues.

However, the human nose as a sensor of olfactometry has several characteristics which affect the design and the performance of olfactometers including (Jones *et al*., 1994):

- It has a very short averaging time;
- It responds to peaks of odour concentration rather than the average;
- The sensitivity varies enormously between individuals;
- Many factors affect the sensitivity to odours, for example, colds and illness can seriously decrease sensitivity;
- Sensitivity to an odour decreases rapidly during prolonged exposure, so the nose tends to adapt to a constant odour and can no longer detect its presence; and

- Humans are much better at making relative rather than absolute judgments about odours.

Therefore, these characteristics have to be considered in the design and methodology development of olfactometry. For instance, the testing environment should be kept odour free to avoid adaptation and desensitisation and a panel of people must be used to account for the variability between individuals.

The first olfactometer that used the principle of diluting odorous air with non-odorous air was built in the last decade of the 19th century. From the mid 70s, olfactometry has been used for the purpose of measuring environmental odours while it remained an academic pursuit with physiologists and psychologists for nearly a century (NZWWA, 2000).

A variety of olfactometry techniques have been used (Jones *et al*., 1994). They include the syringe dilution method, the Scentometer, the butanol olfactometer, and various dynamic olfactometers (Sweeten, 1988). Dynamic-dilution olfactometry is now widely accepted as the standard and is used in most research and regulatory institutions in Europe and Australia (Mannebeck & Mannebeck, 2001; Hartung *et al.*, 2001; Dravnieks *et al*., 1978). Therefore, dynamic-dilution olfactometry and its standardising process protocol are presented in section 4.3. The ILSU/NCEA olfactometer, which is used for this dissertation, is discussed in section 4.3.7.

4.3.2 Dynamic olfactometry

A dynamic olfactometer is a device that uses a dynamic odour dilution system. An odorous air stream is continuously diluted with an odour-free air stream using various flow meters and gauges. The diluted odorous air is presented to a number of panellists. The operator presents a series of different odour/odour-

free air dilutions to the panellists who are situated in an odour-free environment (Watts, 1999a).

Odour concentration is determined by finding the dilutions-to-threshold. This is defined as the dilution of the original odour sample at which half the panel can just detect the odour (the other half cannot detect the odour). The dilutions-to-threshold is found by presenting the panel with a series of dilutions of the sample. These dilutions should cover the range from where none of the panel detects the odour to where all panellists detect the odour. This procedure allows determination of the perception curve (DNI, 1990), that is, the relationship between dilution and the percentage of the panel that correctly detects the odour.

There are two methods for conducting dynamic dilution olfactometry; the Yes/No and Forced Choice methods.

Yes/no response

In this method each panellist has one sniffing port. When a test is run they must sniff the port and indicate if they can smell an odour. When they can smell an odour, the panellist press a button. This technique is the simplest to implement as only one sniffing port and one response button are needed per panellist. This method was common in the early 1990's but is now being replaced by the more sensitive forced choice response method.

Forced choice response

The forced choice technique differs from the simple yes/no technique. Each panellist has two or three sniffing ports. At any one time, one port will contain the diluted odour sample while the other(s) has clean air. The port containing the odour is randomly changed after each presentation. Panellists have no prior knowledge about which port. They are forced to guess if they cannot detect an odour from either port.

When indicating their choice of port, the panellists also indicate if they were 'guessing' 'uncertain' or 'certain' about their choice. From these responses, it is possible to arrive at two endpoints. The first is where the panellist is constantly correct in their choice of port without reference to guessing or certainty. This is often reported as simply the detection threshold and is given the units OU_d/m^3. The second is where the panellist is constantly correct in their choice of port, but is also certain about the choice. This is often reported as the certainty threshold and can be given the units OU_c/m^3. Since the use of the certainty threshold is becoming standard practice, the subscript is usually dropped so the units are OU/m^3. In theory, odour concentrations calculated using certainty thresholds are one half to one third of that calculated using detection thresholds, although in practice this ratio can be much greater (NZWWA, 2000).

Dynamic olfactometry (in one form or another) is now the regulatory standard for odour measurement in Australia, New Zealand and Europe. The method is gaining popularity in the USA. It is currently the only method suitable for measuring odour concentrations to determine odour emission rates. It is also the only odour measurement method, accepted by regulatory authorities in Australia (Watts, 1999a). However, it is costly and time consuming and this is a significant disadvantage for some types of odour studies.

Dynamic olfactometry has been changing over the past twenty years. The areas in which dynamic olfactometers vary include (Watts, 1999a):

- Number of panellists (3 to 8);
- Method (yes/no → forced-choice);
- Odour dilution presentation series (ascending, random);
- Presentation flow rate (8 - 20 L per minute per panelist);
- Sniffing port design (mask diameters from 3 to 15 cm);
- Number of sniffing ports (1, 2 or 3);
- Dilution ranges (upper and lower limits);
- Dilution system performance monitoring;

- Calculation methods;
- Detection method (guessing, certainty, recognition); and
- Panellist selection (none, butanol screening, vanillin / methyl salicylate screening, hydrogen sulphide screening, subjective screening).

As a result of these differences, olfactometer performance has varied considerably between and within laboratories.

Many laboratories now use butanol to screen and validate the sensitivity of human panels. In this case, it is assumed that panellist's sensitivity to various odours is similar to their response to butanol. This may not be the case. Furthermore, the sensitivity of different dynamic olfactometers has varied by at least a factor of 10 depending on their design and operation. A factor of 40 has been suggested in other literature. Klarenbeek & van Harreveld (1995) suggested a factor of 15 for their olfactometer. Schulz *et al.* (1995) stated that after the introduction of screening in 1992, observed group butanol thresholds dropped from around 100 ppb to 12-14 ppb. It has since been found that variability within laboratories is of a similar magnitude. In present, inter-laboratory testing programs have been initiated and standards developed to reduce variability.

4.3.3 Olfactometry standards

To improve the repeatability and reproducibility of odour measurements using olfactometry, a series of standards have been suggested and evaluated. These are:

- Queensland Department of Environment method 6;
- EPA (Victoria) method;
- Dutch draft standard – NVN 2820;
- German standard – VDI 3881;
- European standard – CEN/TC264/WG2/prEN 13725;
- USA standard ASTM E679-91; and
- Australian standard – AS/NZS 4323.3:2001.

However, some standards are only included for historical importance. In this research, the Australian standard (AS/NZS 4323.3:2001) is applied to calibrate and to operate the DPI/NCEA olfactometry. It is discussed in following paragraph.

AS/NZS 4323.3:2001- Determination of odour concentration by dynamic olfactometry

Standards Australia published an Australian/New Zealand standard "Stationary source emissions - Determination of odour concentration by dynamic olfactometry" in 12 September, 2001. The Standard was prepared by the Joint Standards Australia/Standards New Zealand Committee EV-007 "Methods for examination of air" and subcommittees/working groups, EV-007-03 (odour measurement) and EV-007-03-01 (odour measurement test method). The standard is based on a CEN (Comite Europeen de Normalisation) pre-draft of the same title (CEN, 1999) with minimal changes for Australian conditions. It includes screening of panellists and allows both yes/no and forced-choice olfactometers. Before publishing the AS/NZS 4323.3:2001, there was a draft Australian standard "Air Quality - Determination of odour concentration by dynamic olfactometry", code DR 99306 dated July, 1999.

There are some differences between standards that prohibit the direct use of data from other olfactometry testing performed under the different design and operating standards. Hence, data conversion between standards becomes an important issue.

McGinley & Mann (1998) presented a comparison between the European and US standards. They concluded that the major differences are the odour presentation parameters (volumetric flow rate, face velocity), panel selection, and differences in instrument calibration. The US standards do not require instrument calibration (Watts, 1999a).

One other difference between standards is the recent change from accepting guessing responses to only accepting certainty responses from panellists. The consequences of this change are not clear. For a given panel, the change from guessing to certainty responses should result in numerical values for odour concentration. However, the European and Australian standards require screening of panellists so that they have a 20-80 ppb butanol threshold. If the screening is done using certainty responses, then more sensitive panellists would be needed but the resulting panel butanol threshold should still be typically about 50 ppb (Watts, 1999a).

Jiang (1997) reported data where his laboratory had calculated data using guessing and certainty criteria. He reported that "for a given sample, the values of the two thresholds may differ by a factor typically from 1.5 to 10 depending on the instrument, the number of sniffing ports and the number of panellists. There is no reliable correlation between these thresholds". Consultants have found it necessary to use NVN 2820 data in odour assessments based on the CEN/TC264 standard. It is generally agreed that the conversion factor should lie in the range of 2 to 5 with 4 commonly used. That is, NVN 2820 data is divided by 4 to convert to CEN/TC 264. This conversion is not scientifically validated and should be used with caution.

4.3.4 Major factors that influence the outcome of olfactometry

It is difficult for olfactometry to have defined accuracy, repeatability and reproducibility. Many factors have been discussed that were considered important to the quality and outcome of odour measurements for olfactometry testing. The major elements that can be distinguished are (NZWWA, 2000):

- The sample bag and its materials: The sampling bag can cause substantial effects by adsorption or transport of substance through the polymer film used to make sampling bag. Therefore, only impervious materials such as

Teflon®, Tedlar™, stainless steel and glass can be used in odour sampling processes;

- Sniffing port of an olfactometer: A certain way of getting the diluted sample into the nose of the panellist is asked. Different types of cups and masks are used. The flow rate of the sample presented through the port is also important;
- Panellists: As the sensor for the olfactometry measurement, the role of panellist's nose is critical;
- Odour analysis laboratory: This provides the environment for the measurement, hence, it must provide odour-free conditions; and
- Data processing method: The calculation method obviously influences the outcome.

4.3.5 Olfactometry in ILSU/NCEA odour research group

The ILSU/NCEA olfactometer was built under the following design specifications, which were based on the recommendation of the Dutch standard (DNI, 1990) for olfactometry equipment and methodology.

- A forced choice response system with three ports per panellist;
- Eight panellists sniffing concurrently;
- A flow rate of 20 L/min from each port;
- Dilution ratios up to 32000;
- An automated panellist response system; and
- An on-line computer for data analysis.

To get a mobile capability, the olfactometer is housed in an air-conditioned caravan with an exhaust system (Jones *et al*., 1994). *Fig 4.1* and *Fig 4.2* show the olfactometer caravan and the human panellists, respectively.

Fig 4.1 The olfactometer caravan

This system dilutes the odour sample over the required range, provides each panellist with three air streams (one odorous and two odour-free) of the same flow rate, and randomly switches the port containing the diluted odorous air flow. The odour-free air is supplied by an air compressor regulated to 600 kPa. The total flow rate into the olfactometer is about 500L/min. A bank of rotameters with a collective flow range of 0.05 to 100L/min registers the odorous air. A three-way valve allows the operator to select either the odour sample or odour-free air for flushing (Jones *et al*., 1994). *Fig 4.3* is a schematic diagram of the dilution system.

The distribution system uses a combination of custom-made distribution manifolds and three-way valves. Each manifold splits a flow into four equal flows. There are 6 manifolds and 24 three-way valves, one at each sniffing port. Stainless steel and Teflon® pipes and fittings were used in all areas where there is contact with the undiluted odour sample. The need to test the olfactometer/panel combination regularly against reference gas (butanol) is necessary to ensure

standardisation and repeatability of the olfactometer results. To allow this, cylinders of 40 and 50 ppm butanol are permanently connected to the dilution system. This allows butanol thresholds to be determined regularly and without the need to fill sample bags (Jones *et al*., 1994).

Fig 4.2 Human panellist workstation in the mobile olfactometer

The communication, data collection and analysis system provides panellists with a simple method of showing which port they believe contains the odour. It also allows the olfactometer operator to signal to the panellists the start and finish of a test. It has the following components (Jones *et al*., 1994):

- Nine press button switches per panellist by which the panellist nominates the port containing the odour, identification of the panellist, and offensiveness responses are also transmitted via these switches;
- Three LEDs per panellist to show that a response has been recorded by a panellist; these are driven by a latch-transistor combination;

- Three coloured flashing LEDs per panellist to allow the operator to signal 'rest', 'ready', and 'sniff';
- Data latches for each button that catch the momentary switch press and remain set until cleared;
- A multiplexing system that allows the data latches for each panellist to be read in sequence through a computer link; and
- A personal computer, linked to the communication system through the parallel printer port, by which the operator logs the panel responses and calculates the detection thresholds (concentrations).

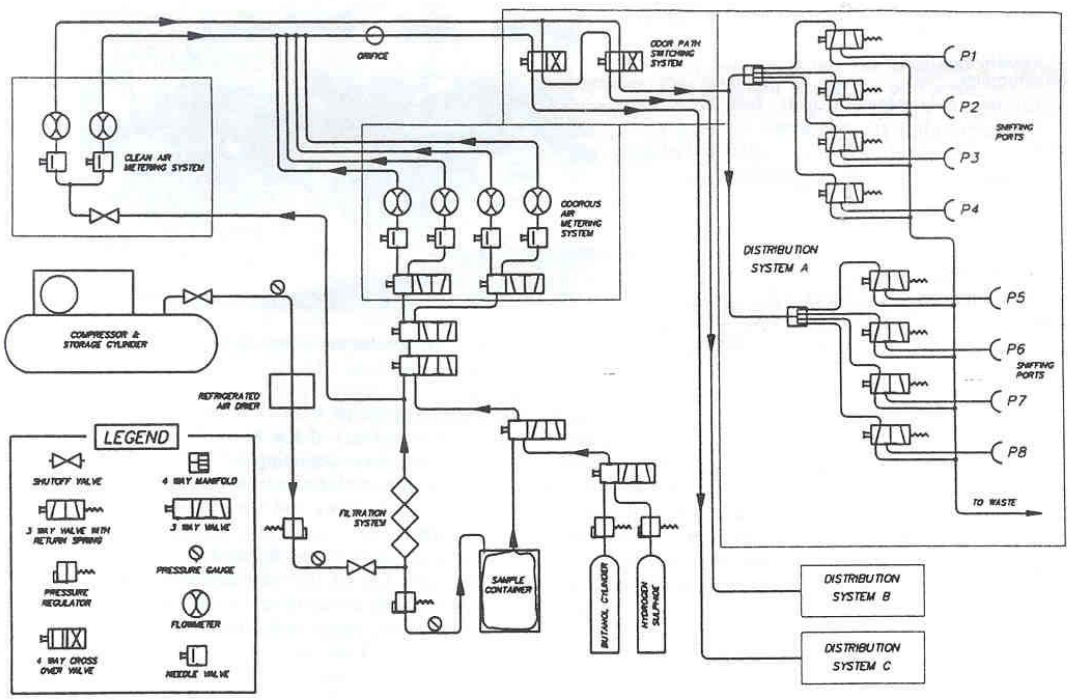


Fig 4.3 Schematic representation of the dilution system in the ILSU/NCEA Olfactometer (reproduced from Jones et al., 1994)

4.4 Electronic nose

4.4.1 Overview

An electronic nose is an instrument consisting of a gas sampling apparatus and an array of gas sensors interfaced to a personal computer. The unique distinguishing feature of the electronic nose technology is the ability of its sensor array to respond differently to various odours. Each odour in the set may contain hundreds or thousands of different VOCs. Classical analytical methods using GC-MS try to identify the individual compounds in an odour and, it is an almost formidable task. On the other hand, the electronic nose examines a changing pattern of sensor(s) response across its sensor array to differentiate odours (Schiffman *et al.*, 1997).

In 1982, the concept of an electronic nose system was proposed at the University of Warwick, UK (Persaud & Dodd, 1982). At the beginning of the 1990s, the term 'artificial' or 'electronic nose' appeared, and several commercial instruments became available. More extended research began and its applications to various industrial fields have been tested (Schaller *et al*., 1998).

Bartlett *et al.* (1993) defined the electronic nose as 'an instrument, which comprises an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system, capable of recognising simple or complex odours'. This seems very far from the human nose. However, the common aspect with the human odour-sensing organ is its function. Like the mammalian nose, it detects gases by means of sensors which send signals to a recognition organ, that is to the brain or to a computer (Schaller *et al*., 1998). The operating principle, the number of sensors as well as the sensitivity and selectivity are, however, very different (Bartlett *et al*., 1997). This is why some scientists prefer to call this instrument by other names, for example, 'flavour sensor', 'aroma sensor' (Mielle, 1996), 'odour-sensing system' (Gardner *et al*., 1993) or 'multi-sensor array technology' (Shiers, 1995).

With regard to the application of the electronic nose in environmental monitoring, it has a number of limitations. However, development work is on-going and it is possible that new environmental odour applications for this technology will emerge. Currently, some potential applications are (Powell, 2000):

- Process control;
- Stack monitoring for odorants;
- Effluent streams monitoring; and
- Boundary monitoring/in-community monitoring.

In section 4.4, sensor array technology, data processing techniques including Pattern Recognition analysis and currently available commercial electronic nose systems will be discussed. In addition, current research work related to the application of the electronic nose to odour monitoring in intensive livestock operations will be discussed.

4.4.2 Sensor technology

An electronic nose system largely depends on an array of chemical, organic and optical sensors which collect chemical data from the odorous air at the headspace of a sample. When appropriate chemical sensors are exposed to a sample, each sensor produces a characteristic response dependent upon the chemical interactions between the sample and the sensor. The data collected from the sensor array for a particular sample can be interpreted as a pattern of responses, or fingerprint of that sample. When patterns for different samples are compared, differences in the patterns can be correlated with differences in perceived sample odour. Samples with similar odours generally give rise to similar patterns, and samples with different odours show differences in their patterns. Using automated pattern recognition algorithms, patterns of different samples can be compared. And then, a library of patterns can be stored in a

computer database, such that data from test samples may be compared to the library, and classification of test samples be made.

The ideal sensors for an electronic nose should fulfil the following criteria (Gardner, 1994; Lantto *et al*., 1988; Bott *et al*., 1984; Shaver, 1967):

- High sensitivity towards chemical compounds, that is, similar to that of the human nose (down to 10^{-12} g/mL);
- Low sensitivity towards humidity and temperature;
- High stability;
- High reproducibility and reliability;
- Short reaction and recovery time;
- Robust, durable and easy calibration;
- Easily processable data output; and
- Small dimensions.

A variety of different sensor technologies are used in sensor array systems (Persaud & Travers, 1997). Some of the most common are metal oxide sensors (MOS), conducting polymers (CP), bulk acoustic wave (BAW), surface acoustic wave sensors (SAW) and metal oxide semiconductor field effect transistor (MOSFET). Their schematic diagrams are depicted in *Fig 4.4*.

Such sensors can be divided into two main classes: hot (MOS, MOSFET) and cold (CP, SAW, BAW). The former operate at high temperatures and are considered to be less sensitive to moisture with less carry-over from one measurement to another (Nanto *et al*., 1986).

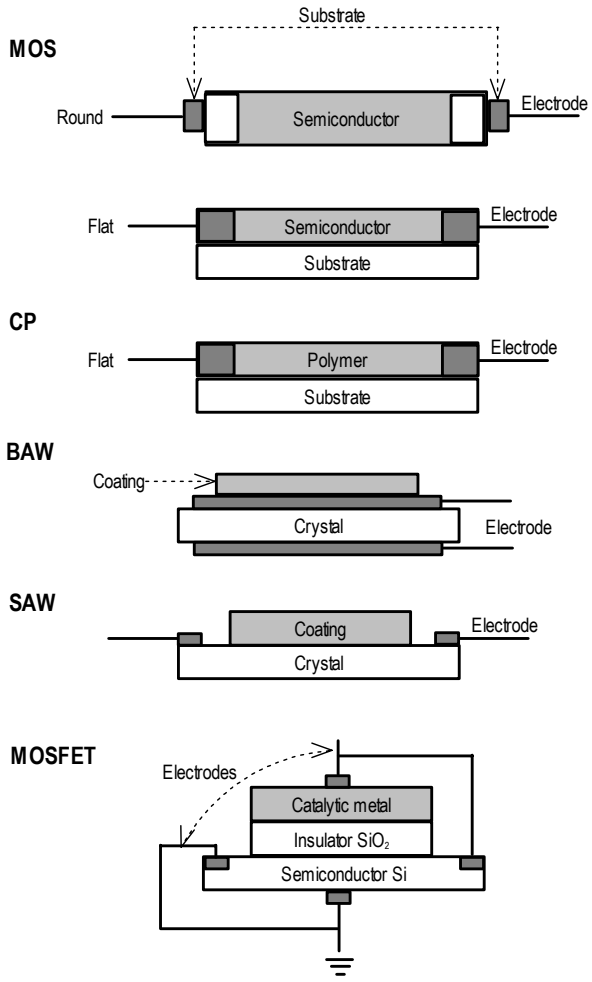


Fig 4.4 Schematic diagrams of 5 different kinds of sensors (MOS: metal oxide semiconductor; CP: conducting polymer; BAW: bulk acoustic wave; SAW: surface acoustic wave; MOSFET: metal oxide semiconductor field effect transistor) (reproduced from Nanto et al., 2003).

The use of an array of non-specific sensors allows for responses from many thousands of chemical species, due to the broad selectivity of the different sensor surfaces (Persaud *et al.*, 1996b). The relative responses between the sensors can be used to produce a unique odour profile that is analogous to the human olfactory system (Gardner & Bartlett, 1994). *Fig 4.5* shows examples of the odour patterns from a piggery and its surrounding area. They were collected from a consulting work during this Ph. D. study.

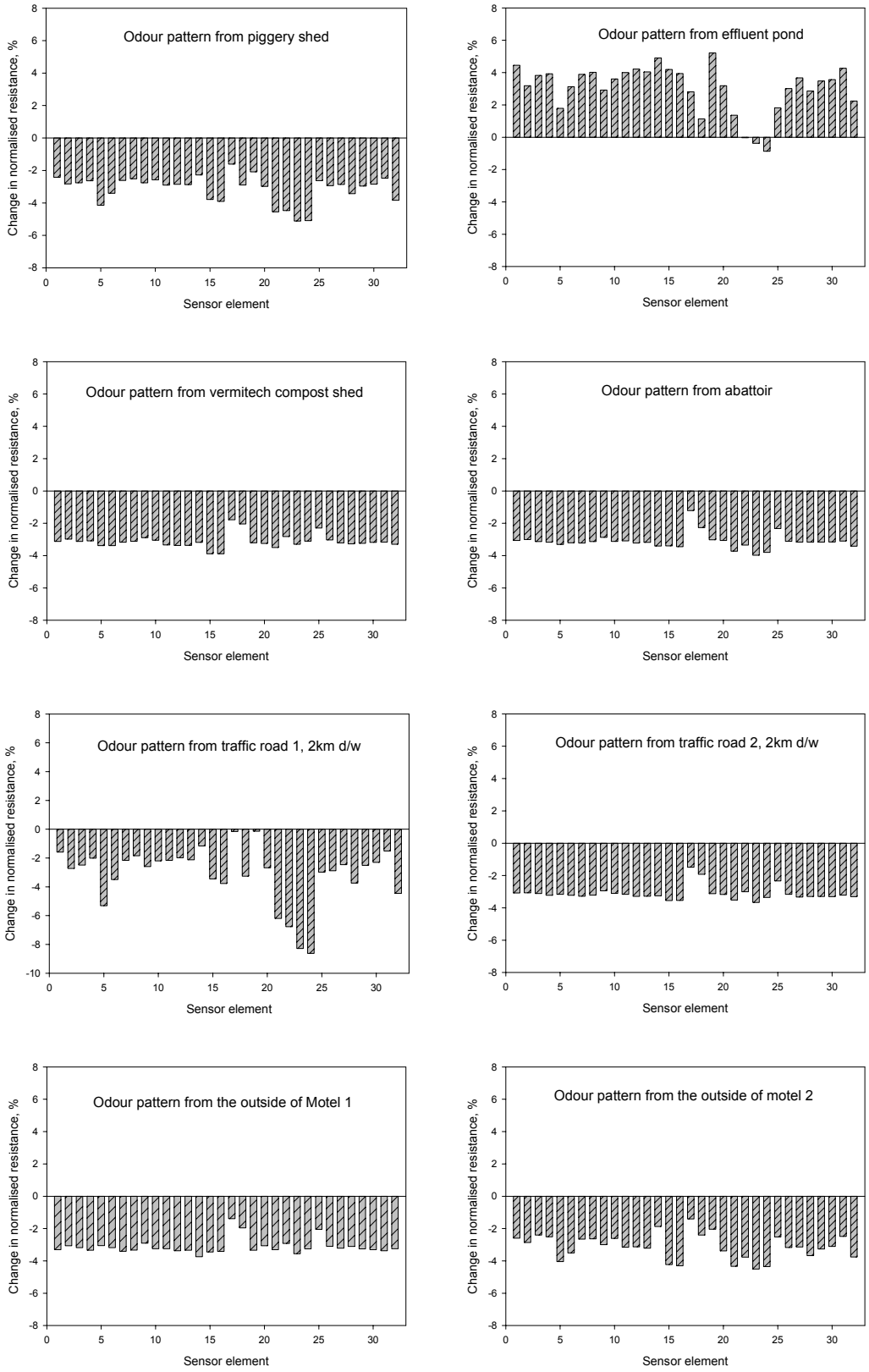


Fig 4.5 AromaScan A32S odour patterns from a piggery and its surrounding area

The most common types of sensors and measurement principles are summarised in **Table 4.2.**

Table 4.2

Most common types of sensors and measurement principles

(modified from Fenner & Stuetz, 1999)

Sensor Types	*Mode of Action*	*Comments*
Conducting polymers	In the presence of a gas species a change in voltage across polymers such as polyaniline, polypyrrole and polythiopenc can be measured.	○ Selectivity is achieved by controlling surface functional groups or by varying anion chemistry during growth ○ Reproducibility good ○ Return to baseline resistances in short times
Metal oxides	Metal oxide sensor passes an electrical current causing oxidation of gas molecules via electron transfer from the gas to the metal oxide leading to a change of resistance.	○ Less selective than other sensor types ○ Can be subject to poisoning ○ Response can be affected by presence of solvents
Quartz crystal microbalances	Measure change in frequency of oscillation of a quartz crystal when a gaseous species is adsorbed.	○ Problems of reproducibility in commercial production of sensors
Surface acoustic wave sensors	Similar to quartz crystal microbalances but operate at much higher frequencies.	○ Can achieve good sensitivity ○ Problems of reproducibility in sensor production
Fiber optic sensors	Use fluorescence measurements from photodeposited polymer/fluorescent dyes on bundles of fibre optics.	○ Provide large quantities of data ○ Recently available in commercial instruments.

Although various kinds of gas, chemical, and optical sensors available, the organic conducting polymer sensors are discussed in this dissertation in detail because the electronic nose, Aromascan A32S, used in this research employs conducting polymer sensors.

Organic Conducting Polymer Sensors (CPs)

The sensors made from CPs exhibit a change in conductance when they are exposed to reducible or oxidisable gases. CPs show reversible changes in conductivity when chemical substances (*e.g.* methanol, ethanol, and ethyl acetate) adsorb and desorb from the polymer. The mechanism by which the conductivity is changed by this adsorption is not clear at present (Nanto & Stetter, 2003).

There are a large number of different electronically conducting polymers. Polypyrrole was first prepared electrochemically in 1968 and has been most extensively studied so far (Dalli'Olio *et al*., 1968). Electroconducting conjugated polymers (ECP) can exhibit intrinsic electronic conductivity. Their structure contains a one-dimensional organic backbone with alternating single and double bonds, which enables a super-orbital to be formed for electronic conduction. The most commonly applied polymers for gas-sensing applications have been polypyrrole, polyaniline, polythiophene, and polyacetylene, which are based on pyrrole, aniline or thiophene monomers (Bidan, 1992). Because of their properties they have remarkable transduction matrices that are sensitive to gases and vapours. Therefore, they result in a straightforward conductance change via the modulation of their doping level.

The early studies of the gas-sensing application of CPs concentrated on the response to reactive gases such as ammonia and hydrogen sulfide (Miasik *et al*., 1986; Gustafsson & Lundstrom, 1987). It was reported that gas sensors using polypyrrole films exhibit a high sensitivity for ammonia (Gustafsson *et al*., 1989). It was also revealed that gas sensors using CPs such as polypyrrole respond to a wide range of organic vapours such as methanol (Batlett *et al*., 1989a; Batlett *et al*., 1989b; Batlett *et al*., 1989c).

More recently, studies have been carried out on preparation of thin-film CPs for gas sensing applications (Miasik *et al*., 1986; Gardner & Bartlett, 1991). Thin films of heteroaromatic monomers such as pyrroles, thiophenes, indoles, and

furans were grown electrochemically on interdigitated electrodes to produce gas-sensitive chemoresistors (Miasik *et al*., 1986).

Sensor arrays using CPs respond to a wide range of polar molecules at temperatures as low as room temperature. Recent reports suggest that a high sensitivity down to 0.1 ppm is possible (Nanto & Stetter, 2003). This result indicates that CPs are potentially useful materials for applications in odour sensing and e-nose applications.

The use of organic CPs as odour sensor materials is very attractive for the following reasons:

- A wide range of materials can be prepared simply;
- They are relatively low cost materials;
- They have a high sensitivity to many kinds of organic vapours;
- Gas sensors using organic CPs operate at low temperatures.

Another way to use CPs is to make non-conducting materials, *e.g.* silicone (Maclay *et al*., 1991) and polystyrene (Stetter *et al*., 1984), conductive by inclusion of carbon-black metal powder. These sensors are used in e-noses and can exhibit high sensitivity (Burl *et al*., 2001). Comparison between the properties of the CPs odour sensor and the MOS odour sensor is shown in **Table 4.3**.

Table 4.3

Comparison of the properties of the conducting polymer odour sensor and the metal oxide odour sensor (thick film and thin-film types) (reproduced from Nanto & Stetter, 2003)

Properties	*Conducting polymer*	*SnO_2 (thick film)*	*SnO_2 (thin film)*
Key Measurand	Conductance	Conductance	Conductance
Fabrication	Electrochemical growth, plasma CVD	Paste	Sputtering, Sol-gel
Choice of materials	Wide	Limited	Limited
Operating Temperature	10 – 110°C	250 - 600°C	250 - 600°C
Molecular Receptive Range	Wide range	Combustible vapours	Combustible vapours
Detection Range	Less than 20ppm	10 – 1,000 ppm	1 – 100 ppm
Response Time	60s	20s	20s
Size	Less than $1mm^2$	1*3 mm	Less than $1mm^2$
Power Consumption	Less than 10mW	800mW	80mW
Integrated array	Yes	No	Yes
Stability	Moderate	Relatively poor	Poor
Interferences	Acidic gases, water	SO_2, Cl_2, H_2O	SO_2, Cl_2, H_2O

4.4.3 Electronic nose methodology development

The purpose of method development is to produce a series of operating conditions for an analysis involving both the instrument and the procedure. It is able to work consistently and give reliable results. The end result of a method development procedure becomes often a standard operating procedure (SOP), which defines exactly how an analysis should be performed. There are five important stages in method development:

- Optimisation of sample preparation
- Selection of sensors
- Optimisation of data acquisition
- Choice of data analysis
- Method validation

Optimisation of sample preparation

The procedure for developing a method starts by preparing the sample for analysis. The preparation method should involve the smallest amount of interference with the sample as possible. This will reduce the amount of other variables/contaminants to be introduced to the sample. Care must be taken to handle the sample in a consistent way before analysis and to avoid contact with any containers or surfaces that could contaminate the product so changing odour characteristics.

Selection of sensors

It is important to select the most suitable sensors for a sample to be analysed by an electronic nose at an early stage. Most electronic nose manufacturers provide a table of specificity of sensors to chemical species. It can be used to select the most appropriate sensors.

Optimisation of data acquisition

The initial objective of the method development program is to obtain a method that gives reproducible results. This is necessary as this technology is a comparative technique, therefore good reproducibility ensures that results can be reliably compared over a period of time and ensures that discrimination is statistically significant.

In order to obtain a reproducible method, it is necessary to consider the variables that are present within the sample acquisition process. Some of the variables can be controlled directly by the operator, for example:

- Temperature;
- Sample type;
- Sensor choice;
- Purge, equilibration and analysis times;
- Relative humidity of purge gases;
- Data manipulation techniques; and

- Sample preparation techniques.

Some of the variables are difficult to control precisely. The most difficult type of variable is one that may represent both a test-to-test variation that should be controlled and a real difference between samples, for instance, relative humidity.

Choice of data analysis

As the data from an electronic nose is complex and multivariate, there are many analysis options available. Further discussion about this subject is presented in section 4.4.4.

Method validation

The final, and perhaps the most important step in method development is validation. The one stage in validation that should always be performed with the electronic nose is method robustness testing. In this procedure, a number of experiments are performed to establish the effect on the results from changing method variables at a number of different levels. This will provide essential data for SOPs.

Fig 4.6 shows a development of SOPs for the AromaScan A32S.

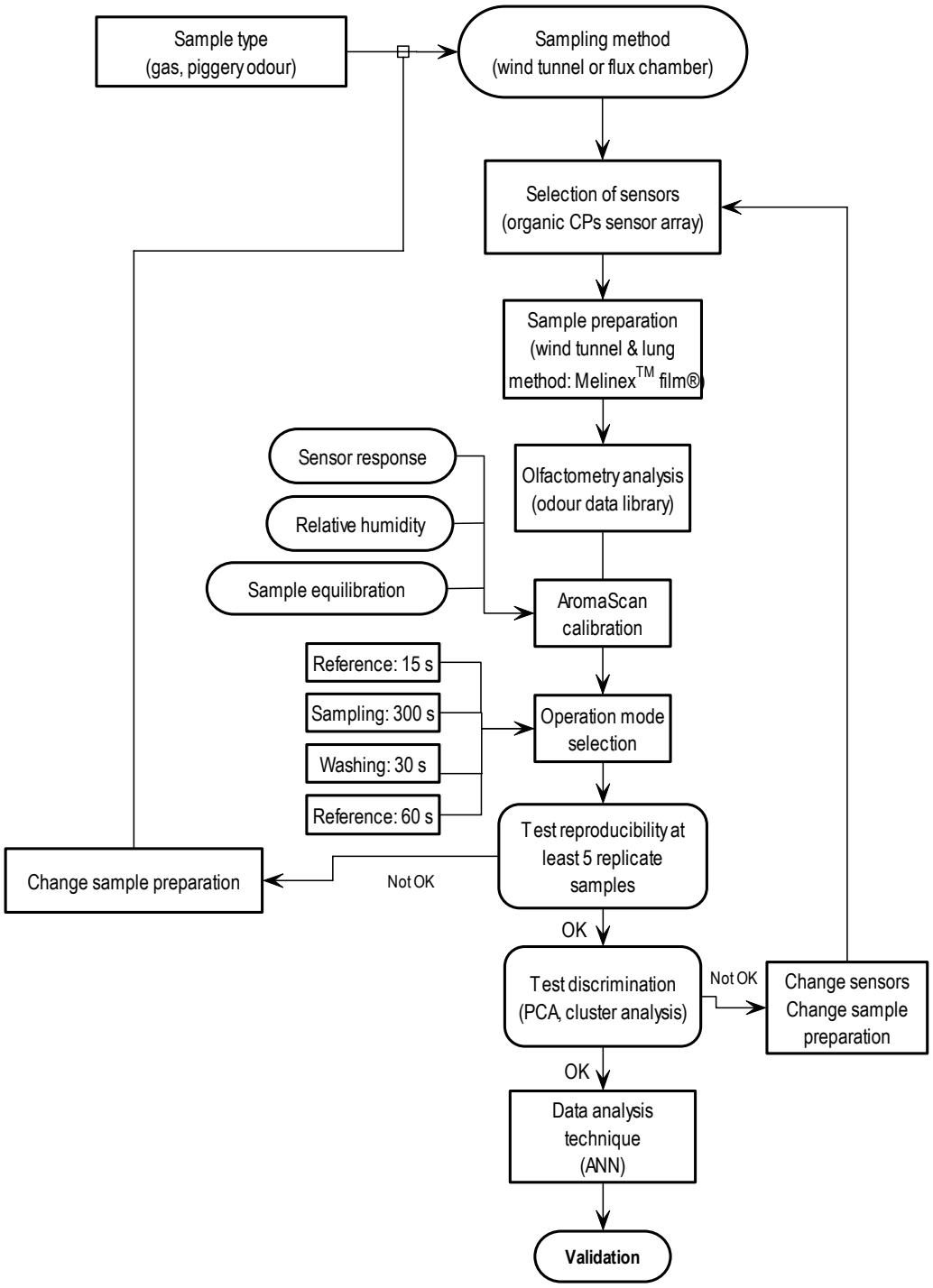


Fig 4.6 Standard operating procedure sequence (SOPs) for the AromaScan, an electronic nose (modified from AromaScan, plc., 1996)

4.4.4 Pattern recognition analysis

Most of the electronic nose system is developed as a match-model for the natural nose comprising the various stages between a volatile odorant and its recognition, namely: interaction, signal generation, processing, and identification, as outlined by the parallel between biological and artificial noses in *Fig. 4.7* (Hines *et al*., 2003). In this system, the pattern recognition acts as a signal processing unit like the brain in the biological olfactory system. Therefore, the interpretation of data obtained from sensor arrays of an electronic nose relies on the use and performance of the pattern recognition engine.

Output from sensor arrays can be displayed using a variety of relatively simple graphical formats that allow comparisons between samples or averaged data over a number of analyses (Hodgins, 1995). However, to cope with a large number of samples and number of variables, pattern recognition is mainly employed to process the sensor array data (Stuetz & Fenner, 2001). Currently available techniques can be classified into several categories:

- Graphical analyses;
- Multivariate analyses;
- Supervised/unsupervised analysis;
- Linear/non-linear; and
- Artificial neural network.

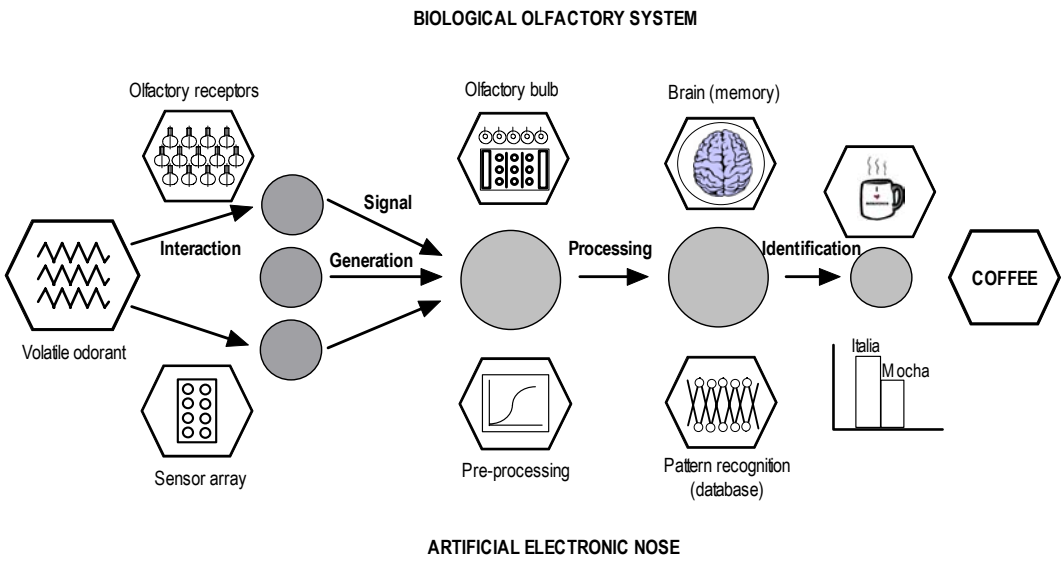


Fig 4.7 Basic diagram showing the analogy between biological and artificial noses (reproduced from Hines et al., 2003)

Graphical analysis

Graphical analysis is the simplest form of data treatment that may be used with an electronic nose. It covers profile, bar chart and polar/offset polar plots. The response from the sensors is displayed in a variety of graphical formats that allows comparison between different samples or averaged data of a number of analyses. However, when several references are used, analysis becomes more complicated and an alternative approach, *i.e.,* pattern recognition techniques may be necessary (Hines *et al*., 2003).

Multivariate analysis

Multivariate data analysis involves data reduction, it reduces high dimensionality in a multivariate problem where variables are partly correlated (*e.g.* sensors with overlapping sensitivities), allowing the information to be displayed in a smaller dimension (typically two or three) (Gardner & Bartlett, 1992; Fukunaga *et al*., 1995)

Supervised/unsupervised

In a supervised learning pattern recognition technique, known odours are systematically introduced to an electronic nose system which then classifies them according to known descriptors or classes held in a knowledge base. Then, in a second stage for identification, an unknown odour is tested against the knowledge base, now containing the learnt relationship, and then the class membership is predicted. Unknown odour vectors are analysed using relationships found a priori from a set of known odour vectors used in an initial calibration, learning, or training stage. The idea of testing a method using unclassified response vectors is well established and is often referred to as cross-validation (Hines *et al*., 2003).

For unsupervised learning, pattern recognition methods learn to separate the different classes from the response vectors routinely, discriminating between unknown odour vectors without being presented with the corresponding descriptors. These methods are closer to the way that the human olfactory system works using intuitive associations with no, or little, prior knowledge (Hines *et al*., 2003).

Linear/non-linear

In the linear pattern recognition methods, a model is simply calculated using linear combinations of input data. However, most sensors have a non-linear response versus odour concentration. The linear pattern recognition techniques work well if a low concentration of odours ensures an approximately linear response. In addition, the use of pre-processing algorithms including averaging, linearisation or normalisation, can improve the performance of linear pattern recognition techniques (Gardner & Bartlett, 1992; Göpel, 1995).

When high concentrations of odours are measured, a non-linear pattern recognition technique, such as an artificial neural network (ANN) or radial basis function (RBF), would be more appropriate (Schaller *et al.*, 1998). Non-linear

models usually need more parameters, since some of them are used to describe the shape of the non-linearity (more input data than linear models). The main advantage of such a method is flexibility, *i.e.* the ability to adjust to more complex data variations. However, caution is necessary when choosing model flexibility; this can be achieved by selecting the number of parameters. If too many parameters are taken into account, the calculated model will be over-flexible, fitting to all relevant data variations and unwanted sensor noise. The best method to avoid an over-fitted model is to use training data to build a non-linear model, and validation data to test this model (cross-validation) (Holmberg, 1997).

Artificial neural network

A neural network consists of a set of interconnected processing algorithms functioning in parallel (Schaller *et al.*, 1998). On a very simplified and abstract level, an ANN is based on the cognitive process of the human brain. Mathematical functions, or neurones, link together to build a network which mimics the human nervous system (Persaud & Pelosi, 1992). A weight is randomly assigned to each neurone and then adjusted by means of an iterative or 'learning' process, for example, error back-propagation, until the desired outputs are obtained. The resultant set of weights and functions is then saved as a 'neural network'.

ANN is a supervised method and so needs a minimum of known data to correctly train the system. If the number of available data is not sufficient an erratic result will be obtained (Hodgins, 1997). Unlike other pattern recognition methods, a neural network is a dynamic, self-adapting system that can modify its response to external forces using previous experience, offering a more flexible and, due to the parallelism, faster method of analysis. In addition, it may more closely mimic mammalian neurone processing of odour stimuli (Persaud & Pelosi, 1992; Newman, 1991). A well trained ANN is very efficient in comparing unknown samples to a number of known references (Hodgins, 1997). ANN is

used as a main pattern recognition engine for this research work. More detailed discussion is presented in chapter 6.

The problem of pattern analysis of e-nose data is closely linked to the multivariate analysis of data sets. *Fig 4.8* summarises the main multivariate data processing techniques, or pattern recognition algorithms, that have been employed in the field of an electronic nose. The classification scheme is made on three levels: a first distinction is made between statistical and biological approaches, then between quantitative and qualitative pattern analysis algorithms, and finally between supervised and unsupervised techniques (Hines *et al*., 2003)

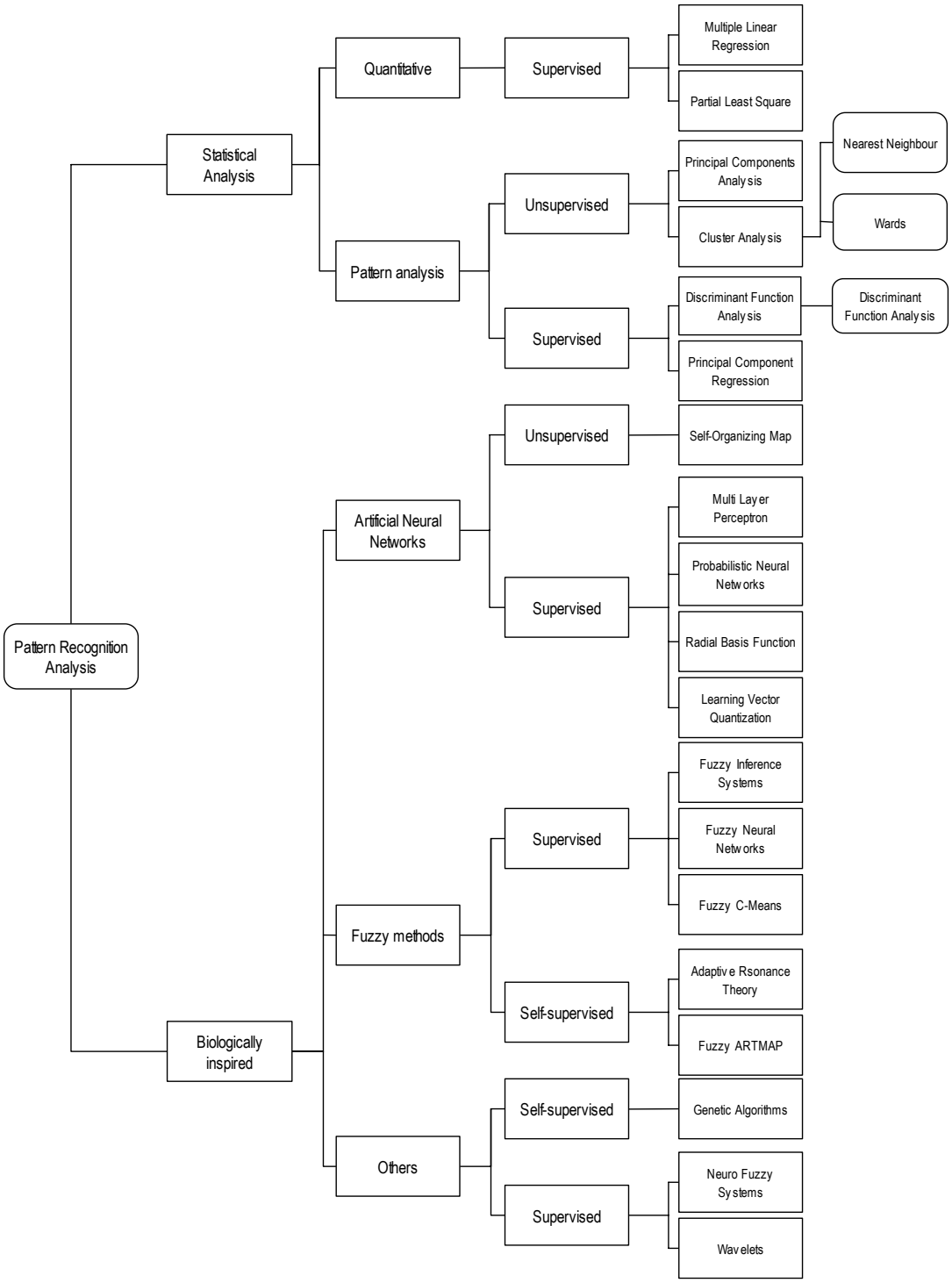


Fig 4.8 Classification scheme of pattern recognition techniques applied to electronic nose data

4.4.5 Commercial electronic nose

The first electronic nose, the Artificial olfaction, was introduced by the Warwick olfaction research group in 1982 (Persaud & Dodd, 1982). However, the expression electronic nose appeared for the first time in 1988. And then, intensive research was undertaken in order to find new and more diverse sensors as well as to improve the pattern recognition engines. Currently, a range of bench-top and handheld style electronic noses is available from a number of commercial manufacturers (Nimmermark, 2001; Vanneste & Geise, 2003; Stuetz & Fenner, 2001). It is summarised in **Table 4.4**.

Table 4.4

Electronic nose manufacturers, models and sensor cores

Company	*Sensor core*	*System*
Agilent Technologies	MS	4440
Alpha M.O.S., France	MOS, CP, SAW MS and MS-EN electronic tongue	Fox 2000,3000,4000,5000, Centauri Alpha Kronos & Prometheus Astree
Applied Sensor	MOSFET, MOS, QCM 4 *x* MOS, 8 x QCM QCM	3320, 3310 VOCseries (Handheld) VOCcheck (Handheld
Bloodhound Sensors, UK	CP	Bloodhound BH114
Cyrano sciences Inc., USA	CP (composite)	Cyanose 320 (Handheld)
Daimler Chrysler Aerospace	QCM, SAW. MOS	SAM system
Electronic Sensor Technology	SAW	ZNose
Element	MOS	FreshSense
Environics Industry	IMCELL	MGD-1
Forschungsrentrum Karlslvhe	MOS, SAW	Sagas
HKR Sensorsysteme, Germany	QCM, MS	QMB6/HS40XL
Lennartz Electronic, Germany	QCM. MOS, electrochemical	MosesII
Marconi Applied Technologies, UK	CP. MOS, QCM	e-Nose 5000
Microsensor Systems	SAW	ProSat
Osmetech	CP	OMA and core sensor module AromaScan A32S
Quartz Technology	QCM	QTS-1
SMart Nose, Switzerland	MS	Smart Nose-300
WMA Airsense Analysentechnik, Germany	MOS	PEN

- CP: conducting polymer; IMCELL: ion-mobility; MOS: metal oxide semiconductor; MOSFET: metal oxide semiconductor field effect transistor; MS: mass spectrometry-based; QCM: quam crystal microbalance; SAW: surface acoustic wave

Most commercial systems have precise temperature control of the sample delivery system and sensor chamber because the variables are known to affect sensor responses. They require a host computer for instrument control, data analysis and manufacturers offer specific software for data acquisition and display and have direct links to spreadsheet packages (such as Microsoft Excel) and statistical packages (such as UNISTAT or STATISTICA) to enable more detailed further data analysis. Furthermore, they have modular plug-in devices, which makes the instruments very flexible (Mills *et al.,* 1996). Several systems are also able to incorporate a number of different sensor types (*i.e.* MOS and CPs) in the same device (Gardner & Bartlett, 1999).

The Aromascan A32S, an example of a commercial sensor array system is shown in *Fig 4.9*.

Fig 4.9 The Aromascan A32S, one of the commercial sensor array system

With regarding to the future prospects of an electronic nose, they have not reached their full potential. In the near future, electronic noses are likely to be classified into three application groups (Stuetz & Fenner, 2001):

- Complex laboratory-based electronic nose;
- On-line monitoring systems; and
- Portable devices for field measurements.

The future electronic nose will be able to provide high sensitivity and reliability over a wide range of QA/QC applications and to play a part in effective product development by allowing rapid, accurate odour or aroma assessment of production line samples (Gibson *et al.,* 2000).

Recent developments of electronic nose systems include on-line systems for process monitoring and portable devices for environmental monitoring. These application specific instruments could be used for a wide range of tasks, which may include continuous on-line monitoring of odour abatement units and field odour intensity measurements (Stuetz & Fenner, 2001).

In addition to the development of application specific instruments, new sensor techniques are being incorporated into sensor array systems. These include the use of mass spectrometry and solid-state spectrometry, which involves bypassing the traditional sample preparation stages and introducing whole samples into the mass spectrometer or the solid-state sensor to give a mass spectrometry fingerprint or a spectroscopic trace (Gibson *et al.,* 2000). Alternatively, new sensor types are being developed that have either a very low response to water vapour or are sensors that are described as water-insensitive chemoresistors (Gibson *et al.,* 2000).

For the current commercial electronic noses, traditional pattern recognition techniques using classical algorithms such as principal component analysis, multiple discriminant analysis are usually integrated. However, for the more challenging task such as predictive classification of unknown odour samples without reference gases or known odour profiles, more sophisticated pre-processing and data analysis protocols are required. Therefore, specially designed

adaptive ANN and fuzzy logic algorithms are being developed for these challenging tasks (Stuetz & Fenner, 2001).

4.4.6 Application of electronic nose to intensive livestock operations

Most studies of odours from intensive livestock operations until now have used olfactometry to measure concentration, intensity and offensiveness. However, there are several disadvantages including expense of operation and difficulty of collecting representative samples (Hamilton & Arogo, 1999).

GC-MS gives information of the concentration of a lot of volatile compounds presented in odorous air samples. O'Neill & Phillips (1992) listed 168 compounds from the analysis of the odorous air in and around animal housing. However, the concentration of different odorous compounds in intensive livestock operations is unknown because many compounds are present at very low concentrations and the concentration of each component is continuously changed. Work has been performed to correlate odour to concentrations of the single component such as ammonia and hydrogen sulphide. However, no such correlation seems to exist (MPCA, 1999).

Until recently, the assessment of environmental odours by electronic nose systems has been based on the use of prototype or commercial laboratory-based instruments. The assessment work has focused on several subjects including (Stuetz & Fenner, 2001):

- Comparing the sensor responses for different sample types; and
- Correlating the sensor responses to known parameters such as threshold odour concentrations (using olfactometry), specific analytical components (using GC-MS) or surrogates for odour strength (using H_2S and NH_3 measurements).

Different techniques for measuring odours from livestock wastes were evaluated by Hobbs *et al.* (1995). Techniques using an electronic nose, a photoionization detector (PID), olfactometry and GC-MS were compared. The electronic nose contained 20 polypyrrole sensors of five types. It was shown that the electronic nose could discriminate between the different odours from livestock wastes (pig and chicken slurry). However, this early instrument was reported to have a low sensitivity compared with olfactometry measurements.

Persaud *et al*. (1996) found a signal proportional to the concentration of volatile compounds when using conducting polymer odour sensors and artificial pig slurry. The response was reproducible for 3 months. It was concluded that the involved chemicals did not damage the sensors.

An electronic nose, AromaScan, was compared to a human panel in a study of odours emanating from acetic acid and synthetic pig slurry (Classen *et al*., 1997). The synthetic pig slurry consist of acetic acid, propanoic acid, 2-methyl propanoic acid, butanoic acid, 3-methylbutanoic acid, pentanoic acid, phenol, 4-methylphenol, indole, and 3-methylindole. Regarding the experiment of acetic acid, the detection thresholds for the human and the electronic nose were approximately the same. In the experiment with the synthetic slurry, the human panel determined odour thresholds but the sensor array of the electronic nose was not able to select a detection boundary. Modifications of the data processing methods were made with somewhat better, but still poor results in detection and classification. Therefore, improvements in experimental set-up were recommended.

Misselbrook *et al*. (1997) measured odour concentrations following application of slurry to grassland by two types of electronic noses (the Aromascan and the Odourmapper developed at the University of Manchester) and by dynamic dilution olfactometry. The sensors in the electronic noses were made from conducting polymers. The Aromascan contained 32 polypyrrole sensors and the

Odourmapper contained 20 polyindole sensors. In the measurements the electronic noses responded to odour concentrations of 50 OU/m^3. This result suggested a potential ability of electronic nose in a range of agricultural applications. A single line was fitted for each electronic nose expressing the relationship to odour concentration (with a variance of 59-62%). A probable factor decreasing the variance is a variation of gas mixture of the volatile organic compounds of the different samples. Variations were also suggested to depend on the environment (background odours).

Byun *et al*. (1997) examined different methods to reduce complex multidimensional data in order to present it in a form easily interpreted by the user. Several pattern recognition techniques were evaluated including linear methods (Karhunen-Loeve expansion), non-linear methods (Sammon's mapping) and neural networks (Kohonen's map). The combined pattern recognition technique using both principal component analysis and Sammon's mapping was revealed to be the best method visualizing multidimensional data. It also resulted in rapid clustering without assumptions of cluster overlapping. Differences between odours emanating from slurry from pigs fed with two different diets were easy visualized.

Rieß *et al*. (2000) measured odours in livestock buildings with an electronic nose and by olfactometry. The electronic nose contained totally 18 sensors in three chambers with 6 metal oxide sensors in each chamber. The distinction between different cattle stables was investigated by samples taken in a beef bull and a dairy cattle stable. The electronic nose found a distinction between the two stables although the samples seemed very similar to the human nose. Four weeks later, new samples were collected in the beef bull stable. The new samples were observed to differ from the original samples. Altered feed, increased animal weight and meteorological fluctuations were suggested to be the reasons. Artificial neural network showed a recognition rate of 95% while other methods showed poorer results.

After reviewing the available literature, Nimmermark (2001) drew several conclusions about the use of an electronic nose for the detection of odour from animal production facilities, as follows:

- Odour concentrations of 40 OU/m^3 or higher can be registered making practical use possible;
- An electronic nose can be calibrated to recognise a specific odour from animals. For environmental studies this capability sometimes seems too good, grouping odours similar to human noses in different categories;
- A relation between the response of an electronic nose and the odour concentration can be derived for odours from the same place during a specific time; and
- Response of an electronic nose to similar odours from different places or from different time periods seem to differ which result in problems when predicting odour concentration. This inconvenience may be a result of different gas mixtures.

In addition, some researchers have made an attempt to correlate the results of an electronic nose with other instruments. Qu *et al.* (2000, 2002) developed an measuring odour concentration with a commercial electronic nose. Adaptive Logic Network (ALN) was used to develop a function to convert the measurement of an electronic nose into odour concentration. Odour samples were collected from four piggeries. It was reported that trained ALNs can measure odour concentrations with about 20% mean error.

4.5 Chapter summary

In this chapter, odour measurement methods were investigated in detail. Gas chromatography is a widely used analytical technique for separating the components of an odorous air sample for identification and quantification. However, GC and GC-MS only give an indication of the nature and concentration of chemical compounds in the sample, not their contributions to the overall odour of the mixture. Therefore, GC and GC-MS are not regarded as an odour measurement method for this research work because the odours emitted from piggery effluent pond are comprised of hundreds of odorous compounds.

Olfactometry, which uses the human nose as the sensor of odours, is the only reliable method of accurately quantifying the odour strength for a complex mixture of compounds. Dynamic-dilution olfactometry technique is now widely accepted as the standard and used in most research and regulatory institutions in Europe and Australia. In this research work, The ILSU/NCEA olfactometry is used to measure odours. However, olfactometry has disadvantages in terms of cost and time taken for analysis because it uses the human nose as a sensor.

An electronic nose is an instrument consisting of a gas sampling apparatus and an array of gas sensors interfaced to a personal computer. As most of the electronic nose system is developed as a match-model for the natural nose, sensors and pattern recognition are an important part of the electronic nose. Through the literature review, it is concluded that an electronic nose can be calibrated to recognise a specific odour from intensive livestock operations. However, much work needs to be done before it can be considered a reliable method for quantifying the concentration of an odour.

A variety of different sensor technologies are used in electronic nose sensor array systems. Some of the most common are metal oxide sensors (MOS), conducting polymers (CP), bulk acoustic wave (BAW), surface acoustic wave sensors (SAW) and metal oxide semiconductor field effect transistor (MOSFET).

pattern recognition acts as a signal processing unit like the brain in the biological olfactory system. Thus, the interpretation of data obtained from sensor arrays of an electronic nose relies on the use and performance of the pattern recognition engine. A neural network is a dynamic, self-adapting system that can modify its response to external forces using previous experience, offering a more flexible and, due to the parallelism, faster method of analysis. In addition, it may more closely mimic mammalian neurone processing of odour stimuli. Therefore, ANN is adopted as the main pattern recognition engine for this research. The development and evaluation of the ANN are presented in Chapters 6 and 7, respectively.

CHAPTER 5
ODOUR EMISSIONS FROM PIGGERY EFFLUENT PONDS

5.1 Introduction

Effluent ponds are widely used for the treatment of wastes from intensive livestock operations because of their low construction cost, convenience of maintenance and labour savings. More than 75 % of the piggery operations in the United States store and process waste anaerobically and 70 % of their dairy production systems have installed liquid manure treatment systems (Hussey *et al*., 1999; Fisher, 1989). This level of use may be understood in that anaerobic ponds are the most trouble free, low maintenance systems available for piggery effluent treatment. Effluent ponds are also widely accepted as the principle animal waste treatment system especially in piggery operations in Australia (Smith *et al*, 1999).

A recognised drawback with effluent ponds is the production of offensive odours, even when managed at an optimum level. The effluent ponds are the major source of odour in typical Australian piggeries contributing about 75 % of all odour emissions (Smith *et al*, 1999; Jiang & Sands, 1998).

Measurements of odour associated with four dairy farms in Texas, USA (Koelsch, 1994) indicated the effluent ponds as the main sources of odour. He indicated that the highest odour intensity in these farms resulted from the primary anaerobic ponds. The ammonia emission rates from effluent ponds are also much higher than from other production facilities. For example, ammonia emission rates

measured from a variety of animal feeding operations are summarised in **Table 5.1**. As a result of problems associated with odour control, odour from the ponds has become a limiting factor for future growth of intensive livestock operations.

Table 5.1

Ammonia emission rates from various animal feeding operations (Arogo et al., 2001)

Situation		*Rate*	*Unit*
Building	Pigs	0.2-5.0	g NH^3-N/h-AU*
	Dairy cattle	0.12-1.48	
	Beef cattle	0.28-0.74	
	Poultry	0.5-10	
Storage/treatment	**Effluent ponds**	**0.25-156**	kg NH^3-N/ha-day
	Storage Tanks	3-90	
Land application	Surface spread	14-83	Percent (%)
	Band spread	6-47	
	Injected manure	0-7	

* AU (1AU=500kg live weight)

To enable the quantitative prediction of odour emission and dispersion from effluent ponds, it is necessary to describe the relationship between pond working condition and odour emission rates. It can then be used for sizing of ponds for odour control. These issues are discussed in Chapter 9.

This chapter is aimed primarily at establishing the context for the quantification of the effects of pond loading rates on odour emissions.

The types of ponds and the factors thought to affect odour emissions are reviewed, with a specific focus on the organic loading rate (OLR). Possible indicators for monitoring pond conditions are discussed. Finally, the available data on piggery pond odour emissions are reviewed.

5.2 Review of effluent ponds

Typically, the wastes from piggery operations are flushed from underfloor-concrete channels into the effluent ponds. The effluent ponds are used in this system to promote digestion and stabilisation of the manure solids through microbiological activity (Merkel, 1981). There can be up to three ponds in such systems plus an additional wet-weather pond. It is common to use recycled effluent from the last pond as flushing water in the piggery (Watts, 1999).

According to the mode of biodegradation (aerobic or anaerobic), the presence or absence of aeration equipment and other design features, ponds are classified as (Martin, 1991; Robertson, 1977):

- aerobic (bacteria require oxygen for digestion);
- anaerobic (bacteria function in the absence of oxygen); and
- facultative (a combination of aerobic and anaerobic).

5.2.1 Aerobic ponds

Aerobic systems produce minimal odour (Martin, 1991) and hence have a distinct advantage over anaerobic systems with regard to odour issues. The aerobic pond system is based on an abundant supply of oxygen to the decomposition process. Generally, these systems entail shallow depth ponds (< 0.5 m) and are operated with predominant aerobic layers in warmer climates. This system is not feasible in cold climates (< - 4 ºC) where the waste liquid can freeze throughout the full depth of the pond during the winter months. Settled sludge should be removed frequently (once in about 2 to 4 years) to reduce the incidence of anaerobic conditions forming in the bottom layers of the pond. These ponds are not common because they require a greater area than the other types and it is not always practicable to maintain dissolved oxygen (DO) at the required levels throughout the year. This system also involves a greater cost in the installation of facilities for aeration and agitation.

5.2.2 Anaerobic ponds

Most of the ponds in use on livestock operations today are anaerobic ponds. Anaerobic pond systems treat more organic matter per volume than aerobic systems and produce less inert sludge due to their low biomass synthesis. Anaerobic ponds contain anaerobic bacteria that thrive and grow without free oxygen. They are generally deep with a small surface area relative to the organic loading rate.

Anaerobic bacteria are very efficient and effective at decomposing most kinds of organic matter. On the other hand, these anaerobic bacteria frequently give off large quantities of unpleasant odour (Kolesch, 1994; Sivers & Iannotti, 1981). The intensity of the odour resulting from anaerobic digestion can, however, be reduced significantly if anaerobic pond systems are managed properly (Koelsch, 1994).

The design criteria for anaerobic ponds is based on an empirical loading rate such as the volatile solids loading rate (VSLR) in kilograms of volatile solids (VS) per unit volume per day and detention times (Merkel, 1981). It has been noted that as the loading rate (VSLR) increases, the likelihood of objectionable odour also increases.

Advantages of anaerobic ponds include (MWPS, 1985):

- labour economics though the ability to handle wastes hydraulically through the use of flushing systems, sewer lines and pumps;
- high degree of stabilisation that results in reduced odour during land application of processed waste;
- high reduction of nitrogen that minimises the land area required for effluent disposal; and
- provision of long-term storage at low cost.

Disadvantages of anaerobic ponds include (Pfost & Fulhage, 1993):

- public perception that a pond is an "open container of manure";
- undesirable odour that may be produced as a result of seasonal changes due to "turnover" and spring start-up; and
- limited nitrogen availability if treated effluent is used as a fertiliser.

5.2.3 Facultative ponds

A facultative pond is a hybrid system that has both aerobic and anaerobic features. The surface layer of the pond has an organic loading rate low enough to allow dissolved oxygen to be present and hence be aerobic. This results in clarification of this surface layer and keeps odour release to a minimum. The bottom layer of the pond has minimal exchange of oxygen and hence an anaerobic zone exists at the base of the pond for the digestion of organic sediments. The intermediate zone favours the growth of facultative bacteria which are capable of operating, growing and thriving in either aerobic or anaerobic conditions as the pond characteristics change. Typically, facultative ponds generate less odour than anaerobic ponds (Tyson, 1998).

5.3 Factors affecting odour emissions from effluent ponds

Biodegradation processes in ponds depend primarily on the aerobic or anaerobic microbial activity. Odour is largely a result of this microbial activity. Due to the biological nature of the process, a large number of factors affect odour emission from effluent ponds. The main factors include:

- loading rate;
- temperature;
- start-up conditions;
- pH; and
- purple sulphur bacteria.

5.3.1 Loading rate

The loading rate of an effluent pond system is expressed as the mass of volatile solids per cubic meters of pond volume added per day. It has a major impact on the amount of odour that is generated from the system. Several field studies have shown a clear relationship between loading rate and odour emissions. Chastain & Henry (1999) indicated that at high loading rates (*i.e.* 480 g VS/m^3day), significant odour will be produced near the pond 80 % of the time. If the loading rate is reduced to 30 g VS/m^3day, the odour will be insignificant. This suggests that one way to control odour is to use a very small loading rate. However, a pond size based on a loading rate of 30 g VS/m^3day will be very large and expensive to build. The maximum recommended loading rate of 80 g VS/m^3day will have an odour near the pond 33 % of the time. In South Carolina in the United States, the recommended loading rate to minimize odour is 60 g VS/m^3day with an odour frequency of 20 %.

Humenik *et al*. (1981) reported an 80 % frequency of odour for field pilot ponds with a volume of 0.6 m^3/45 kg hog and 60 to 20 % frequencies at 2.3 and 4.6 m^3/45 kg. At 9.2 m^3/45 kg, there was little odour. Volatile solids loading rates

at these volumetric allowances were 380, 96, 48 and 24 g VS/m^3day, respectively. The authors concluded that the 20 % frequency detection of odour was acceptable (Loading Rate Value (LRV): 48 g VS/m^3day). However, the loading values suggested by this study are significantly lower than the actual operating conditions and lower than loading rates recommended for design of anaerobic ponds (DPI-Tasmania, 1996; Clyde, 1985; ASAE, 1984; USDA-SCS, 1983; MWPS, 1983).

If solids or sludge are allowed to build up in the pond, the treatment volume will be greatly reduced. The decreased treatment capacity has the same effect as an increase in loading rate with a resultant increase in odour frequency. The amount of storage volume provided depends upon the expected life of the pond or the frequency with which the sludge will be pumped from the pond (Barth *et al*., 1978). Using field studies and results from other investigators, they reported average sludge accumulation rates in animal waste ponds to be approximately 8.8 m^3 per year for a 590 kg dairy cow; 0.37 m^3 for a 61 kg finishing hog; and 0.02 m^3 for a 2 kg laying hen.

Biochemical oxygen demand (BOD_5), chemical oxygen demand (COD) and volatile solid concentration (VS) are also used as indicators of loading rate in effluent ponds.

5.3.2 Temperature

Biological activity is regulated by temperature and will be slower during periods of low temperature. At temperatures below 4 °C, biological activity largely ceases and as a result, manure decomposition ceases. In climates where the average winter temperature is below 4 °C, very little odour is produced during the winter due to the cessation of microbial activity. In the spring of the year as the temperature of the pond water begins to rise (*i.e.* > 4 °C), acid forming bacteria become active and produce the compounds that feed methane forming

bacteria. Unfortunately, a delay in the decomposition process occurs where mesophilic methane forming bacteria do not become fully active until temperatures reach 15 °C (Pain & Hepherd, 1985). This delay combined with the fact that manure is continuously fed into the pond or storage during the winter results in an overloading of the pond system that leads to sub-optimal conditions and an attendant increase in odour.

Where surface water temperatures fall below 3 °C, both Spring and Autumn turnover can occur. Turnover can be defined as a convective vertical mass movement of liquid in the pond. At 3 °C, when the pond surface cools to this temperature, the density of water is at a maximum and pond surface water sinks and bottom water rises. The mixing action created during the turnover period can cause odorous material from the bottom to temporarily rise to the surface and increase odour. Generally, anaerobic ponds and manure storages are relatively shallow hence the turnover period and period of odour release lasts only a few days. One way of decreasing the duration of the turnover period, and the associated odour, is to mechanically agitate the pond or storage basin. This will increase the intensity of the odour for a short period of time, but the duration of the odour will be greatly reduced (Schmidt, 1998).

5.3.3 Start-up condition

A new pond should be filled to 50 percent of its permanent volume with liquid before manure loading begins. Start-up during warm weather and seeding with bottom sludge from a working pond will speed establishment of a stable bacterial population. Manure should be added to anaerobic ponds in a regular stream without 'shock' loadings, which can cause sharp increases in odour production and wide fluctuations in nutrient content. Liquid levels should not be allowed to fall below the design treatment level, so that adequate pond volume is maintained for optimum bacterial digestion (NCSU, 1998).

5.3.4 pH

An anaerobic pond that is operating properly will have a pH ranging from 7 to 8 (Tchobanoglus & Burton, 1991). When the anaerobic pond is operated properly, the biochemical reactions will maintain the pH in the proper range. If imbalance develops, the acid forming bacteria exceed the methane formers causing a build-up of volatile acids in the pond. If this continues, the buffer capacity is exceeded causing the pH to drop below 6.0. Under this condition, the anaerobic ponds start to produce odour.

pH has a strong interaction with the concentration of volatile organic acids. The lowest pH values occur when the volatile organic acids are at the maximum concentration. The pH in new ponds without adequate dilution water or in overloaded ponds can be reduced to 6.5 or less (acidic), thereby causing odour problems. This condition can be temporarily corrected by evenly distributing agricultural lime (preferable hydrated) on the liquid surface.

5.3.5 Purple sulphur bacteria

Many ponds exhibit a purple colour in the liquid, caused by naturally occurring purple sulphur bacteria. These are phototropic organisms that oxidise sulphide under anaerobic conditions. When these organisms are dominant, pond odour, ammonium nitrogen and soluble phosphorous are reduced. The purple colour is a good indicator of a pond working at its optimum (NCSU, 1998).

To encourage desirable purple sulfur bacteria, the first factor is proper pond size in terms of the amount of manure produced. Ponds with small permanent pools often tend to produce odour because they are too small to adequately handle wastewater. Ponds with a large permanent pool have less odour problems. However, lower loading rates may not support the opportunity for ponds to turn purple. Consequently, a moderately loaded pond could yield high purple sulfur

bacterial populations. In terms of the rapid growth of the bacteria, seeding ponds with purple sulfur bacteria may be another option. This would entail hauling a charge of wastewater from a purple pond to a non-purple pond. Early summer would be the best time to do this. However, there is concern regarding possible disease if the pond's top water is recycled to the piggery shed (Alberts, 2000).

Work by van Lotringen & Gerrish (1978) indicates that purple sulfur bacteria can be promoted successfully in an anaerobic pond by proper management techniques. Their suggestions include;

- loading of an anaerobic pond should be done on a regular and frequent basis, preferably twice a day to reduce shock loads which upset the microbial balance. Under no conditions should be an entire pit be emptied into a pond. Continuous loading is preferable if possible;
- loading rates should be 0.062 m^3/kg of animal weight; and
- provide a sludge storage volume to accommodate a 3-year sludge accumulation.

5.4 Indicators for monitoring pond condition

There are several indicators that can be used to monitor pond conditions. Although the interactions between these indicators and the anaerobic process are not fully revealed now, they have potential as easy-to-measure indicators to monitor and evaluate pond conditions in terms of odour.

5.4.1 pH

The pH values have a strong interaction with the operational status of an anaerobic pond. Since the anaerobic decomposition process is the main process in the pond, the activity of methanogenic bacteria controls the overall performance in the pond. Although gas production takes place between a pH of 6.6 and 7.6, the optimum pH range for methane production of methanogenic bacteria is between 7.0 and 7.2. When the pH drops below 6.6, methane bacteria are significantly inhibited (Merkel, 1981). Therefore, the continuous monitoring of pH values can be an effective tool to monitor the pond conditions. If the pH is lower than certain value, for example 6.6, the system could alert the operator that the pond is malfunctioning and there is the possibility of offensive odour.

5.4.2 Electrical conductivity

The build-up of salts is toxic to bacterial organisms and inhibits pond performance. Work done by Georgacakis & Sivers (1979) showed an excellent correlation between electrical conductivity and gas production. They showed that low level salt concentration can stimulate bacterial activity with peak stimulation occurring at an electrical conductivity (EC) of 6.5 dSm^{-1}. Electrical conductivities between 10 and 13 dSm^{-1} cause a large reduction in anaerobic digestion efficiency; higher EC levels rapidly increase toxicity resulting in a 90 % inhibition at levels of 33 dSm^{-1}. Therefore, regular use of a conductivity meter may be a useful management tool for judging the possibility of odour production.

5.4.3 Ammonia nitrogen

In an anaerobic system, ammonia exists in equilibrium as an ammonium ion or as dissolved ammonia gas. Un-ionised ammonia is quite toxic to methanogenic bacteria. A rapid increase in pH shifts the equilibrium, placing more free ammonia in solution, which is toxic to the methane bacteria. There are few data about ammonia toxicity. Ammonia is inhibitory to methanogenic bacteria at a level of 1500 to 3000 mg/L. However, free ammonia in concentrations greater than 150 mg/L cause anaerobic units to stop functioning (Bhattacharya & Parkin, 1988)

5.4.4 Carbon/nitrogen (C/N) ratio

The nutrients required for anaerobic digestion are carbon, nitrogen, hydrogen, and phosphorus. The more important nutrients among this group are carbon and nitrogen. For best results, the carbon:nitrogen ratio of the substrate should always be within the range of 18:1 to 20:1 (Alken-Murray, 2004). If the C/N ratio is too high, the process is limited by nitrogen availability; if it is too low, ammonia may exist in quantities large enough to inhibit bacterial activity (Merkel, 1981). Hence, this ratio can be an indicator of the performance of anaerobic pond.

5.5 Piggery pond odour emission data

Schulz & Lim (1993) derived pond emission rates using a wind tunnel floating on the pond surfaces. Emission rates from anaerobic ponds ranged from 18.9 – 38 OU/m^2s. However, it was impossible to assign emission rates to specific pond conditions because of the poor pond descriptions provided. Though the results were obtained using sound sample handling and storage procedures, the olfactometry data cannot be compared to current methods because they were not obtained by a standard method using butanol thresholds (Watts, 1999a). The data acquired by Schulz & Lim is reproduced in **Table 5.2**.

Table 5.2

Piggery pond odour emission rates (reproduced from Schulz & Lim, 1993)

Odour source	*Odour emission rates (OU/m^2s)*
Anaerobic pond	38.0 ± 5.7
Aerobic pond	21.7 ± 2.6
Facultative pond	29.3 ± 4.9
Anaerobic treated effluent pond (no scum)	18.9 ± 1.9
Anaerobic treated effluent pond (with scum)	25.7 ± 3.3
Aerobic treated effluent pond (no scum)	14.9 ± 2.8
Aerobic treated effluent pond (with scum)	21.3 ± 3.4
Facultative treated effluent pond (no scum)	19.0 ± 1.9
Anaerobic treated effluent pond (with scum)	23.8 ± 3.3

Smith *et al*. (1999) measured odour emission rates from piggery ponds in Queensland, Australia using both wind tunnel and back-calculation methods. The emission rates from primary anaerobic ponds were 20 – 40 OU/m^2s. The odour emission rate data from secondary facultative ponds were typically less than 10 OU/m^2s. Olfactometry analysis was carried out to the NVN 2820 method with butanol thresholds recorded. From this research, the 'standard' odour emission rates were derived to develop the separation guidelines for piggeries in

Queensland, Australia. They were averaged from the results of Smith *et al.* (1999) as 30 OU/m^2s for primary (anaerobic) ponds and 5 OU/m^2s for secondary (facultative) ponds.

Although the documentation is not clear, it is understood that the work of Schulz & Lim (1993) and Smith *et al*. (1999) was conducted on what could be described as heavily-loaded ponds. Characteristics of this type of pond include (FSA environmental, 2001):

- Organic loading rate greater than recommended by the Rational Design Method;
- Dark colour;
- Dark, floating scum;
- Upsurging of sludge from the pond bed on large odour 'bubbles';
- Non-uniform bubbling across the surface; and
- Acrid or sour character to the odour.

Fig 5.1 shows a heavily-loaded anaerobic pond with upsurging of sludge.

Fig 5.1 Heavily-loaded anaerobic pond with upsurging of sludge

Heber (2002) measured odour emission rates from the piggery effluent ponds of a 6000 head pig grow-finish facility to evaluate the effect of pond aeration on odour emissions. Odours were sampled from the pond surface using a buoyant convective flux chamber with a wind speed of 1.1 m/s. The odour emissions rates ranged from 1.48 to 2.05 OU/m^2s and averaged 1.67 OU/m^2s. The aerated pond emitted 82 % less odour than similar unaerated ponds with only half the volumetric loading rate.

Lim *et al.* (2004) reported odour emission measurements from two anaerobic ponds with different loading rates. Samples were collected using a buoyant wind tunnel (Lim *et al*., 2003). Odour samples were analysed using an AC'SCENT olfactometer using methods compatible with the 1999 CEN TC264 Olfactometry Standard. Pond liquid effluent was analysed for pH, total solids (TS), volatile solids (VS), chemical oxygen demand (COD), total kjeldahl nitrogen (TKN), ammonium nitrogen (NH_4^+-N) and phosphorous (P). Pond A was estimated to have a typical loading rate equating to 62.5 g VS/m^3day. Pond B was estimated to have a light loading rate equating to 22.4 g VS/m^3day. The mean odour emission rate from pond A was 6.2 OU/m^2s and from pond B was 2.9 OU/m^2s. The results indicated generally higher emissions from pond A. In terms of the effluent characteristics, pond A had higher concentrations of TS, TKN, NH_4^+-N and P, but lower VS (FSA environmental, 2001).

The conclusion of Smith *et al*. (1999) and Schulz & Lim (1993) that odour emissions from a heavily-loaded anaerobic pond are much higher than lightly-loaded facultative ponds is supported by the research done by Heber *et al.*, (2002) and Lim *et al.*, (2003, 2004).

5.6 Chapter summary

As noted in the introduction, the aim of this chapter was to establish the context to quantify effects of pond loading rates on odour emissions.

Effluent ponds are widely used in piggery and dairy husbandry for the treatment of wastes because of their low construction cost, convenience of maintenance and labour savings. However, a recognized drawback with effluent ponds is the production of offensive odour, even when managed at an optimum level. The effluent ponds are the major source of odour in typical Australian piggeries contributing about 75 % of all odour emissions.

Ponds are classified as aerobic, anaerobic and facultative depending on the biodegradation (aerobic or anaerobic), the presence or absence of aeration equipment and other design features. In piggery operations, most of the ponds are anaerobic because anaerobic pond systems treat more organic matter per volume than aerobic systems and produce less inert sludge due to their low biomass synthesis. However, anaerobic ponds frequently give off large quantities of unpleasant odour than aerobic and facultative ponds.

Although there is a large number of factors affecting odour emission from effluent ponds, it is concluded that organic loading rate has a major impact on the amount of odour that is generated from ponds. Smith *et al*. (1999) and Schulz & Lim (1993) showed that odour emissions from a heavily-loaded anaerobic pond are much higher than lightly-loaded facultative ponds. This was supported by Heber *et al.*, (2002) and Lim *et al.*, (2003, 2004). In addition, pH, EC, NH_3-N and C/N ratio are suggested as potential, easy-to-measure indicators to monitor and evaluate pond condition in terms of odour.

CHAPTER 6
APPLICATION OF THE ELECTRONIC NOSE FOR ODOUR QUANTIFICATION

6.1 Introduction

The intensive livestock operations developed to meet the needs of modern society have raised serious environmental issues regarding waste management, water quality and odour. Odours associated with livestock operations arise from a mixture of urine, fresh and de-composting manure, and spilled feed. In piggery operations, odours are emitted from confinement buildings via the ventilation air, waste storage and handling systems including effluent ponds, and the field application of liquid waste (Schiffman *et al*., 1997). Although there is limited evidence that serious risks to physical health occur downwind of livestock confinement facilities, some research suggests that odour-causing substances can cause health effects such as eye, nose and throat irritation, headache and drowsiness, and possibly aggravate allergies, asthma and bronchitis (Swine Odor Task Force, 1998).

A confident, rapid, and cost-effective technique for odour measurement is required to develop a piggery odour control program as well as to evaluate the effectiveness of the methods for reducing odour. At present, olfactometry in which human panels are employed as the odour sensor, has been regarded as the industry standard method. However, olfactometry has a considerable disadvantage in terms of cost and labour requirements (Nimmermark, 2001). In addition, olfactometry is often thought to be an unreliable measurement technique because of its dependence on subjective human responses. Recent developments in the

electronic nose technology and artificial neural networks (ANN) provide an opportunity to extend the scope of odour measurement.

Electronic nose systems have been used for a broad range of applications, including: quality control of raw and manufactured products (Lacey & Osborn, 1998); process, freshness and maturity monitoring (Han *et al*., 2001; Shindo *et al*., 2001); shelf-life investigations (Ko *et al*., 2000); discrimination of the origin for agricultural products (Noh & Ko, 1997; Noh *et al.,* 1998); classification of scents and perfumes; microbial pathogen detection (Pometto III & Moizuddin, 1998); air quality in indoor environments (Schreiber & Fitzner, 1999) and in piggery facilities (Gralapp *et al.*, 2000); water and wastewater quality control (Stuetz, 2001); and agricultural malodour measurement (Persaud *et al.*, 1996b) and monitoring (Persaud *et al.*, 1996a).

As sensor technology plays a crucial role in the performance of an electronic nose, various kinds of gas sensors have been investigated. However, four technologies are mainly used in commercialised electronic nose sensors: metal oxide semiconductors (MOS); metal oxide semiconductor field effect transistors (MOSFET); conducting organic polymers (CP); piezoelectric crystals (bulk acoustic wave = BAW) (Schaller *et al.*, 1998). The 'zNose' using acoustic wave resonator sensor technology is a more recent development (Staples, 2000).

Since the raw data from the electronic nose is a 'fingerprint' for each specific gas or odour, pattern recognition techniques can be used to analyse the raw response generated by the sensors. A variety of pattern recognition techniques have been utilised such as graphical analyses (bar chart, profile, polar and offset polar plots), multivariate analyses (principal component analysis, canonical discriminant analysis, feature weighting and cluster analysis) and network analyses (artificial neural network and radial basis function). However the choice of method depends on the available data and the type of result that is required (Schaller *et al.*, 1998). Although graphical and multivariate analyses are an

effective means of comparing samples and of reducing the high dimensionality in multivariate problems, they may be not always be suitable methods for the analysis of piggery odours. This is because of noise in the sensor responses caused by the complex odour background.

An ANN is able to provide a better alternative to traditional statistical methods because of its computational efficiency and generalisation ability. Unlike other pattern recognition methods, an ANN inspired by biological nervous systems is a dynamic, self-adapting system that can modify its response to external forces using previous experience, offering a more flexible and, due to the parallelism, faster method of analysis (Chelani *et al.*, 2002). In addition, it may more closely mimic mammalian neuron processing of odour stimuli (Schaller *et al.*, 1998). It has proved more adaptable to events occurring in real analytical situations because it is much more resistant to random error, and drift in sensor signal magnitudes.

ANNs have been applied to predict SO_2 concentration in Delhi (Chelani *et al.*, 2002), to process the signal from odour sensor arrays for near-real-time odour identification (Roppel *et al.*, 1998), with electronic nose data to predict the shelf-life of soymilk (Ko *et al.*, 2000), to mimic animal odour space and olfactory processing (Hopfield, 1999) and to quantify piggery odour using electronic nose data (Hanumantharaya *et al.*, 1999). Hanumantharaya developed a feed-forward back propagation ANN model as an interface for the output of the Aromascan electronic nose, to correspond to the result of a human olfactory panel. The simulation result of the study showed that the neural network model could be trained with the response of the AromaScan to obtain a low mean squared error value of 0.0015 and 0.01. However, the ANN model required about 100,000 training epochs and 30 minutes of training time to reach that mean square error. This was not sufficiently fast for the model to be used for real or near-real time odour measurement and quantification.

Qu *et al.*, (2000, 2002) developed a function to convert the measurements of a commercial electronic nose, the AromaScan A32S, into odour concentrations using the Adaptive Logic Network (ALN). Principle component analysis (PCA) was used to reduce the number of input variables in the data set from 34 to 3. It was reported that the trained ALN could measure odour concentrations with about 20% mean error. However, the computation time of their ALN model was not reported. The software realisation of ANN demands a heavy process load to the CPU, because it is implemented in sequential form (inherent of the general purpose computer architecture where the program is running). This fact limits its use to off line applications or real time applications of very slow processes. Certain neural network adaptation algorithms (or training) require extremely high computation time when the dimension of the network to be adapted is relatively big. Although the trained network could be used in a fast way, the necessary time for its training is so high that it makes its use impractical. In addition, there were no attempts to improve generalisation to minimise over-fitting and under-fitting of the network in their work.

In this chapter, the context is established within which the instrumental odour quantification method developed for this research work has been undertaken. The AromaScan and ANN techniques are described in detail in this chapter. The specific features of the AromaScan A32S and the odour sampling protocol for this instrument are discussed.

ANN techniques are outlined and network architectures are considered to determine the most appropriate network configuration for odour quantification work. Principal component analysis and network generalisation techniques, which have been applied in this research are presented.

6.2 The AromaScan

6.2.1 Overview

The AromaScan is an analytical instrument which can electronically sense odours and aromas. The AromaScan's digital odour technology was first developed at the University of Manchester Institute of Science & Technology (AromaScan plc., 1996). The AromaScan mimics the three phases of the human olfactory system - detection, signal processing and recognition /interpretation. These three activities allow the human nose to detect, analyse and react to changes in the smell of its environment (AromaScan plc., 1996).

In the human nose, detection is carried out by the olfactory epithelium in which approximately 50 million receptors (made up of at least 30 different types) are exposed to the external environment. Olfactory receptors have broad specificity across chemical species. The size, shape and distribution of polar groups determine the odour description and hence the response of the nose.

The olfactory region in the nose carries out chemical analysis after which signals pass to the brain's cerebral hemispheres, where odour recognition is combined with other sensory inputs. This data is then used to monitor and evaluate the environment and react to changes. The average human nose recognises some 2000 odours whereas an expert 'Nose' can be trained to differentiate up to 10000. The chemical structure of these odours is very diverse and ranges from small molecules such as ammonia to larger molecules such as androstenone (AromaScan plc., 1996).

The sensors of the AromaScan emulate the olfactory receptors' capacity in its discrimination of stereo-chemical and polar characteristics of volatile chemicals. The sensor array of the AromaScan has 32 polymer types, which detect a spectrum of compounds similar to that of the 30 receptor families in the human nose. Initial data processing, carried out in the human olfactory bulb, is performed

in the AromaScan by the processor which provides odour 'fingerprints' and aroma 'maps'. Finally, ANN processing imitates the brain to provide pattern recognition off-line or real-time quality descriptive evaluation of odours (AromaScan plc., 1996).

Therefore, the AromaScan is able to produce an effective 'fingerprint' to distinguish specific odours emanating from different sources. The typical sensor output pattern results from the AromaScan for piggery odour samples 1 and 2, water vapour and activated carbon filtered clean air are shown in *Fig. 6.1*. It is observed that the sensor output patterns produced from piggery odours 1 and 2 have similar 'fingerprints'.

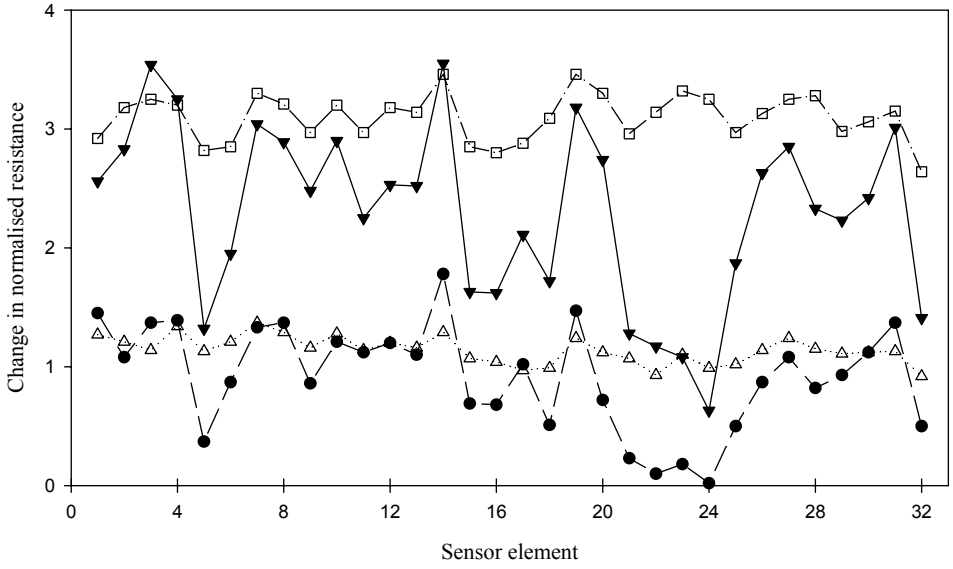


Fig. 6.1 Typical sensor output pattern results from the Aromascan: ▼ piggery odour 1; ● piggery odour 2; □ water vapour; Δ clean air

6.2.2 Features of the AromaScan

The detector unit of the AromaScan consists of an array of 32 electrically conducting organic polymer sensors. The polymers are based on heterocyclic

compounds such as aniline and pyrole and are usually the derivatives of polypyrole and polythiophene (AromaScan plc., 1996). The organic polymers are sensitive to the steric, ionic, hydrophobic and hydrophilic variations of a sample (AromaScan plc., 1996). When these sensors are exposed to the odour sample, there is a reversible change in the electrical resistance of the sensors due to the adsorption and desorption of the molecules in the sample. The change in the electrical resistance is measured relative to a predetermined zero reference baseline (AromaScan plc., 1996).

Each of the 32 polymers exhibits a wide range of selectivity to different chemicals. Therefore, the AromaScan can detect and measure thousands of chemical substances. It takes only a few seconds for each sensor to react to a volatile chemical and come to a point of equilibrium which is a steady state between adsorption and desorption of the volatiles in the sample (AromaScan plc., 1996).

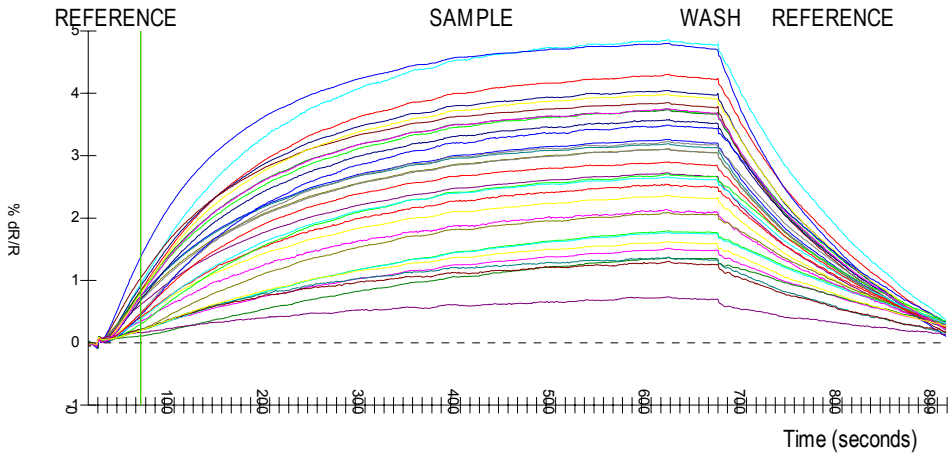


Figure 6.2 Response of the AromaScan sensors.

Fig 6.2 shows a typical response of the 32 sensors and the four stages: reference - sample – wash (purge) – reference during odour sampling. In the figure, the regions of greatest instability are those at the start and end of the

sampling run (AromaScan plc., 1996). The responses of the sensors reach an equilibrium after the initial stages in the sampling. The third stage corresponds to the 'wash phase' in the sampling process. Wash phase is the process during which the sensor unit of the AromaScan is washed with water vapour to prevent cross-contamination and sensor drift.

6.2.3 Odour analysis using the Aromascan

Temperature and humidity should be precisely controlled to produce consistent results because these variables can cause changes in the sensors' response. This can be accomplished by adjusting the temperature and humidity of the reference air and by conditioning the sample.

Conditioning the odour sample

The sample should be conditioned by maintaining it in stable conditions of temperature and humidity before presenting it to the AromaScan. The sample should be analysed at the same temperature and humidity at which it is conditioned. For best results, reference air at the same temperature and humidity as that of the sample air should be used (AromaScan plc., 1996).

The sensors of the AromaScan are highly sensitive to many polar compounds and hence to water. For any sample with high humidity content, its fingerprint will include the intensity due to the presence of water (AromaScan plc., 1996). It is necessary to maintain the humidity of the reference air at the same level as that of the sample because the sensors zero themselves during the calibration part of the data acquisition phase - before the actual data acquisition, the AromaScan calibrates itself and sets all the sensor readings to zero (AromaScan plc., 1996). This also reduces the effect of the humidity and increases that of the volatile chemicals in the headspace (AromaScan plc., 1996).

AromaScan analysis process

There are 3 stages in the analysis (AromaScan plc., 1996):

1. Reference: The conditions in the AromaScan should be stabilised before the sample is analysed. This is done by stabilising conditions in the reference line. More specifically, a dry sample should be referenced by dry air and a wet sample with wet air. This conditioning ensures that the sample is analysed under the conditions in which it is stored or under which it is collected and stored. As the humidity of the sample is quite important to the whole analysis, it is necessary to maintain the relative humidity of the reference air at a level of 10% RH below that of the sample (AromaScan plc., 1996).

2. Sampling: This is the phase where the sample air from the headspace is drawn across the sensors and the resistances of the sensors change depending upon the adsorption and desorption of the volatiles from the sample (AromaScan plc., 1996). The percentage change in resistance of each of the 32 sensors is converted into a digital signal for further data processing using pattern recognition techniques or ANN.

3. Wash: After sampling, a wash is done using water or a solution of 5% 2-butanol in water, depending upon the sample type, to remove any traces of the sample inside the instrument and also to avoid cross-contamination for the subsequent samples used.

The reference gas is generally produced by filtering and dehydrating ambient air to make dry air and bubbling the dry air through a bottle of water to generate high humidity air (AromaScan plc., 1996). By mixing the dry and high humidity air sources using solenoid valves and a valve controlling program, an odour free reference gas with the same level of humidity as that of the sample is obtained (AromaScan plc., 1996).

Fig 6.3 shows the block diagram of the AromaScan. The main components of the AromaScan instrument are the sensor array, the temperature control unit and the humidifier unit.

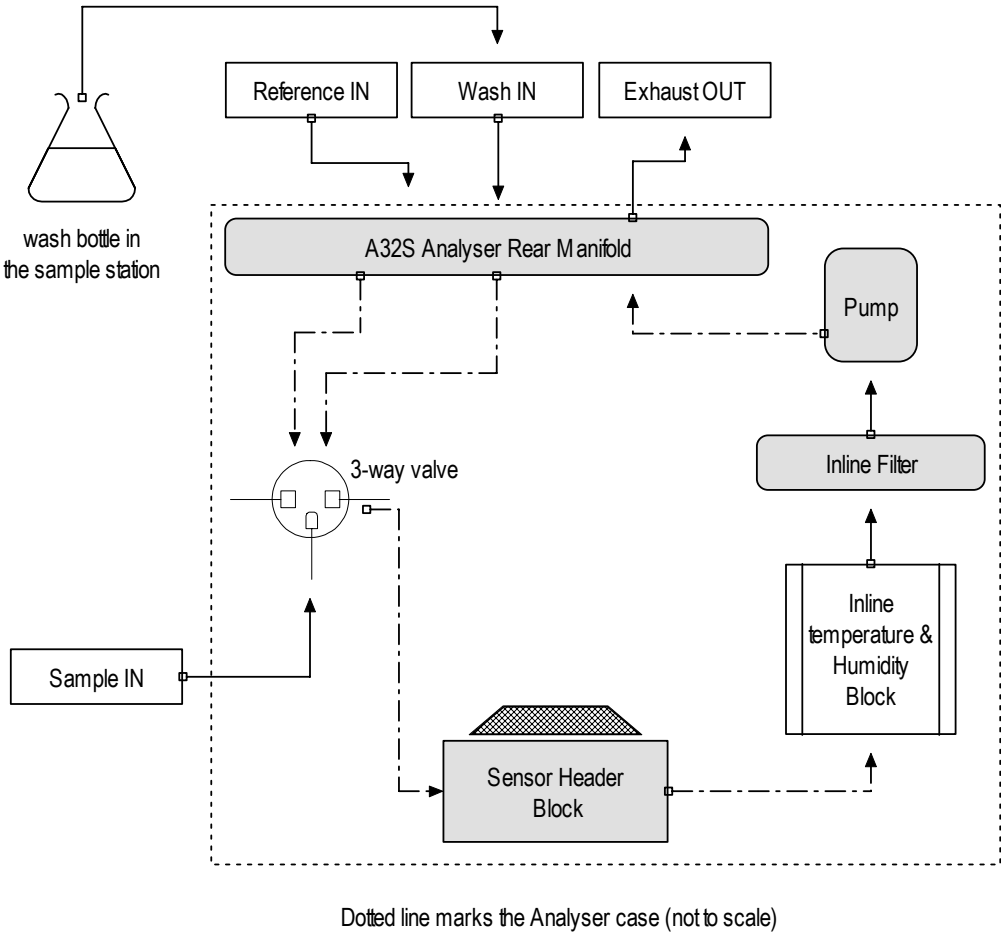


Fig 6.3 AromaScan block diagram (reproduced from AromaScan plc., 1996)

6.2.4 Sampling time and humidity calibration

When analysing odour samples using the AromaScan, it is important to develop an efficient and effective analysis method for each specific odour. The first step in developing an analysis method is to determine the sensor responses for a representative range of the samples intended for testing. To do this, it is

necessary to recognise that some volatile chemical compounds can take up to 10 to 15 minutes to cause a sensor response. For example, this can be the case with low concentrations of amines, which are often found in piggery odours.

Therefore, the process of determining the optimal sampling time is as follows:

1. The sampling container with the air sample bag inside is connected to the sampling port of the A32S unit through a Teflon^{TM} tube. The odour sample is then sampled directly at room temperature.
2. Set the humidity of the 'reference' air stream. As the relative humidity of the reference air should be 10 % below that of the sample, the relative humidity of the reference air is set to this value.
3. The sample is then analysed with the following A32S, the sampling station of AromaScan, valve sequence (The washing air was generated by passing dry air over a washing liquid agent of 5 % 2-butanol):
   - Reference: 15 seconds
   - Sample: 300 seconds
   - Wash: 30 seconds
   - Reference: 180 seconds
4. Repeat steps 1 and 2 for 3 times in order to establish reliable sensor response.
5. Apply the data reduction package in the AromaScan software to evaluate the sensor responses. The time taken to establish stable responses is determined. The example of sensor response is shown in *Fig 6.4*.

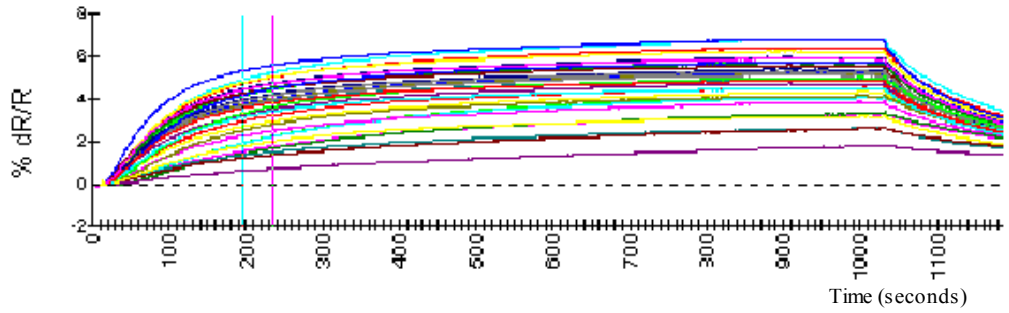


Fig 6.4 Sensor response type A from the AromaScan A32S

From *Fig 6.4*, it can be seen that the sensor response is relatively stable after about 200 seconds. Beyond this point it is simply increasing in intensity. Now consider a different sensor response depicted in *Fig 6.5*.

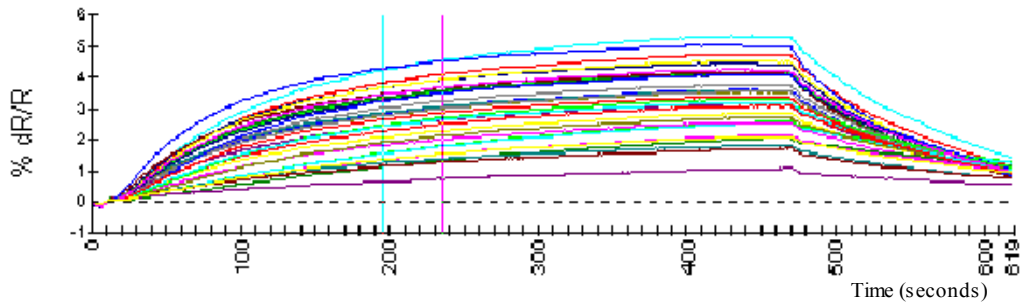


Fig 6.5 Sensor response type B from AromaScan A32S

From *Fig 6.5*, it can be seen that the response does not stabilise as quickly as that in *Fig 6.4*. Between 195 seconds and 235 seconds, one of the sensors has not stabilised (the two highest intensity responses cross over). Beyond this point, the sensor response is stable. Therefore if these two examples were the extent of the sample variation, the analysis time would have to be long enough to take into account the longer response stabilisation time. Once this initial analysis time has been established, repeat analyses of each sample can be conducted.

As the humidity of the collected air samples varies widely and directly affects the change of the sensor response, it was important to measure the humidity of each sample collected, and to adjust the 'reference' gas humidity accordingly to provide a fixed difference between the two. Therefore, a simple protocol to set the range of humidity and temperature for each analysis was developed as follows:

1. Connect the sampling container to the sampling port of the A32S analyser with the 'reference' gas set to a mid-range value (around 30 % RH as measured by the AromaScan A8S humidity generator).
2. Then run the humidity test method with the following A32S valve sequence;
    - Reference: 15 seconds
    - Sample: 300 seconds
    - Wash: 30 seconds
    - Reference: 180 seconds
3. The temperature and humidity reading on the A32S inline sensors are examined during the 'sample' sequence. For analysis of the air sample the 'reference' air stream humidity is set at 10 % RH below that of the sample. This is determined using the humidity calibration chart that is included in the operation manual of the AromaScan. For example, if the sample has a humidity of 36.2 % RH at 26.64 ^{o}C, as measured by the inline sensors, therefore the 'reference' air stream should have a humidity of 16.64 % RH under the same temperature conditions. As the reference humidity is generated at 30 ^{o}C inside the A8S unit, the required humidity of 16.64 % RH must be translated to 30 ^{o}C, maintaining the same absolute water content. The humidity calibration chart give this as 21.47 % RH. It is important to note that the A32S inline humidity sensor will respond to other gases in addition to water vapour. There is therefore a small error in the humidity reading, but the sensor still offers a valuable guideline in setting the reference air stream humidity.
4. Prior to analysis of the air sample, the reference gas should be set to 21.47% RH as measured by the A8S humidity generator.

5. Test the air samples, a minimum of 5 times each, by the selected analysis method in order to acquire the repeat analyses required for the cluster analysis software.

These data can then be processed in the data reduction software. Databases can be created from the beginning, the middle and the end of the sensor responses, and then these databases compared by both Sammon mapping and PCA analysis (Aromascan plc., 1996). By finding the portion of the response that gives the best discrimination, the analysis time may be modified again. For instance, if databases created from the end of the sensor response give the best sample discrimination, then the analysis time is unchanged. However, if the databases created from the middle of the sensor response indicate superior discrimination, then the analysis time can be reduced even further.

The Sammon maps shown in *Fig 6.6*, *6.7*, and *6.8*, which were created from the start, middle and end of the sensor responses, showed the different data clustering depending on the portion of the sensor response. It was observed that the results collected at the ending range of sensor response show best clustering. The Euclidean distance can determine the level of clustering.

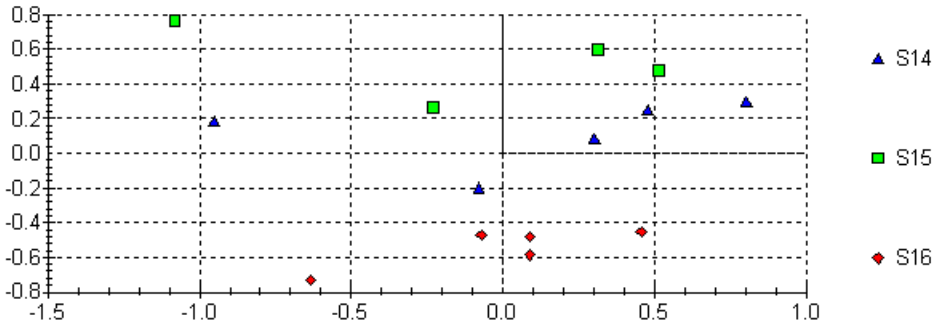


Fig 6.6 Data clustering at the starting range of sensor response

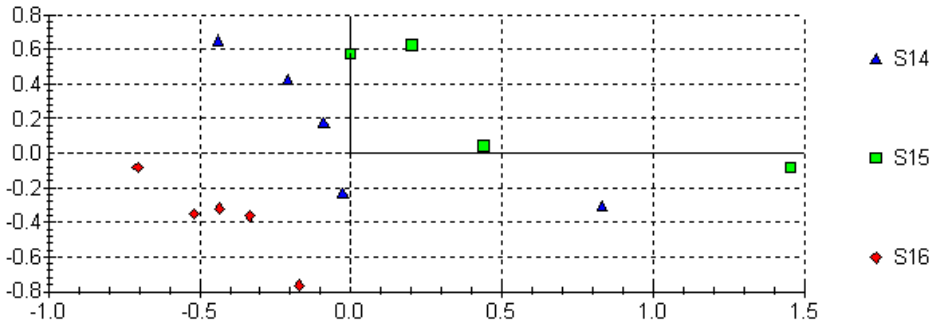


Fig 6.7 Data clustering at the middle range of sensor response

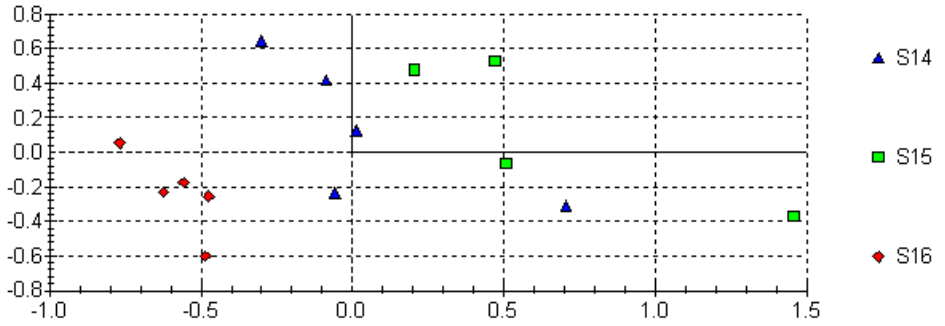


Fig 6.8 Data clustering at the ending range of sensor response

6.3 Artificial neural network

6.3.1 Overview

An ANN attempts to model the working of biological nervous systems. Although biological nervous systems are much more complicated, most of the theory of ANNs is based on studies of biological nervous systems. ANNs are also referred to as neural networks, connectionism, adaptive systems, adaptive networks, neurocomputers, and parallel distribution processors (Simpson, 1990).

There are three important matters to consider when attempting to build an effective and efficient model to predict real odour concentration from electronic nose data with an ANN.

The first issue is to reduce the dimensionality of the input vectors with suitable preprocessing algorithms such as scaling and PCA. The digital odour data from the AromaScan, the dimension of the input vector, used for this research work is too large to do effective training. In addition it may contain noise caused by background odour emissions.

The second issue is to obtain a good generalisation with minimal computation time. In order to develop a real or near-real time practical odour measurement system, the ANN model must be able to predict odour concentration from electronic nose data, which is not in the training set, with minimal computation time or epochs. The number of epochs, which is defined as the presentation of the set of training (input and/or target) vectors to a network and the calculation of new weights and biases, is one way to show the computation time in an ANN.

To get a good generalisation, the ANN model is required to decrease errors caused by underfitting or overfitting. Although the best way to avoid overfitting is to use lots of training data, it is not always possible in practical situations. One method for improving network generalisation is to use a network large enough that is able to provide an adequate fit. However, it is difficult to know beforehand how large a network should be for a specific problem. Besides, a large network may be not an efficient model because it may need more computation time or epochs. This topic is addressed in more detail in section 6.3.5.

The last issue is the network architecture including the number of neurons in the hidden layers because it is closely related to training error and the performance of an ANN.

6.3.1.1 Definition

In its simplest form, an artificial neural network can be considered to be a black box that receives some input and then, calculates an output by mapping the input to the output based on some underlying transformation process (Hanumantharaya, 2000). A black box model is shown in *Fig 6. 9*.

Fig 6.9 A neural network viewed as a "black box" which receives an input and outputs a result

Some of the definitions put forward for an artificial neural network are:

1. According to Nigrin (1993), "A neural network is a circuit composed of a very large number of simple processing elements that are neurally based. Each element operates only on local information Furthermore each element operates asynchronously; thus there is no overall system clock."

2. According to Haykin (1994), "A neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects
   (a) Knowledge is acquired by the network through a learning process,
   (b) Interneuron connection strengths known as synaptic weights are used to store the knowledge."

3. According to Patterson (1996), "Artificial neural networks are networks of highly interconnected neural computing elements that have the ability to respond to input stimuli and to learn to adapt to the environment."

6.3.1.2 Features of artificial neural network

The main features of an ANN can be described as follows:

High degree of parallelism

The processing elements, *i.e.*, neurons, in an ANN function are independent of one another. Every neuron in a layer receives its own set of inputs and outputs which are results based on these inputs. The processing of these neurons is parallel in nature. Parallel processing is a very important feature of an ANN (Nelson & Illingworth, 1991).

Connectivity

Information in an ANN is encoded in a parallel and a distributed framework (Patterson, 1996). Every neuron in a layer of an artificial neural network is connected to every other neuron in the next layer. Therefore, if a neuron or its connecting links are damaged, the network's performance is not adversely affected because the information stored in the network is distributed over all the processing elements and no single neuron corresponds to a piece of data as the weights store the 'knowledge' of an ANN (Patterson, 1996; Picton, 1994; Haykin, 1994).

Input-Output Mapping

An ANN performs a mapping from the input space onto the output space, given any input vector z of dimension m, the neural network transforms it into an output vector y of dimension n by learning the mapping function between the input vector and the output vector. The mapping can be either associative (when the mapping is onto an original pattern from a given noisy version of the original pattern) or heteroassociative (when the mapping is onto a different pattern from a given input pattern) (Haykin, 1994).

Generalisation.

The problem-solving nature in the case of ANN is in sequential steps of increasing detail or in other words, in 'hierarchical steps' with emphasis on the topological aspects of the problem rather than the logical relations between the components of the problem (Patterson, 1996). A highlight of this nature of problem solving is that the network is potentially capable of classification and generalisation (Patterson, 1996). Generalisation is a property of an ANN, *i.e.,* the ability of the network to perform on data that the ANN has never seen before during the learning process.

6.3.1.3 Classification of artificial neural network

ANNs can be grouped as follows (Hanumantharaya, 2000):

1. Classification based on architecture. This classification is based on the number of hidden units or hidden layers in the ANN.
2. Classification based on learning models. This classification is based on the method of learning, *i.e.*, the learning process could be aided by an external "teacher" or the ANN learns by extracting features from the inputs.
3. Classification based on learning algorithm. In this classification, ANNs are classified based on the learning algorithm employed to update the synaptic weights during the learning process.

In general, three different classes of network architecture can further be classified as follows:

1. Single layer feedforward neural networks have a single layer of computational neurons that process input signals in a forward direction, *e.g.* perceptron, adaline, and linear associative memory (Sarle, 1997; Haykin, 1994).
2. Multilayer feedforward neural networks have two or more layers of neurons connected by synaptic weights with the signals propagated in a forward direction only. There are no lateral connections between the neurons in a layer, *e.g.* backpropagation neural networks, radial basis function neural networks, etc. (Smith, 2003).
3. Recurrent neural networks have loops or feedback connections which propagate outputs of some neurons to the inputs of other or same neurons (self feedback connections). *e.g.* Hopfield nets, Boltzmann machines (Gurney, 2003).

6.3.2 Application of backpropagation network

The architecture of the ANN chosen for this research work was a two-layer backpropagation network, with a tan-sigmoid transfer function in the hidden layers and a linear transfer function in the output layer. The training algorithm used to set the neural network weight matrix was the Levenberg-Marquardt algorithm. This training algorithm is regarded as one of the fastest methods for training moderate-sized (up to several hundred weights) backpropagation neural networks. It has also shown high performance in function approximation problems. This section outlines the backpropagation learning network, transfer function and training algorithms which are used in this research.

6.3.2.1 Backpropagation learning rule

The backpropagation learning rule was developed independently by several research groups around 1985 (Hanumantharaya, 2000). It was created by generalising the Widrow-Hoff learning rule to multilayer networks and nonlinear differentiable transfer functions. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function, associate input vectors with specific output vectors, or classify input vectors. Networks with biases, a sigmoid layer, and a linear output layer are capable of approximating any function with a finite number of discontinuities (Sarle, 2001).

Standard backpropagation networks have a gradient descent algorithm, as does the Widrow-Hoff learning rule, in which the network weights are moved along the negative of the gradient of the performance function. The term ‘backpropagation’ refers to the manner in which the gradient is computed for nonlinear multilayer networks (Sarle, 2001).

The backpropagation learning rule is an optimisation technique based on gradient descent, which adjusts the weights in order to reduce the system error or optimise any cost function based on the system error. Therefore, properly trained backpropagation networks tend to give reasonable answers when presented with

inputs that they have never seen. Typically, a new input leads to an output similar to the correct output for input vectors used in training that are similar to the new input being presented. This generalization property makes it possible to train a network on a representative set of input and target pairs and get good results without training the network on all possible input and output pairs.

6.3.2.2 Activation functions (tan-sigmoid and linear transfer function)

Most units in neural networks transform their net input by using a scalar-to-scalar function called an 'activation function', yielding a value called the unit's 'activation'.

Activation functions for the hidden units are needed to introduce nonlinearity into the network. Without nonlinearity, hidden units would not make nets more powerful than just plain perceptrons. The reason is that a linear function of linear functions is again a linear function. However, it is the nonlinearity (*i.e.* the capability to represent nonlinear functions) that makes multilayer networks so powerful. Almost any nonlinear function does the job, except for polynomials (Sarle, 2001).

For backpropagation, the activation function must be differentiable, and it helps if the function is bounded; the sigmoidal functions such as logistic, tanh and the Gaussian function are the most common choices. Functions such as tanh or arctan that produce both positive and negative values tend to yield faster training than functions that produce only positive values such as logistic, because of better numerical conditioning.

For hidden units, sigmoid activation functions are usually preferable to threshold activation functions. Networks with threshold units are difficult to train because the error function is a stepwise constant, hence the gradient either does not exist or is zero, making it impossible to use backpropagation or more efficient

gradient-based training methods. With sigmoid units, a small change in the weights will usually produce a change in the outputs, which makes it possible to tell whether that change in the weights is good or bad. With threshold units, a small change in the weights will often produce no change in the outputs (Sarle, 2001; Mathwork Inc., 2001).

For the output units, the identity or 'linear' transfer function is a good choice for the continuous-valued targets with no known bounds.

6.3.2.3 Levenberg-Marquardt training algorithm

Standard backpropagation uses two training algorithms: gradient descent, and gradient descent with momentum in general. However, these two methods are often too slow for practical problems. Therefore, high performance algorithms that can converge from ten to one hundred times faster than the standard algorithms are required.

These faster algorithms fall into two main categories. The first category uses heuristic techniques, which were developed from an analysis of the performance of the standard steepest descent algorithms. One heuristic modification is the momentum technique. The second category of the fast algorithms uses standard numerical optimisation techniques. There are three types of numerical optimisation techniques for neural network training (Mathworks Inc., 2001): conjugate gradient, quasi-Newton and Lavenberg-Marquardt, which was applied for this work.

The Levenberg-Marquardt training algorithm was designed to approach second-order training speed without having to compute the Hessian matrix like the quasi-Newton methods. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as (Mathworks Inc., 2001):

$$H = J^T J \tag{6.1}$$

And the gradient can be computed as:

$$g = J^T e \tag{6.2}$$

where, J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases of turbulence intensity; e is the vector of network errors.

The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex computing than the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$x_{k+1} = x_k - \left[J^T J + \mu \cdot I\right]^{-1} J^T e \tag{6.3}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes the gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm (Mathworks Inc., 2001).

6.3.3 Application of principal component analysis

Principal component analysis (PCA) is probably the oldest and best known of the techniques used for multivariate analysis. The overall goal of PCA is to reduce

the dimensionality of a data set, while simultaneously retaining the information present in the data (Lavine, 2000).

The method consists of expressing the response vectors X_j in terms of linear combinations of orthogonal vectors along a new set of coordinate axes, and is sometimes referred to as vector decomposition. Therefore, it helps to display multivariate data in two or three dimensions. Along the new axes the sample variances are extremes and uncorrelated so that an analysis in terms of principal components can show linear interdependence in data. Each orthogonal vector, *i.e.* principal component, accounts for a certain amount of variance in the data with a decreasing degree of importance. The scalar product of the orthogonal vectors with the response vectors gives the value of the p_{th} principal component (Hines *et al*., 2003):

$$Z_p = a_{1p}X_{1j} + a_{2p}X_{2j} + \ldots a_{ip}X_{ij} + \cdots + a_{np}X_{nj} \tag{6.4}$$

The variance of each principal component score, Z_p, is maximized under the constraint that the sum of the coefficients of the orthogonal sectors or eigenvectors $a_p = (a_{ip}, \ldots, a_{jp}, \ldots, a_{np})$ is set to unity, and the vectors are uncorrelated. The corresponding eigenvalues give an indication of the amount of information the respective principal components represent. The eigenvector associated with the largest eigenvalue has the same direction as the first principal component. The eigenvector associated with the second largest eigenvalue determines the direction of the second principal component (Hines *et al*., 2003).

As there is often a high degree of sensor co-linearity in electronic nose data, the majority of the information held in response space can often be displayed using a small number of principal components. PCA is in essence a data dimensionality reduction technique for correlated data, such that a two or three-dimensional plot can describe an n-dimensional problem. It can be applied to high dimensional data-sets to explore the nature of the classification problem in gas

sensor applications and determine the linear separability of the response vectors (Hines *et al*., 2003).

In this work, the data matrix used for training the backpropagation ANN is preprocessed using PCA for the following reasons:

- The reduction of dimensionality would indicate an overlap in the responses of the AromaScan's sensor array. This would further imply some redundancy in the sensor data.
- PCA reduces the linear correlation of the data, allowing the ANN to learn the residual non-linear characteristics of the underlying data.
- The training time could be reduced greatly by reducing the dimensionality of the training data. Comparing with the ANN training to search for a minimum in the 35 dimensional error-weight surface, the number of computations and hence the complexity involved in finding a minimum in the error surface can be reduced if the dimensionality of the problem is reduced (Hanumantharaya, 2000).

6.3.4 Network generalisation

The critical issue in developing an ANN is 'generalisation', *i.e.*, the capability of an ANN to predict the cases that are not in the training set (Sarle, 2001). In order to try generalisation, it is necessary that the ANN can compute the mapping function at different points corresponding to the vectors which have not been presented or 'not seen' by the ANN during the training process (Hanumantharaya, 2000). ANNs generalise when they compute or recall full patterns from partial or noisy input patterns, when they recognise or classify objects not previously trained on, or when they predict new outcomes from past behaviours (Patterson, 1996).

If an ANN is properly trained on data that adequately covers the range of the input patterns and if the function that is to be approximated is sufficiently smooth,

then it is possible for an ANN to interpolate well and hence generalise. Generalisation depends on the following factors (Hanumantharaya, 2000):

- Learning algorithm;
- Training set; and
- Network architecture.

A network that is too complex may fit the noise, however, leading to overfitting. Overfitting is especially dangerous because it can easily lead to predictions that are far beyond the range of the training data. Overfitting can also produce wild predictions in multilayer perceptrons even with noise-free data (Sarle, 2001).

The best way to avoid overfitting is to use lots of training data. However, it is often impossible to get enough data in practical situations. Given a fixed amount of training data, there are at least six approaches to avoiding underfitting and overfitting, and hence getting good generalization (Sarle, 2001):

- Model selection;
- Jittering;
- Early stopping;
- Weight decay;
- Bayesian learning; and
- Combining networks.

The early stopping generalisation technique was chosen for this work because it has the following advantages:

- It is fast;
- It can be applied successfully to networks in which the number of weights far exceeds the sample size; and
- It requires only one major decision by the user: what proportion of validation cases to use.

In addition to the above advantages, the early stopping technique is able to decrease the number of epochs. The number of training epochs was up to 50,000 in the previous attempt at odour quantification work with an ANN and electronic nose (Hanumantharaya *et al.*, 1999). With this number of epochs, it is not possible to develop an efficient odour prediction model.

'Early stopping' or 'Stopped training' can be performed by the following procedures (Sarle, 2001):

1. Divide the available data into training and validation sets.
2. Use a large number of hidden units.
3. Use very small random initial values.
4. Use a slow learning rate.
5. Compute the validation error rate periodically during training.
6. Stop training when the validation error rate 'starts to go up'.

6.4 Chapter summary

In this chapter, the AromaScan A32S and artificial neural network techniques were addressed.

The AromaScan is an electronic nose which can electronically sense odours and aromas. It mimics the three phases of the human olfactory system: detection, signal processing and recognition/interpretation. The sensor array of the AromaScan has 32 polymer types, which detect a spectrum of compounds similar to that of the 30 receptor families in the human nose. For the odour analysis using the AromaScan, temperature and humidity should be precisely controlled to produce consistent results because these variables can affect changes in the sensors' response. Conditioning the odour samples and humidity control method were discussed in this chapter. In addition, a simple method to determine the sensor responses for a representative range of the samples was suggested.

The artificial neural network is proposed as the interface for the output of the AromaScan A32S to correspond to the results of forced-choice dynamic dilution olfactometry. The architecture of the ANN chosen for this research work was a two-layer back propagation network, with a tan-sigmoid transfer function in the hidden layers and a linear transfer function in the output layer. The training algorithm used to set the neural network weight matrix was the Levenberg-Marquardt algorithm. This training algorithm is regarded as one of the fastest methods for training moderate-sized (up to several hundred weights) backpropagation neural networks. It has also shown high performance in function approximation problems.

PCA was selected for the preprocessing of the data matrix used for training the ANN because it can reduce the dimensionality of the training data as well as the training time of ANN could be reduced greatly.

One of the critical issues in developing an ANN is generalisation. In other words, the trained ANN has a capability to predict the cases that are not in the training set. An early stopping generalisation technique was chosen in this work because it is fast; it can be applied successfully to networks in which the number of weights far exceeds the sample size; and it requires only one major decision by the user: what proportion of validation cases to use.

CHAPTER 7
CALIBRATION OF THE ODOUR QUANTIFICATION TECHNIQUE

7.1 Introduction

It is necessary to develop a rapid, accurate and cost-effective odour measurement method to substitute current odour measurement method, *i.e.*, olfactometry analysis. Through the intensive literature review, the odour quantification methodology based on the AromaScan, an electronic nose, and artificial neural network was suggested.

To calibrate and evaluate the methodology, replicable experiments were conducted. Odour samples from five different piggery effluent ponds were analysed simultaneously using the AromaScan and dynamic dilution olfactometry. The resulting sensor data was used to train an artificial neural network to correlate the responses to the real odour concentrations. The effectiveness of the ANN was evaluated through simulation work using various pre-processing techniques and network architecture. Finally, further odour samples from an effluent pond were presented to the trained ANN to predict real odour concentrations.

7.2 Odour sampling and analysis

7.2.1 Odour sampling sites

The odour samples were collected from effluent ponds at piggeries near Toowoomba, Queensland, Australia during February to April 2002. A total of 246 samples were collected from five ponds, as part of a project by the Queensland Department of Primary Industries (QDPI), for the purpose of relating odour emission rates to pond loading rate or condition. The operating condition of each effluent pond is given in **Table 7.1**.

Table 7. 1

The operating conditions of piggery effluent ponds used for odour sampling

Piggery	*VS added to pond (kg/day)*	*VS loading rate (g VS/m^{3}day)*	*% loading of max design*	*Size (m)*	*SPU [*1]*
A	375	178	223	52 x 56	1457
B	400	50	51	59 x 69	1426
C	2,076	166	185	75 x 110	6767
D	4,406	84	93	116 x 147	14,992
E	852	363	371	26 x 34	2860

SPU: Standard Pig Unit. Piggeries in Queensland are licensed by the maximum number of Standard Pig Units (SPU) housed in a piggery. The SPU is a unit of measurement for determining the size of a piggery based on its waste output. One SPU produces volatile solids equivalent to that produced by an average size grower pig (approximately 40kg) (QDPI, 2000)

7.2.2 Odour sample collection

Odour samples were collected using a portable wind tunnel as described by Jiang *et al.* (1995) and Bliss *et al.* (1995) and modified by Wang *et al.* (2001) to improve sampling efficiency. A 240-volt fan assembly was used to force carbon-filtered air into the wind tunnel to generate an internal air velocity of between 0.3 and 0.5 m/s in the sampling section of the tunnel. A Thermo Systems

Incorporated (TSI) Model 8355 hot wire anemometer was used to measure the air velocity in the tunnel exhaust section.

Melinex™ (Polyethylene Terephthalate) sample bags were used to collect and transport odour samples. Sample bags were placed into a rigid sampling container and the air inside the container was evacuated at a controlled rate using 12-volt diaphragm pumps to fill the bags. All components used for sampling were composed of stainless steel or polytetrafluoroethylene (PTFE). The bags were pre-conditioned as per the Australian Standard (AS4323.3) by filling them with odorous air from the source prior to the sample being collected. After finishing odour sampling, the containers were then sealed and transported to the olfactometer for analysis, and then to the AromaScan A32S instrument for final testing. The time between sample collection and testing was always less than 24 hours.

7.2.3 Olfactometry analysis

Odour concentrations were determined using an eight panellist, triangular, forced choice dynamic olfactometer developed by the Department of Primary Industries, Queensland, Australia. This olfactometer was constructed to meet the requirements of the Australian/ New Zealand Standard for Dynamic Olfactometry (AS4323.3) (Standards Australia, 2001).

Each panellist was first screened with the reference gas (n-butanol) according to the Australian standard (Standards Australia, 2001) to ensure their detection thresholds for the reference gas was between 20 and 80 parts per billion (ppb). The 20 to 80 ppb applies to the running average of the last 10 samples so a panellist could be outside the range for an individual session.

Odorous air was diluted and presented to the olfactometer panellists in one of three ports, while the other two ports emitted clean odour free air. The panellists

were then asked to sniff from the ports and determine whether they could detect a difference between the three ports. Each panellist was allowed a maximum of 15 seconds to detect a difference. The panellists were then asked to answer whether they were certain, uncertain or guessing from which port the odour (if any) was emitted.

This process was repeated by doubling the strength of the previous presentation until all panellists had responded with certainty and correctly for two consecutive presentations. The panellists' individual threshold estimate (Z_{ITE}) were then determined by calculating the geometric mean of the dilution at which the panellists did not respond with certainty and correctly and the first of the two dilutions where the panellists responded with certainty and correctly. This dilution series was defined as a round. Three rounds were undertaken for each sample where sufficient sample was available.

At the end of the three rounds, the results of the first round were discarded as per the Australian standard (Standards Australia, 2001). The results from rounds two and three were then geometrically averaged ($\overline{Z}_{ITE}$). The ratio between Z_{ITE} and $\overline{Z}_{ITE}$ is defined as ΔZ. The calculation of ΔZ is as follows (Galvin *et al*., 2002).

$$\text{if } Z_{ITE} \geq \overline{Z}_{ITE} \text{ then } \Delta Z = \frac{Z_{ITE}}{\overline{Z}_{ITE}} \tag{7.1}$$

$$\text{if } Z_{ITE} \leq \overline{Z}_{ITE} \text{ then } \Delta Z = \frac{\overline{Z}_{ITE}}{Z_{ITE}} \tag{7.2}$$

If ΔZ is greater than ± 5 then all ITEs of the panel member with the largest ΔZ are excluded from the data set. The screening procedure is then repeated, after recalculation of $\overline{Z}_{ITE}$ for that measurement. If panel member(s) again do not comply, the panel member with the largest ΔZ is omitted. This is repeated until all panel members in the dataset comply (Standards Australia, 2001). The last value

of $\overline{Z}_{ITE}$ is then defined as the odour concentration and expressed as odour units per cubic metre (OU/m^3) (Galvin *et al*., 2002).

Table 7. 2

The number of samples, mean and range of odour concentrations for each pond.

Piggery	*Number of Samples*	*Odour concentration (OU/m^3)*		
		Mean	*Range of odour conc.*	*SD*
A	36	17.71	4.1 - 39.8	11.44
B	81	20.67	5.5 - 49.5	11.85
C	54	46.47	1.9 - 83.9	27.17
D	45	31.51	12.8 - 61.1	12.21
E	30	29.83	10.8 - 61.1	15.20
Total	246	29.00	1.9 - 83.9	19.50

7.2.4 Odour analysis and data acquisition methods using the AromaScan

All samples were analysed using the AromaScan A32S analyser, in conjunction with the AromaScan A8S sample station. The method for odour data acquisition for AromaScan is outlined in **Table 7.3**.

Table 7. 3

Data acquisition procedure used with the Aromascan A32S analyser

Operating Stage	*Time*
Reference	15 s
Sample	300 s
Wash	30 s
Reference	180 s
Washing Solution: 5% 2-Butanol	
Repetition: 3 times per each sample	

For analysis of each air sample, the reference air stream humidity was set at about 10 %RH below that of the sample to maintain the same absolute water content. For this calculation, a humidity calculation program provided by Aromascan, plc., UK was used.

7.2.5 Preprocessing of the AromaScan data for network training

7.2.5.1 Data processing

The resulting data from the 32 sensors of the AromaScan were converted into a digital signal and stored in a personal computer (PC) in a binary format. This information was transformed into ASCII format and was used to build a database. The database consisted of 246 data files that were obtained from the five different effluent ponds and the subsequent sampling by the AromaScan.

These ASCII files were then imported into MATLAB to establish a data library. The MATLAB's neural network toolbox was used for the artificial neural network in this research work. The whole data process resulted in 246 matrices each having 35 columns.

The 35 columns corresponded to the 32 sensor responses and three other factors, namely:

- Base temperature: This is the in-line temperature of the sample;
- Base sensor temperature: This is the base temperature of the sensors; and
- Relative humidity: This is the humidity of the reference air which is maintained relatively close to that of the sample. In most cases, a level of about 10% relative humidity below that of the sample has been found to be effective (AromaScan plc., 1996).

Since these factors do affect the measurement process and odour of a sample, they have been included as inputs to the ANN.

The corresponding odour concentrations (expressed in OU/m^3) for the 246 data files were determined by the olfactometry panel. The results were stored in a text file in ASCII format. And then, this file was also imported into MATLAB. The odour concentration values were saved in a column vector of size 524 ×1. This vector is henceforth referred to as the target outputs' vector.

Fig 7.1 shows the transformation of the raw data from AromaScan to the training data for ANN as well as odour prediction procedure from unknown odour samples.

The following steps explain the transformation of the raw data as depicted in *Fig 7. 1*:

1. The odours from the field measurements were measured using the AromaScan.
2. The response of the sensors were saved in binary format (.dat files in the figure).
3. The sensor data in the binary files was converted into csv file format using the AromaScan software (*.csv files in the figure).
4. The csv files containing the sensors' responses were imported into MATLAB.
5. From the matrices, the sensor responses corresponding to the equilibrium phase were extracted and used as training data for the ANN.
6. The odours were presented to the olfactometry panel to determine odour concentration (OU/m^3).
7. The odour concentrations were saved in csv file format for making database.
8. This database was imported into MATLAB.
9. The odour concentrations were saved in a vector.

10. The vector served as the target outputs during ANN training
11. The database from unknown odour samples was provided to trained ANN for odour prediction

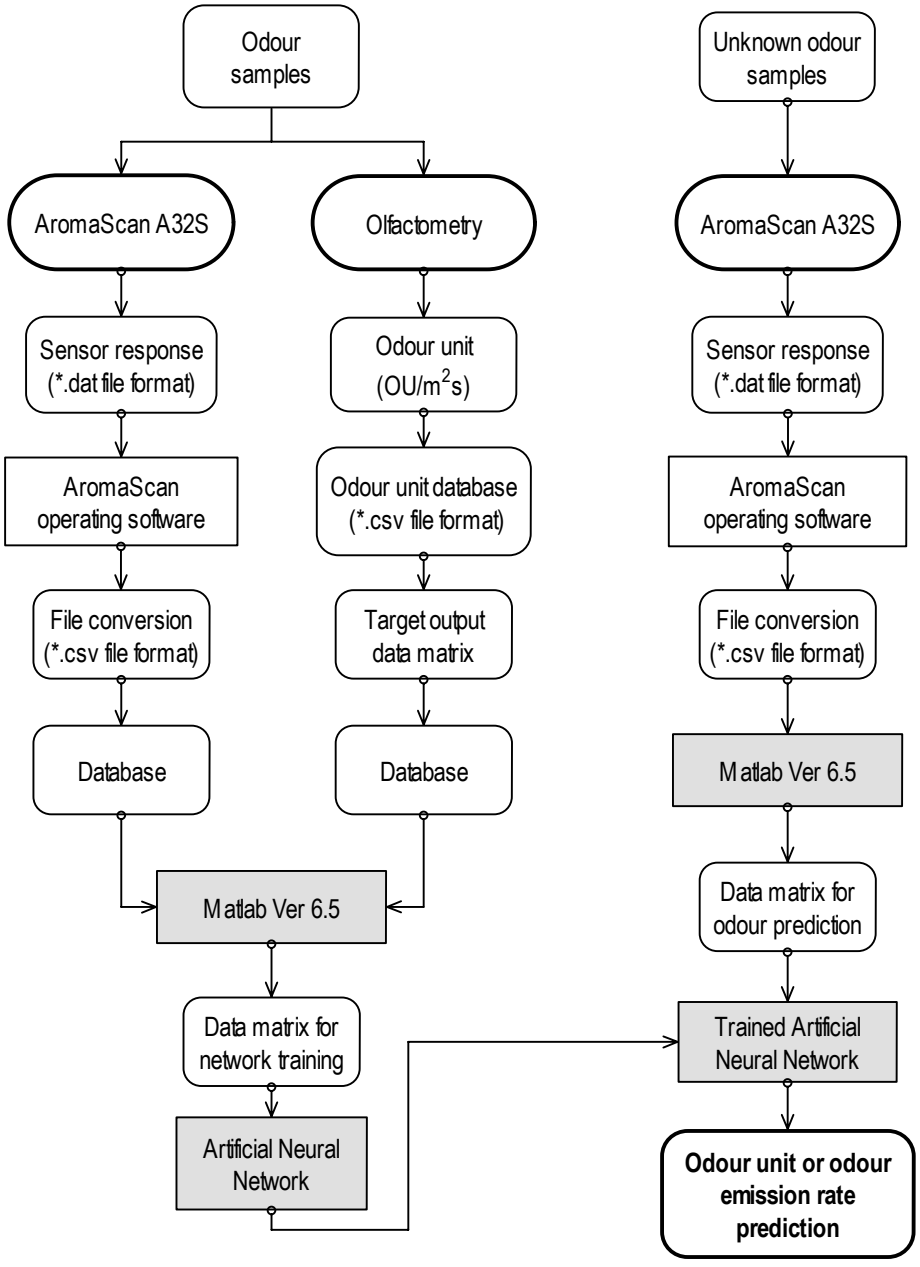


Fig 7.1 The transformation of the raw data from the AromaScan A32S for the odour prediction from unknown odour samples

7.2.5.2 Input scaling

Since inputs to the neural network must be small in magnitude, the inputs and their corresponding outputs are scaled accordingly. ANN become saturated when they are used with large input values

A function provided by MATLAB's Neural Network Toolbox scaled the data matrix to have a dynamic range of ±0.9 and mean of zero. The responses (numerical values) of the sensors lie in the range of ±10 (on an average) and around 40 for the other three parameters - namely base temperature, base sensor temperature and relative humidity. By scaling the inputs, it is ensured that the inputs lie between ±1 in order to avoid saturation of the neurons.

By scaling the inputs, it ensured that the inputs were between –0.9 and 0.9 for the tangent sigmoid transfer function in the hidden layer and the linear transfer function in the output layer. The reason for scaling between –0.9 and 0.9 instead of between –1 and 1 is that for inputs with odour unit values equal to the limiting values of the each transfer function, *i.e.*, -1 or 1, the weight adjustment will be small and hence the network tends to 'saturate'. The backpropagation ANN was trained using the scaled inputs and their respective scaled outputs in this work.

7.2.6 Neural network training

The architecture of the artificial neural network chosen for this paper was a two-layer back propagation network, with a tan-sigmoid transfer function in the hidden layers and a linear transfer function in the output layer. The training algorithm used to set the neural network weight matrix was the Levenberg-Marquardt (trainlm) algorithm available in MATLAB's Neural Network Toolbox 4.0. This training algorithm is regarded as one of the fastest methods for training moderate-sized (up to several hundred weights) backpropagation ANN. It has also shown high performance in function approximation problems. The two-layer backpropagation ANN with two hidden layers is depicted in *Fig 7.2*.

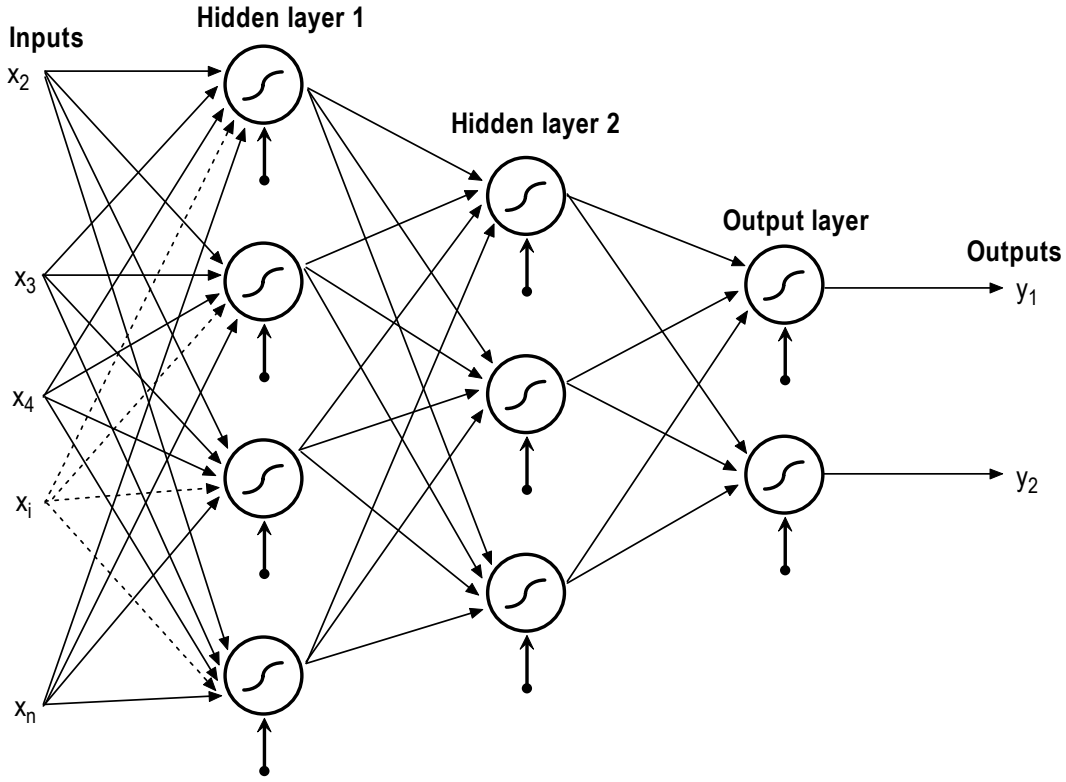


Fig 7.2 Two-layer backpropagation neural network architecture with two hidden layers: $x_1 \ldots x_n$, (coded input node); $y_1 \ldots y_n$ (output node) (reproduced from Hanumantharaya, 2000)

7.3 Analysis and discussion

In this section, the effect of scaling, principal component analysis (PCA), early stopping technique and number of neurons in the hidden and output layers on the performance of the ANN are discussed in each section respectively.

7.3.1 Results using the preprocessing algorithms

Scaling and PCA were used to pre-process the data acquired from the electronic nose. Pre-processing, *i.e.*, scaling the inputs, is necessary to avoid saturation of the ANN when it is used with large values. There are several rules for scaling the inputs. One of the rules is that each input variable should be preprocessed so that its mean value, averaged over the entire training set, is close to zero, or else it is small compared to its standard deviation (Haykin, 1994).

The principal component analysis (PCA) is a linear transformation technique generally used for data compression and reduction of dimensionality while simultaneously retaining the information present in the data (Lavine, 2000). In the analysis of responses from the electronic nose, the PCA acts as a decorrelator at the pre-processing stage and maximizes the variance within the data before the classification procedure is performed (Kermit & Tomic, 2001). In this paper, the data matrix used for training the ANN was preprocessed using the PCA with the intention of dimensionality reduction and to find a coordinate system that makes the original responses as independent of each other as possible. The 35 dimensions of the data matrix were reduced to 3 using PCA preprocessing.

The simulations were carried out under the condition of 10^{-8} of mean square error, which was the objective of the network, for the same initial condition with preprocessing algorithms and without preprocessing algorithms respectively. In these simulations, both of the ANN had five neurons in the hidden layer. The neural network performance with preprocessing of the test data was better than for the network without preprocessing algorithms. Without preprocessing, the ANN

was saturated at 1095 epochs and could not meet the training objective. The value of mean square error and gradient were 76.05 and 2.84×10^{-4} respectively. The ANN with preprocessing showed the best performance at 1119 epochs. At this epoch, the value of mean square error and gradient were 1.58×10^{-1} and 1.05×10^{-006} respectively.

Fig 7.3 and *7.4* show the plots of the mean squared error versus training epochs on a logarithmic scale for the training simulation of the network with and without preprocessing algorithms, respectively. It can be seen from *Fig 7.3* that the ANN could not perform the training process effectively because of saturation of the neurons in the hidden layer.

The scatter plot of the actual odour concentration and the predicted neural network output (scaled into the odour unit domain) for the test data using the results from these training simulations are shown in *Fig 7.5* and 7.6*,* respectively. The value for the correlation coefficient (*r*) in *Fig 7.5* and *7.6* are 0.89, respectively. However, intensive clustering of neural network output is observed especially at the low range of prediction in *Fig 7.5*. Therefore, the value for *r* in *Fig 7.5* could not represent the correlation between the measured and predicted odour units.

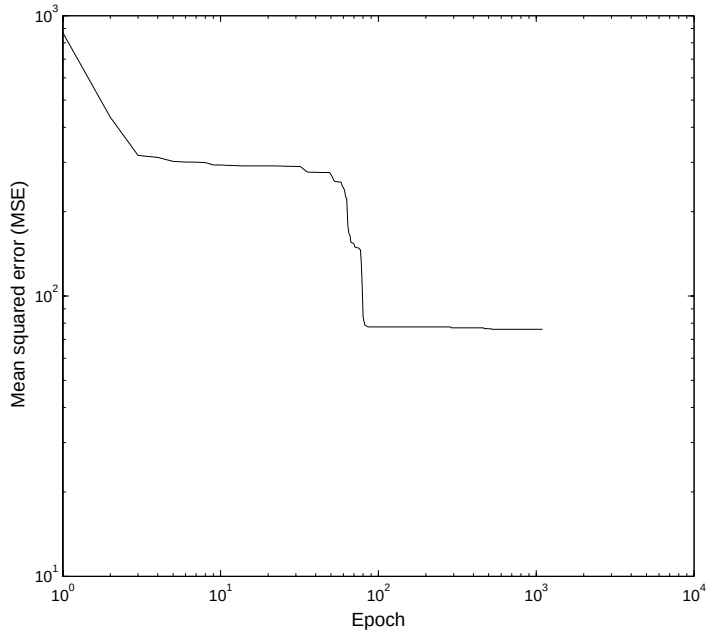


Fig 7.3 The result of artificial neural network training without preprocessing.

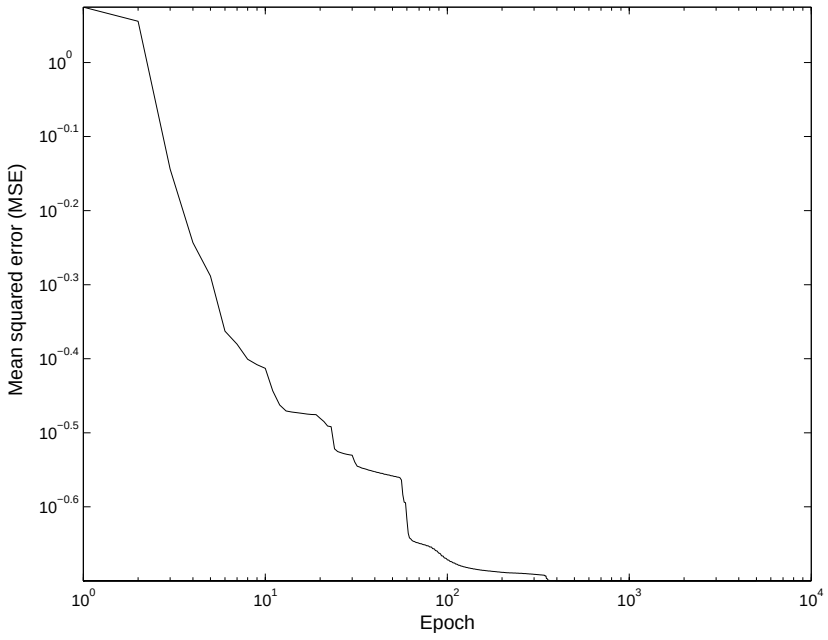


Fig 7.4 The result of artificial neural network training with preprocessing.

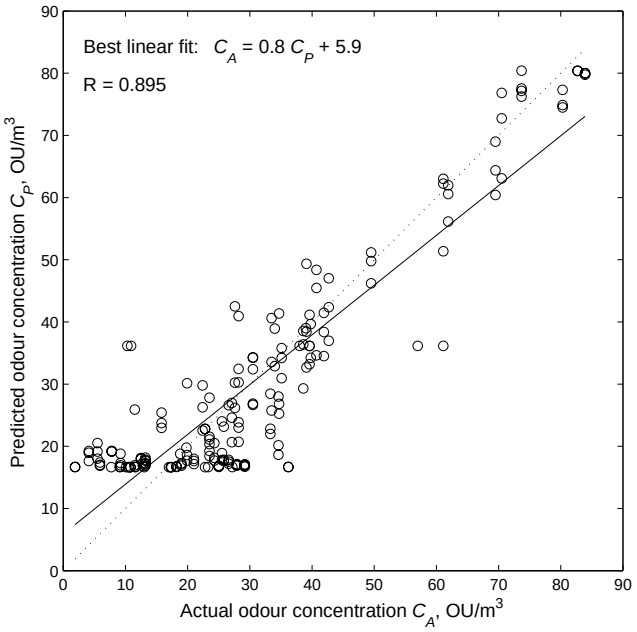


Fig 7.5 The odour prediction results using artificial neural network without preprocessing.

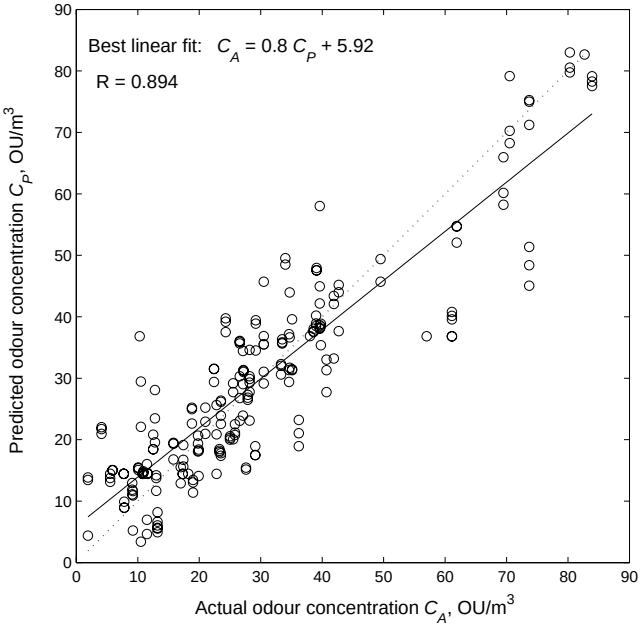


Fig 7.6 The odour prediction results using artificial neural network with preprocessing.

7.3.2 Improving network performance using an early stopping technique

The early stopping technique was used to get good generalisation performance and to decrease the number of epochs. The data obtained from Aromascan analysis was divided into four equal subsets. The first and the third subset are the training set, which was used for computing the gradient and updating the network weights and biases. The second set is the test set. The test set error was not used during the training, but it was used to compare different models. It is also useful to plot the test set error during the training process. If the error in the test set reaches a minimum at a significantly different iteration number than the validation set error, this may indicate a poor division of the data set. The fourth subset is the validation set. The error on the validation set is monitored during the training process. It controls the total training process of an ANN. The validation error normally decreases during the initial phase of training, as does the training set error. However, when the network begins to overfit the data, the error on the validation set typically begins to rise. When the validation error increases for a specified number of iterations, the training is stopped, and the weightings and biases at the minimum of the validation error are returned (Demuth & Beale, 1994).

The results using the early stopping method indicated that it has the possibility to decrease the computation time and the required number of epochs. The number of training epochs, which were required for the simulation, was 22. *Fig 7.7* is the plot of the mean squared error versus the training epochs on a logarithmic scale for the training simulation of the network with an early stopping algorithm. The PCA was not applied to this simulation work.

The value of mean square error and gradient resulted in 1.19×10^{-2} and 63.45 respectively. However, it can be seen that the test errors decrease as the training proceeds and after reaching a certain minimum, the errors on the test data start to increase even as the errors on the training data are still decreasing. From the

above results, it could be concluded that the network was overfitted. Therefore, there is a need to enlarge the network size by increasing the number of neurons in the hidden layer. The scatter plot of the actual odour concentrations and the predicted neural network output from the training simulations is shown in *Fig 7.8*.

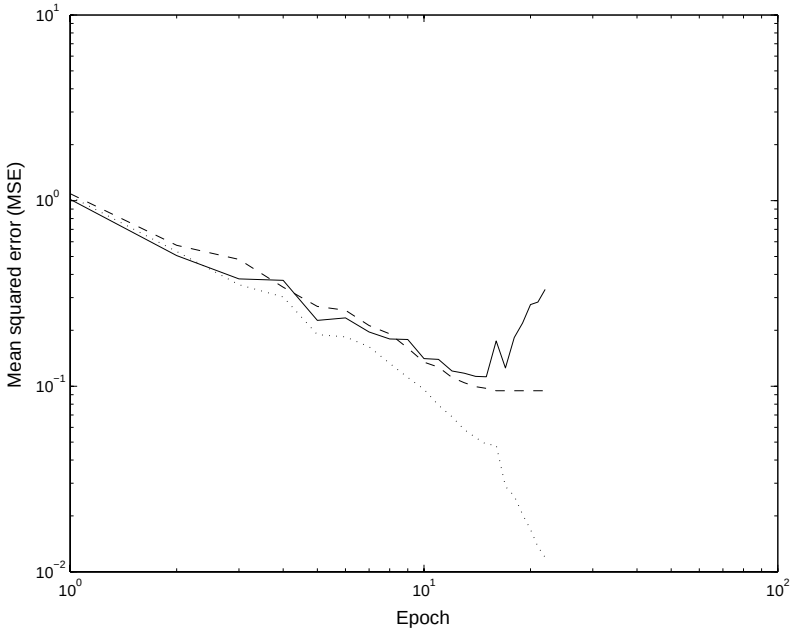


Fig 7.7 The result of artificial neural network training using the early stopping technique: ——,training; - - - -, validation; ------, test

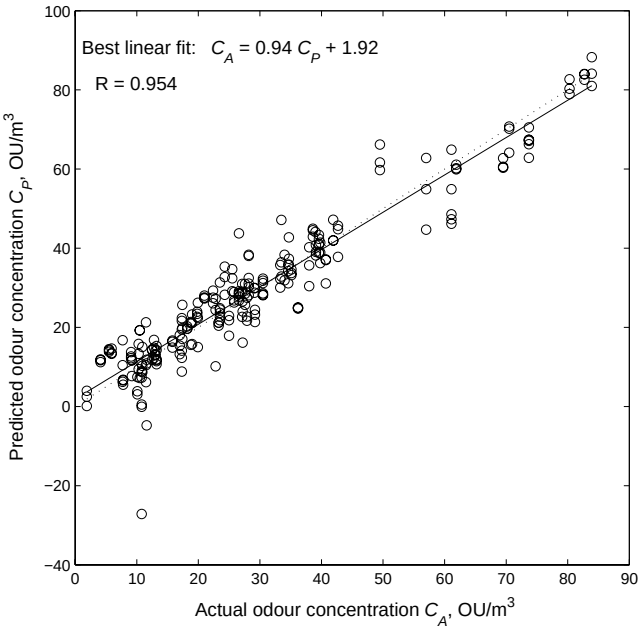


Fig 7.8 The odour prediction results using artificial neural network with the early stopping technique

7.3.4 Effect of the number of hidden neurons on network performance

It is important to determine the number of neurons in the hidden layer in order to build an ANN. An ANN with too few hidden neurons has a tendency to produce high training error and high generalisation error due to underfitting and high statistical bias. The ANN with too many hidden neurons can show low training error, but high generalisation error due to overfitting. Generally, the number somewhere between the input layer size and the output layer size is recommended using 'the rule of thumb' given by various articles (Blum, 1992; Swingler, 1996; Berry & Linoff, 1997; Boger & Guterma, 1997). However, this rule is not suitable because the number of training cases, the amount of noise in the targets and the complexity of the function are not considered.

The network was tested with 3, 5, 10 and 20 hidden neurons to find the optimal number of hidden neurons. Although there seems to be no upper limit in the

neural network using an early stopping algorithm, it is not necessary to use too many hidden neurons because it needs more computation time and memory requirement. These numbers are larger than in the work reported by Hanumantharaya (2000).

All of the training simulations were performed with the same architecture, which is the two-layer back-propagation network, with tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer. A preprocessing and an early stopping algorithm were applied as well.

Although it had same network architecture as the simulation in *Fig 7.7* except the PCA preprocessing, the increase of the errors on the test data set was not observed in the simulation using 5 hidden neurons. Hence, it can be concluded that PCA preprocessing not only reduces dimensionality of training data but also enhances the generalisation of the network.

The mean square error decreased with an increase in the number of neurons in the hidden layer. The neural network performed the best with 20 hidden neurons. The values of the mean square error, gradient and r with 3, 5, 10, 20 and 30 hidden neurons are given at **Table 7.4**.

Table 7.4

The artificial neural network simulation results for 3, 5, 10, 20, and 30 hidden neurons

	The ANN simulation				
Hidden Neurons	3	5	10	20	30
Number of epochs	16	39	47	55	54
Mean square error	4.06×10^{-1}	1.70×10^{-1}	8.74×10^{-2}	3.06×10^{-3}	4.71×10^{-3}
Gradient	5.87	3.52	1.59	20.33	3.06
Correlation coefficient	0.79	0.84	0.93	0.98	0.98

The scatter plots of the actual odour concentrations and the predicted neural network output from each training simulation are shown in *Figs 7.9, 7.10, 7.11* and *7.12*. The correlations between the measured and predicted data were 0.79, 0.84, 0.93, 0.98 and 0.98 for 3, 5, 10, 20 and 30 hidden neurons, respectively. The simulation results were influenced by the number of hidden neurons. The best performance of the ANN was observed in the network using 20 neurons. The results show that the network has an ability to give satisfactory predictions of piggery odour concentration with the data set provided by the electronic nose.

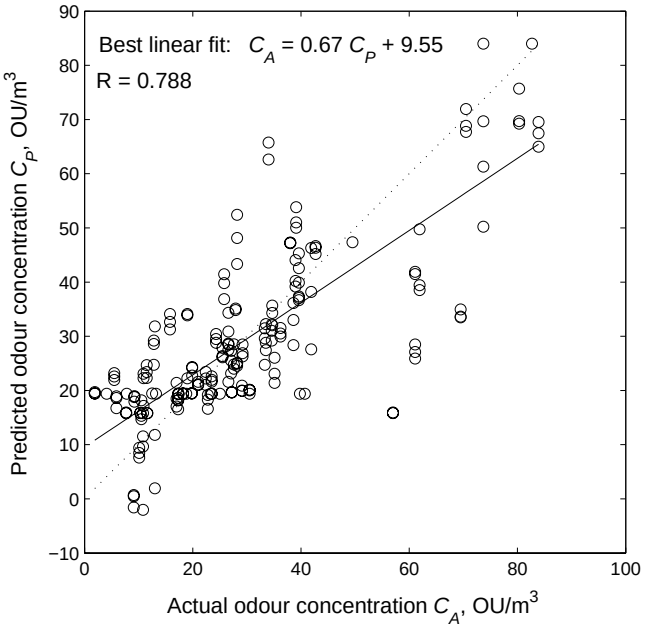


Fig 7.9 The odour prediction results using artificial neural network with 3 hidden neurons: ○, data point; ———, best linear fit; - - - - -, 1:1

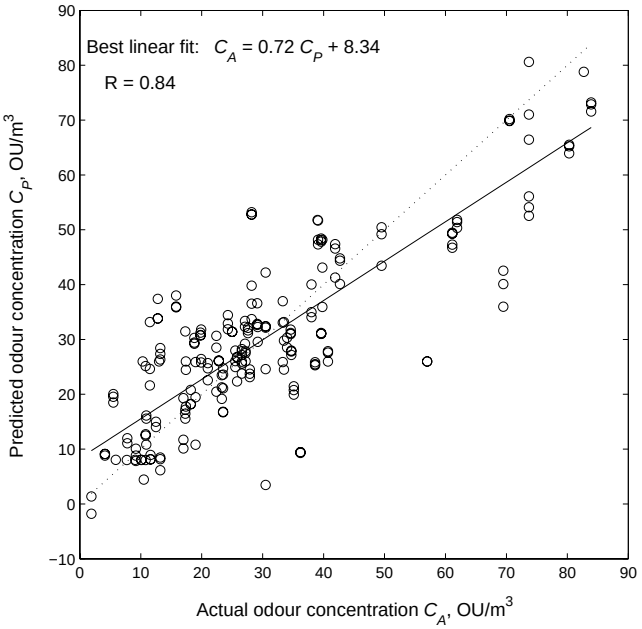


Fig 7. 10 The odour prediction results using artificial neural network with 5 hidden neurons: ○, data point; ———, best linear fit; - - - - -, 1:1

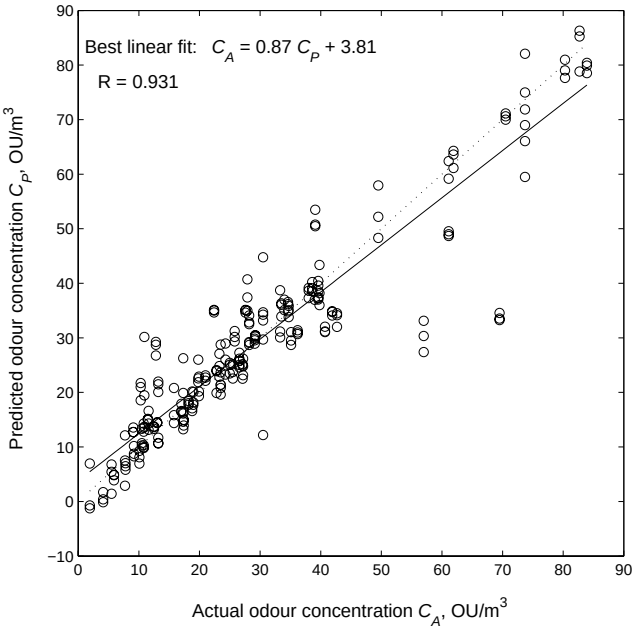


Fig 7.11 The odour prediction results using artificial neural network with 10 hidden neurons: ○, data point; ———, best linear fit; - - - - -, 1:1

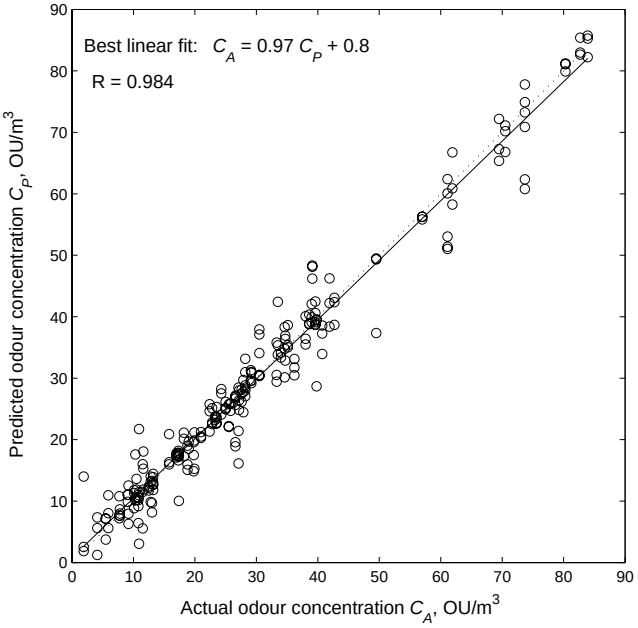


Fig 7. 12 The odour prediction results using artificial neural network with 20 hidden neurons: ○, data point; ———, best linear fit; - - - - -, 1:1

7.3.4 Prediction of the odour concentration with unknown air samples

Nine air samples were collected from effluent pond B in September, 2002 to test the ability of the ANN to predict odour concentrations from electronic nose data. The same sampling methodology was used in the previous trials. The atmospheric conditions, pond loading rate and chemical constituents of the effluent were not measured but it is unlikely that they were the same as in the previous trials.

The odour concentration of each sample was determined by olfactometry as before. As well, three sets of Aromascan responses were taken for each odour sample. The three data sets from each odour sample were used in the trained ANN to predict odour concentrations. The predictions were repeated three times giving nine predictions from each odour sample. **Table 7.5** shows the results of the ANN predictions in the form of an average concentration and range of the predictions.

Table 7.5

The artificial neural network prediction results for effluent pond B.

Sample ID	*Odour concentration, OU/m³*					
	Olfactometry	*AromaScan results using neural network*				*Ratio, %*
		Mean	*Max*	*Min*	*SD**	
1	64.4	78.0	82.4	72.2	3.29	121.1
2	58.8	66.5	69.1	64.1	1.63	113.1
3	45.5	68.8	70.7	66.4	1.58	151.2
4	39.2	11.9	19.4	5.2	4.74	30.4
5	41.2	46.6	49.6	40.6	4.41	113.1
6	44.1	41.1	45.1	36.6	2.78	93.2
7	16.4	18.1	20.7	14.7	1.93	110.4
8	37.0	48.2	52.5	44.6	2.45	130.3
9	14.8	54.1	58.5	51.3	2.52	365.5

*SD, Standard Deviation

The predicted odour concentrations for these samples were consistently higher than the olfactory measurements. The ratio of the predicted to the actual odour concentrations ranged from 30.4% to 365.5%, with an average of 136.4%. The value for the coefficient of determination, r^2 of statistical regression analysis was 0.59. However, the value for r^2 can be improved to 0.92 by excluding samples ID 4 and 9 because most of the error came from these samples. Therefore, except for samples ID 4 and 9, the ANN was able to predict the actual odour concentration of unknown air samples reasonably successfully.

7.4 Chapter summary

In this study, an artificial neural network and the AromaScan A32S, electronic nose, were used to predict the odour concentrations emanating from a piggery effluent pond. The sensor data analysed by an electronic nose was used to train an artificial neural network, and to correlate the responses to the actual odour concentration provided by a human olfactometry panel.

In order to find an optimal model for piggery odour quantification, various preprocessing techniques and network architectures were evaluated through network simulation.

The simulation results showed that the two-layer back-propagation neural network, which has a tan-sigmoid transfer function in the hidden layer and a linear transfer function in the output layer, can be trained to predict piggery odour concentrations correctly with a low mean squared error. The results from the application of scaling and principal component analysis suggest that these preprocessing algorithms are necessary to avoid the failure of the network caused by saturation.

With regard to the early stopping technique for network generalisation, it is possible to provide benefits to network performance in terms of the decrease of computation time and overfitting. It was observed that the optimal number of hidden neurons is 20. The values of the mean square error, gradient and value for r for 20 hidden neurons are 3.06×10^{-3}, 20.33 and 0.98, respectively.

The trained artificial neural network model was able to predict the odour concentration of unknown nine air samples with a value for the coefficient of determination, r^2 of 0.59.

CHAPTER 8
THE USQ WIND TUNNEL

8.1 Introduction

Wind tunnel techniques have been identified as the best available method for the sampling of odour emissions from area sources (Smith & Watts, 1994; Jiang & Kaye, 1996). After Lindvall (1970) used wind tunnel techniques to compare the strength of odour from different areal odour emission sources, a range of wind tunnels has been developed for estimating gaseous emissions. These include determining ammonia emissions from dairy cow collecting yards (Misselbrook *et al*., 1998), from arable land (Loubet *et al*., 1999b), estimating odour emissions from piggeries (Smith & Dalton, 1999), from feedlots (Smith & Watts, 1994; Watts *et al*., 1994), from poultry manure (Jiang & Sands, 1998), from anaerobic piggery pond (Galvin *et al*., 2002), and the effect of permeable covers on anaerobic pond (Hudson *et al*., 2002).

However, there is no standard for the design of wind tunnels. Differences between the various tunnels include the material used in the construction of the tunnel, the length/width ratio, the surface area sampled and the height. Consequently, there are substantial effects on the aerodynamics over the emitting surface. A further complication is the variation in wind speed from one device to another (Smith & Watts, 1994). In addition, most wind tunnels are portable wind tunnel systems, designed for the collection of odour samples from field emission sources (Wang *et al*., 2001). However, these simple tunnels are inadequate for more demanding tasks, such as the precise measurement of the kinetics of odour emissions from liquid effluent.

An ideal wind tunnel for odour sampling work would have the capability to duplicate natural ground level wind conditions in the sampling chamber. This requirement is almost impossible to achieve in a small portable wind tunnel. Therefore, portable wind tunnels have been developed to create an environment where the boundary layer is well developed and convective mass transfer occurs (Bliss *et al*., 1995). The rate at which odour is emitted from liquid effluents derived from intensive animal operation, human sewage and food processing is known to depend on the chemical and microbial characteristics of the effluent, as well as meteorological factors such as wind speed, humidity and temperature (Harper *et al*., 1983; Smith & Watts, 1994a: Smith & Watts, 1994b). However, the currently available portable wind tunnel systems are not able to adequately control these factors.

In addition to this, few studies have been reported on the aerodynamics of the airflow inside wind tunnels. Van Belois & Azion (1992) reported on the wind speed profile inside a tunnel, with important crosswind gradients highlighting the need for a careful analysis of the turbulence inside the tunnel. Moreover, measurements of acetone concentration in the tunnel exhibited strong vertical gradients, suggesting that the design of the sampling system may be of great importance in determining the average concentration downwind of the emitting area (Loubet *et al.*, 1999a).

Loubet *et al.* (1999a, 1999b) evaluated the wind tunnel technique for estimating ammonia volatilisation from land. The wind tunnels were constructed according to the system proposed by Lockyer (1984). The hypothesis that the airflow is completely mixed downwind of the emission plot of a wind tunnel, was tested using a homogeneously distributed CO_2 source. It showed that the vertical profiles of wind velocity and CO_2 concentration were non-uniform in the measurement section of the tunnel. The airflow was far from being completely mixed leading to a recovery rate ranging from 77 to 87%. The research suggested

that an improved sampling system, consisting of a modified duct section with a four branch and 20 point sampling system, could decrease the error due to sampling to a small percentage.

Baldo (2000) compared two different types of wind tunnels. One was the University of New South Wales model, modified and tested by Jiang (1995). The other was the Lockyer hood that is used throughout Europe. The main objective of the study was to map wind speed profile over the emission section. She indicated the parameters that affect the wind speed profile in the tunnels. It includes surface type, tunnel wind speed, entrance characteristics, wind tunnel shape and modifications of tunnel geometry such as flat vanes, fixed inlet duct and baffle.

A novel wind tunnel, with the capability to control factors such as airflow rate, has been developed to measure the odour emissions from liquid effluent for this study. The USQ wind tunnel allows for the emission of odours and other volatiles in an atmospheric transport system under conditions similar to ambient conditions.

In this chapter, the USQ wind tunnel is described and then evaluated in terms of the aerodynamics of the airflow inside the tunnel, and the gas recovery efficiency rate, in order to further improve its performance. These data will also be used to calibrate the odour emission rates measured using the USQ tunnel to provide more reliable data for the further research. Particular attention has been given to the effect of experimental variables such as airflow rate and tracer gas supply rates on the aerodynamics and the gas recovery rates of the tunnel.

8.2 Development of the USQ wind tunnel

8.2.1 Overview of the USQ wind tunnel

The novel wind tunnel was developed for evaluating the kinetics of offensive odour emissions from area sources including liquid effluents. The basic concept of the wind tunnel was based on the much larger emission chamber used at the Silsoe Research Institute in the UK for the measurement of odours and gases from ageing pig waste (Hobbs *et al*., 1999) and for ammonia emissions from slurry (Cumby *et al.*, 1995). However, it was able to be smaller than the tunnel in the UK because odour measurement using an electronic nose requires only 5L of air sample rather than the 150L required for olfactometry analysis.

The wind tunnel was designed to control factors such as wind speed, and the meteorological conditions (temperature and humidity) that directly effect the emission of odours. In addition, as the wind tunnel has modular design, it can be easily modified to achieve specific experimental requirements. After development into fully functional status, the USQ wind tunnel will take the form of a sealed, insulated, recirculating wind tunnel as shown in *Fig 8.1*.

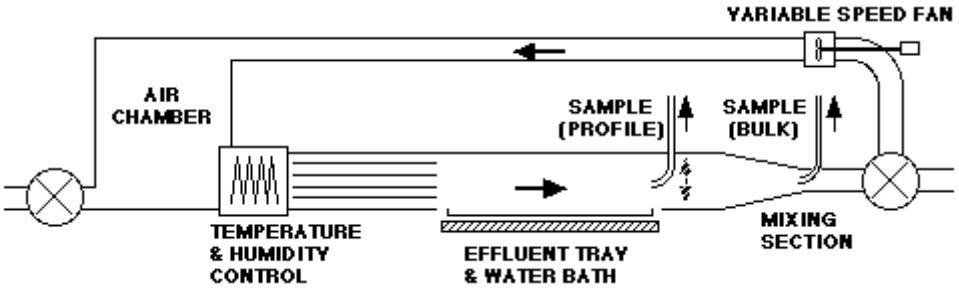


Fig 8.1 Schematic diagram of the USQ wind tunnel configured to recirculate air for conditioning purposes

8.2.2 Design considerations

As the major objectives of the wind tunnel are to have capabilities to control wind speed as well as the meteorological conditions (temperature and humidity), the basic design assumptions for the wind tunnel included the following:

- An air chamber of about 1 m^3 capacity to control temperature and humidity of air;
- A flow establishment/straightening section leading to and of similar dimensions to the emission section to regulate the characteristics of airflow stream;
- An emissions section (0.5 m long by 0.5 m wide and 0.3 m high) designed to be placed over the odour emission source (with a surface area 0.5 m long by 0.5 m wide);
- A tapered mixing section to provide complete mixing of the emissions with the passing air stream;
- Air sampling points at the downstream ends of the emission and mixing sections;
- A fan to recirculate the air with a capacity to produce wind speeds typical of atmospheric conditions (speeds up to 0.5 m/s or flow rates up to 0.03 m^3/s) through the emissions section; and
- Wind speed, the atmospheric conditions of temperature and humidity, and the effluent characteristics (such as volatile solids, temperature and pH) which effect the generation of odour will be precisely controlled.

8.2.3 Construction of the USQ wind tunnel

The wind tunnel has an emission section of 0.25m^2, the dimensions of which are 0.5m long by 0.5m width. The tunnel is rectangular in cross-section and 0.5m high. Air is drawn into the tunnel by a variable speed axial-type vent fan connected to the upper part of wind tunnel. A flow establishment/straightening module leads to the emission section. A tapered mixing section provides mixing of the emissions with the passing air stream. There is an air sampling port at the

downstream ends of the emission and mixing sections. The axial-type fan is capable of producing wind speeds typical of atmospheric conditions (wind speeds up to 0.5m/s or flow rates up to 0.03m^3/s) through the emission section. The wind tunnel and all accessories were manufactured from food-grade stainless steel. The USQ wind tunnel facility and odour sampling work are shown in *Fig 8.2*. This facility is constructed on the field experimental station of USQ.

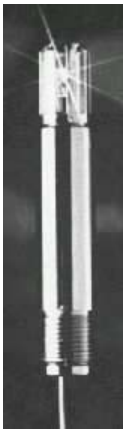
(a) The USQ wind tunnel facility

(b) *Variable speed fan and odour sampling*

Fig 8.2 The USQ wind tunnel facility and odour sampling work

Sensors and a fan speed controller installation

Temperature and relative humidity can be measured simultaneously at the inlet and outlet using the HUMITTER® 50U/50Y(X) integrated humidity and temperature transmitter. A data logger, ADAMS 4000®, is used to collect these data. A TECO-Westinghouse® variable controller is used as a speed controller of the fan, SPEEDLOCK® AF-300-304 S/S. Sensors and a data-logger are shown in *Fig 8.3*. The variable speed fan and a fan speed controller are depicted in *Fig 8.4*.



(a) *Integrated humidity and temperature transmitter*

(b) *Data logger, ADAMS 4000*

Fig 8.3 Sensor and data-logger installed in the tunnel

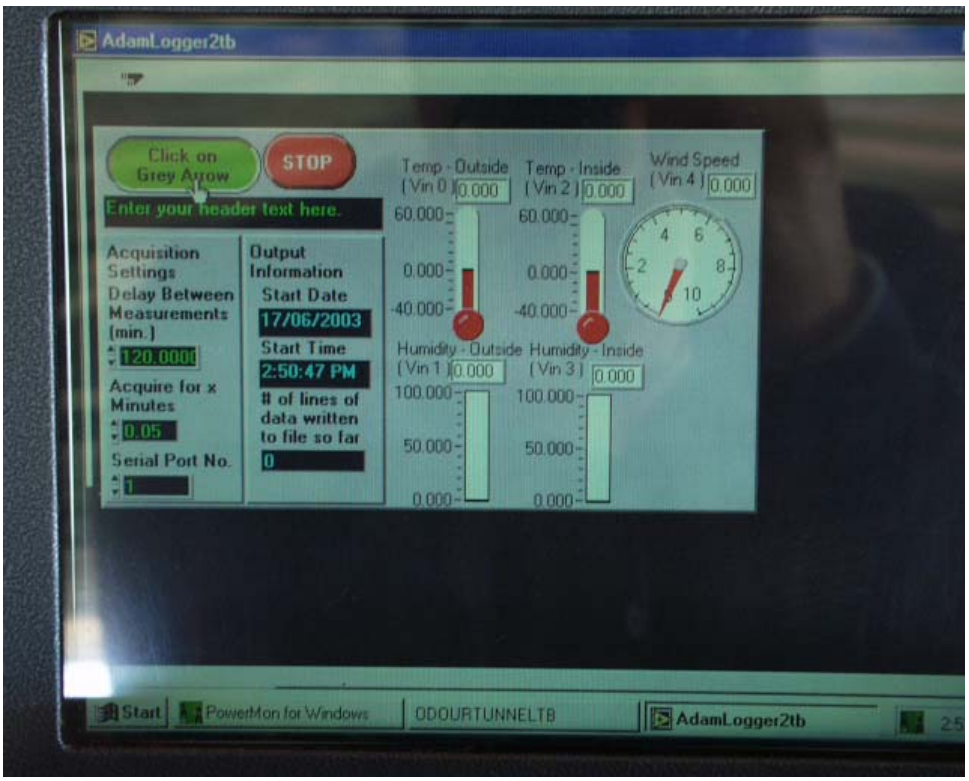
(a) Variable speed axial type vent fan

(b) *Fan speed controller*

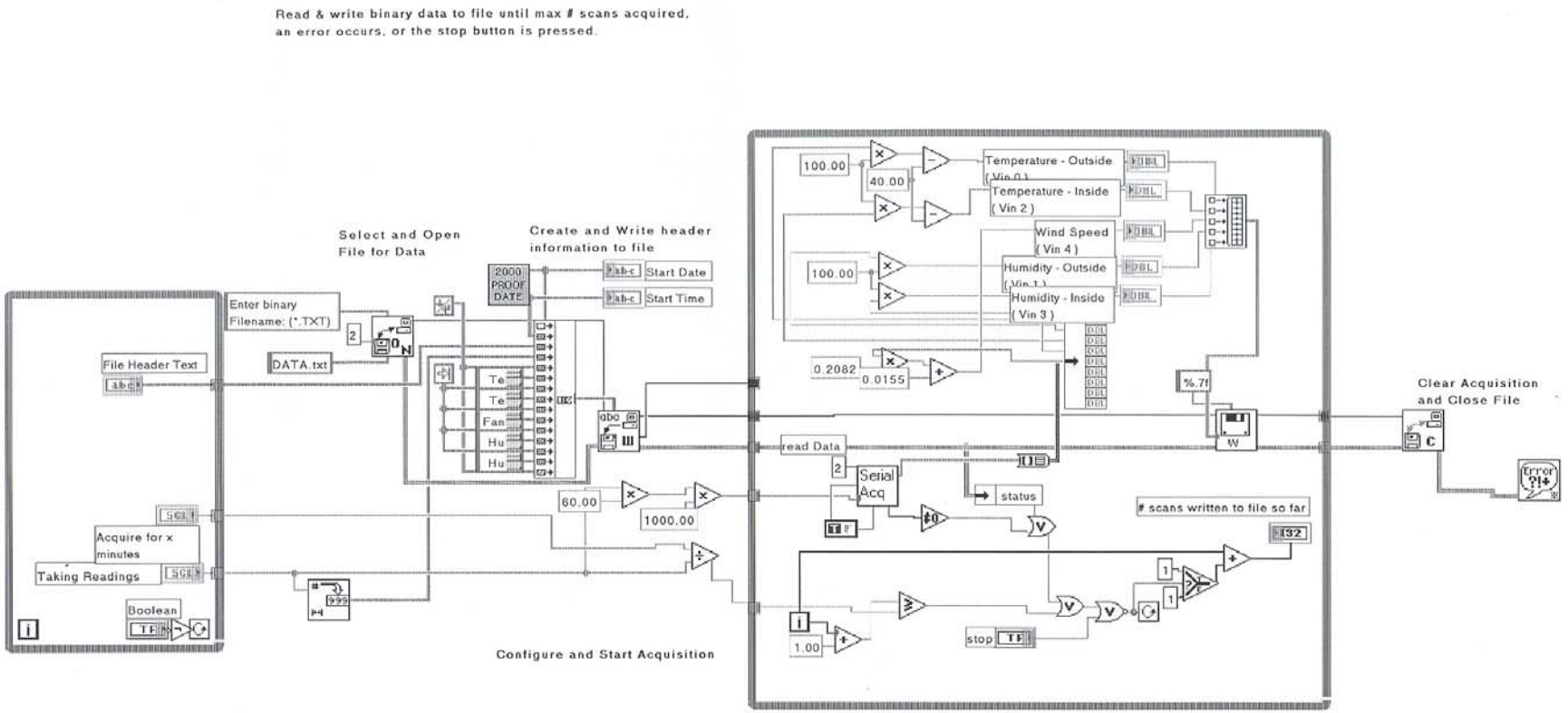
Fig 8.4 The variable speed fan and a fan speed controller installed in the tunnel

Operating software development for monitoring of the USQ wind tunnel

Operating software was developed for real-time monitoring of the tunnel and data logging using a scientific graphical user interface (GUI) language tool, Labview Ver. 5.1. It shows the wind speed, relative humidity and temperature of air at inlet and outlet locations on the front panel of the software. The front panel and block diagram for the operating software for the USQ wind tunnel made by Labview 5.1 are shown in *Fig 8.5*.



(a) Front panel of the software



(b) *Block diagram*

Fig 8.5 The front panel and block diagram for the operating software of the tunnel programmed with Labview™ 5.1

8.3 Experimental evaluation of the wind tunnel

8.3.1 The USQ wind tunnel

The USQ wind tunnel was used in this study. The aerodynamics of the airflow inside the tunnel and the gas recovery efficiency were evaluated for further improvement of the performance of the tunnel. The tunnel was operated in non-recirculating mode under different airflow rates. The functions controlling the atmospheric conditions of temperature and humidity were not applied for this research work.

8.3.1.1 Sampling points for wind speed profile measurements

As the USQ wind tunnel has the shape of a rectangular duct, the locations of points for wind speed sampling were selected by the standard method of the Australian Standard 4323.1. The sampling plane is divided into equal areas by imaginary lines, which are parallel to the side of the duct. A sampling point is to be located at the centre of each such area which is shown in *Fig 8.6*. If the lengths of the sides of the sampling plane, *L* and *l*, are divided into *N* parts and n parts respectively, the number of sampling points will be $N \times n$ and the smallest distance from a wall of the duct to a sampling point will be $L/2N$ and $l/2n$ (Australian Standard4323.1: Stationary source emission, 1995). An example of this procedure is also shown in *Fig 8.6.* The vertical and horizontal sampling point distances applied for this research work are presented in **Table 8.1**. In total, there are 25 sampling points which are located at the centre of the emission section of the tunnel.

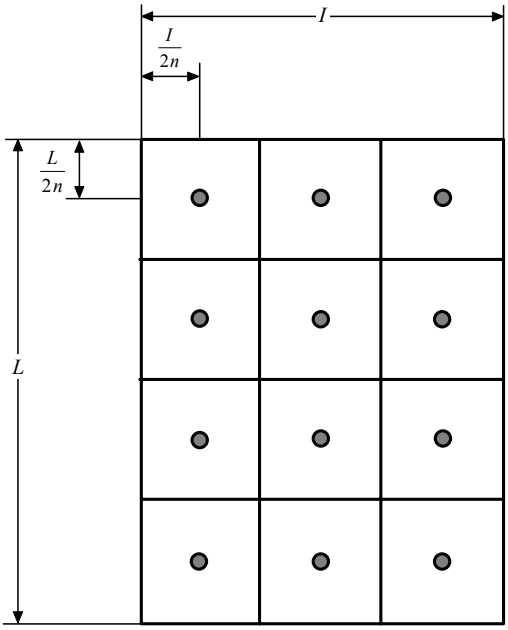


Fig 8.6 Sampling point positions in rectangular and square ducts (reproduced from AS 4323.1, 1995)

Table 8.1

Vertical and horizontal distances for sampling points

Horizontal Distances (m)	*Vertical Distances (m)*
0.08	0.05
0.17	0.10
0.25	0.15
0.33	0.20
0.42	0.25

8.3.1.2 Sampling port for gas recovery efficiency measurements

For gas recovery efficiency measurements, data initially were derived from samples collected using a one point sampling port installed in the end of the mixing section of the tunnel. The measured sample recovery efficiency ranged between 20.0% to 81.3%.

Subsequently, a modified sampling port with four branches and five sampling holes per branch was applied to the USQ wind tunnel. The 20 sampling points are quadratically spaced across the sampling port. According to the numerical simulation test carried out by Loubet *et al.* (1999a), this type of sampling port showed a theoretical sample recovery efficiency of 100.4%.

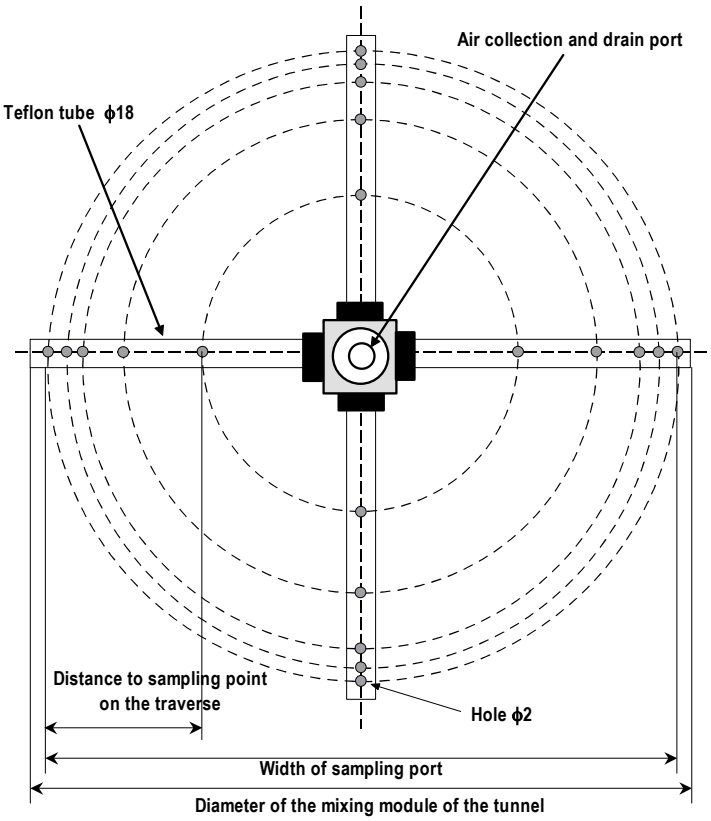


Fig 8.7 The schematic diagram of sampling port with four branches and quadratically spaced five sampling holes per branch

8.3.2 Experiments

Four experiments were undertaken concurrently:

Experiment 1: Identify the effect of surface type on the aerodynamic characteristics of the tunnel.

Two different types of surface, a solid surface with different roughness heights and a liquid surface, were applied to the tunnel and their effect on aerodynamic characteristics including wind speed profile, turbulent intensity, and gas concentration profile were examined. To represent a solid surface, a foam mattress with various roughness heights was used to simulate actual conditions. Roughness heights varied between 5 and 25mm (Hancock & Smith, 1994; Baldo, 2000). For the liquid surface, the liquid piggery effluent contained in pond simulating reactor vessel was used.

Experiment 2: Identify the effect of airflow rate on the aerodynamic characteristics of the tunnel.

As the tunnel has the capability to control airflow rate using a variable speed fan, a series of trials was performed to identify the relationship between airflow rates and the aerodynamic characteristics. The tunnel was operated at five different airflow rates, ranging from 0.001 to 0.028m^3/s.

Experiment 3: Identify the effect of sampling port design on gas recovery efficiency.

Two different types of sampling ports were tested for their effect on gas recovery efficiency. Initially, a simple one-point sampling port was installed centrally at the end of the mixing section and evaluated. Later, a new sampling port with four branches and five quadratically spaced sampling holes per branch, was installed in the tunnel and evaluated.

Experiment 4: Determine the effect of airflow rate and CO supply rate on gas recovery efficiency of the tunnel.

The effects of airflow rate and gas supply rate on gas recovery efficiency rate were tested. Five different airflow rates, ranging from 0.001 to 0.028m^3/s, were applied to this experiment 4. The gas supply rates were 2.5, 5.0, 7.5 and 10.0 litre/min respectively.

In experiments 3 and 4, pure carbon monoxide gas was introduced from a cylinder into the tunnel through perforated tubes. Four tubes were laid out under the testing module of the tunnel in parallel rows. Each tube had 50 tiny holes per metre to provide homogeneous gas emissions to the tunnel. A gas regulator and a visual flowmeter were

used to control the CO supply rate. The basic concept of the carbon monoxide injection system was based on the similar system used for estimating ammonia volatilization from land (Loubet *et al.,* 1999a).

8.3.3 Measurements

Temperature and relative humidity

Temperature and relative humidity were measured simultaneously at the inlet and outlet of the tunnel using an integrated sensor unit. These parameters were monitored by the operating program which is addressed in section 8.2.3. Each measurement was made over a 900s period at a sample rate of 20Hz. A data logger was used to collect these data.

Carbon monoxide concentration

The CO concentration in samples collected from the sampling port was measured with the 300E gas filter correlation CO analyser at a frequency of 10Hz. Air was continuously sampled at the sampling port and drawn to the analyser through polytetrafluoroethylene (PTFE) tubes. The analyser was regularly calibrated with two reference standard CO gases at 206 and 1000 ppm. The detection limit was 0.04ppm. Linearity was better than 1% full scale for CO concentrations greater than 10ppm, and better than 0.2ppm for lower concentrations. The precision was 0.5% of the value read.

Wind speed

The wind speed was measured with a Velocicalc® velocity meter. The wind velocity meter was regularly calibrated by the supplier. It was located as described in section 8.4.1.1 for the vertical wind speed profiles and cross-sectional wind speed profiles. For the gas recovery efficiency trials, the probe was placed in the middle of the testing section of the tunnel as a reference. The results were compared with the data derived from the wind speed profiles and turbulence intensity profiles to calculate airflow rates. The air temperature data was corrected by a factor of T/294.55 under a standard temperature and pressure condition to obtain actual wind speeds, where T is the air

temperature in °K. Absolute accuracy was 1% of full-scale, which corresponded to 0.01m/s.

Standardisation of airflow rate

The volume airflow rate at standard conditions (0 °C and 101.3kPa) was then calculated in accordance with ISO 10780 using equation 8.1 (modified from AS4323.1, 1995)

$$\overline{Q}_{R,0} = \overline{Q}_s \times \frac{(273+0)}{(273+t)} \times \frac{P_s}{101.3} \tag{8.1}$$

where, $\overline{Q}_{R,0}$ is the volume airflow rate at standard conditions (0 °C and 101.3kPa), m^3/s; P_s is the absolute pressure in the tunnel, kPa; $\overline{Q}_s$ is the mean volume airflow rate through the tunnel, m^3/s; and t is the tunnel temperature, °C.

Turbulence Intensity

The turbulence intensity, I is defined by two variables: the fluctuating components of wind speed v' and the mean wind speed in the profile $\overline{V}$. v' is defined as:

$$v' = \overline{V} - V \tag{8.2}$$

Using the equation 8.2, the turbulence intensity is defined as:

$$I = \frac{\sqrt{\overline{v'^2}}}{\overline{V}} \tag{8.3}$$

Gas recovery efficiency rate

The recovery rate of the tunnel was calculated using the equation 8.4 (modified from Loubet *et al.,* 1999a).

$$\alpha = \left(\frac{\overline{Q}}{A_{exp}} \right) \cdot \left(\frac{\overline{C}_m}{\Phi_{exp}} \right) \tag{8.4}$$

where, α is the recovery rate of the sampling system; $\overline{Q}$ is the mean volumetric airflow rate through the tunnel, m^3/s; A_{exp} is the experimental area covered by the tunnel, m^2; C_m is the measured average concentration in the measurement section, kg/m^3; Φ_{exp} is the CO emission rate emitted from the ground of the testing section, kg/m^2s.

8.4 Results and discussion

8.4.1 Wind speed profiles

The mean vertical wind speed profiles were measured at the centre of the emission section of the tunnel for the solid surface and for the liquid surface respectively. The results are presented in *Fig 8.8* and *Fig 8.9* as a function of height (z).

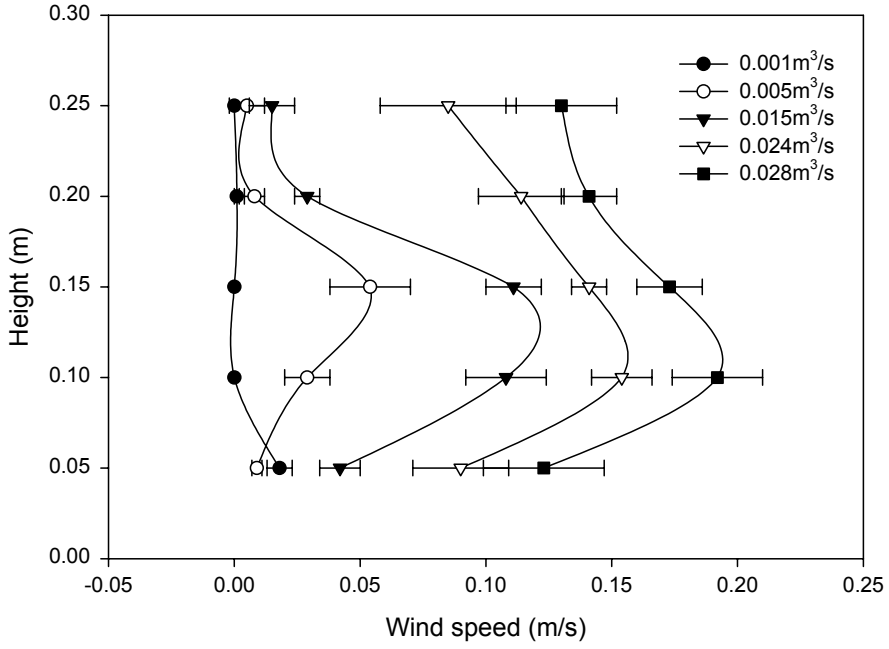


Fig 8.8 Mean wind speed profiles over the solid surface for various airflow rates

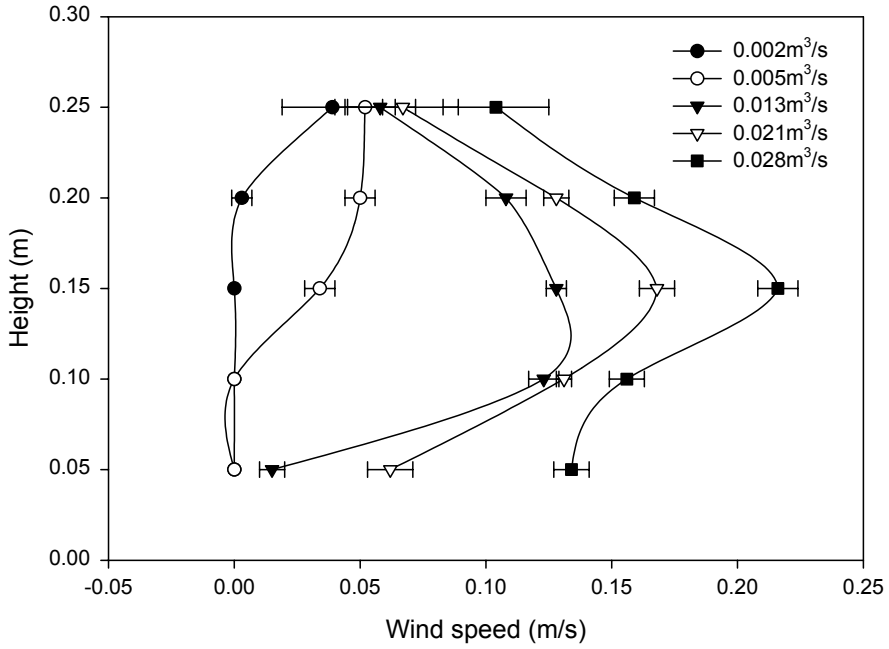


Fig 8.9 Mean wind speed profiles over the liquid surface for various airflow rates

As shown in *Fig 8.8* and *Fig 8.9*, while the airflow rate was increasing, the vertical wind speed was increasing accordingly. However, the vertical profiles of wind speed are not uniform regardless the airflow rate. For all of the higher airflow rates, there was a pronounced peak in the profile at about 0.1m above the bottom of the emission section for the solid surface and 0.15m for the liquid surface, respectively. The lowest velocity was usually recorded at the bottom of the emission section and the vertical profiles exhibited a logarithmic shape near the tunnel walls. Moreover, it was observed that for any given airflow rate, the peak speed over the liquid surface was higher than over the solid surface.

Both sets of profiles indicated incomplete development of the flow, caused by an insufficient straight length of ducting prior to the sampling section. The difference between the profiles for the solid and liquid surfaces is due to the different surface roughness.

In order to examine the cross-sectional air flow distribution, contour plots were made of the wind speeds collected from 25 sampling points. The contour plot for the cross-sectional wind speed profile over the solid surface is shown in *Fig 8.10.* The profiles for the liquid surface are plotted in *Fig 8.11*.

As well as the wind speed variation in the vertical direction, these profiles show a considerable variation in velocity across the width of the tunnel. In each case, two zones of high wind speed are observed near the centre of each half of the cross section. Again this reflects the inadequate performance of the flow straightening and flow development section of the wind tunnel.

Differences between the lateral wind speed profiles for the two surfaces were not significant except for the higher peak velocities over the liquid surface as mentioned previously.

In order to get a more evenly distributed airflow profile, the installation of a perforated baffle (Wang *et al.*, 2001; Baldo, 2000; Jiang & Kaye, 1996) upstream of the sampling section could be one option to improve the overall aerodynamic performance of the tunnel.

As will be discussed in section 8.4.5, the non-uniform velocity profile could be one cause of reduced gas recovery efficiencies. Therefore, modifications including increasing the wind speed with a higher speed fan, baffle installation and narrowing of the testing module to increase wind speed may be required to improve the performance of the USQ wind tunnel.

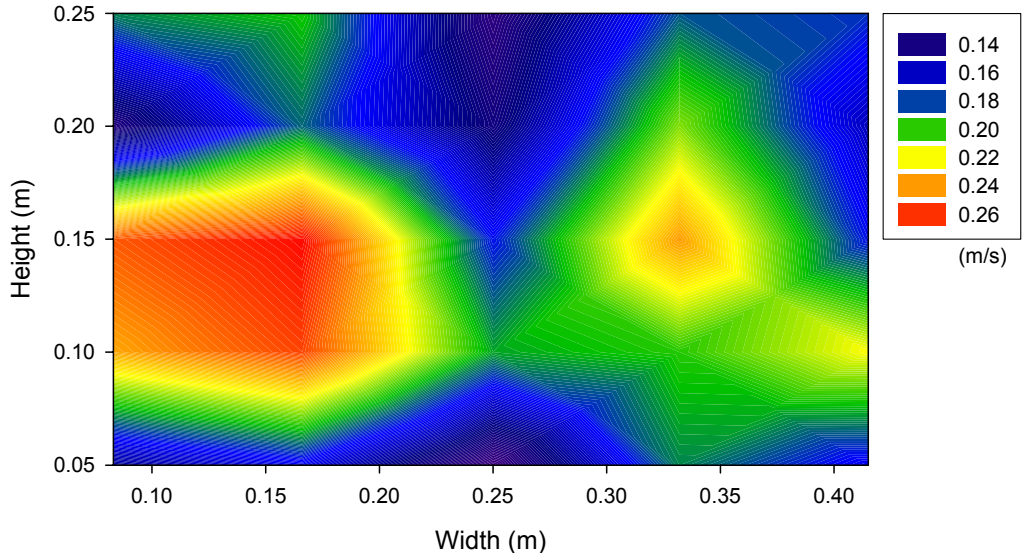


Fig 8.10 Cross-sectional wind speed profiles over the solid surface (airflow rate, $0.028m^3/s$)

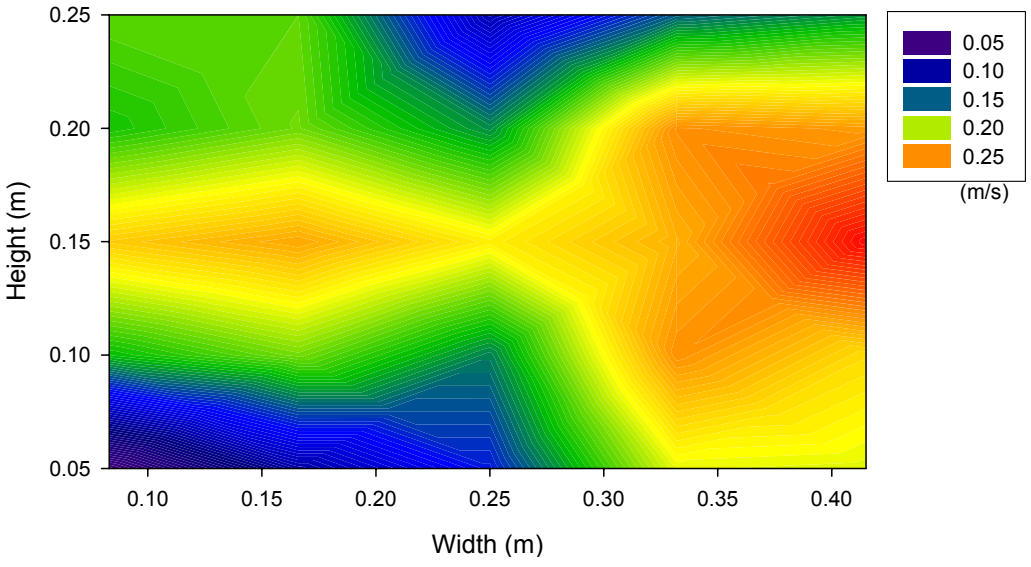


Fig 8.11 Cross-sectional wind speed profiles over the liquid surface (airflow rate, $0.028m^3/s$)

8.4.2 Turbulence intensity profiles

The turbulence intensity profiles over the solid surface and the liquid surface are shown as a function of height in *Fig 8.12* and 8.13, respectively. As with wind speed, the vertical profiles of turbulence intensity are not uniform regardless of the airflow rate and surface type. In fact, the turbulence intensity shows a strong inverse relationship with velocity. The highest intensity is located where velocity is lowest, that is, close to the wall of the wind tunnel.

It was observed that the peak turbulence intensity over the liquid surface is higher than for the solid surface for the same fan speed stage. The turbulence intensity profiles are similar to those reported by Loubet *et al.* (1999a). Loubet *et al.* (1999a) also indicated that Laufer (quoted in Hinze, 1959) presented similar results for turbulent flow in a cylindrical duct.

Reynolds numbers above 1×10^4 are associated with turbulent flow. The Reynolds number is defined as:

$$\mathrm{Re} = \frac{LV\rho}{\nu} \qquad (8.5)$$

where, *Re* is the Reynolds number; L is the characteristic length of the duct, m; V is the wind speed in the duct of the wind tunnel, m/s; ρ is the density of the air, kg/m^3; υ is the dynamic viscosity of the air, kg/ms.

The dynamic viscosity of air at 20 °C is about 1.8×10^{-5} kg/ms. Hence, the Reynolds number was estimated to 1.4×10^4 in this wind tunnel. Therefore, the airflow inside the duct is revealed to be turbulent flow. However, this number is lower than the Reynolds number of between 3×10^4 and 9×10^4 presented by Loubet *et al.* (1999a) for their wind tunnel.

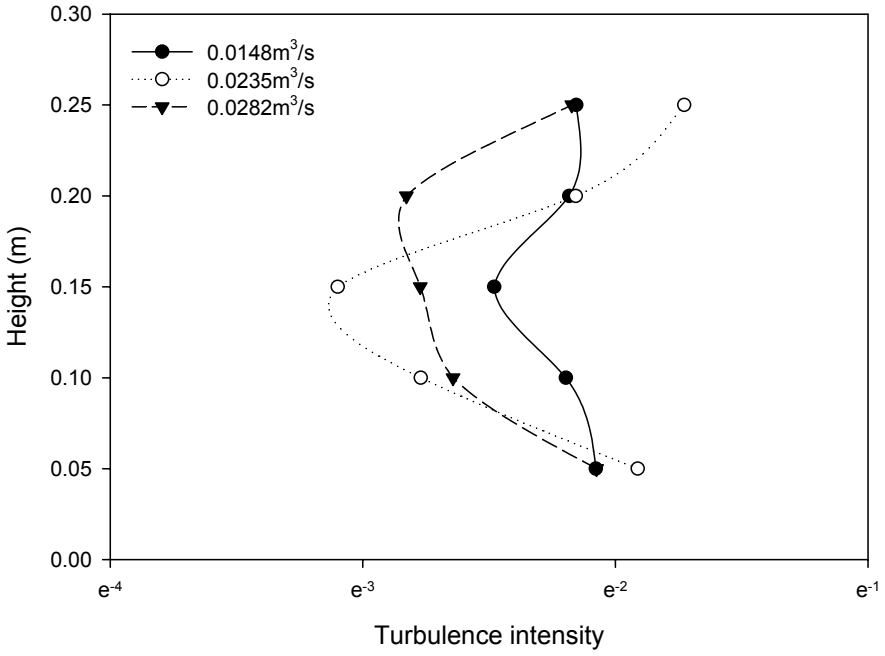


Fig 8.12 Turbulence intensity profiles over the solid surface

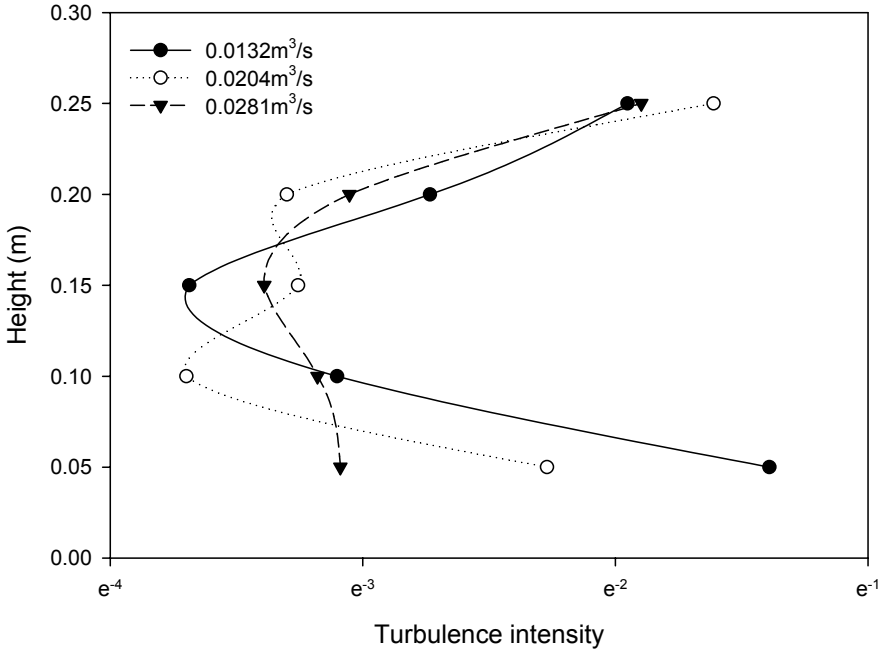


Fig 8.13 Turbulence intensity profiles over the liquid surface

8.4.3 Gas concentration profiles in the testing section of the tunnel

The result of the trial to reveal gas concentration profiles is presented in *Fig 8.14*. The gas supply rate applied in the trial was 5 L/min. The trial was done over the solid surface, with the gas concentration profiles measured within the sampling section of the tunnel.

In order to get normalized gas concentration, the mean volumetric concentration increase in a section of the tunnel $\overline{C}_{inc}$ is calculated as the ratio of the CO volumetric flow injected into the tubes Q_{CO}, to the volumetric airflow in the tunnel Q (modified from Loubet *et al*., 1999a):

$$\overline{C}_{inc} = \frac{Q_{CO}}{Q} \tag{8.6}$$

The normalized concentration is then defined as the ratio of the concentration at a given position C_Z minus the background concentration C_B to the mean concentration increase $\overline{C}_{inc}$ in the same cross-section:

$$C_{norm} = \frac{\left(C_Z - C_B\right)}{\overline{C}_{inc}} \tag{8.7}$$

It is observed that the normalized concentration profiles showed a strong asymmetry, with much greater concentration at the bottom. However, the normalized concentration profiles were very similar for the five different airflow rates. These results are similar with the gas concentration profiles of a conventional wind tunnel, which was reported by Loubet *et al*. (1999a). They indicated that the asymmetric shape would likely be independent of the wind speed in the tunnel, for a given geometric configuration of the experimental area.

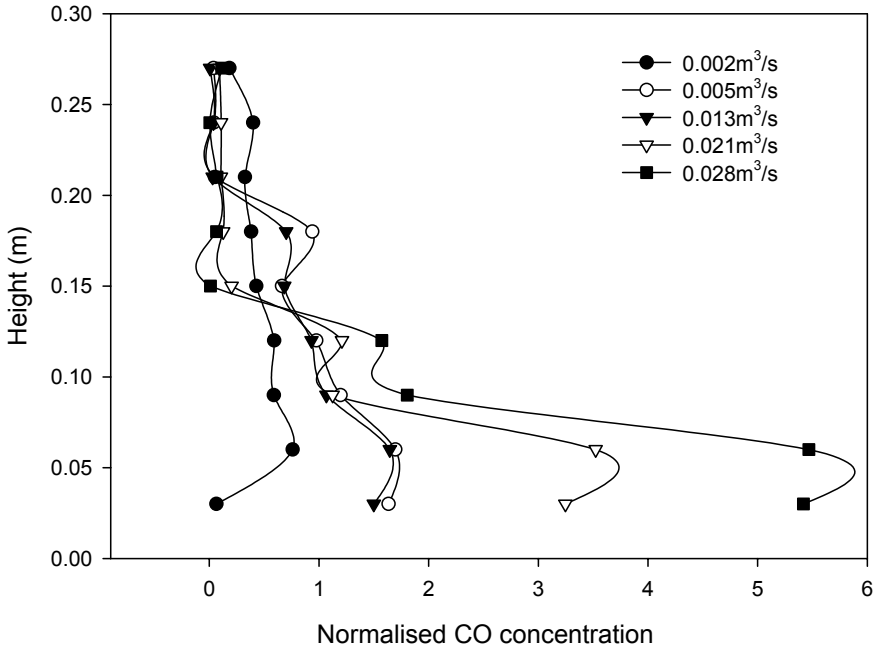


Fig 8.14 Normalised gas concentration profiles over the solid surface with 5 L/min CO supply rate

8.4.4 Effect of sampling port design on the gas recovery efficiency

The results of experiment 3 regarding the sampling port design are summarised in **Table 8.2** and *Fig 8.15*. When the CO gas was supplied at a rate of 5.0 L/min, the sample recovery efficiency using the one point sampling port ranged between 20.0 % to 81.3 %. The mean±sd recovery efficiency was 49.0±28.9 %. In contrast, the 20-point integrated sampling port, produced a mean±sd recovery efficiency of 71.4±10.7 %. The range of recovery efficiency was 63.6 to 89.7 %. It is proposed that this improvement was mainly due to the number of sampling points and the hole distribution. Loubet *et al*. (1999a) reported 'simulated' recovery efficiencies of a 1-point and a 20-point sampling port (with a linear distribution) of 61 % and 89 % respectively. In addition, the 20-point sampling port with a quadratic distribution showed 100.4 % efficiency. The reason is due to the number of sampling points per unit area. For the linear distribution of sampling points,

the number of sampling points per unit area will decrease with distance to the centre of the duct, whereas in the case of a quadratic distribution, it remains constant.

Table 8.2

Experimental results for wind tunnel sampling system between one point sampling port (port A) and 20-point four branched sampling port with quadratic (port B).

	Port design	*Airflow rate*	*CO supply rate*	*Inlet CO*	*Theoretical CO*	*Measured CO*	*Recovery efficiency*
		(m^3/s)	*(l/min)*	*(ppm)*	*(ppm)*	*(ppm)*	*(%)*
Test 1	A	0.001	5.0	15450	14.24	2.85	20.0
	B					9.30	65.3
Test 2	A	0.005	5.0	15450	4.02	0.68	16.8
	B					2.68	66.6
Test 3	A	0.015	5.0	15450	1.27	0.79	61.9
	B					0.91	71.9
Test 4	A	0.024	5.0	15450	0.78	0.51	65.2
	B					0.51	63.6
Test 5	A	0.028	5.0	15450	0.67	0.54	81.3
	B					0.59	89.7

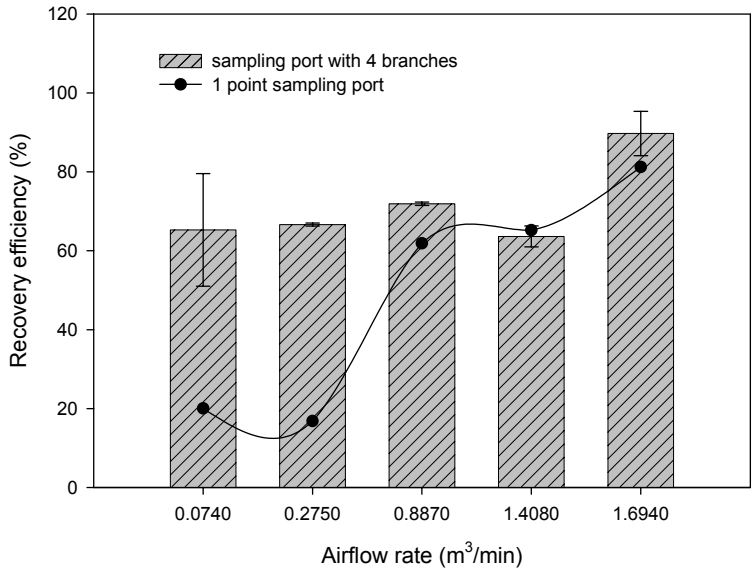


Fig 8.15 Sample recovery efficiency rates between one point sampling port and 20 point four branched sampling port with quadratic

8.4.5 Effect of airflow rate and gas supply rate on gas recovery efficiency

The results of experiments regarding the relationship between airflow rates and gas supply rates are presented in *Fig 8.16*. The results reveal gas recovery efficiencies for individual tests ranging from 61.7 to 106.8%, while the average result for the entire data set was 81.1%.

With regard to the airflow rate, it was observed that the optimal sample recovery efficiency was 88.9±3.96% at an airflow rate of 0.028m^3/s. This optimal recovery efficiency is similar to or higher than efficiencies reported in other studies using different wind tunnel systems. Other researchers reported recovery efficiencies in a range from 70% to 103% under varying tunnel geometry and operating condition (Mannheim *et al*., 1994; van der Weerden *et al*., 1996; Reitz *et al*., 1997; Loubet *et al*., 1999; Wang *et al*., 2001).

At the airflow rate of 0.015m^3/s, the tunnel showed the highest efficiency rate of 95.0±15.86%. However, it included overestimated CO concentrations of 106.8 and 103.6% as well as high variability. It is proposed that this was due to inadequate mixing and dispersion of CO within the air stream.

Sample recovery efficiencies at gas supply rates of 2.5, 5.0, 7.5 and 10.0 litre/min were 80.4 ± 17.28%, 71.4 ± 10.68%, 80.8 ± 13.54% and 91.5 ± 9.94% respectively. The results suggest that the estimated emission rates are closely related to the uniformity of odour concentration profile and hence, degree of mixing developed inside the tunnel. Therefore, non-uniform odour concentration profiles caused by low emission rates will have negative effects on the sample recovery efficiency rate of the wind tunnel. In addition, some leakage of CO gas was observed through the joints between sections of the tunnel. It could be another cause of errors

The results of this study suggested that the developed wind tunnel will give estimates of the odour emission rate with significant level of precision. However, the wind tunnel

needs to be calibrated to compensate for the different recovery efficiencies caused by different airflow rates and odour emission rates. In order to get more reliable and repeatable results, improvements to the wind tunnel in terms of aerodynamics and boundary layer effect will be required.

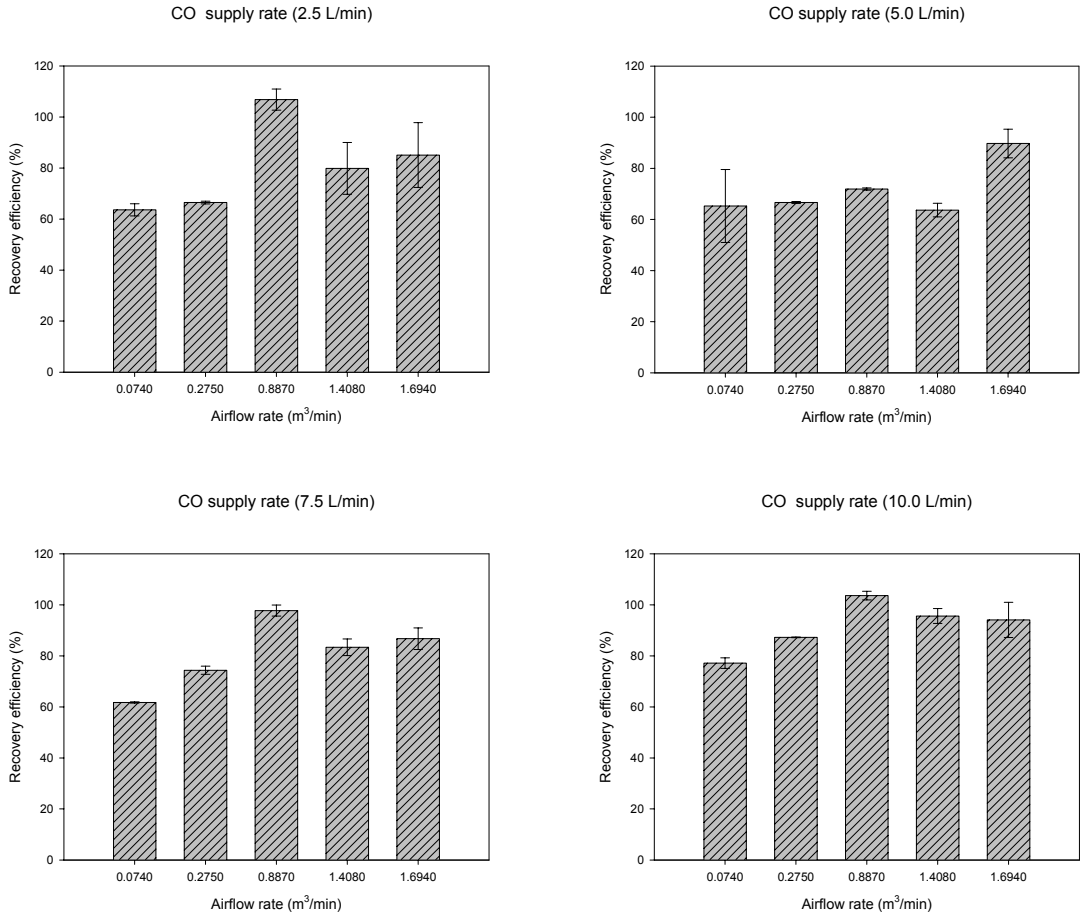


Fig 8.16 Sample recovery efficiency rates between different airflow rates and gas supply rates

8.5 Chapter summary

In this chapter, a novel wind tunnel was developed with the capability to control wind speed and airflow rate. Later, it will also be able to control other meteorological factors, such as humidity and temperature. The USQ wind tunnel was evaluated in terms of the aerodynamics of the airflow inside the tunnel, and the gas recovery efficiency rate, in order to further improve the performance of the wind tunnel. Conclusions are made from the results of this evaluation.

While the airflow rate increased, the vertical wind speed was increasing accordingly. However, the vertical profiles of wind speed are not uniform regardless of the airflow rate. Wind profile results indicated incomplete development of the flow, caused by an insufficient straight length of ducting prior to the sampling section. The difference between the profiles for the solid and liquid surfaces is due to the different surface roughness.

Cross-sectional wind speed profiles results showed a considerable variation in velocity across the width of the tunnel. Two zones of high wind speed were observed near the centre of each half of the cross section. This reflects the inadequate performance of the flow straightening and flow development section of the wind tunnel. Therefore, the installation of a perforated baffle upstream of the sampling section was suggested to get more evenly distributed airflow profiles.

From the results of turbulent intensity profiles, the Reynolds number was estimated between 4.11×10^3 and 7.80×10^3 in the USQ wind tunnel under the current configuration. Therefore, the airflow inside the duct is revealed to be turbulent flow;

The developed wind tunnel showed that sample recovery efficiencies ranged from 61.7 to 106.8 %, while the average result from the entire test was 81.1 %. The optimal sample recovery efficiency of the tunnel was observed to be 88.9 % from statistical analysis. The values of airflow rate and gas supply rate corresponding to the optimal sample recovery efficiency were 0.028 m^3/s and 10.0 litre/min respectively.

It can be suggested that the wind tunnel will give estimates of the odour emission rate with a significant level of precision. However, the wind tunnel needs to be calibrated to compensate for the errors caused by different airflow rates and odour emission rates.

CHAPTER 9
EFFECTS OF POND LOADING RATES ON ODOUR EMISSIONS

9.1 Introduction

The odour emissions from effluent treatment ponds have been defined as a main contributor of the nuisance to neighbours in the piggery industry. In order to solve this problem, the first step is to quantify the emission rates of odour from effluent ponds. Current methods for estimating odour nuisance use standard emission rates that do not take into account the effect of loading rates and effluent characteristics. Consequently, there is considerable difference between estimated and real measured values.

Appropriately designed and well-managed ponds produce a lower odour than overloaded and undersized ponds, but there are few data to corroborate this perception. A more complete data set of gross odour emission rates and effluent characteristics are required for a range of piggery effluent treatment ponds to assist in the planning process of new and expanding piggery developments. Also required are easy-to-measure indicators of pond condition and the likelihood of odour emissions. Allied to this is the need for a convenient and low cost method of odour measurement, using the electronic nose and newly emerging pattern recognition techniques like an artificial neural network.

An experimental facility consisting of reactor vessels to simulate the operation of effluent ponds and the USQ wind tunnel for odour sampling was developed. The USQ wind tunnel is described in Chapter 8. The machine-based odour quantification technique using the AromaScan and ANN was also developed. This odour quantification technique is presented in Chapter 7.

The purpose of this chapter is to establish the relationship between pond loading rate and odour emission rate through replicable experimental studies using an experimental facility and the machine-based odour quantification technique.

9.2 Experimental design

Two experiments have been conducted to investigate the effect of key variables such as organic loading rate (OLR) and hydraulic retention time (HRT) on odour emission rate. The experimental methodology and operation of the experimental facility were modified slightly for each experiment. A brief summary of the two main experiments is outlined in **Table 9.1**.

Table 9.1
The summary of experimental design

	Experiment	
	Exp. 1	*Exp. 2*
Variable 1	OLR[1]	OLR
Variable 2	HRT[2] (30 days)	HRT (60 days)
Materials	Piggery effluent	Piggery effluent
Operation periods	12 months	6 months
Season	4 seasons	Summer-Autumn
Temperature	8 – 25 °C	25 – 15 °C
Odour measurement	Aromascan A32s	Aromascan & Olfactometry

1. OLR: organic loading rate
2. HRT: hydraulic retention time

9.2.1 Determination of organic loading rate

As the most common method for designing anaerobic treatment ponds is the Rational Design Standard (RDS), it was applied to determine standard VS loading rate for the reactor vessels. This standard was developed by Barth (1985) and is based on 3 requirements (FSA environmental, 2001):

- Control of pond odour.
- Allowance for sludge accumulation.
- Maintenance of a minimum treatment volume

Since climate has a large effect on the biological activity of a pond, anaerobic activity within piggery ponds is reduced with lower average ambient temperatures. The volatile solids (VS) loading rate is adjusted using a factor (*k*), which varies according to piggery location. Higher average ambient temperatures in an area give a higher optimum pond loading rate. The standard VS loading rate (100g VS/m³day) is multiplied by the temperature dependent *k* factor to calculate the minimum required active volume of a pond as shown in equation 9.1.

$$VOL_A = \frac{VS_L}{k \cdot 100} \tag{9.1}$$

where, VOL_A is the active volume of the effluent pond, m^3; VS_L is the volatile solid loading rate, g/day; *k* is the temperature factor according to piggery location, g/m³day.

Not all the solids that enter the pond are degradable. Approximately 20% of the solids in fresh piggery waste are fixed (ash) and are not degradable. The rate at which solids accumulate in the bottom of the pond is expressed in the term of the sludge accumulation rate (*SAR*). This is generally measured as a volume per kg of total solids (TS) added. Although the most widely accepted *SAR* figure is 0.00303 m³/kg of TS added (Barth, 1985), this figure is regarded in Queensland as being an over-estimate of *SAR*, with measured SAR for piggeries in southern Queensland being lower than this. The research by Anderson *et a*l. (2000) obtained an accurate estimate of the sludge volume in an anaerobic pond after 15 years continuous use. The figure they obtained was found to be 79% lower than the sludge volume estimated using the ASAE method (FSA environmental, 2001).

For the calculation of the required volume for sludge, equation 9.2 can be used:

$$VOL_s = TS_L \cdot SAR \cdot L_P \tag{9.2}$$

where, VOL_s is the sludge volume in the effluent pond, m^3; TS_L is the total solid loading rate, kg/year; SAR is the sludge accumulation rate in pond, m^3/kg; L_P is the pond life, year.

The minimum required active volume is added to the sludge volume to give a total required pond volume (VOL_T) as shown in equation 9.3.

$$VOL_T = VOL_A + VOL_S \tag{9.3}$$

The RDS method requires the calculation of a maximum volatile solid loading rate based on a 20% odour detection rate. This is calculated from a standard VS loading rate for odour control (61 g VS/m³day), multiplied by the temperature dependent k factor as shown in equation 9.4.

$$VOL_O = \frac{VS_L}{VS_O} \cdot k \tag{9.4}$$

where, VOL_O is the volume of effluent pond for odour control, m^3; VS_O is the standard VS loading rate for odour control, 61 g VS/m³day

Since this research work was conducted in Toowoomba, Queensland, the following figures were used to determine standard VS loading rates for the reactor vessels.

- Typical VS_L: 85 g VS/m³ day (100 g VS/m³day times a k factor of 0.85)
- k factor: 0.85
- VS producing per a Standard Pig Unit (SPU): 250 g VS/day (90 kg/yr)
- Sludge accumulation rate: 0.00303 m³/kg of TS
- Pond life: 10 years
- Volume for odour control: $0.25m^3$(0.5m×0.5m×1.0m high)
- Standard VS loading rate for odour control: 61 g/m³day

From the above design assumptions, the VS loading rate for odour control expecting a 20% odour detection of a reactor vessel could be calculated to be 18.0 g/day. Since the reactor vessels were fed weekly, the VS loading rate for odour control was 126.0 g/week. This figure was used as the standard loading rate for this research.

9.2.2 Determination of hydraulic retention time

One of the key factors for successful design and operation of piggery ponds is the hydraulic retention time (HRT). Wood (1986) indicated that the design of a waste stabilisation pond depends substantially on two factors: an adequate description of its mixing characteristics and an adequate estimation of its biological degradation rate constant. HRT is closely related to the mixing characteristics of a pond. HRT is estimated by dividing the pond liquid volume by the average flow rate of piggery effluent.

The theoretical mean HRT can be defined by equation 9.5 (Martin, 1991).

$$HRT_T = \frac{VOL_P}{\overline{Q_E}} \tag{9.5}$$

where, HRT_T is a theoretical mean hydraulic retention time, days; VOL_P is the total liquid volume of pond; $\overline{Q_E}$ is the average flowrate of the piggery effluent entering the pond

However, piggery effluent ponds are neither precise plug flow reactors nor completely mixed systems. Therefore, it is necessary to consider the actual mean HRT (HRT_A). HRT_A can be calculated by equation 9.6.

$$HRT_A = \frac{EVOL_P}{\overline{Q_E}} \tag{9.6}$$

where, $EVOL_P$ is the effective or useful liquid volume of the pond

$EVOL_P$ is usually less than VOL_P due to short-circulation in ponds. Allan & Jeffreys (1987) reported that about 40% of the volume of an effluent pond in Whitehorse, Yukon, Canada was unused due to short-circuiting. Tracer tests conducted in the Whitehorse

pond showed that HRT_A was about 60 % of HRT_T. Pena *et al.* (2002) reported HRT_A values around 30 – 50 % of HRT_T in his dispersion studies in anaerobic ponds. LiCl was used as a tracer to show the hydrodynamic behaviour of the pond.

The recommended design HRT for piggery effluent ponds is normally 30 - 60 days (ISU, 2003). Canter & Englande (1970) estimated average HRT values of 31 days for anaerobic effluent ponds used in the warmer southern states in USA (cited from Martin, 1991). Therefore, an HRT of 30 days was applied in experiment 1 as a standard HRT. In experiment 2, an HRT of 60 days was used to compare the results with that of experiment 1. HRT_A was considered to be 60 % of HRT_T.

9.3 Materials and methods

An experimental facility was established at the field experimental station of the University of Southern Queensland (USQ) in Toowoomba, Queensland, Australia to conduct the proposed experiments. An experimental building with 5.8m×5.8m×2.3m dimension was customised to provide a controlled laboratory experimental environment. The facility was operated for 18 months.

9.3.1 Raw piggery effluent

Two hundred litres of fresh piggery effluent were collected from beneath the slatted floor of a commercial intensive piggery operation unit by pump twice a month and used as raw feed material to the reactor vessels. The raw feed material was sourced from the Donley piggery at Highfields, near Toowoomba, and stored in an airtight 200L steel tank.

9.3.2 Experimental facility

The experimental facility consists of two main parts. First is the pond simulating reactor vessels and the second is the wind tunnel. The main role of the reactors is to simulate the operation of real effluent ponds under controlled laboratory conditions and is the odour producing source. The second part of the experimental facility is the USQ wind tunnel, used for the sampling of odour emitted from the reactor vessels. The detailed physical dimensions and description of the USQ wind tunnel are provided in Chapter 8.

Pond Simulating Reactor Vessels

The pond simulating reactor vessels were designed to simulate the workings of effluent ponds. They have worked as the odour-producing source for the further odour analysis work using the novel wind tunnel and the AromaScan A32S, an electronic nose. Since anaerobic ponds are comparable to single-stage, unmixed, unheated digesters, the basic design concept of the reactors is based on the simple single-stage digester system model. With five independent reactor vessels, five different loading rates can be tested at the same time under controlled environmental conditions. It consists of:

- five reactor vessels each about 0.25m^3 capacity (0.5m×0.5m×1.0m high); and
- five sampling port per each reactor vessel for liquid and sludge sampling.

The CAD design of the experimental facility is shown in *Fig 9.1*, *9.2*, and *9.3*. The completed experimental facility is depicted in *Fig 9.4*.

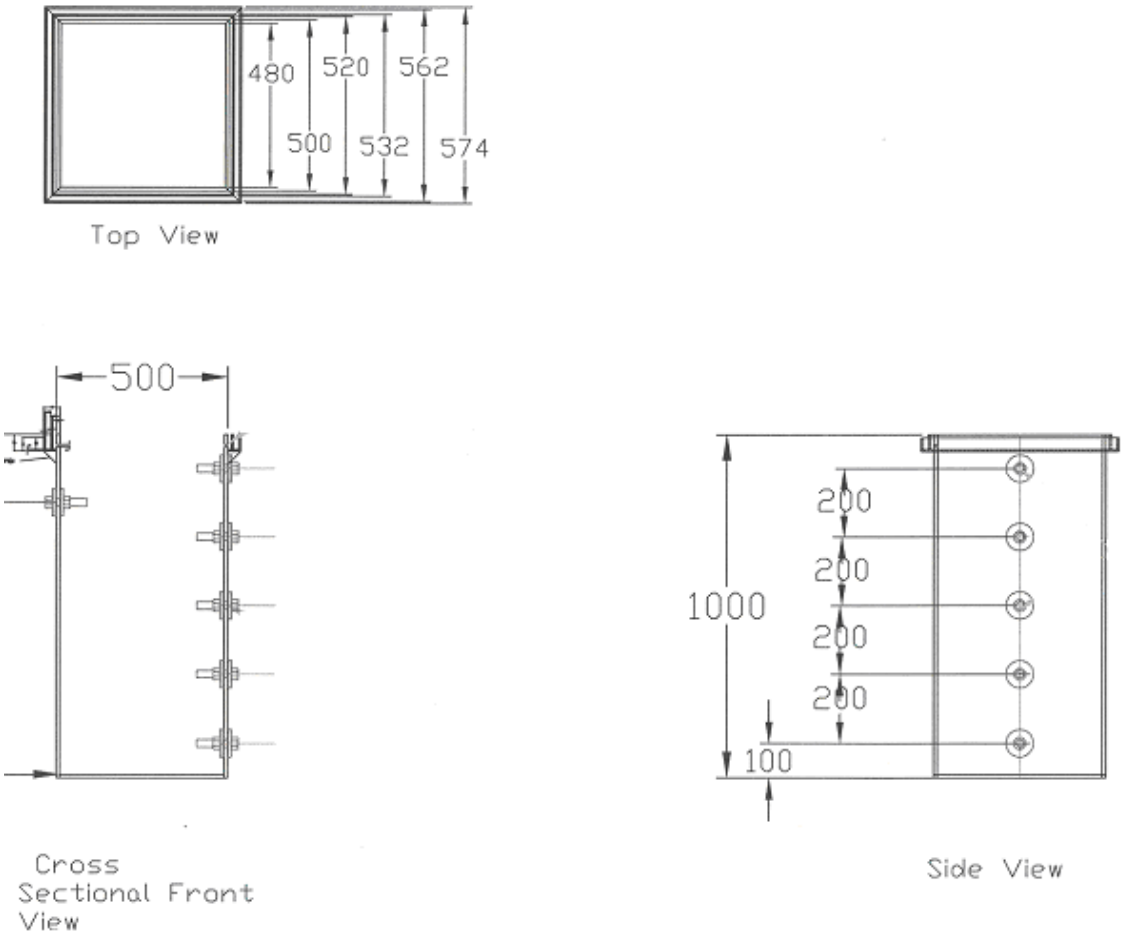


Fig 9.1 A CAD drawing for reactor vessels

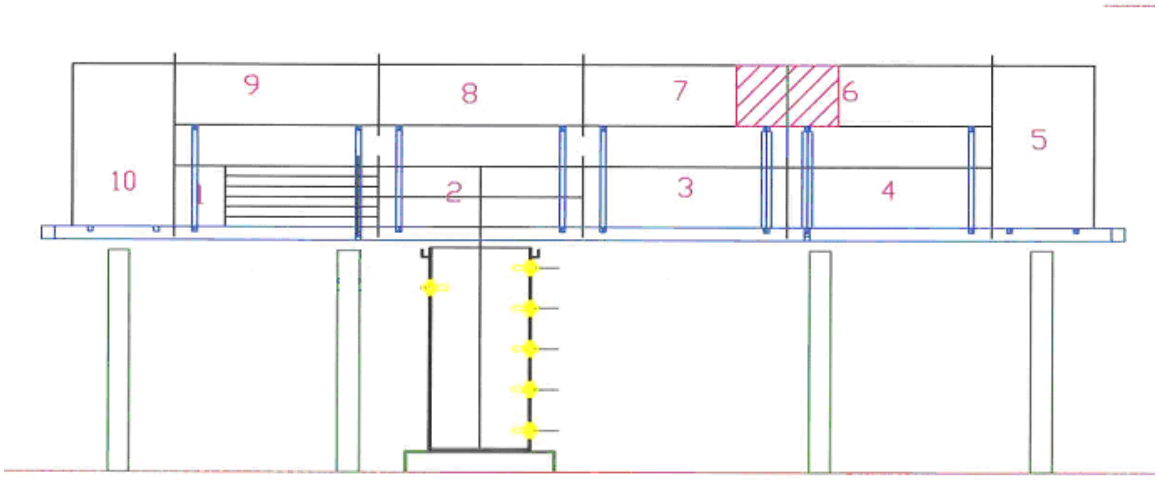


Fig 9.2 A CAD drawing for the experimental facility consisting of a wind tunnel and reactor vessels, front view

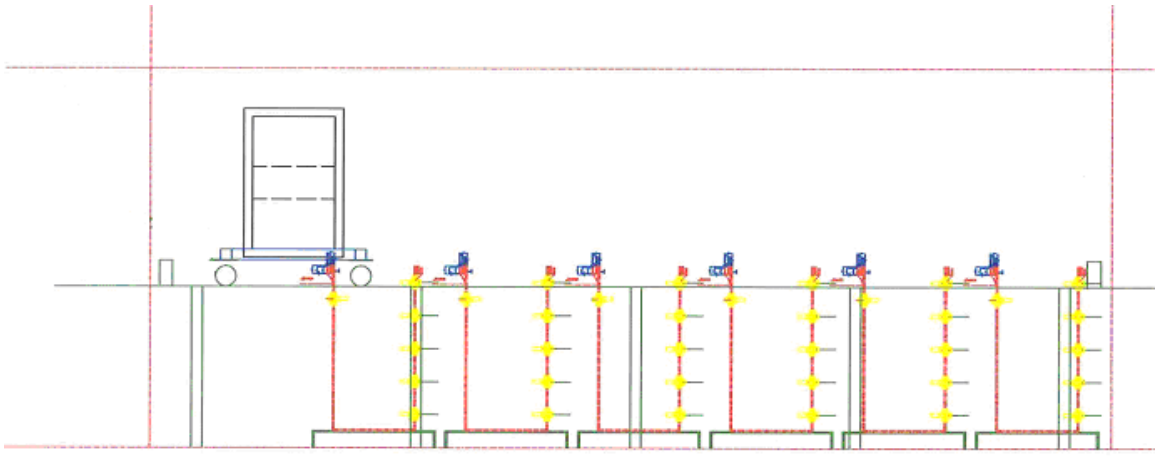


Fig 9.3 A CAD drawing for the experimental facility consisting of a wind tunnel and reactor vessel, side view

Fig 9.4 Experimental facility used to quantify effects of pond loading rates on odour emissions

The method of operation was adopted from the upflow anaerobic sludge blanket (UASB) system (Sohn, 1997):

- Start-up: At the beginning of the experiments, the reactor vessels were seeded with sludge and water from an existing pond operating under optimum conditions. After first seeding, the loading rate was gradually increased for 2 or 3 weeks to prevent shock loading and to give enough time for anaerobic microbes to propagate;
- Feeding of wastewater: After monitoring of the condition of start-up, weekly feeding with raw effluent was started with a different pre-designed loading rate to each vessel;

- Monitoring: During the operating period, chemical analysis and physical measurements were undertaken to monitor the condition of the reactor vessels; and
- Disposal of effluent from reactor vessels: At the conclusion of each experiment the effluent was collected and disposed of in accordance with work place health and safety requirements.

9.3.3 Reactor vessel initiation

Once the five reactor vessels and the wind tunnel were installed, the reactor vessels were filled with anaerobic effluent and mature sludge, which were collected from a mature piggery effluent pond. Exposure of the anaerobic sludge to oxygen was minimised as far as possible through the transport using an airtight container. Equivalent volumes of sludge (50L which is 20% of reactor volume) and effluent (200L, 80% of reactor volume) were discharged to each reactor vessel with minimal aeration. Once the digesters were filled, they were allowed to equilibrate.

A regular programme of adding fresh effluent from the sump of the Donley piggery to the reactor vessels commenced soon after the initial filling. A small volume (2.5L) of sump effluent was added to each reactor vessel daily after the same volume of effluent were removed from the reactor to maintain a constant liquid level and headspace volume. Measurement of pH and electrical conductivity (EC) in the reactor vessels at initiation are shown in *Fig 9.5*.

The values of pH and EC were measured to check the effluent condition of each reactor vessel. The results showed minimal variations between reactor vessels. After completion of the initiation process of 45days duration, experiment 1 commenced.

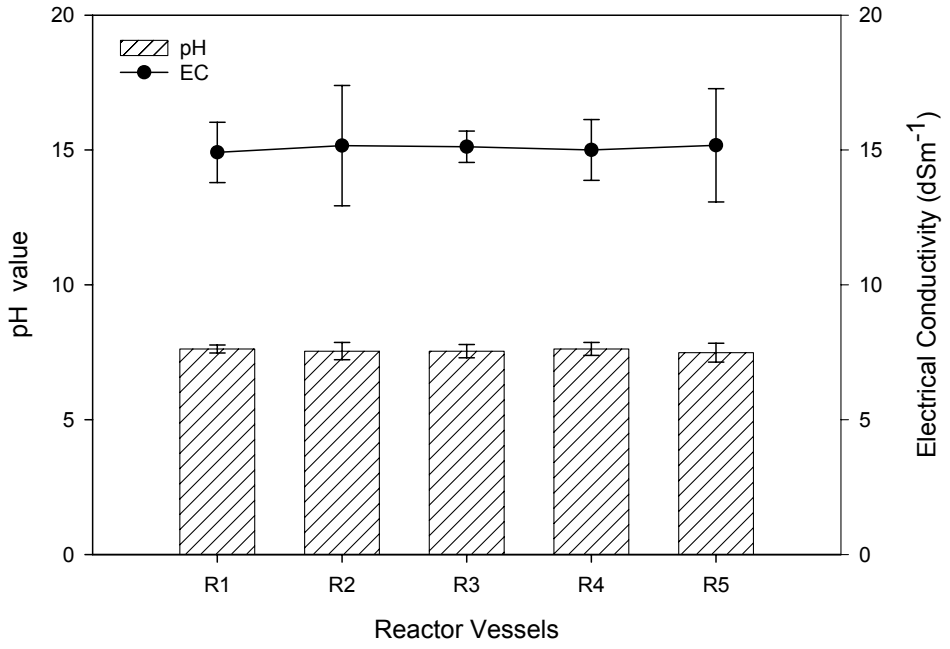


Fig 9.5 The results of reactor vessels initiation

9.3.4 The experiments

After the reactor vessels were initiated, experiment 1 was conducted for 12 months from 8th August 2001 to 14th August 2002. The reactor vessel 2 operated with the organic loading (OLR) of 72 g VS/m^3·day recommended by the Rational Design Standard method. It was used as a control reactor to compare it with the other reactor vessels. Reactors 1, 3, 4 and 5 were operated with the OLR of 36, 108, 144 and 180 g VS/ m^3·day, respectively. Average HRT was 30 days.

At the conclusion of experiment 1, the reactor vessels were allowed to equilibrate for 60 days each with the same OLR of 72 g/m^3·day. Experiment 2 was then conducted for 6 months from 13th November 2002 to 26th March 2003. The same OLR used in experiment 1 were applied in experiment 2. Averaged HRT was 60 days. A summary of OLR and HRT used for the experiments is presented in **Table 9.2**.

In addition to the chemical parameters analysed in experiment 1, more chemical parameters including total phosphorus, potassium, sulphide and sulphate were analysed in experiment 2 to ascertain the relationship between odour emission rates and chemical parameters. The surface layer grab sampling method, which is addressed in section 9.3.8, was used in experiment 2.

The detailed results of physical and chemical parameters collected from experiment 1 and 2 are presented in Appendices C and D, respectively.

Table 9.2

Summary of organic loading rate and hydraulic retention time used for experiments

	Experiment 1		*Experiment 2*	
	OLR (VS g/m^{3}day)	*HRT (days)*	*OLR (VS g/m^{3}day)*	*HRT (days)*
Reactor 1	36	30	36	60
Reactor 2	72	30	72	60
Reactor 3	108	30	108	60
Reactor 4	144	30	144	60
Reactor 5	180	30	180	60

9.3.5 Odour sampling

Odour samples were collected in Melinex^{TM} (Polyethylene Terephthalate) sample bags. The sample bags were placed into a rigid 30L or 120L sample containers which were customised for this research work. The 30L and 120L sample container were used for the AromaScan and olfactometry analysis, respectively. They are shown in *Fig 9.6* and *Fig 9.7* respectively. One end of a polytetrafluoroethylene (PTFE) tube is fixed to the sampling port of the USQ wind tunnel and the other end of which was attached to a sampling container, fitted with a Melinex^{TM} bag insert. An air sample is drawn into the

Melinex^{TM} bag with a diaphragm pump that evacuates the air space between the container and the Melinex^{TM} bag.

All components used for sampling were composed of stainless steel or PTFE material. The bags were pre-conditioned by filling them with odorous air from the wind tunnel prior to the sample being collected. The sampling container was then sealed and transported to the Aromascan A32S instrument for analysis, and then onto the olfactometer for final testing. The time between sample collection and testing should be less than 24 hours in order to minimise the effect of rapid decomposition of odours.

Fig 9.6 The 30L odour sample container for the AromaScan analysis

Fig 9.7 The 120L odour sample container and a diaphragm pump for olfactometry analysis

9.3.6 Odour analysis using olfactometry

Odour concentrations were determined using an eight-panellist, triangular, forced choice dynamic olfactometer developed by the Department of Primary Industries, Queensland, Australia (Galvin *et al*., 2002). The methodology to determine odour concentrations is addressed in section 7.2.3. Using the odour concentration, the odour emission rate (OER) was calculated using equation 9.7 (modified from Galvin *et al*., 2002).

$$OER = C_s V_t \frac{A_t}{A_s} \tag{9.7}$$

where, C_s is the odour concentration in the bag, OU/m^3; V_t is the wind speed inside the tunnel, m/s; A_t is the cross sectional area of the tunnel, m^2; A_s is the surface area covered by the tunnel, m^2

Equation 9.7 assumes that the incoming air has had all background odour removed by the activated charcoal filter of wind tunnel and that there is complete mixing between the emissions and the airflow in the tunnel (Smith, 1996).

The calculated OER was then scaled to a standard tunnel wind speed of 1m/s according to Smith & Watts (1994a). They compared two different sized wind tunnels and concluded that the emission rate OER_v at a particular tunnel wind speed V_t was related to the emission rate OER_1 at a tunnel wind speed of 1m/s. This is shown in equation 9.8 (Galvin *et al*., 2002).

$$\frac{OER_v}{OER_1} \approx V_t^{0.63} \tag{9.8}$$

The exponent of 0.63 was derived as a factor for wind tunnels when used on solid surfaces at feedlots and does not apply to ponds. However, Pollock (1997) discussed the use of an exponent of 0.5 for pond surfaces. This value has been adopted for the purposes of calculations for this research work.

9.3.7 Odour analysis using the AromaScan

The AromaScan A32S "Electronic nose", in conjunction with the AromaScan A8S sample station, was used as the main odour measurement instrument for the collected odour samples in this study. The AromaScan A32S and experimental set-up for odour sample analysis is shown in *Fig 9.8*.

The calibration of this instrument including the training of the artificial neural network system, was described in Chapters 6 and 7, respectively.

For this study, the ANN retrained using olfactometry data obtained during experiment 2. Odour concentrations and odour emission rates were then determined for each sample by presenting the AromaScan sensor responses to the trained ANN.

Fig 9.8 The Aromascan A32S and experimental set-up for odour sample analysing

9.3.8 Liquid sampling and analysis

In experiment 1, the liquid effluent in each of the reactor vessels was sampled for analysis every two weeks. A 500 mL sample was collected from four levels of each reactor vessel, through their respective sampling taps, and aggregated to make a 2 L sample. This procedure minimises the variance caused by the depth from the surface of the vessel.

In experiment 2, the reactor vessels were sampled every two weeks. In this case, grab samples were taken from within the top 300 mm of the surface of reactor vessels. Samples were collected to exclude scum on the surface. Each grab sample was then

placed into a large bucket and mixed. The composite samples were then drawn from this bucket for chemical and physical analysis.

The liquid sampling method in experiment 2 was used for the following reasons:

- The chemistry of the surface layer of an effluent pond is assumed to be the main contributor to the odour emissions (Hudson, 2002); and
- Other related research on odour emissions from piggery effluent ponds used the surface effluent sampling method (Galvin *et al*, 2002; FSA Environmental, 2001; Hudson *et al*, 2001)

Liquid samples were stored at 4 ºC and analysed within three days to minimize any change in concentration caused by microbiological processes. Various chemical and physical analyses were conducted. They can be classified under four groups:

- Physical and chemical characteristics of raw feed material (pH, Alkalinity, EC, TS, VS, VS/TS, T-N, NH_3-N, COD, K, T-P, Sulphide, Sulphate)
- Determination of volatile organic loading rate (VS);
- Physical operating condition of reactor vessel (pH and EC); and
- Chemical operating condition of reactor vessel (Alkalinity, EC, TS, VS, VS/TS, T-N, NH_3-N, COD, K, T-P, Sulphide, Sulphate).

A summary of equipment and methods used for the chemical and physical analysis is presented in **Table 9.3**.

Table 9.3

Summary of analytical methods and instrument used for the experimental work (Hach, 2004)

Item	*Applied method*	*Instrument*	*US EPA Approved**
Total Solid (TS) Volatile Solid (VS)	○ Gravimetric method	○ Memmert® forced-ventilating drying oven ○ Satorius® micro balance	√
Chemical Oxygen Demand (COD)	○ Reactor digestion method	○ HACH® DR-2000 analyser	√
Electrical Conductivity (EC)	○ Electrode method	○ TPS® MC-84 conductivity-salinity meter	√
Total Kjeldahl Nitrogen (TKN)	○ Nessler method ○ Photometric determination	○ HACH® DR-2000 analyser ○ HACH® Digesdahl digester	√
Ammonia Nitrogen (NH_3-N)	○ Nessler method ○ Photometric determination	○ HACH® DR-2000 analyser ○ HACH® Digesdahl digester	√
Phosphorus, Total	○ Acid Persulphate digestion ○ Photometric determination	○ HACH® DR-2000 analyser	√
Sulphate	○ SulphaVer 4 method	○ HACH® DR-2000 analyser	√
Sulphide	○ Methylene Blue method	○ HACH® DR-2000 analyser	√
pH	○ Electrode method	○ HANNA® HI 9017 pH meter ○ ORION® ROSS M81-02 electrode	√
Total alkalinity	○ Buret titration method	○ HANNA® HI 9017 pH meter ○ ORION® ROSS M 81-02 electrode	√

9.3.9 Statistical analysis

All data were analysed with the statistical package SPSS Version 11.5 for Windows. It was used mainly to derive the relationship between odour emission rate and the experimental variables through paired samples Student's T-test, Pearson's correlation and linear/non-linear regression statistical analysis.

9.4 Results and Discussion

9.4.1 Characteristics of raw piggery effluent

The results of the chemical and physical analysis for the raw piggery effluent, used as the feed material to the reactors, are summarised in **Table 9.4** below.

Table 9.4

The chemical and physical analysis of the raw piggery effluent

Parameter	*Unit*	*Mean*	*N*[1]	*Min*	*Max*	*SD*[2]
pH		7.42	35	6.68	8.28	0.34
Total Alkalinity	mg/L as $CaCO_3$	7227	21	2280	12240	3146
EC	dS/m	19.64	35	13.80	25.12	3.22
TS	mg/L	21796	35	5628	77249	19042
VS	mg/L	13442	35	1968	54349	13583
VS/TS	%	54.3	35	36.0	76.0	14.37
Total Nitrogen	mg/L	2479	18	1920	3420	446
Ammonia Nitrogen	mg/L	2164	18	1480	3110	455
COD	mg/L	10629	18	4460	22220	5084
Potassium	mg/L	1125	5	985	1330	126.6
Sulphates	mg/L	18	3	8.2	34.8	14.62
Sulphides	mg/L	5.53	4	2.4	14.1	5.76
Total Phorphorus	mg/L	294.2	5	150	401	94.35

1. N: Number of samples
2. SD: Standard deviation

As can be seen in **Table 9.4**, significant variation was observed in the characteristics of the raw effluent from the piggery. These variations are mainly due to the irregular maintenance of the piggery housing. Moreover, there are additional factors affecting the physical and chemical characteristics of raw piggery effluent. The factors are:

- Seasonal variance;
- Changing feedstuff;
- Growth stage of pig; and
- Manure storage time in sump.

The range of chemical and physical parameters was similar to that reported by the other researchers (FSA Environmental, 2001; Pieters *et al.*, 1999; MWPS, 1997).

9.4.2 Odour quantification using the AromaScan

The odour quantification technique, which was developed as a part of this research work was applied to get odour emission rates from sensor output data of the AromaScan. The detailed methodology of the odour quantification technique is addressed in Chapter 6. The odour emission rates predicted by the technique, were used to derive a relationship between odour emission rates and volatile organic loading rates in experiment 1 and 2.

The odour emission rates (determined by olfactometry) from the five reactor vessels in experiment 2, are depicted in *Fig 9.9*. Though it was expected that a relationship would exist between odour emission rate and organic loading rate, it was observed that the relationship was not strong in each individual trial. However, with the increase in the volatile organic loading rates, an increase in the odour emission rates was observed. With regard to the mean odour emission rate over experiment 2, the highest mean odour emission rate was from reactor vessel 5. Galvin *et al*. (2002) reported similar results from his field study on the effect of loading rate on odour emissions from anaerobic effluent ponds.

The results of olfactometry and the Aromascan in experiment 2 were used to train the ANN. Five sensor output results of the AromaScan were produced from each odour sample. Two sensor outputs were used to train the ANN. The others were left for use as unknown data sets. After the network was trained, the unused data sets were presented to the trained ANN to predict odour emission rates in experiment 2. The same prediction technique, using the trained ANN and sensor output results of the AromaScan, was then applied to the results from experiment 1.

The architecture of the ANN used for this work was a two-layer back propagation network, with a tan-sigmoid transfer function in the hidden layers and a linear transfer function in the output layer. It has 20 neurons in the hidden layer. A preprocessing algorithm and an early stopping technique were applied to improve the performance of the ANN.

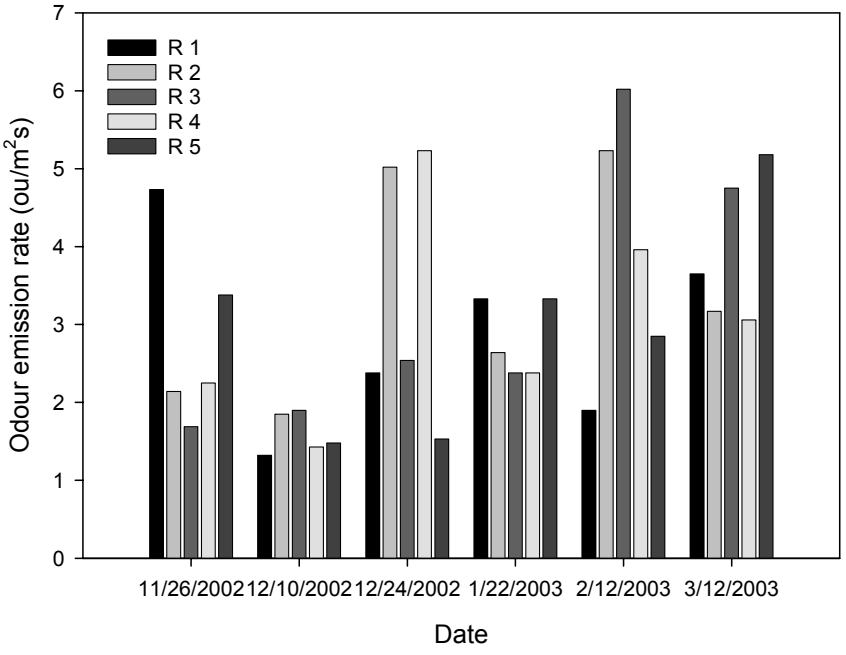


Fig 9.9 Course of the odour emission rate analysed by olfactometry in the five reactor vessels in experiment 2: R1, OLR 36 g VS/m^{3}day; R2, 72; R3, 108; R4, 144; R5, 180

The plots of mean squared error versus the training epochs on a logarithmic scale for the training simulation of the network is presented in *Fig 9.10*. The value of mean square error and gradient were 3.22×10^{-3} and 25.47 respectively. The training was stopped at epoch 85. The scatter plot of the actual odour emission rates and the predicted neural network output (scaled into the odour emission rate domain) for the test data using the results from this training simulation is shown in *Fig 9.11*. The value for the correlation coefficient (*r*) in *Fig 9.11 was* 0.97. The best linear fit was observed in $OER_A = 0.99\ OER_P+0.007$. As seen in *Fig 9.11*, the trained ANN explains 94 % of the total variance of the training data. The predicted odour emission rates obtained by the neural regression, are well distributed around the ideal 1:1 straight line. Therefore, the result of training simulation shows that the trained ANN model is able to predict the odour emission rate of unknown air samples correctly with a low mean squared error.

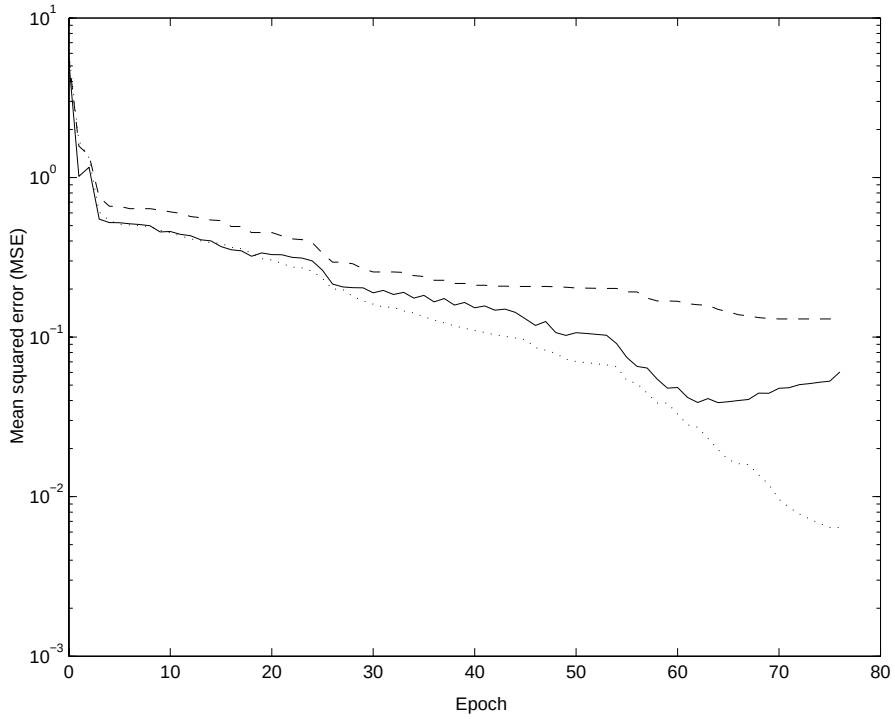


Fig 9.10 The result of artificial neural network training using preprocessing algorithms and 20 hidden neurons

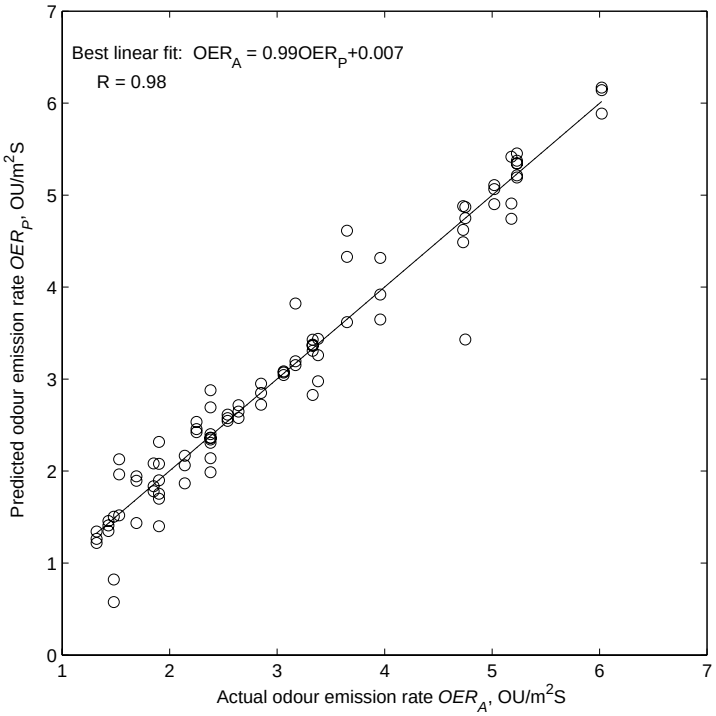


Fig 9.11 The odour emission rate prediction results using AromaScan and artificial neural network

The three unused sensor data for each odour sample were presented to the trained ANN to predict the odour emission rates. The results were compared with the results of olfactometry. The comparison plots of odour emission rates between olfactometry and the Aromascan in reactor vessel 5 over the experiment 2 are shown in *Fig 9.12*. The results for reactor vessels 1, 2, 3, and 4 are presented in Appendix E. From the comparison plots, it is observed that the predicted odour emission rates have high correlation with the actual odour emission rates measured by olfactometry.

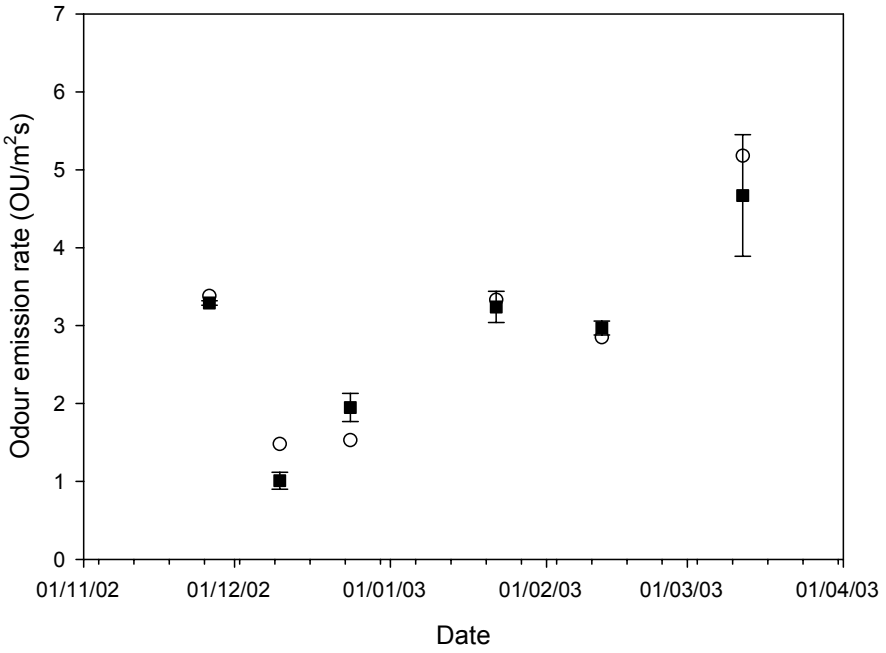


Fig 9.12 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 5 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN

The non-linear regression result of odour emission rates between olfactometry and the AromaScan data, which was predicted by the trained ANN in experiment 2, is depicted in *Fig 9.13*. The value for the coefficient of determination, r^2 of statistical non-linear regression analysis was 0.96. The relationship of odour emission rate between olfactometry and the AromaScan was expressed using equation 9.9.

$$OER_p = -0.027 OER_A^{\ 2} + 1.18 OER_A - 0.27 \quad (9.9)$$

where, OER_P is the predicted odour emission rate by the AromaScan, OU/m^{2}s; OER_A is the actual odour emission rate measured by olfactometry, OU/ m^{2}s

The final evaluation of a statistical non-linear regression was made on unknown data, *i.e.*, data which had not been used for training the ANN. As seen in *Fig 9.13*, the non-linear regression model explains 96% of the total variance of the analysing data.

The odour quantification technique using ANN gives the ability to predict odour emission rate from the sensor response of the AromaScan with a high level of confidence. However, one must keep in mind that the regression process must only be used for interpolations. In addition, this odour quantification technique needs sufficient reliable odour data from olfactometry to train the ANN.

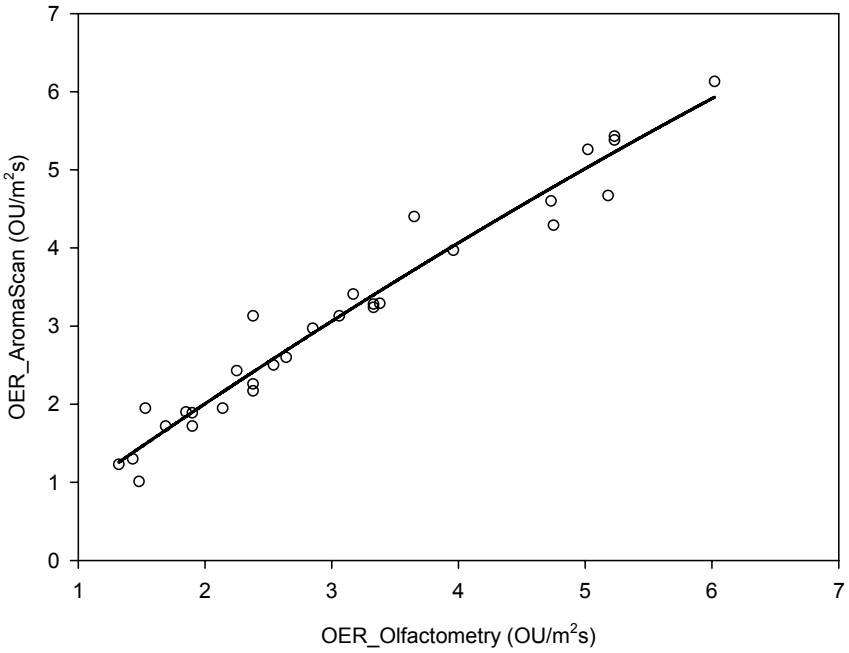


Fig 9.13 The non-linear regression result of odour emission rate between olfactometry data and the predicted values using the AromaScan and artificial neural network in experiment 2

9.4.3 Effect of organic loading rate on the physical and chemical characteristics of reactor vessels

In order to investigate the effect of OLR on the physical and chemical characteristics of the reactor vessels, paired-sample Student's T-test with 95% confidence were used to analyse the results. This statistical method will verify if the differences in data between the reactor vessels as a result of OLR are statistically significant. The results of T-test in experiment 1 and 2 are summarised in **Table 9.5** and **Table 9.6**, respectively.

Table 9.5

The results of paired-sample Student's T-test from effect of organic loading rate on the physical and chemical parameters in the reactor vessels in experiment 1

	TS	*VS*	*pH*	*Alkalinity*	*EC*	*COD*	*TKN*	*NH_3-N*
	T-test significant (2-tailed)							
R1:R2	0.005*	0.005*	0.501	0.089	0.000*	0.017*	0.420	0.437
R3:R2	0.022*	0.078	0.228	0.285	0.000*	0.735	0.704	0.340
R4:R2	0.000*	0.001*	0.803	0.000*	0.000*	0.022*	0.005*	0.814
R5:R2	0.001*	0.001*	0.194	0.001*	0.000*	0.001*	0.005*	0.661

*: 95% Probability ($P < 0.05$)

Table 9.6

The results of paired-sample Student's T-test from effect of organic loading rate on the physical and chemical parameters in the reactor vessels in experiment 2

	TS	*VS*	*pH*	*Alkalinity*	*EC*	*COD*	*TKN*	*NH^3-N*	*TP*	*K*	*S^{2-}*
	T-test significant (2-tailed)										
R1:R2	0.089	0.898	0.905	0.009*	0.000*	0.055	0.149	0.112	0.014*	0.007*	0.077
R3:R2	0.255	0.196	0.086	0.054	0.056*	0.595	0.192	0.085	0.017*	0.001*	0.198
R4:R2	0.443	0.291	0.827	0.002*	0.006*	0.083	0.020	0.012*	0.012*	0.042*	0.065
R5:R2	0.046*	0.169	0.650	0.014*	0.000*	0.285	0.027	0.022*	0.009*	0.020*	0.053

*: 95% Probability ($P < 0.05$)

Strong relationships between OLR and physical and chemical parameters were observed except for pH and NH_3-N. In terms of VS, as the OLR has been determined by the concentration of VS, it is a logical conclusion that the results of VS have direct relationship with OLR. The results of TS have a similar tendency to VS because the concentration of TS in piggery effluent has a linear relationship with VS. Piggery effluent has a relatively constant VS/TS ratio of about 60% (MWPS, 1985).

It was observed that pH has no relationship with OLR. This is due to the buffering capacity of piggery effluent. Piggery effluent used in this research, has a high alkalinity value ranging from 2280 to 12240 mg/L as $CaCO_3$. Another contributing factor is the process stability of the reactor vessels. Even under the highest loading rate of 250% of recommended OLR in reactor vessel 5, the process was stable. Therefore, the rapid decrease of pH value mainly caused by 'shock loading' has not occurred in any reactor vessel.

The results of EC show clear differences between reactor vessels with varying of OLR ($P<0.05$). Similar results were observed in the results of COD ($P<0.05$). *i.e.* these two parameters have strong relationship with OLR. Therefore, it indicates that these

parameters can be used as an indicator of the operating condition of a piggery effluent pond.

In the T-test of TKN value, the effect of OLR is significant under high loading conditions (200% and 250% of the recommended OLR, $P<0.01$) *i.e.* reactor vessel 4 and 5. However, the lower loading rates (ranging from 50 to 150%) show a poor relationship.

It was observed that there is no relationship between NH_3-N and OLR. In the 'Nitrogen Cycle', NH_3-N is converted to NO_2^--N and NO_3^--N through the nitrification process under the aerobic condition. The bacteria groups of *Nitrosomonas* and *Nitrobacter* are involved in this nitrification process. Under the anaerobic condition, denitrification occurs, where NO_2^--N and NO_3-N are the terminal electron acceptor to produce nitrogen gas as a final product. Thus, NH_3-N can be converted to NO_2^--N and NO_3^--N at the surface layer of reactor vessels because the surface layer (less than about 50cm) may have dissolved oxygen, depending on wind, temperature and OLR (Thirumurthi, 1991). Therefore, NH_3-N could not show a strong relationship with OLR because it is unstable. In addition, some portion of nitrogen is used for microbial cell synthesis. Thirumurthi (1991) indicated that microbial cells contain about 50% carbon, 20% oxygen, 10-15% nitrogen, 8-10% hydrogen, 1-3% phosphorus, and 0.5-1.5% sulphur on a dry weight basis.

The results of experiment 2 made an interesting comparison with the results of experiment 1. In **Table 9.6**, the parameters of TS, VS and COD show no relationship with OLR. However, these same parameters revealed strong relationships in experiment 1. A contributing factor may be the application of different methods of liquid sampling, *i.e.*, from mixing sampling to surface sampling. This finding is discussed in more detail in the following section because it is closely related to the odour emission rates.

The additional chemical parameters of total phosphorus, potassium, sulphide and sulphate were analysed in experiment 2. It was observed that total phosphorus and potassium show a strong relationship with OLR ($P<0.05$). On the contrary, sulphide

showed a weak relationship. Like NH_3-N, sulphur compounds are converted and restored in the 'Sulphur Cycle'. Hence, this may cause the weak relationship with OLR. No statistical analysis was carried out for sulphate because of missing data and the low sensitivity of the method of analysis.

Pearson's correlation analysis was used to determine the correlation between the raw feed effluent and the liquid samples collected from the reactor vessels. The results are shown in **Table 9.7**. In **Table 9.7**, the physical and chemical parameters analysed in this research work show no correlation with the raw feed effluent except pH, which showed a weak correlation ($P<0.05$). However, the results of pH were not significant because the value of the correlation coefficient, *r* was low ranging from 0.47 to 0.58.

Consequently, it can be concluded that it is not possible to predict the concentration of physical and chemical parameters in the reactor vessels based on the concentration of raw feed effluent. Similar results were obtained in experiment 2. The detailed results of the correlation analysis in experiments 1 and 2, are provided in Appendices C and D, respectively.

Piggery effluent ponds are generally operated on a long-term basis (10-15 years). Furthermore, under the proper management, there is no rapid change of OLR. Under such conditions, it is possible to predict the physical and chemical concentration of effluent ponds except pH and NH_3-N. To prove this hypothesis, non-linear regression statistical analysis was conducted using the mean value of OLR and parameters. The results of the non-linear regression analysis for EC, COD and NH_3-N are shown in *Fig 9.14*, *9.15* and *9.16,* respectively. The results of the non-linear regression analysis for the other parameters in experiments 1 and 2, are provided in Appendices C and D, respectively.

The regression results for EC and COD show that these two parameters can be predicted accurately with the values of the correlation coefficient, *r* of 0.99 and 0.98, respectively. The regression analysis for NH_3-N had an *r* value of 0.69. It was observed that the data points were widely dispersed in the scatter plot for NH_3-N.

Table 9.7

The results of Pearson's correlation analysis to show the relationship between raw feed piggery effluent and liquid sample in reactor vessels in experiment 1

		PH	*Alkalinity*	*EC*	*COD*	*TKN*	*NH_3-N*
Reactor 1	*Pearson correlation*	0.467*	0.319	0.083	0.144	0.104	0.096
	Sig†. (2-tailed)	0.019	0.288	0.692	0.638	0.735	0.755
Reactor 2	*Pearson correlation*	0.476*	0.283	0.085	0.190	0.136	0.119
	Sig. (2-tailed)	0.016	0.349	0.685	0.535	0.657	0.698
Reactor 3	*Pearson correlation*	0.547*	0.269	0.140	0.257	0.192	0.205
	Sig. (2-tailed)	0.005	0.374	0.504	0.397	0.530	0.501
Reactor 4	*Pearson correlation*	0.584*	0.251	0.047	0.254	0.140	0.148
	Sig. (2-tailed)	0.002	0.409	0.824	0.403	0.649	0.629
Reactor 5	*Pearson correlation*	0.529*	0.290	0.025	0.195	0.036	-0.003
	Sig. (2-tailed)	0.007	0.337	0.906	0.523	0.907	.993

†: significant, 2-tailed

*: 95% probability ($P<0.05$)

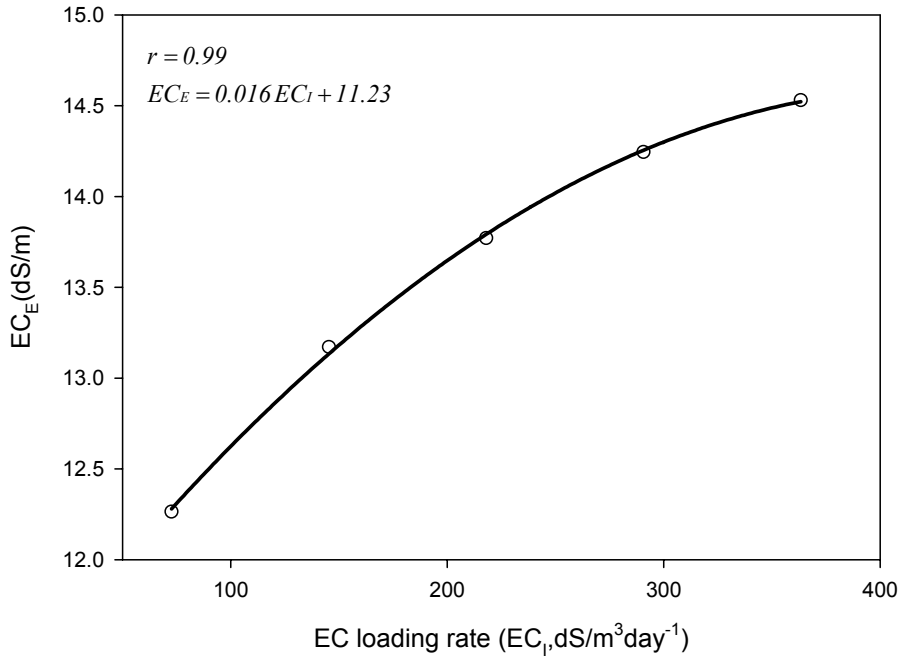


Fig 9.14 EC non- linear regression result between EC loading rate and expected EC values

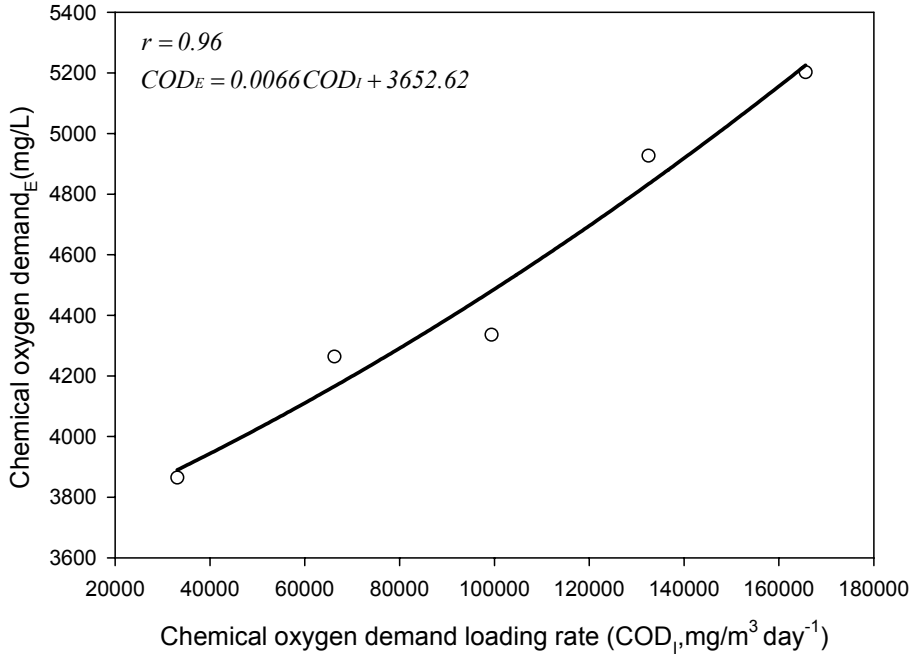


Fig 9.15 COD linear regression result between COD loading rate and expected COD values

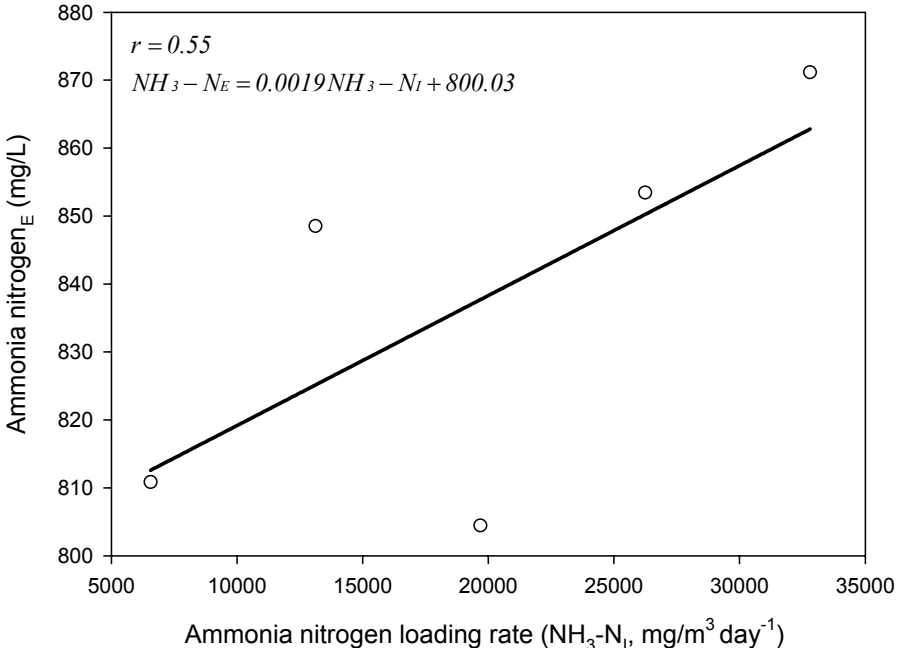


Fig 9.16 NH_3-N linear regression result between NH_3-N loading rate and expected NH_3-N values

9.4.4 Effect of organic loading rate on the odour emission rates

The odour emission rates in experiment 1 were acquired by the odour prediction process described in section 9.4.3. The results are shown in *Fig 9.17*.

As they are shown in trial sets 7, 8 and 9, it is observed that the missing or erroneous data were predicted by the trained ANN. These erroneous data were mainly due to the fuzzy sensor responses from the AromaScan. These data are excluded in following statistical analysis. In *Fig 9.17*, the predicted odour emission rate does not obviously increase as a function of organic loading rate, while the physical and chemical properties show strong relationships with organic loading rate. Odour emissions vary significantly in each trial and in time. One of the suggested reasons is that high odour emissions may be related to activity in the pond sludge layer. FSA environmental (2001)

noted odour concentrations up to three times higher than average emissions where sludge upwellings had occurred.

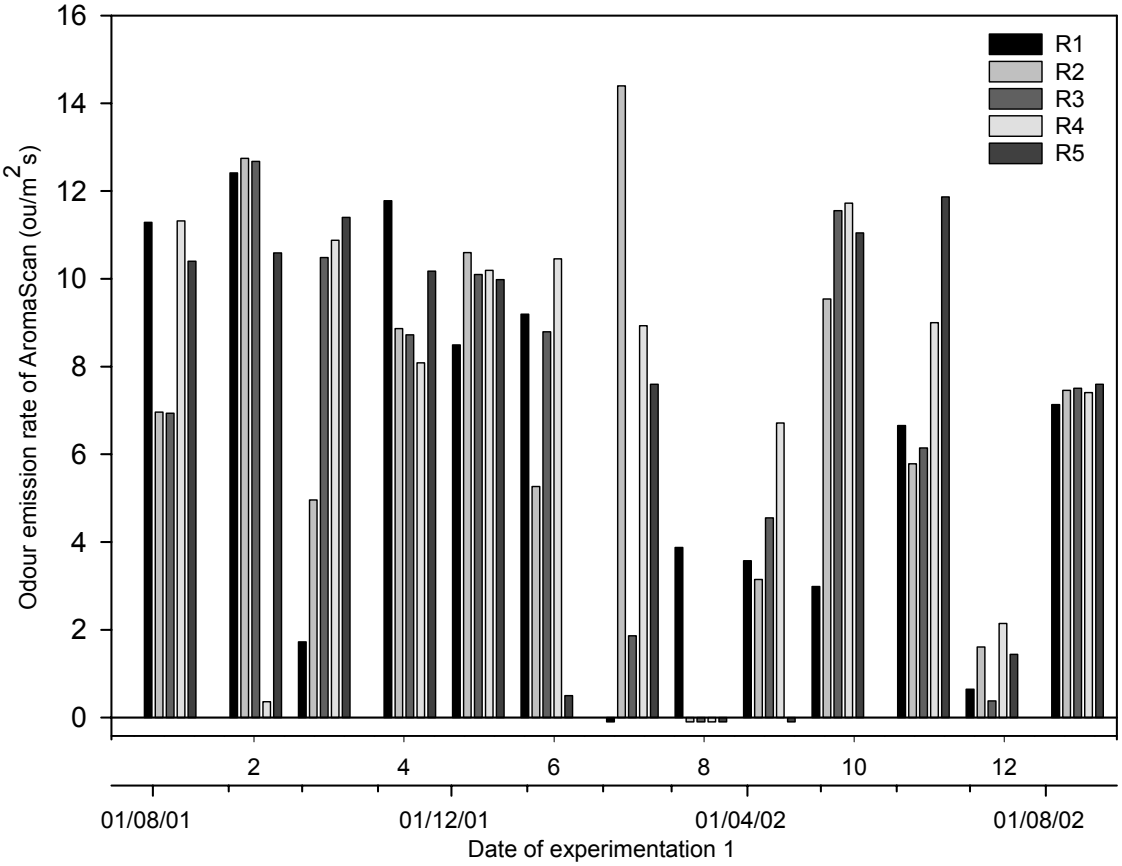


Fig 9.17 Course of the odour emission rate predicted by the AromaScan in five reactor vessels in experiment 1: R1, OLR 36g VS/m^{3}day; R2, 72; R3, 108; R4, 144; R5, 180

While individual measurements show no trend, the time averaged odour emission rate does increase with organic loading rate though it shows high values of standard deviation. The results of time averaged odour emission rate in experiment 1 and 2, are presented in *Fig 9.18.* It also shows that the odour emission rate does not necessarily increase linearly with OLR.

From the linear regression analysis between OLR and time averaged odour emission rate in experiments 1 and 2, the time averaged odour emission rate increases with OLR with high value of the correlation coefficient, r^2 of 0.96 and r^2 of 0.95, respectively. Therefore, it can be concluded that a heavily loaded effluent pond would produce more odour.

However, it is difficult to get these strong relationships between OLR and odour emission rate or odour concentration from each individual data. Taking a few odour samples during short time period is unlikely to provide a representative odour emission rate from the effluent pond. A continuous odour monitoring instrument will be required for that kind of more demanding task.

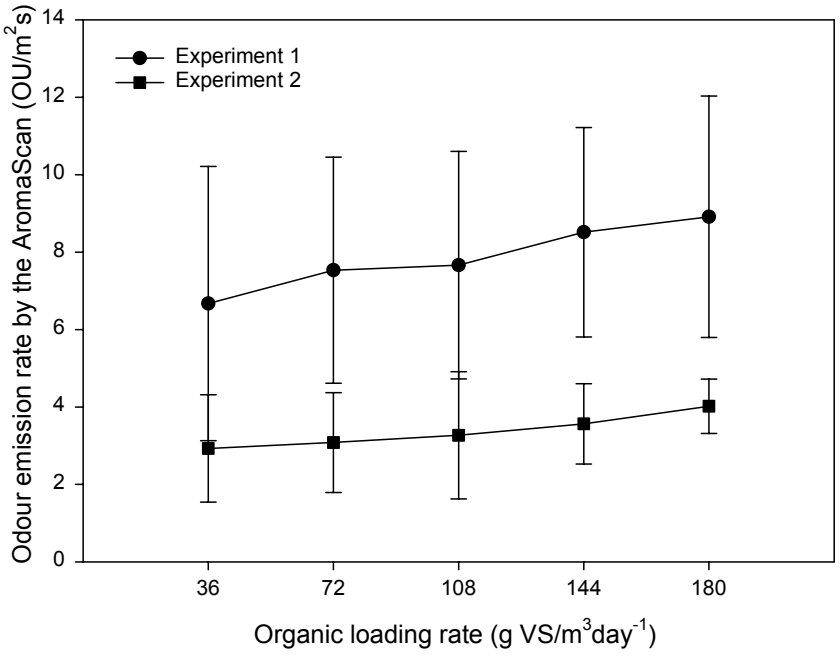


Fig 9.18 The relationship between the time averaged odour emission rates predicted by the AromaScan and organic loading rates in experiment 1 and 2

Pearson's correlation results between odour emission rate and chemical parameters in experiment 1 are presented in **Table 9.8**. No correlation was found between odour emission rate and the chemical parameters. However, the correlation results presented in **Table 9.9** show that in experiment 2, the odour emission rates measured by the AromaScan show a correlation with the chemical parameters ($P<0.05$) except TS, VS and S^{2-}. However, because of the lower number of data, the odour emission rates measured by olfactometry show no correlation with the chemical parameters except for total phosphorus.

One of the reasons to explain the difference between experiment 1 and 2, is the change of liquid sampling method to 'surface liquid sampling'. It is observed that odour emissions are more strongly related to the chemistry of the surface layer of effluent ponds.

As seen in **Table 9.9**, the odour emission rate measured by the AromaScan shows stronger correlation to chemical parameters ($P<0.05$) than olfactometry. It suggests that the sensor of the AromaScan may be more sensitive than the human nose to some specific volatile chemical compounds, *i.e.,* it has a tendency to show stronger response to the volatile chemical compounds than actual human nose. However, there are insufficient data to allow firm conclusion to be drawn.

Table 9.8

The results of Pearson's 2-tailed correlation analysis between odour emission rates and chemical parameters in experiment 1

		TS	*VS*	*pH*	*Alkalinity*	*EC*	*COD*	*TKN*	*NH_3-N*
OER_EN[1]	*Correlation*	-0.047	-0.132	0.287	0.177	0.269	-0.043	0.072	0.176
	Sig.[2] *(2-tailed)*	0.805	0.488	0.124	0.351	0.150	0.839	0.731	0.401
	N[3]	65	65	65	65	65	65	65	65

1. OER_EN: predicted odour emission rate by the AromaScan, OU/m^2s
2. Sig: significant value
3. N: number of samples used for the statistical analysis

Table 9.9

The results of Pearson's 2-tailed correlation analysis between odour emission rates and chemical parameters in experiment 2

	TS	*VS*	*pH*	*Alkalinity*	*EC*	*COD*	*TKN*	*NH_3-N*	*TP*	*K*	*S^{2-}*
OER[1]											
Correlation	-.021	-.104	.266	.191	.297	-.097	.095	.205	.487*	.186	-.092
Sig.[2] *(2-tailed)*	.911	.585	.155	.312	.111	.646	.650	.326	.013	.373	.707
N[3]	30	30	30	30	30	25	25	25	25	25	19
OER_EN[4]											
Correlation	-.017	-.030	-.360*	-.366*	.308*	.325*	.262*	.245*	.482*	.157	-.117
Sig. (2-tailed)	.891	.814	.003	.003	.013	.008	.035	.049	.015	.454	.634
N	30	30	30	30	30	25	25	25	25	25	19

1. OER: actual odour emission rate by olfactometry, OU/m^2s
2. Sig: significant value
3. N: number of samples used for the statistical analysis
4. OER_EN: predicted odour emission rate by the AromaScan, OU/m^2s
5. *: 95% Probability ($P<0.05$)

9.4.5 Effect of hydraulic retention time on the odour emission rates

The effect of HRT was examined. The results are presented in **Table 9.10**. The HRT was increased from 30 days of experiment 1 to 60 days of experiment 2, resulting in a significant decrease in odour emission rates from the reactor vessels. The reactor vessel 2 was used as a control with 72 g/m^3day of standard OLR. The mean odour emission rates of reactor vessel 2 in experiment 1 and 2 were 7.53 and 3.08 OU/m^2s, respectively, a decrease of about 60 %. The decrease over all reactor vessels ranged from 59.1 % to 54.9 %, with an average of 57.1 %. Therefore, it can be concluded that an increase in HRT will decrease the odour emission rate. However, caution is required in the use of this conclusion due to the high standard deviation of measured odour emission rates indicated in **Table 9.10**.

Table 9.10

Effect of hydraulic retention time on the odour emission rates

	OLR (VS g/m3day	*Experiment 1*		*Experiment 2*		*Ratio of OER decrease (%)*
		OER (OU/m^2s)	SD	OER (OU/m^2s)	SD	
Reactor 1	36	6.67	3.54	2.93	1.39	56.2
Reactor 2	72	7.53	2.92	3.08	1.29	59.1
Reactor 3	108	7.67	2.93	3.27	1.65	57.3
Reactor 4	144	8.51	2.70	3.57	1.04	58.1
Reactor 5	180	8.91	3.12	4.02	0.70	54.9

9.5 Chapter summary

The aim of this chapter was to demonstrate the relationship between odour emission rates and the pond loading rates through replicable experimental studies using a novel experimental facility and the machine-based odour quantification technique.

The results of olfactometry and the AromaScan in experiment 2 were used to train the ANN. This training was rapid and accurate (as reflected by a low mean square error). The trained network was able to predict the odour emission rates for the test data with a correlation coefficient of 0.975.

A strong relationship between OLR and the physical and chemical parameters of the effluent in the reactor vessels was observed except for pH and NH_3-N. The pH was not affected by OLR. This is mainly due to the buffering capacity of piggery effluent. The results of EC show a clear difference between reactor vessels depending on the change of OLR ($P<0.05$). Similar results were observed for COD ($P<0.05$). The regression results for EC and COD show that these two parameters can be predicted accurately by OLR with the values of the correlation coefficient, r of 0.99 and 0.98, respectively. Therefore, these parameters can be used as an indicator of the operating condition of the piggery effluent pond.

The odour emission rates measured by the AromaScan showed a stronger correlation to chemical parameters ($P<0.05$) than the results of olfactometry. It suggests that the sensor of the AromaScan is more sensitive than the human nose to some specific volatile chemical compounds.

The effect of HRT was examined. The HRT was increased from 30 days in experiment 1 to 60 days in experiment 2, resulting in a significant decrease in odour emission rates from the reactor vessels. The decrease for the five reactor vessels ranged from 59.1% to 54.9%. Therefore, it can be concluded that an increase of HRT will decrease odour emission rates.

While the individual odour emission rates exhibited a high variance, time averaged odour emission rates were strongly correlated with OLR. Consequently, it can be concluded that a heavily loaded effluent pond would produce more odour. However, it is difficult to find strong relationships between OLR and odour emission rate or odour concentration from each individual data. Taking a few odour samples during a short time period is unlikely to provide a representative odour emission rate from an effluent pond.

CHAPTER 10
CONCLUSION

10.1 Review of research

Odours caused by intensive piggery operation units have become a major environmental issue in the piggery industry in Australia. Effluent ponds are the major source of odours in typical Australian piggeries. It is assumed that the odour emissions from ponds are mainly driven by pond loading rate. However, there are few data to corroborate this assumption. A more complete set of data on gross odour emission rates and effluent physical and chemical characteristics is required to investigate the relationship.

In addition, sensitive and cost effective odour measurement techniques have always been critical areas to achieve this requirement. Olfactometry, in which a human panel evaluates the odours, has been accepted as the only available technique for quantifying odour concentration. Human assessment, however, can be time-consuming, expensive and often impractical because of its use of subjective human panels.

This Ph. D. study successfully addressed these issues in three key areas. These are:

- Development and experimental verification of a novel wind tunnel for odour sampling;
- Application of the electronic nose and artificial neural network (ANN) for odour quantification; and
- Application of the sampling and measurement methods in the investigation of the effects of pond loading rate on odour emissions.

10.2 Major outcomes and key findings

The major outcomes and key findings are provided in the following sections according to the three key areas.

10.2.1 Application of the electronic nose for odour quantification

An ANN and the electronic nose, the AromaScan A32S, were used to predict the odour concentrations emanating from a piggery effluent pond. The sensor data analysed by an electronic nose were used to train the ANN, and to correlate the responses to the actual odour concentration provided by a human olfactometry panel. In an effort to find an optimal artificial neural network model for piggery odour quantification, various preprocessing techniques and network architectures were evaluated through network simulation.

1. The simulation results showed that a two-layer back-propagation neural network, which has a tan-sigmoid transfer function in the hidden layer and a liner transfer function in the output layer, can be trained to predict piggery odour concentrations correctly with a low mean squared error (See *Fig 7.12*). Odour concentrations were predicted for the test data with a coefficient of determination, *r* of 0.98.

2. The results from the application of scaling and principal component analysis suggested that these preprocessing algorithms are necessary to avoid the failure of the network caused by saturation.

3. The early stopping technique was used for network generalisation to provide benefits to network performance in terms of a decrease in computation time and overfitting. It was observed that the optimal number of hidden neurons is 20.

4. The trained ANN was able to predict the odour concentration of nine unknown air samples with a value for the coefficient of determination, r^2 of 0.59.

10.2.2 Development and experimental verification of the USQ wind tunnel for odour sampling

A novel wind tunnel was developed in University of Southern Queensland (USQ). The USQ wind tunnel was designed to have a capability to control wind speed and airflow rate. The USQ wind tunnel was evaluated in terms of the aerodynamics of the airflow inside the tunnel, and the gas recovery efficiency, in order to quantify and improve its performance. From the results of this evaluation, it can be concluded that:

1. Wind speed and turbulence intensity profiles within the tunnel were statistically non-uniform. Two zones with higher wind speeds were observed at the centre of each half of the cross section. These non-uniform wind speed profiles could be one cause of low gas recovery efficiency rates. The installation of perforated baffle at the upstream of emission section is suggested to get more evenly distributed airflow profiles.

2. The USQ wind tunnel showed sample recovery efficiencies ranging from 61.7 to 106.8%, while the average result from the entire test was 81.1%. The optimal sample recovery efficiency of the tunnel was observed to be 88.9% from statistical analysis. The values of airflow rate and gas supply rate corresponding to the optimal sample recovery efficiency were 0.028m^3/s and 10.0 litres/min, respectively (See *Fig 8.16*).

3. Consequently, it can be suggested that the USQ wind tunnel will give estimates of the odour emission rate with significant level of precision.

However, the tunnel needs to be calibrated to compensate for the varying gas recovery efficiencies caused by different airflow rates and odour emission rates.

10.2.3 Application of the sampling and measurement methods in the investigation of the effects of pond loading rate on odour emissions

To investigate the relationship between pond loading rate and odour emission rate, replicable experimental studies were conducted using a novel experimental facility and the machine-based odour quantification technique. The experimental facility consisted of reactor vessels to simulate the operation of effluent ponds and the USQ wind tunnel for odour sampling. The machine-based odour quantification technique used the AromaScan for odour measurement as well as ANN for data interpretation.

1. The ANN training results showed that the trained network was able to use the sensor response of the AromaScan to predict odour emission rate from the reactor vessels with a high level of confidence. The value for the correlation coefficient, *r* in this case was 0.975.

2. A strong relationship between organic loading rate (OLR) and physical and chemical parameters was observed except for pH and NH_3-N. The pH was not affected by OLR. This is mainly due to the buffering capacity of piggery effluent. The results of EC showed clear differences between reactor vessels depending on the change of OLR ($P<0.05$). Similar results were observed for COD ($P<0.05$). The regression results of EC and COD showed that these two parameters can be predicted accurately by OLR with the values of the correlation coefficient, *r* of 0.99 and 0.98, respectively. It is concluded that these parameters can be used as indicators to estimate the operating condition of a piggery effluent pond.

3. The time averaged odour emission rates from the reactor vessels showed a strong relationship with OLR, confirming the empirical evidence that a heavily loaded effluent pond would produce more odours.

4. The effect of hydraulic retention time (HRT) was examined. The HRT was increased from 30 days in experiment 1 to 60 days in experiment 2, resulting in a significant decrease in odour emission rates from the reactor vessels. This decrease ranged from 59.1 % to 54.9 %, with an average of 57.1 %. Therefore, it can be concluded that increasing HRT will decrease odour emission rate.

5. This trial confirmed the value of the project methodology in obtaining unambiguous data on odour emission processes. However, more data are required for a wider range of OLR, HRT and other pertinent variables before a usable model can be formulated.

10.3 Recommendations for further research

Through the course of this Ph. D. study, it has become apparent that a heavily loaded effluent pond would produce more odours. However, it was difficult to find strong relationships between OLR and odour emission rate or odour concentration due to the high variance in the individual odour emission measurements. Taking a few odour samples during a short time period is unlikely to provide a representative odour emission rate from the effluent pond. Therefore, it is necessary to improve current odour sampling and measurement methods. A summary of key topics identified for further research and study is provided below.

1. Improvement of the USQ wind tunnel

- Further improvement of the USQ wind tunnel in order to control other meteorological factors including humidity and temperature
- Evaluation of the wind tunnel performance in recirculating mode
- Development of a standard operation protocol for the USQ wind tunnel to minimise and compensate for the varying gas recovery efficiency caused by different experimental conditions
- Evaluation of the kinetics of odour emissions from different odour sources for odour modelling work

2. Odour measurement using an electronic nose

- Training of the electronic nose and ANN for a range of odour sources, types and characters
- Determination of the minimum number of samples for effective training of the electronic nose and ANN
- Investigation of on-site continuous odour measurement methods using a micro-size electronic nose
- Development of a signal processing engine using artificial neural network and conventional statistical approaches
- Improvement of the artificial neural network pattern recognition system using image processing technique

3. Effect of pond loading rate on odour emissions

- Estimation of the operating condition of piggery effluent ponds focused on the odour emission rate using EC and COD analysis
- Further trials to refine the relationship between odour emission rates and OLR, HRT and the other key variables and the development of a process model of emissions
- Investigation of the effect of sludge accumulation and up-welling on pond odour emissions

REFERENCES

1. AAFRD (2002) Livestock Mortality Management (Disposal). Information Booklet, Alberta Agriculture, Food and Rural Development, Edmonton, AB, Canada

2. Abeles-Allison M; Conner L (1990) An analysis of local benefits and costs of Michigan hog operation experiencing environmental conflicts. Agricultural Economics Report No. 536, Department of Agricultural Economics, Michigan State University, East Lansing, 1990

3. Aiken-murray (2004) Swine (hog, pig) Farm Prescription. [on-line], available from: http://www.alken-murray.com/BioInfo2-10.htm

4. Alberts C (2000) Purple sulfur bacteria make ponds less odouriferous. [on-line], available from: http://ianwww.unl.edu/ianr/ard/0300/pond.html

5. Anderson J B; Hill D T; Tyson T W (2000) Physical and chemical properties of undisturbed stratified sludge in swine waste anaerobic lagoons. Proceedings of the 8th International Symposium on Animal, Agricultural and Food Processing Wastes, Des Moines, Iowa, October 2000, 171-178

6. APL (2003) Pig stats 2002. [on-line], available from: http://www.australianpork.com.au/index.cfm?menuid=87AB1342-9027-E533-1F06DB0528CD9EFA

7. Arogo J; Westerman P W; Heber A J; Robarge W P; Classen J J (2001) Ammonia in Animal Production – A Review. 2001 ASAE Annual International Meeting. Paper No. 014089. St. Joseph, MI.

8. AromaScan, plc. (1996) AromaScan Software & Operators Manual. AromaScan plc., Crewe, UK

9. ASTM (1999) Standard practices for referencing suprathreshold odour intensity. American Society for Testing and Materials, West Conshohocken, PA.

10. Baldo L J (2000) Wind velocity profiles in odour sampling wind tunnels. Bachelor thesis of Faculty of Engineering & Surveying, University of Southern Queensland, Toowoomba, Australia

11. Bardsley T; Demetriou J (1997) Odour measurements that don't stink. Proceedings of the National Workshop on Odour Measurement Standardization, Eds, Jiang K, University of New South Wales, Sydney, Australia, 20-22 August, 46-52.

12. Barth C L (1985) The rational design standard for anaerobic livestock lagoons. Proceedings of the 5rd International Symposium on Livestock Wastes, ASAE, 638-647

13. Barth C L; Hegg R O; King T G (1978) The sweet smell of success. Paper presented at southeast-southwest reg., ASAE, Houston

14. Bartlett P N; Archer P B M; Ling-Chung S K (1989a) Conducting polymer gas sensor Part I. Fabrication and characterization. Sensors and Actuators, Vol 19, 125-140

15. Bartlett P N; Archer P B M; Ling-Chung S K (1989b) Conducting polymer gas sensor Part II. Response of polypyrrole to methanol vapour. Sensors and Actuators, Vol 19, 141-150

16. Bartlett P N; Archer P B M; Ling-Chung S K (1989c) Conducting polymer gas sensor Part III. Results for four different polymers and five different vapours. Sensors and Actuators, Vol 20, 287-292

17. Bartlett P N; Blair N; Gardner J W (1993) Electronic nose. Principles, applications and outlook. ASIC, 15e Colloque, Montpellier, pp. 478–486

18. Bartlett P N; Elliot J M; Gardner J W (1997) Electronic noses and their application in the food industry. Food Technology, Vol 51, 44–48

19. Berry M J A; Linoff G (1997). Data mining techniques. John Wiley & Sons, New York, USA

20. Bhattacharya S K; Parkin G F (1988) The effect of ammonia on methane fermentation processes. Journal of Water Pollution, Control, Feb. Vol 61, 531-536

21. Bidan G (1992) Electroconducting conjugated polymers: new sensitive matrices to build up chemical or electrochemical sensors: A review, Sensors and Actuators B, Vol 6, 45-56

22. Bliss P; Jiang K; Schulz T (1995) The development of a sampling system for determining odor emission rates from areal surfaces: Part II.

Mathematical model. Journal of Air & Waste Management Association, Vol 45, 989-994

23. Blum A (1992) Neural networks in C^{++}. John Wiley & Sons, New York, USA

24. Boger Z; Guterman H (1997) Knowledge extraction from artificial neural network Models. IEEE Systems, Man and Cybernetics Conference, Orlando, FL, USA

25. Burl M C; Doleman B J; Schaffer A; Lewis N S (2001) Assessing the ability to predict human percepts of odor quality from the detector responses of a conducting polymer composite-based electronic nose. Sensors and Actuators B, Vol 72 (2), 149-159

26. Byun H G; Krishna C; Persaud K C; Khaffaf S M; Hobbs P J; Misselbrook T H (1997) Application of unsupervised clustering methods to the assessment of malodour in agriculture using an array of conducting polymer odour sensors, Computers and Electronics in Agriculture, Vol 17, 233-247

27. CASANZ (1998) Odour Special Interest Group 2nd National Odour Workshop Position Paper. Clean Air Society of Australia and New Zealand, Cape Schanck, Victoria, Australia

28. CEN (1999) Air quality: Determination of odour concentration measurement by dynamic olfactometry. Draft prEN 13725, European Committee for Standardisation, Brussels

29. Chapin A; Boulind C; Moore A (1998) Controlling odor and gaseous emission problems from industrial swine facilities. Yale Environmental Protection Clinic, Kerr Center, Poteau, Oklahoma, USA

30. Chastain J P; Henry S (1999) Management of ponds and storage structures for swine manure, [on-line], available from: http://hubcab.clemson.edu/scafrs/Peedee/certifi/Chapt%204/chapt4.html

31. Chelani A B; Chalapati Rao C V; Phadke K M; Hasan M Z (2002) Prediction of sulphur dioxide concentration using artificial neural networks. Environmental Modelling & Software, Vol 17, 161-168

32. Clark J A; Schmidt C E; D'Avanzo T (1988) Overview of applicable emission measurement technologies for the measurement of volatile hazardous waste emissions. International Symposium on Measurement of Toxic and Related Air Pollutants, EPA/APCA, Research Triangle Park, North Carolina, 383-398

33. Classen J J; Schiffman S S; Nagle H T; Guitierrez-Osuna R (1997) Electronic nose evaluation of synthetic hog farm odor. International symposium: Ammonia and odour control from animal production facilities, Eds, Voermans J A M; Monteny G J, Vinkeloord, The Netherlands Oct. 6-10, 1997, Vol 1, 77-82

34. Cumby T R; Moses B; Nigro I (1995) Gases from livestock slurries; emission kinetics. 7th International Conference on Agricultural and Food Wastes

35. Demuth H; Beale M (1994) Neural network toolbox user's guide. The MathWorks Inc, USA

36. Denmead O T (1979) Chamber systems for measuring nitrous oxide emission from soils in the field. Soil Science Society of America Journal, Vol 43, 89-95

37. Department of Primary Industry and Fisheries, Tasmania (1996) Design and management of Tasmanian sewage lagoon systems, Printing Authority of Tasmania, Tasmania, 103-105

38. DNI (1990) Dutch pre-standard on olfactometry. Dutch Normalisation Institute Publ. No. NVN 2820, Aug. 1990 (Amendments to May 1992)

39. Donham K J; Rubino M; Thedell T D; Kammermeyer J (1977) Potential health hazards to agricultural workers in swine confinement buildings. Journal of Occupational Medicine, Vol 19, 383-387

40. Dravnieks A; Prokop W H; Boehme W R (1978) Measurement of ambient odors using dynamic forced-choice triangle olfactometer. Journal of the Air Pollution Control Association, Vol 28 (11), 1124-1130

41. EPA NSW (2001) Draft policy: Assessment and management of odour from stationary sources in NSW. Technical notes, NSW Environmental Protection Agency, Sydney, Australia

42. Fisher R A (1989) Vermont experiences with manure transfer and storage. NRAES-31, Proceedings from the Dairy Manure Management Symposium, Syracuse, New York, February 1989

43. Freeman T; Needham C; Schulz T (2000) Draft 3: Analysis of options for odour evaluation for industrial or trade processes. Auckland Regional Council, Auckland, New Zealand

44. FSA Environmental (2000) Tong Park Pty Ltd Pink pond odour research study. Final report, APL project No. 1628, Toowoomba, Australia

45. Fukunaga T; Mori S; Nakabayashi Y; Kanda M; Ehara K (1995) Application of flavor sensor to coffee. ASIC, 16th International Scientific Collopuium on Coffee, 9–14 April, Kyoto, 478–486

46. Fulhage C D (1994) Minimizing odor problems in lagoons/composting of dead animals. Iowa State University, Ames, IA. 72-77

47. Galvin G; Lowe S; Atzeni M; Casey K (2002) Spatial variability of odour emissions from anaerobic piggery ponds. In Enviro 2002 Convention and Exhibition & IWA World Water Congress, Melbourne

48. Gardner J W; Barlett P N (1999) Electronic nose: principles and applications. Oxford University Press, New York, USA

49. Gardner J W; Bartlett (1991) Potential applications of electropolymerized thin organic films in nanotechnology. Nanotechnology, Vol 2, 19-33

50. Gardner J W; Bartlett P N (1992) Sensors and sensory systems for an electronic nose. NATO ASI Series E: Applied Sciences, Vol 212, Kluwer Academic Publishes, Dordrecht/Boston/London

51. Gardner J W; Bartlett P N (1993) A brief history of electronic noses. Sensors and Actuators B, Vol 18, 211–220

52. Gardner J W; Bartlett P N (1994) A brief history of electronic noses. Sensors and Actuators B, Vol 18, 211-221

53. Georgacakis D; Sievers D M (1979) Bacterial response to salts in an anaerobic dairy lagoon. Trans. ASAE, Vol 22 (1), 162-168

54. Gholson A R; Albritton J R; Jayanty R K M (1989) Evaluation of the flux chamber method for measuring volatile organic emissions from surface impoundments. EPA/600/3-89/008, US Environmental Protection Agency, Research Triangle Park, NC, PB89-148589

55. Gholson A R; Albritton J R; Jayanty R K M; Knoll J E; Midgett M R (1991) Evaluation of an enclosure method for measuring emissions of volatile organic compounds from quiescent liquid surfaces. Environmental Science Technology, Vol 25 (3), 519-524

56. Gibson T D; Prosser O; Hulbert J (2000) Electronic noses: an inspired idea?. Chemistry and Industry (April), 287-289

57. Gőpel W (1995) Analysis of complex gas mixtures by pattern recognition. Olfaction and Electronic Nose, 2nd International Symposium, Toulouse

58. Gralapp A K; Powers W J; Bundy D S (2000) Comparison of olfactometry, gas chromatography and electronic nose technology for measurement of indoor air from swine facilities. ASL-R683, Iowa State University, USA

59. Gurnay K (2003) Neural nets by Kevin Gurney. [on-line], available from: http://www.shef.ac.uk/psychology/gurney/notes/download.html

60. Gustafsson G.; Lundström I.; Liedberg G; Wu C R; Inganäs O; Wennerström O (1989) The interaction between ammonia and poly (pyrrole). Synthetic Metals, Vol 31, 163-179

61. Gustafsson G; Lundström I (1987) The effect of ammonia on the physical properties of polypyrrole. Synthetic Metals, Vol 21, 203-208

62. Hach (2004) DR/4000 Spectrophotometer Procedures. [on-line], available from: http://www.hach.com/hc/browse.product.documentation/|

63. Hamilton D W; Arogo J (1999) Measuring farmstead odour. F-1740. Oklahoma Cooperative Extension Service, Division of Agricultural Sciences and Natural Resources, Oklahoma State University, Stillwater, Oklahoma, USA

64. Han K Y; Kim J H; Noh B S (2001) Identification of the volatile compounds of irradiated meat by using electronic nose. Food Science and Biotechnology, Vol 10 (6), 668-672

65. Hanumantharaya U; Leis J; Hancock N (1999) Quantitative odour modelling using electronic nose information. 5th International Symposium on Signal Processing and its Applications, ISSPA 99, Brisbane, August, 163-166

66. Hanumantharaya, U. (2000) Quantitative odour modelling using electronic nose information, Master thesis of Faculty of Engineering & Surveying, University of Southern Queensland, Toowoomba. Australia

67. Harper L A; Catchpoole V R; Davis R; Weir K L (1983) Ammonia volatilization: soil, plant, and microclimate effects on diurnal and seasonal fluctuations. Agronomy Journal, Vol 75, 212-218

68. Hartung E; Hauser A; Jungbluth (2001) Comparative evaluation of different olfactometers and different measuring procedures. 1st IWA

International Conference on Odour and VOCs, UNSW, Sydney, Australia, 37-44

69. Haykin S (1994) Neural networks: A comprehensive foundation, Prentice Hall, New Jersey, USA

70. Heber A J; Ni j Q; Lim T T (2002) Odor flux measurements at a facultative swine lagoon stratified by surface aeration. Applied Engineering in Agriculture Vol 18(5), 593-602

71. Hines E L; Boilot P; Gardner J W; Gongora M A (2003) Pattern analysis for electronic noses. In Handbook of machine olfaction, eds Pearce T C; Schiffman H T; Gardner J W, WILEY-VCH, Weinheim, Germany

72. Hinze J O (1959) Turbulence, An Introduction to its mechanism and theory. McGraw-Hill Series in Mechanical Engineering. McGraw-Hill, New York, USA

73. Hobbs P J; Misselbrook T H; Cumby T R (1999) Production and emission of odours and gases from ageing pig waste. Journal of Agricultural Engineering Research, Vol 72, 291-298

74. Hobbs P J; Misselbrook T H; Pain B F (1995) Assessment of odours from livestock wastes by photoionisation detector, an electronic nose, olfactometry and gas chromatography-mass spectrometry, Journal of Agricultural Engineering Research, Vol 60, 137-144

75. Hodgins D (1995) The development of an electronic nose for industrial and environmental applications. Sensors and Actuators B, Vol 27, 255-258

76. Hodgins D (1997) The electronic nose: Sensor array-based instruments that emulate the human nose. In Techniques for analyzing food aroma, Eds. MARSILI R, Marcel Dekker Inc., New York, 331–371

77. Holmberg M (1997) Data evaluation for an electronic nose. Doctoral thesis at the Department of Physics and Measurement Technology, Linkőping University

78. Hopfield J J (1999) Odor space and olfactory processing: collective algorithms and neural implementation. Proceedings of National Academy of Sciences, Vol 96 (22), 12506-12511

79. Hudson N; Casey K; Duperouzel D; Lowe S; Gies A (2002) Assessment of Supported Permeable Covers for Reduction of Odour Emissions from Anaerobic Ponds. In Enviro 2002 Convention and Exhibition & IWA World Water Congress, Melbourne

80. Humenik F J; Overcash M R; Barker J C; Westerman P W (1981) Lagoons: State-of-the-art. Livestock Waste: A Renewable Resource. ASAE, St Joseph, MI, 211-216

81. Hussey R; Zhang Y; Funk T L; Riskowski G L (1999) The Use of an air supported pneumatic structure to reduce earthen pond odour intensity and volatile organic compound (VOC) emissions, Unpublished, University of Illinois at Urbana-Champaign, Urbana

82. Hwang S T (1985) Model prediction of volatile emissions: A comparison of several models for predicting emissions for hazardous waste treatment facilities. Environmental Progress, Vol 4 (2), 141-144

83. ISU (2003) Anaerobic lagoons. Department of Agricultural and Biosystems Engineering, Iowa State University, [on-line], available from: http://www.abe.iastate.edu/Ae573_ast475/anaerobic_lagoons_notes.htm

84. ISU Odour Group (2002) Iowa concentrated animal feeding operations air quality study, Final report, Iowa state university and the university of Iowa study group, Ames, USA

85. Jiang J K (1997) Towards odour measurement standardisation in dynamic olfactometry. Proceedings of the National Workshop on Odour Measurement Standardization, University of New South Wales, Sydney, Australia, August 20-22 1997, Eds. Jiang J K, 33-41

86. Jiang J K; Bliss P J; Schultz T J (1995) The development of a sampling technique for determination of odour emission rate from areal surfaces: I. Aerodynamic performance. Journal of Air and Waste Management Association, 45, 917-922

87. Jiang J K; Bliss P J; Schulz T J (1995) The development of sampling technique for determination of odour emission rate from areal source. 16th Federal Convention, Australian Water and Wastewater Association, 2-6 April, 1995 Darling Harbour, Sydney, Vol 1, 853-859.

88. Jiang J K; Kaye R (1996) Comparison study on portable wind tunnel system and isolation chamber for determination of VOC's from areal sources. Water Science and Technology. 34 (3-4), 583-589

89. Jiang J K; Kaye R (2001) Sampling techniques for odour measurement. In odours in wastewater treatment, Eds Stuetz R; Frechen F-B, IWA publishing, Padstow, Cornwall, UK

90. Jiang J K; Sands J R (1998a) Controlling noxious animal odours: An imperative at the rural-urban interface, Centre for Water and Wastes Technology, Proceedings of Pre-Conference Symposia, the 8th World Conference on Animal Production, Seoul, Korea, June 1998

91. Jiang J K; Sands J R (1998b) Report on odour emissions from poultry farms in Western Australia. Principle technical report, Centre for Water and Waste Techniques, The University of New South Wales, Sydney

92. Jiang J K; Sands J R (2000) Odour and ammonia emission from broiler farms. A report for the Rural Industries Research and Development Corporation, RIRDC Publication No 00/2, Kingston, ACT, Australia

93. Jones M; Watts P J; Smith R J (1994) A mobile dynamic olfactometer for feedlot odor studies. Applied Engineering in Agriculture, Vol 10 (3), 417-423

94. Kaye R; Jiang J K (2000) Development of odour impact criteria for sewage treatment plants using odour complaint history. Water Science and Technology, Vol 41, 57–64

95. Kephart K B; Mikesell R E (2000) Manure odors. Pennsylvania State University, [on-line], available from: http://www.das.psu.edu/Swine/Manure_odor.pdf

96. Kermit M; Tomic O (2001) Increased discrimination between odor signals by independent component analysis. Proceeding of Artificial Intelligence and Soft Computing (ASC 2001), Cancun, Mexico

97. Klarenbeek J V; Van Harreveld A (1995) On the regulation, measurement and abatement of odours emanating from livestock housing in the

Netherlands. Proceedings of the International Livestock Odor Conference 1995, Iowa State University, USA, 16 - 18 October, 16-21.

98. Klenbusch M R (1986) Measurement of gaseous emission rates from land surfaces using an emission isolation flux chamber user's guide. EPA/600/8-86/008; US Environmental Protection Agency, Las Vegas, USA

99. Ko S H; Park E Y; Han K Y; Noh B S; Kim S S (2000) Development of neural network analysis program to predict shelf-life of soymilk by using electronic nose. Food Engineering Progress, Vol 4 (3), 193-198

100. Koelsch R (1994) Planning and managing for odour control. NRAES-79, Proceedings from the Liquid Manure Application Systems Conference, Rochester, New York, December 1994

101. Lacey R E (1998) Characterization of swine production odors by an electronic nose, NPPC final report, Texas A&M Univ

102. Lacey R E; Osborn G S (1998) Application of electronic noses in measuring biological systems. ASAE Annual International Meeting, 98-6116, Disney's Coronado Springs Resort, Orlando, Florida, USA

103. Lavine B K (2000) Clustering and classification of analytical data. In Encyclopedia of Analytical Chemistry, Eds. Meyers R A, John Wiley & Sons Ltd,, Chichester, USA

104. Lim T T; Heber A J; Ni J Q; Kendall D; Richert B T (2004) Effects of manure removal strategies on odor and gas emission from swine finishing. Trans. ASAE (*in press*)

105. Lim T T; Heber A J; Ni J Q; Sutton A L; Shao P (2003) Odor and gas release from anaerobic treatment lagoons for swine manure. Journal of Environmental Quality, Vol 32 (2), 406-416

106. Lindvall T (1970) On sensory evaluation of odours air pollutant intensities. Lord. Hyg. Tidskr., Suppl. 2. Stockholm: Karolinska institute and national institute of public health

107. Lockyer D R (1984) A system for the measurement in the field of losses of ammonia through volatilisation. Journal of the science of food and agriculture, Vol 35, 837-848

108. Loubet B; Cellier P; Flura D; Genermont S (1999a) An evaluation of the wind tunnel technique for estimating ammonia volatilization from land: Part 1. Analysis and improvement of accuracy, Journal of Agricultural Engineering Research, Vol 72, 71-92

109. Loubet B; Cellier P; Genermont S; Flura D (1999b) An evaluation of the wind-tunnel technique for estimating ammonia volatilization from land: Part 2. Influence of the tunnel on transfer processes. Journal of Agricultural Engineering Research, Vol 72, 83-92

110. Lyons D; Johnson (1998) New device analyzes livestock odors. News for the USDA Agricultural Research Service, [on-line], available from: http://www.ars.usda.gov/is/pr/1998/980424.htm

111. Mackay-Sim A (1992) Electronic odour detection-problems and possibilities. In odour update '92, Proceedings of a Workshop on Agricultural Odours, MRC Report No. DAQ 64/24, Department of Primary Industries, Toowoomba, Queensland, Australia. 57-61

112. Mackie R I (1994) Microbial production of odor components. Iowa State University, 18-19

113. Maclay G J; Yue C; Findlay M W; Stetter J R (1991) Sensor for detecting the exhaustion of an adsorbent bed. Applied Occupational and Environmental Hygiene, Vol 6 (8), 677-682

114. Mannebeck D; Mannebeck H (2001) Interlaboratory comparison of dynamic olfactometry in central Eeurope 2000. 1st IWA International Conference on Odour and VOCs, UNSW, Sydney, Australia, 31-36

115. Mannheim T; Braschkat J; Marschner H (1994) Measurement of ammonia emission after liquid manure application: II. Comparison of the wind tunnel and the IHF method under field conditions. Planzernernähr, Bodenk, 158, 215-219

116. Martin A M (1991) Biological degradation of wastes. Elsevier Applied Science, London, 231-246

117. Mathworks Inc. (2001) Matlab User's guide. The MathWorks Inc., USA

118. MBAH (1996) Best Management Practices – Carcass Disposal. Minnesota Board of Animal Health, St. Paul, MN, USA

119. McGinley M A; Mann J (1998) European versus United States odour / odor standards of evaluation. Water Environment Federation 71st Annual Conference, Orlando, Florida, 3-7 October

120. Merkel J A (1981) Managing livestock wastes. AVI Publishing Company, Inc., Westport, Connecticut, USA, 249-259

121. Miasik J J; Hooper A; Tofield B C (1986) Conducting polymer gas sensor. J. Chem. Soc. Faraday Trans I, Vol 82, 1117-1126

122. Mielle P (1996) Electronic noses-towards the objective instrumental characterization of food aroma. Trends in Food Science & Technology, Special Issue on Flavour Perception, Vol 7, 432–438

123. Mills G; Walsh F; Whyte I (1996) A sense of (electronic) smell. Chemical Technology Europe (July/August), 26-30

124. Miner J R (1975) Management of odors associated with livestock production. Proceedings of the 3rd International Symposium on Livestock Wastes, ASAE, 378-380

125. Misselbrook T H; Clarkson C R; Pain B F (1993) Relationship between concentration and intensity of odours for pig slurry and broiler houses. Journal of Agricultural Engineering Research, Vol 55, 163-169

126. Misselbrook T H; Hobbs P J; Persaud K C (1997) Use of electronic nose to measure odour concentration following application of cattle slurry to grassland. Journal of Agricultural Engineering Research, Vol 66, 213-220

127. Misselbrook T H; Pain B F; Headon D M (1998) Estimates of ammonia emission from dairy cow collecting yards, Journal of Agricultural Engineering Research, Vol 71, 127-135

128. MPCA (1999) Feedlot air quality summary: data collection, enforcement and program development. Minnesota Pollution Control Agency, BAE, University of Minnesota

129. MWPS (1985) Livestock waste facilities handbook. MWPS-18, Midwest Plan Service, Iowa State University, Ames, Iowa

130. Nanto H; Minami T; Takata S (1986) Zinc-oxide thin-film ammonia gas sensors with high sensitivity and excellent selectivity. Journal of Applied Physics, Vol 60 (2), 482-484

131. Nanto H; Stetter J R (2003) Introduction to chemosensors. In Handbook of machine olfaction, Eds. Pearce T C; Schiffman S S; Nagle H T; Gardner J W, WILEY-VCH, Weinheim, Germany

132. NCMAWM (2001) White Papers - odour mitigation for concentrated animal feeding operations: white paper and recommendations. MWPS, Iowa State University, Ames, IA. USA

133. NCSU (1998) Control of odour emissions from animal operation. [on-line], available from: http://www.cals.ncsu.edu:8050/waste_mgt/newodour.htm

134. Nelson M M; Illingworth W T (1991) A practical guide to neural nets. Addison Wesley Publishing Company, Massachusetts, USA

135. New Zealand Ministry for the Environment (1995) Odour management under the resource management act. Wellington, New Zealand

136. Newman A R (1991) Electronic noses. Analytical Chemistry, Vol 63, 585A–588A

137. Nicolai R E (1996) Managing odors from swine waste. AEU-8, [on-line], available from: http://www.bae.umn.edu?extens/aeu/aeu8.htm

138. Nigrin A (1993) Neural networks for pattern recognition. MIT Press, Cambridge, MA, USA

139. Nimmermark S (2001) Use of electronic noses for detection of odour from animal production facilities: A review. 1st IWA International Conference on Odour and VOCs, UNSW, Sydney, Australia, 51-59

140. Noh B S; Ko J W (1997) Discrimination of the habitat for agricultural products by using electronic nose. Food Engineering Progress, Vol 1 (2), 103-106

141. Noh B S; Ko J W; Kim S Y; Kim S J (1998) Application of electronic nose in discrimination of the habitat for special agricultural products. Korean Journal of Food Science Technology, Vol 30 (5), 1051-1057

142. NZWWA (2000) Manual for wastewater odour management, New Zealand Water and Wastes Association, Onehunga, Auckland, New Zealand

143. Oke T R (1987) Boundary layer climates. Routledge, New York, USA

144. O'Neill D H; Phillips V R (1992) A review of the control of odour nuisance from livestock buildings: Part 3, Properties of the odorous substances which have been identified in livestock wastes or in the air around them. Journal of Agricultural Engineering Research, Vol 53, 23-50

145. Pain B F; Rees Y J; Lockyer D R (1987) Odour and ammonia emission following the application of pig or cattle slurry to land. In volatile emissions from livestock farming and sewage operations, Eds. Nielsen V C; Voorburg J H; L'Hermite P, Elsevier Applied Science Publishers, London, 2-11

146. Pain F; Hepherd R Q (1985) Anaerobic digestion of farm waste. Technical bulletin 7, The National Institute for Research in Dairying, Reading, England, 15-28.

147. Palmquist R (1997) Hog Operations, environmental effects, and residential property values. Land Economics, Vol 73 (1), 114-124

148. Patterson D W (1996) Artificial Neural networks. Prentice Hall, Simon & Schuster, Singapore

149. Pena M R; Mara D D; Sanchez A (2002) Dispersion studies in anaerobic ponds: implications for design and operation. Water Science and Technology, Vol 42, Nos 10 –11, 273–282

150. Persaud K C; Khaffaf S M; Hobbs P J; Misselbrook T H; Sneath R G (1996a) Application of conducting polymer odour sensing arrays to agricultural malodour monitoring. International Conference on Air Pollution from Agricultural Operations, Kansas City, Missouri, USA. 249-253

151. Persaud K C; Khaffaf S M; Hobbs P J; Sneath R W (1996b) Assessment of conducting polymer odour sensors for agricultural malodour measurement. Chemical Senses, Vol 21, 495-505

152. Persaud K C; PELOSI P (1992) Sensor arrays using conducting polymers for an artificial nose. In: Sensors and sensory systems for an electronic nose, Eds. Gardner J W; Bartlett P N, Dordrecht: Kluwer Academic Publishers, 237–256

153. Persaud K; Dodd G H (1982) Analysis of discrimination mechanisms in the mammalian olfactory system using a model nose. Nature, Vol **299**, 352–355

154. Persaud K; Travers P J (1997) Arrays of broad specificity films for sensing volatile chemicals. In Handbook of Biosensors and Electronic Noses, ed. E. Kress-Rogers, CRC Press. Boca Raton, Florida, 563-592

155. Pfost D L; Fulhage C D (1993) Ponds for storage/treatment of dairy waste. [on-line], available from: http://muextension.missouri.edu/xplor/waterq/wq0304.htm

156. Piction P (1994) Introduction to neural networks. The Macmillan Press Ltd., Hampshire, UK

157. Piction P (2000) Neural Networks. Palgrave publishers Ltd.

158. Pieters J G; Neukermans G G J; Colanbeen M B A (1999) Farm-scale membrane filtration of sow slurry. Journal of Agricultural Engineering Research, Vol 73, 403-409

159. Pollock T J (1997) Dispersion modelling to predict off-site impact of odour sources. Proceedings of the National Workshop on Odour Measurement Standardisation, UNSW, Sydney Australia, 20-22 August, 95-104

160. Polmetto A L; Moizuddin S (1998) Electronic nose for rapid detection of food borne pathogens in meats. ASL-R1605, Iowa State University, USA

161. Powell L (2002) Integrated pollution prevention and control (IPPC): Horizontal guidance for odour, Part 2: Assessment and control, Scottish Environment Protection Agency, Bristol, Scotland

162. Power V (2000) Odour impacts and odour emission control measures for intensive agriculture. Final report, R&D report series No.14, Environmental Protection Agency, Wexford, Ireland

163. Power V; Stafford T (2001) Odour impacts and odour emission control measures for intensive agriculture. EPA, Wexford, Ireland

164. Qu G; Feddes J J R; Armstrong W W; Coleman R N; Leonard J J (2000) Measuring odour concentrations with an electronic nose, Trans ASAE 44(6), 1807-1812

165. Qu G; Feddes J J R; Armstrong W W; Leonard J J (2002) Method and apparatus for estimating odour concentration using an electronic nose, U.S. Patent No. 6,411,905

166. Reinhart D R; Copper D C; Walker B L (1992) Flux chamber design and operation for the measurement of municipal solid waste landfill gas emission rates. Journal of Air and Waste Management Association, Vol 42, 1067-1070

167. Reitz P; Kutzbach H D (1997) Accuracy of wind tunnel for measuring ammonia emissions after slurry application. Proceeding of the International Symposium on 'Ammonia and odour emissions from animal production facilities', Vinkeloord, Netherlands, 6-10 October. Published by NVTL, Rosmalen, 1997: Section 2, 595-602

168. Reynolds S (1996) Longitudinal evaluation of dose-response relationships for environmental exposures and pulmonary function in swine production workers. American Journal of Industrial Medicine, Vol 29, 33-40

169. Rieß G; Maier B; Gronauer A; Schőn H (2000) Development of a system for the continuous detection of the odour emissions from agriculture. Paper 00-Ap-002, AgEng2000, Warwick, UK

170. Robertson A M (1977) Farm wastes handbook. The Scottish Farm Buildings Investigation Unit, Aberdeen, Scotland, 75-77

171. Roppel T A; Padgetta M L; Waldemark J; Wilson D (1998) Feature-level signal processing for near-real-time odor identification. SPIE Aerosense 98, Orlando, FL, USA

172. Sarle W S (1994) Neural networks and statistical models. Proceedings of the nineteenth annual SAS users group international conference

173. Sarle W S (2001) Neural network FAQ, part 3 of 7: generalization. [on-line], Available from: ftp://ftp.sas.com/pub/neural/FAQ3.html, Usenet newsgroup comp.ai.neural-nets, Discussion list

174. Schaller E; Bosset J O; Escher F (1998) Electronic noses and their application to food. Food Science and Technology, Vol 31 (4), 305-316

175. Schauberger G; Piringer M; Petz E (1999) Diurnal and annual variation of odour emission from animal houses: a model calculation for fattening pigs. Journal of Agricultural Engineering Research, Vol 74, 251-259

176. Schiffman S (1994) Psychological effects of swine odor on humans. Iowa State University, 8-11

177. Schiffman S (1995) The effect of environmental odors emanating from commercial swine operations on the mood of nearby residents. Brain Research Bulletin, Vol 37 (4), 369-375

178. Schiffman S; Nagle H T; Gutierrez R; Ho H T; Walden T (1997) Development of a testing protocol using an electronic nose to evaluate methods for odor remediation. National Pork Producers Council, USA

179. Schiffman S; Walker J; Dalton P; Lorig T; Raymer J; Shusterman D; Williams C (2000) Potential health effects of odor from animal operations, wastewater treatment and recycling of byproducts. J Agromed, Vol 7, 7-81

180. Schmidt C E (2001) Downhole flux chamber testing. [on-line], available from: http://www.ceschmidt.com/downhole.htm

181. Schmidt D (1998) Odor control 15. [on-line], available from: http://hubcap.clemson.edu/~blpprt/odor_15.html

182. Schmidt D R (2002) Odour - from research to practical solutions. [on-line], available from: http://www.ctic.purdue.edu/Core4/Nutrient/ManureMgmt/Paper77.html

183. Schmidt D; Jacobson L (1995) Odor and odor policy criteria. AEU-11, Minnesota Extension Service, Department of Biosystems and Agricultural Engineering University of Minnesota

184. Schreiber F W; Fitzner K (1999) Electronic nose: investigation of the perceived air quality indoor environments. Proceedings of Indoor Air ´99, Edinburgh, 624-629

185. Schulte D D; Kottwitz D A; Gilbertson C B (1985) Nitrogen content of scraped swine manure, 321-328, Proceedings of the 5th International Symposium on Agricultural Waste, ASAE, St. Joseph, MI.

186. Schultz T; Lim B P L (1993) Piggery odours - monitoring and management. Agricultural odours workshop, AWWA, CASANZ, 19-20 August, Dubbo

187. Schulz T; Jiang K; Bliss P (1995a) The development of a sampling system for the determination of odour emission rates from the areal surfaces: Part 1. Aerodynamic performance. Journal of Air & Waste Management Association, Vol 45, 917-922

188. Schulz T; Jiang K; Bliss P (1995b) The development of a sampling system for the determination of odour emission rates from the areal surfaces: Part 2. Mathematical model. Journal of Air & Waste Management Association, Vol 45, 989-994

189. Schulz T; Kaye R; Von Harreveld A (1995) A review of developments in olfactometry. 16th Federal Convention, Australian Water and Wastewater Association, 2-6 April, 1995 Darling Harbour, Sydney, Vol 1, 53-59.

190. Shiers V P (1995) Electronic nose technology-evaluations and developments for the food industry. In: Marrssen (Ed), Food Ingredients Europe: Conference Proceedings. Frankfurt: Miller Freeman Technical, 198–200

191. Shindo S; Kumagai M; Watanabe S; Takahashi S (2001) Evaluation of sake by an odor sensor. American Society of Brewing Chemists, Vol 59 (2), 77-79

192. Shusterman D (1992) Critical review: the health significance of environmental odor pollution. Arch Environ Health, Vol 47, 76-87

193. Shusterman D; Lipscomb J; Neutra R; Satin K (1999) Symptom prevalence and odor-worry interaction near hazardous waste sites. Environ Health Perspect, Vol 94, 25-30

194. Sievers D M; Iannotti E L (1981) Anaerobic processes for stabilization and gas production. MWPS-25, Midwest Plan Service, Iowa State University, Ames, Iowa

195. Simpson P K (1990) Artificial neural systems foundations, Paradigms, applications, and implementations, first edn, Pergamon press Inc., New York, USA

196. Smith L (2003) An introduction to neural network. [on-line], available from: http://www.cs.stir.ac.uk/~lss/NNIntro/InvSlides.html

197. Smith R J (1993) Dispersion of odours from ground level agricultural sources. Journal of Agricultural Engineering Research, Vol 54, 187-200

198. Smith R J (1995) A Gaussian model for estimating odour emissions from area sources. Mathematical Computer Modelling, Vol 21, No. 9, 23-29

199. Smith R J; Dalton P A (1999a) Environmental odours from Australian piggeries, Australian Environmental Engineering Conference, Auckland, New Zealand, 10-14 July.

200. Smith R J; Dalton P A (1999b) Factors affecting the rate of odour emissions from Australian piggery buildings. Australasian Environmental Engineering Conference, Auckland, New Zealand, 10-14 July.

201. Smith R J; Dalton P A; DeBruyn J (1999) Assessment and reduction of the odour impact of piggeries. Final report, Pig Research & Development Corporation, Canberra, ACT

202. Smith R J; Hancock N K (1992) The predictions of feedlot odour emissions from downwind measurements and downwind measurements of odour concentrations. AgEng '92, International Conference on Agricultural Engineering, 1-4 June, Uppsala, Sweden

203. Smith R J; Kelly J P (1996) A comparison of two methods for estimating odour emissions from area sources. International Conference on Air Pollution from Agricultural Operations, 7-9 February, Kansas City, Missouri, 263-269

204. Smith R J; Watts P J (1994a) Determination of odour emission rates from cattles feedlots: Part 1, A Review. Journal of Agricultural Engineering Research, Vol 57, 145-155

205. Smith R J; Watts P J (1994b) Determination of odour emission rates from cattle feedlots: Part 2, Evaluation of two wind tunnels of different size. Journal of Agricultural Engineering Research, Vol 58, 231-240

206. Sohn J H (1997) Experimental studies on the applicability of UASB system to treatment of swine slurry, Master thesis of Seoul National University, 125-138

207. Sohn J H (2001) Quantify effects of pond loading rate on odour emission. Ph. D dissertation proposal, In Faculty of Engineering & Surveying, University of Southern Queensland, Toowoomba, Australia

208. St. Croix Sensory (2000) “Odour School" Workbook 5.1.01. St. Croix Sensory Inc., Stillwater, MN, USA

209. Standards Australia (1995) Stationary source emissions (AS/NZS 4323.1). Standards Australia, Sydney, Australia

210. Standards Australia (2001) Stationary source emissions: Determination of odour concentration by dynamic olfactometry (AS/NZS 4323.3), Standards Australia, Sydney, Australia

211. Staples E J (2000) The znose^{tm}, a new electronic nose using acoustic technology. Acoustical Society of America, Vol 108 (5), 2495-2502

212. Stetter J R; Zaromb S; Findlay M W (1984) Monitoring of electrochemically inactive compounds by amperometric gas sensors. Sensors and Actuators, Vol 6 (4), 269-288

213. Steutz R M; Fenner R A (2001) Odour measurements using sensor arrays. In odours in wastewater treatment, eds Stuetz R; Frechen F-B, IWA publishing, Padstow, Cornwall, UK

214. Stuetz R (2001) Using sensor arrays for on-line monitoring of water and wastewater quality. American Laboratory News, International Scientific Communications Inc, Shelton, Connecticut, USA

215. Sweeten J M (1988) Odor measurement and control for the swine industry: Recent developments. Journal of Environmental Health. Vol 50 (5), 282-286

216. Swine Odor Task Force (1995) Options for managing odour. published by the North Carolina Agricultural Research Service, North Carolina State

University, [on-line], available from: http://www.ces.ncsu.edu/whpaper/swineodor.html

217. Swingler K (1996) Applying neural networks: A practical guide. London, Academic Press

218. Tchobanoglous G; Burton F L (1991) Wastewater engineering treatment, disposal, and reuse. McGraw-Hill International Editions, New York, 434-439

219. Thirumurthi D (1991) Biodegradation in waste stabilization ponds (facultative Lagoons). In Biological Degradation of wastes, Eds. Martin A M, Elsevier Applied Science, NEW York, NY, USA

220. Tyson T W (1998) Sizing swine ponds for odour control, [on-line], available from: http://www.aces.edu/department/extcomm/publications/a…/anr1090main.htm

221. Van Belois H J; Anzion C J M (1992) Measurement of emissions over surface areas using the hood method. In Biotechniques for air pollution abatement and odour control policies (Draft A J; van Ham J, eds). Elsevier, Amsterdam

222. Van der Weerden T; Moal J F; Martinez J; Pain B F; Guiziou F (1996) Evaluation of the wind tunnel method for measurement of ammonia volatilisation from land. Journal of Agricultural Engineering Research, Vol 58, 231-240

223. Van Lotringen T J M; Gerrish J B (1978) H_2S removal by purple sulfur bacteria in swine waste lagoons. Paper presented at 33rd Annual Purdue Industrial Waste Conference, Purdue University, West Lafayette, IN

224. Vanneste E; Geise H J (2003) Commercial electronic nose instruments. In Handbook of machine olfaction, Eds. Pearce T C; Schiffman H T; Gardner J W, WILEY-VCH, Weinheim, Germany

225. VDI (1992) VDI 3882 Part 1 Determination of odor intensity. Verein Deutscher Ingenieure, Berlin, Germany.

226. Veenhuizen M A (1996) Odor-An environmental challenge for the pork industry. Final report, National Pork Producers Council, USA

227. WA DEP (2002) Odour methodology guideline. Department of Environmental Protection of Western Australia, Perth, Australia

228. Wang X; Jiang K; Kay R (2001) Improvement of wind tunnel sampling system for odour and VOC's, Proceedings of 1st IWA International Conference on Odour and VOC's, Sydney, 2001

229. Watts P J (1999a) Development of a pig effluent emissions database and analysis of promising control strategies: Final Report (Part A) Database on odour research and emission rates. Pig Research and Development Corporation, Canberra, ACT, Australia Project No. FSE 1/1503

230. Watts P J (1999b) Development of a pig effluent emissions database and analysis of promising control strategies: Final Report (Part B) Summary of preferred emission reduction strategies. Pig Research and Development Corporation, Canberra, ACT, Australia Project No. FSE 1/1503

231. Watts P J (2000) Development of a pig effluent emissions database and analysis of promising control strategies. A final report prepared for the Pig Research and Development Corporation, Australia.

232. Watts P J; Jones M; Lott S C; Tucker R W; Smith R J (1994) Feedlot odor emissions following heavy rainfall. ASAE, Vol 37 (2), 629-636

233. Wilson J D; Thurtell G W; Kidd G E; Beauchamp E G (1981) Estimation of the rate of gaseous mass transfer from a surface source plot to the atmosphere. Journal of Atmospheric Environment, Vol 16, 1861-1867

234. Wood T (1986) Wastewater stabilisation kinetics: a semicontinuous view. JWPCF, Vol 58 (9), 937–942.

235. Woodward-Clyde LTD. (2002) A review of available assessment methodologies for air quality impact assessments. Auckland Regional Council, Auckland, New Zealand

236. Yokoyama M (1994) Ozonation to reduce odors generated from swine waste slurry. Michigan State University

237. Zahn J A; Hatfield J L; Do Y S; DiSpirito A A (2000) Air pollution from swine production facilities differing in waste management practice. Proceeding of Water Environment Federation Conference, Cincinnati, OH. USA

238. Zhang Q; Feddes J; Edeogu I; Nyachoti M; House J; Small D; Liu C; Mann D; Clark G (2002) Odour production, Evaluation and control. Final report submitted to Manitoba Livestock Manure Management Initiative Inc., Project MLMMI 02-HERS-03, Manitoba

239. Zhang R; Dugba P N; Rashid N; Bundy D S (1996) Surface aeration of anaerobic lagoons for odor control of swine manure. International Conference on Air Pollution from Agricultural Operations, Kansas City, Missouri, 7-9 February, 387-394

240. Zhang Y; Gaakeer W (1996) A low cost balloon - type lagoon cover to reduce odour emissions. International Conference on Air Pollution from Agricultural Operations, Kansas City, Missouri, 7-9 February, 395-401

241. Zhu J (2000) Early separation of fresh swine manure may enhance separation efficiency. Minnesota/Wisconsin Engineering Notes, Summer 2000, [on-line], available from: www.bae.umn.edu/

GLOSSARY

Accuracy: Closeness of agreement between test result and the accepted reference value.

Adaptation(sensory): Temporary modification of the sensitivity of a sense organ due to continued and/or repeated stimulation. **[ISO 5492:1992]**

Adaptive: Adaptive neural networks classify patterns. Input data similar to previously seen patterns are classified as one of them. Patterns not similar to previous ones have a new class of patterns created for them.

Adaptive learning(or "Hebbian learning"): Learning where a system programs itself by adjusting weights or strengths until it produces the desired output.

Adaptive learning rate: In artificial neural networks, training time of some networks can be decreased by the use of an adaptive learning rate which attempts to keep the learning step size as large as possible while keeping learning stable. The learning rate is made responsive to the complexity of the local error surface.

Adsorption: Electrochemical attraction of positively or negatively charged molecules on solid surfaces with an opposite charge.

Aerobic: A process that requires oxygen.

Aerobic bacteria: Bacteria that require free elemental oxygen for their growth. Oxygen in chemical combination will not support aerobic organisms.

Aerosols: An assembly of liquid or solid particles suspended in a gaseous medium long enough to enable observation or measurement.

AI: Artificial intelligence.

Algorithm: A detailed sequence of actions to perform to accomplish some task. Named after an Iranian mathematician, Al-Khawarizmi.

Ambient: Surrounding, as in the surrounding environment. The medium surrounding or contacting an organism (e.g., a person), such as outdoor air, indoor air, water, or soil, through which chemicals or pollutants can be carried and can reach the organism.

Ambient air quality: Quality of the outdoor air to which humans are exposed during the course of their normal lives.

American Standard Code for Information Interchange: The predominant character set encoding of present-day computers. The modern version uses seven bits for each character, whereas most earlier codes (including an early version of ASCII) used fewer.

Ammonia volatilisation: Loss of ammonia (NH,) to the atmosphere.

Anaerobic: A process that does not require oxygen.

Anaerobic bacteria: Bacteria not requiring the presence of free or dissolved oxygen. Facultative anaerobes can be active in the presence of dissolved oxygen, but do not require it.

Anaerobic pond design and management: Anaerobic ponds are less odorous than manure storage pits. Ponds usually have the largest surface area per animal of all storage structures. This implies a significant potential for odour release (*i.e.* emission rate) if the pond is not functioning properly. Design and management considerations have a great impact on the odour generation of ponds. Odour of low intensity and offensiveness will be detectable from well-designed and managed anaerobic ponds.

Anaerobic pond loading rates: The "health" of an anaerobic pond is controlled primarily by the volatile solids loading rate. Loading rates should not exceed the biological limits of the bacteria. Primary overloading problems can be caused by expanding animal numbers, sludge loading, concentrated waste input, inadequate dilution water, or conditions that are not favourable for methane forming bacteria (cold temperatures, low pH). The result is incomplete anaerobic decomposition and can lead to stronger odours from the pond. As a rule, reducing the volatile solids loading rate reduces the potential for odours. Smaller daily or weekly loading results in best performance; this assures a continuous food supply for the bacteria and helps keep the bacteria populations in balance. A two or three stage pond system may improve management capabilities and thereby lower odour emissions as compared to a single step system.

Anaerobic pond start-up: Ponds will have elevated odour levels until reaching maturity, which usually takes at least one year. Ponds should be carefully managed during start-up to minimise potential odours. Ponds should be started in the late spring or summer to allow the bacteria opportunity to become established since they grow and reproduce faster at warmer temperatures. The minimum treatment volume or two-thirds of the pond should be filled with water prior to introducing manure. Manure loading should be gradually increased over a 2 to 3 month period. Rapid loading of an immature pond will increase odours.

Anaerobic pond storage volumes: Anaerobic ponds must have adequate capacity (*i.e.*, low volatile solids loading rate) to produce relatively little odour. Design criteria have been developed based on the volatile solids loading rate, which is proportional to the volume per kilograms of animal liveweight. Pond capacity should be sufficient to allow liquid removal to coincide with beneficial nutrient utilisation on crops and advantageous weather conditions.

Anosmia: Lack of sensitivity to olfactory stimuli – unable to detect odours at all (compare with hyposmia).

Area source: Surface-emitting source, which can be solid (for example the spreading of wastes, material stockpiles, surface of a biofilter) or liquid (storage ponds, effluent treatment plant).

Artificial neural network(ANN): A man-made neural network as opposed to a biological one (a brain).

Assessor: A person who participates in odour testing.

Asthma: A lung disease with the following characteristics: 1) airway obstruction (or airway narrowing) that is reversible (but not completely so in some patients) either spontaneously or with treatment; 2) airway inflammation; and 3) airway hyper-responsiveness to a variety of stimuli.

Ausplume: An air dispersion model developed by the Victorian Environment Protection Authority.

Backpropagation (generalised delta-rule): A learning algorithm for modifying a feed-forward neural network which minimises a continuous error function. Back-propagation is a gradient descent method of training in that it uses gradient

information to modify the network weights to decrease the value of the error function on subsequent tests of the inputs.

Bias: Binary output, an output that can only take one of two values. For example, in a control system an output neuron that indicated a fault had occurred would have a binary output (cf. continuous output).

Bioaerosol: Includes the sub-class of viable particulates that has an associated biological component.

Biodegradation: The breakdown of organic and inorganic matter by bacteria.

Biofilters: Filters constructed of biologically active materials, such as compost, straw, wood chips, peat or soil, that contain microorganisms that break down volatile organic compounds and oxidisable inorganic gases and vapours into non-malodorous compounds such as water and carbon dioxide.

Biological Oxygen Demand (BOD): The amount of oxygen required to decompose the biodegradable organic wastes in a given volume of water during a 5 day period at 20 ^{o}C.

Biomass: Organic plant materials like cornstalks, small grain straw, and other plant fibres. Total amount of living material, plants and animals, above and below ground in a particular area.

Bronchiolitis obliterans: A disease of the airways of the lung that is characterized by fibrosis (scarring) of the small airways (bronchioles). Known causes include some viral infections, rejection of a transplanted lung, and inhalation of some mineral dusts and irritant fumes.

Buffer distance: Minimum distance between a shed and a specified potential odour receptor.

Character descriptors: Terms used by trained odour panellists to describe an odour's character (e.g., mint, citrus or earthy).

Chemical Oxygen Demand (COD): The amount of oxygen required for the chemical conversion of organic waste matter.

Chronic effects: Effects produced by prolonged exposures of three months to a lifetime.

Cognitive: Relating to thinking processes and related brain functioning.

Composting: Controlled aerobic microbial degradation of organic waste yielding an environmentally safe and nuisance-free soil conditioner and fertiliser.

Concentrate feed: Animal feed containing mineral supplements.

Control condition: Condition in which no treatment occurs, thus allowing comparison of the effects of the experimental treatment.

Cross ventilated shed: Shed provided with mechanical ventilation across its medial axis.

Data processing: The input, verification, organisation, storage, retrieval, transformation, and extraction of information from data. The term is normally associated with commercial applications such as stock control or payroll.

Dehydration: Dehydration is one common technique for inhibiting anaerobic decomposition, thereby reducing odours in solid manure. When the moisture

content of manure is lowered to 50 percent or less (preferably 30%), the manure is sufficiently porous to permit air diffusion and to preclude anaerobic decomposition.

Detection threshold: The point at which an increasing concentration of an odour sample becomes strong enough to produce a first sensation of odour in 50% of the people to whom the sample is presented. The odour concentration at the detection threshold is one odour unit.

Diffuse sources: Sources with defined dimensions (mostly surface sources) which do not have a defined waste air flow, such as waste dumps, lagoons, fields after manure spreading, non-aerated compost piles.

Digesters: Odour control is a substantial benefit of digesters. There are three types of digesters: batch, complete mix, and plug flow. The batch digester is loaded in a single charge and does not accommodate a continuous flow of manure. The complete mix digester is characterized by continuous feeding and mixing to enhance bacterial performance. The plug-flow digester is an elongated tube in which manure solids are introduced to one end and allowed to proceed to the other end with no mixing while digestion takes place.

Dilution factor: The dilution factor is the ratio between flow or volume after dilution and the flow or volume of the odorous gas.

Disposal: The discharge, deposit, injection, dumping, spilling, leaking, or placing of any solid waste or hazardous waste into the environment (land, surface water, ground water, and air).

Drainage: Open feedlots should include sufficient drainage to minimise puddling and wet surfaces. For open feedlots, manure treatment for odour control consists of maintaining aerobic conditions to the extent possible. All pens should be well

drained (e.g., uniform slopes of 2% to 5% away from feeding troughs). Keeping the feedlot surface, alleys, and ditches cleaned and graded to shed water rapidly minimises anaerobic conditions after rainfall events. Pen-to-pen drainage should be avoided in favour of discrete pen drainage.

Dynamic olfactometer: A dynamic olfactometer delivers a flow of mixtures of odorous and neutral gas with known dilution factors to a common outlet.

Effluent: Liquid discharge of a manure treatment process.

Eigenvalue: The factor by which a linear transformation multiplies one of its eigenvectors.

Electronic nose: An electronic instrument that detects a select number of individual chemical compounds to measure an odour.

Emissions: The rate at which gases or particulates leave a surface or ventilated structure. An emission rate is calculated by multiplying the concentration of a gas (mass or volume basis) by the airflow rate (volume of air per unit time) associated with this concentration.

Emissions inventory: The list of all applicable regulated pollutants and their expected annual emissions.

Emulation: One system is said to emulate another when it performs in exactly the same way, though perhaps not at the same speed. A typical example would be emulation of one computer (by a program running on) another.

Epoch: One complete presentation of the training set to the network during training.

Exposure: Concentration × duration × frequency of the odour to which a receptor is exposed.

Facultative: A process that utilizes free oxygen when it is available and use other substances as electron acceptor (*i.e.* oxidants such as nitrate and sulphate ions).

Facultative bacteria: Bacteria that can grow in the presence, as well as the absence, of oxygen.

Facultative ponds: Facultative ponds combine anaerobic and aerobic bacteria treatment by "capping" an anaerobic pond with an aerobic surface. Mechanical aerators can be used to aerate the pond surface. This treatment system can be utilised to reduce odours liberated to the atmosphere.

Farrow-to-Finish: Piggery operation encompassing from birth to slaughter/death.

Feed: See rations.

Field sniffer: Trained panellist who determines odour intensity in the field.

Flushing liquid: Many producers recycle pond liquid for pit flushing in order to reduce the amount of water added to a treatment system and consequently reduce the quantity of pond liquid to be land applied and thus the odour exposure. Second stage pond effluent is preferable to primary pond effluent for flushing due to lower odour potential and solids content.

Flushing systems: Flushing systems generate less odours than any other manure handling system for confinement buildings due to very frequent manure collection. Flushing or draining manure prior to the onset of manure decomposition is recommended 3-4 times daily for controlling ammonia generation.

Forced choice method: An olfactometric method in which assessors are forced to make a choice out of two or more air flows, one of which is the diluted sample, even if no difference is observed.

Fugitive emissions: Emissions identified with a discrete process but not traceable to a single emission point such as the end of a stack. Fugitive emissions from a cattle feedlot or an open lot dairy include dust resulting from cattle activity on the feedlot surface or from vehicle traffic on unpaved roads. Analogous to non-point source water pollution.

Fugitive sources: Elusive or difficult to identify sources releasing undefined quantities of odorants e.g. valve and flange leakage, passive ventilation apertures etc.

Gas chromatograph/mass spectrometer: Research laboratory device that both identifies and measures gas concentrations by having very small samples of air injected into a carrier (nitrogen or helium) gas stream. This gas stream is passed through a column that adsorbs and desorbs the chemicals in the air at different rates plus a detector, which identifies individual chemicals and the amount in the sample.

Generalisation: A measure of how well a network can respond to new images on which it has not been trained but which are related in some way to the training patterns. An ability to generalize is crucial to the decision making ability of the network.

Hazard: Potential for radiation, a chemical or other pollutant to cause human illness or injury.

Health: Health is a state of complete physical, social and mental, and social well-being and not merely the absence of disease or infirmity.

Hebbian: Refers to the most common way for a neural network to learn, namely supervised learning. Using a training sample which should produce known responses, the connection weights are adjusted so as to minimise the differences between the desired and actual outputs for the training sample.

Hedonic tone: A judgement of the relative pleasantness or unpleasantness of an odour made by assessors in an odour panel. Odours which are more offensive will have a negative hedonic score whilst less offensive will tend towards a positive score. Scale that ranges from -10, which is unpleasant, to +10, which is pleasant, to describe an odour.

Housing unit: Any facility used to house livestock or poultry incorporating either a mechanical or natural ventilation system for providing fresh-air exchange.

H_2S: Hydrogen sulfide.

Hyposmia: Partial inability to detect odours (compare with anosmia).

Image recognition: The identification of objects in an image. This process would probably start with image processing techniques such as noise removal, followed by (low-level) feature extraction to locate lines, regions and possibly areas with certain textures. The clever bit is to interpret collections of these shapes as single objects, e.g. cars on a road, boxes on a conveyor belt or cancerous cells on a microscope slide. One reason this is an AI problem is that an object can appear very different when viewed from different angles or under different lighting. Another problem is deciding what features belong to what object and which are background or shadows etc. The human visual system performs these tasks mostly

unconsciously but a computer requires skilful programming and lots of processing power to approach human performance.

Indicator tube: Glass tube with both ends sealed that measures a wide range of gases.

Individual threshold: Detection threshold applying to an individual.

Instrumental assessment: An assessment of an odorous sample using instrumentation to provide information on the concentration and possibly provide identification of the chemical species present. Compare with "sensory" assessment.

Input layer: Neurons whose inputs are fed from the outside world.

Intensity: Describes the strength of an odour sample.

Intensive farming: The strong trend of monopolization and vertical integration in agricultural production, processing, and marketing, as well as in the manufacturing of farm inputs.

International Organization for Standardization (ISO): A voluntary, nontreaty organization founded in 1946, responsible for creating international standards in many areas, including computers and communications. ISO produced the seven layer model for network architecture (Open Systems Interconnection). Its members are the national standards organizations of 89 countries, including the American National Standards Institute. The term "ISO" is not actually an acronym for anything. It is a pun on the Greek prefix "iso-", meaning "same". Some ISO documents say ISO is not an acronym even though it is an anagram of the initials of the organization's name.

Irritant: Toxicant that exerts its deleterious effects by causing inflammation of mucous membranes with which they came into contact. Irritants principally act on the respiratory system and can cause death from asphyxiation due to lung edema. Other mucous membranes that may be affected by irritants are those of the eyes.

Iteration: Repetition of a sequence of instructions. A fundamental part of many algorithms. Iteration is characterised by a set of initial conditions, an iterative step and a termination condition. A well known example of iteration in mathematics is Newton-Raphson iteration.

Land application: Application of manure, sewage sludge, municipal wastewater, and industrial wastes to land either for disposal or for utilization of the fertilizer nutrients, organic matter, and improvement of soil tilth.

Layer: A group of neurons that have a specific function and are processed as a whole. The most common example is in a feedforward network that has an input layer, an output layer and one or more hidden layers.

learning algorithms (supervised, unsupervised): An adaptation process whereby synapses, weights of neural network's, classifier strengths, or some other set of adjustable parameters is automatically modified so that some objective is more readily achieved. The backpropagation and bucket brigade algorithms are two types of learning procedures.

Learning rule: The algorithm used for modifying the connection strengths, or weights, in response to training patterns while training is being carried out.

Low-emission housing: Livestock housing with a lower ammonia emission than conventional housing.

Lower detection limit, LDL: Lowest value of the air quality characteristic which, with 95% probability, can be distinguished from a zero sample [ISO 6879].

Manure: The fecal and urinary excretion of livestock and poultry. Often referred to as livestock waste. This material may also contain bedding, spilled feed, water or soil. It may also include wastes not associated with livestock excreta, such as milking centre wastewater, contaminated milk, hair, feathers, or other debris. Manure may be described in different categories as related to solids and moisture content. These categories are related to handling equipment and storage types.

Manure storage unit: Any structure used to store manure, including long-term storage inside the housing unit. Includes above- and below-ground structures.

MATLAB: An interactive program from The MathWorks for high-performance numeric computation and visualisation. MATLAB integrates numerical analysis, matrix computation, signal processing, and graphics in an easy-to-use environment. MATLAB is built on sophisticated matrix software for analysing linear equations. The tools supplied can be used for applied mathematics, physics, chemistry, engineering, finance and other areas dealing with complex numerical calculations.

Mechanically ventilated shed: Shed provided with mechanical ventilation.

Mesophilic: Temperature range of 15 - 35^{o}C.

Meteorological: Pertaining to the atmosphere and its phenomena, especially of its variations of heat and moisture, of its winds, etc.

Methanogenic: Bacteria that produce methane while breaking down organic matter.

Methane: A gas that is released during the digestive processes of ruminants or the anaerobic decomposition of waste. Methane is a greenhouse gas.

Microorganism: Microscopic organisms such as bacteria, protozoa, algae and fungi.

Multilayer Perceptron (MLP): A network composed of more than one layer of neurons, with some or all of the outputs of each layer connected to one or more of the inputs of another layer. The first layer is called the input layer, the last one is the output layer, and in between there may be one or more hidden layers.

Naturally ventilated shed: Shed using natural forces produced by operation of shed openings together with energy from ambient wind, temperature and direct radiant energy, to achieve ventilation.

Neural net: See neural network.

Neural Network (NN): A network of neurons that are connected through synapses or weights. Each neuron performs a simple calculation that is a function of the activations of the neurons that are connected to it. Through feedback mechanisms and/or the nonlinear output response of neurons, the network as a whole is capable of performing extremely complicated tasks, including universal computation and universal approximation. Three different classes of neural networks are feedforward, feedback, and recurrent neural networks, which differ in the degree and type of connectivity that they possess.

Neuron: A simple computational unit that performs a weighted sum on incoming signals, adds a threshold or bias term to this value to yield a net input, and maps this last value through an activation function to compute its own activation. Some

neurons, such as those found in feedback or Hopfield networks, will retain a portion of their previous activation.

NH_3: Ammonia.

Nitrification: The biological oxidation of ammoniacal nitrogen to nitrite and then to nitrate.

NO_2: Nitrogen dioxide.

Nonlinear (Scientific computation): A property of a system whose output is not proportional to its input. The behaviour of a system containing non-linear components is thus harder to model and to predict.

Nonpoint source (NPS): Entry of effluent into a water body in a diffuse manner so there is no definite point of entry.

Nonpoint source pollution: Nonpoint source pollution, unlike pollution from industrial and sewage treatment plants, comes from many diffuse sources. Nonpoint source pollution is caused by rainfall or snowmelt moving over and through the ground. As the runoff moves, it picks up and carries away natural and human-made pollutants, finally depositing them into lakes, rivers, wetlands, coastal waters, and even our underground sources of drinking water. In rural areas these pollutants include bacteria and nutrients from livestock, soil sediments, fertilizers, herbicides, and insecticides.

Normalisation: A transformation applied uniformly to each element in a set of data so that the set has some specific statistical property. For example, monthly measurements of the rainfall in London might be normalised by dividing each one by the total for the year to give a profile of rainfall throughout the year.

Normalised: Resulting from normalisation.

Nuisance: Any condition that inhibits the reasonable use or enjoyment of property.

Objective method: Any method in which the effects of personal opinions are minimised. [ISO 5492]

Odour: Organoleptic attribute perceptible by the olfactory organ on sniffing certain volatile substances. [ISO 5492]

Odour annoyance: Odour impact perceived by a receptor as unpleasant.

Odorant: A substance which stimulates a human olfactory system so that an odour is perceived.

Odour concentration: Number of odour units per unit of volume. The numerical value of the odour concentration is equal to the number of dilutions to arrive at the odour threshold (OU/m^3).

Odour detection: To become aware of the sensation resulting from adequate stimulation of the olfactory system.

Odour detection threshold: An estimate of the odour detection threshold concentration.

Odour impact: Effect perceived by an individual receptor or group of receptors at a distance from an odour-emitting source.

Odour impact criterion: A rule providing an objective means for assessing or testing odour impact.

Odour intensity: The intensity of sensation stimulated by an odorant as assessed on a scale of 0 1 2 3 4 5 6.

Odorous gas: Gas that contains odorants.

Odour panel: See panel.

Odour plume: A downwind air mass containing odorous gases from an odour source like an animal production building or a manure storage facility.

Odour sensitive receptor: The closest fixed building or installation where odour annoyance may occur, such as residential homes, school, hospital, overnight facility for holidays etc.

Odour strength: The strength of an environmental odour determined as an odour concentration (*i.e.* the number of times a sample of air carrying the environmental odour needs to be diluted to arrive at the odour threshold). By definition the odour threshold corresponds to an odour concentration of one odour unit per cubic metre (*i.e.* 1 OU/m^3).

Odour threshold: The lowest concentration of an odour in air that can be detected by the human olfactory sense.

Odour unit: Quantity of a gaseous substance or mixture of substances which, when evaporated into 1 m^3, is distinguished from odourless air by half the panel members.

Offensiveness: An expression of the degree of unpleasantness of one odour relative to another. The perceived offensiveness of an odour will vary between individuals as a result of both physical and psychosocial differences, but in a

population a relatively consistent response on the relative offensiveness of different odours is returned.

Olfactometer: Device that delivers known concentrations of an odorous air sample to a sniffing port for evaluation by trained human panellists who determine the odour detection or recognition thresholds that are reported in odour units.

Olfactory: Pertaining to the sense of smell. [ISO 5492]

Olfactory receptor: Specific part of the olfactory system which responds to an odorant. [after ISO 5492]

Olfactory stimulus: That which can excite an olfactory receptor. [ISO 5492, modified]

Output neuron: A neuron within a neural network whose outputs are the result of the network.

Panel: A group of panel members.

Panel member: An assessor who is qualified to judge samples of odorous gas, using olfactometry.

Panel selection: Procedure to determine which assessors are qualified as panel members.

Panel threshold: Detection threshold applying to a panel.

Particulate: Includes the class of both inert and viable aerosols. Includes total, inhalable, and respirable fractions.

Pattern recognition: A branch of artificial intelligence concerned with the classification or description of observations. Pattern recognition aims to classify data (patterns) based on either a priori knowledge or on statistical information extracted from the patterns. The patterns to be classified are usually groups of measurements or observations, defining points in an appropriate multidimensional space.

Perception: Awareness of the effects of single or multiple sensory stimuli. [ISO 5492]

Perceptron: An artificial neural network capable of simple pattern recognition and classification tasks. It is composed of three layers where signals only pass forward from nodes in the input layer to nodes in the hidden layer and finally out to the output layer. There are no connections within a layer.

pH: A value used to express acidity and alkalinity (scale 1 to 14, with 1 being very acidic and 14 very being alkaline; water typically has an a pH value of 7); an alternative way to express H^+ ion concentration.

Point source: An intentional point of release such as a vent or stack, where it may be possible to obtain a sample in order to quantify the concentration and determine the mass release rate.

Point source pollution: Pollution from a particular source.

Pollutant: A contaminant that adversely alters the physical, chemical, or biological properties of the environment. The term includes toxic metals, carcinogens, pathogens, oxygen-demanding materials, heat, and all other harmful substances, contaminants, or impurities.

Pollution: Presence of a contaminant to such a degree that the environment (land, water, or air) is not suitable for a particular use.

Pond: An earthen facility for the biological treatment of wastewater. It can be aerobic, artificially aerated, anaerobic or facultative depending on the loading rate, design, and type of organisms present.

Ppb: Parts per billion.

Ppm: Parts per million.

Real-time: Describes an application which requires a program to respond to stimuli within some small upper limit of response time (typically milli- or microseconds). Process control at a chemical plant is the classic example. Such applications often require special operating systems (because everything else must take a back seat to response time) and speed-tuned hardware.

Recognition threshold: The odour concentration which has the probability of 0.5 of being recognised under the conditions of the test. The recognition threshold is generally a higher concentration than the detection threshold. It is generally two or three odour units in a laboratory setting but may be higher than this outside the lab.

Regulation: A requirement or rule passed by an agency or department of federal, state, or local government that is authorized to create and enforce a requirement or rule through an authorizing statute or constitutional authority.

Repeatability: Precision under repeatability conditions. [ISO 5725-part 1]

Repeatability conditions: Conditions where independent test results are obtained with the same method on identical test material in the same laboratory by the

same operator using the same equipment within short intervals of time. [ISO 5725-part 1]

Reproducibility: Precision under reproducibility conditions. [ISO 5725-part 1]

Reproducibility conditions: Conditions where test results are obtained with the same method on identical test material in different laboratories with different operators using different equipment. [ISO 5725-part 1]

Risk assessment: The characterization of the potential adverse health effects of human exposures to environmental hazards.

Sample: The odorous gas sample which is assumed to be representative of the gas mass or gas flow under investigation, and which is examined to determine the odour concentration, to characterize the odour or to identify constituent compounds.

Scentometer: Hand-held device that can be used to measure ambient odour levels in the field.

Sensitive receptor: People who are exposed to odour released from a given source, or have the potential to be exposed. Unlike other pollutants, odour at environmental exposure levels is not considered in terms of possible detrimental effects on animals and plants.

Sensory: Relating to the human response to a particular stimulus (in this case, odour). Compare with "analytical" methods of assessment.

Setback: Specific distance that a structure or area must be located away, from other defined areas or structures.

Setback distance: Minimum distance between a group of sheds and a specified potential odour receptor.

Sigmoid function: An S-shaped function that is often used as an activation function in a neural network.

Smell: To detect or to attempt to detect an odorant.

Specific emission rate: The emission rate per unit of area of liquid or solid.

Standard conditions for olfactometry: At room temperature (293 K), normal atmospheric pressure (101.3 kPa) on a wet basis [as in ISO 10780].

Standard pig unit (SPU): Piggeries in Queensland are licensed by the maximum number of standard pig units (SPU) housed in a piggery. The SPU is a unit of measurement for determining the size of a piggery based on its waste output. One SPU produces volatile solids equivalent to that produced by an average size grower pig (approximately 40 kg).

Static olfactometer: A static olfactometer dilutes by mixing two known volumes of gas, odorous and odourless, respectively. The rate of dilution is calculated from the volumes.

Statistically significant difference: A research finding that is unlikely (usually less likely than 5 percent) to be due to chance.

Step factor: The factor by which each dilution factor in a dilution series differs from adjacent dilutions.

Stress: Emotional, physical, behavioural, and social reactions to stressors.

Stressor: Short-term or ongoing conditions, situations, or relationships that cause stress, often involving change, conflict, or pressure.

Subjective method: Any method in which the personal opinions are taken into consideration. [ISO 5492]

Substance: Species of matter of definite chemical composition.

Test result: The value of a characteristic obtained by completely carrying out a specific measurement, once.

Thermophilic: Temperature range of 50 - 60^{o}C.

Tolerance: Condition in which repeated exposure increases the size of the dose required to produce lethality.

Unnormalised: Before normalisation.

Ventilation rate: Ventilation rate for a shed is the product of the measured escape air velocity and the cross sectional area of the side opening through which escape air leaves the shed.

Volatile organic compounds (VOCs): Organic molecules, usually arising from the decomposition of manure, that tend to move from liquid into the air above animal facilities (*e.g*., ammonia, carbon dioxide, and methane).

Weight: In a neural network, the strength of a synapse (or connection) between two neurons. Weights may be positive (excitatory) or negative (inhibitory). The thresholds of a neuron are also considered weights, since they undergo adaptation by a learning algorithm.

APPENDIX A

Application of Gas Chromatography for Odour Measurement

A. 1 Introduction

Gas chromatography (GC) is a widely used analytical technique for separating the components of an odorous air sample for identification and quantification. Generally, GC using standards of known substances, or gas chromatography coupled with mass spectrometry (GC-MS) when the composition of a gas sample is unknown, is an accurate and very sensitive method of chemical analysis of the nature of the gas (down to 0.1 ppb levels) (NZWWA, 2000).

The basic steps for GC analysis are (Powell, 2002):

- Sampling - which may involve pre-concentration of a gaseous sample onto a solid adsorbent or absorption in a reagent;
- Thermal desorption or solvent extraction;
- Separation of the components by passing through a GC column; and
- Detection and identification.

Under the situation where the odour sample has an unknown composition, a GC-MS has more practical usefulness. Identification of the resulting mass spectrographic pattern is made with reference to a computer based spectrum library, although identification of compounds with similar structures and/or masses can be difficult.

The application of GC and GC-MS in odour measurement can be summarised in below (Powell, 2002):

- Provides reasonable quantitative analysis for a broad range of aliphatic, aromatic, alcohols and ketones;
- Provides semi-quantitative analysis for certain organic sulphides;
- Does not detect inorganic species, e.g. ammonia, hydrogen sulphide; and
- Poor response to highly reactive species, e.g. amine and certain organic sulphides.

However, GC and GC-MS only give an indication of the nature and concentration of chemical compounds in the sample, not their contributions to the overall odour of the mixture. Furthermore, odorous compounds often create nuisance at very low concentrations, while non-odorous components of the air sample may be present at much higher concentrations, making interpretation of the chromatogram difficult. A sample may result in literally hundreds of peaks, with only a fraction of them formed by odorous substances. Odour concentrations of most of them are not yet available (NZWWA 2000).

Powell (2002) summarised the disadvantages of GC and GC-MS in odour measurement as follow:

- Direct calibration for analysing odours is difficult because the composition mixture will often be unknown;
- The concentration in ambient air of individual compounds may be below or close to the lower limit of detection; and
- Longer term samples will average out any peaks, although this may be of secondary importance in source/compound identification.

In this chapter, the theory of GC is presented. And then the selection of columns and detectors, which are appropriate to the purpose of odour measurement, are discussed. In addition, the odour measurement case study using GC or GC-MS technique is presented in the end of this chapter.

A. 2 Basic theory for gas chromatography

Gas chromatography technique principally involves a carrier gas that passes over a stationary phase for which the volatile components have a differential affinity to effect separation. The efficiency of the chromatography is improved by precision temperature control of the column and constant flow of carrier gas (Hobbs, 2001).

In detail, Gas chromatography method can be defined as a method of continuous chemical separation of one or more individual compounds between two phases. One phase remains fixed (stationary phase); the other, the mobile phase (carrier gas), flows over the stationary phase. The components enter the stationary phase simultaneously at the injector but move along at different rates. The lower the vapour pressure of the compound (higher boiling point), the longer the compound will remain in the stationary phase. The time that each compound remains in the stationary phase depends on two factors: the vapour pressure of the compound and its solubility in the stationary phase. These compounds are then detected at the end of the column. A plot of the output of the detector response versus time is termed a chromatogram. In order to separate a narrow boiling range of solutes, Gas chromatography can be run isothermally (Driscoll, 1999).

The Retention time is defined as the time measured from the start of injection to the peak maximum and can be used to identify resolved components in mixtures. The retention time is characteristic for a compound and the stationary phase at a given temperature and is used for identification when the mixture of compounds is completely resolved (Driscoll, 1999).

A range of detectors can be attached to the end of the column with the mass spectrometer proving the most effective for the identification of unknown components of an odour. If a flame ionisation detector (FID) is used, volatile components can be recognised by matching the retention time with a known compound on the column. Often the flow to the detector can be split and an odour

port used to identify the odour note for a given component. Odour components are introduced into the column through an injector inlet: However, with the introduction of capillary columns small volumes have to be introduced and pre-concentration of an odour is required (Hobbs, 2001). In summary, successful analysis in Gas chromatography depends upon its inlet, column and detector configuration.

A. 3 Sample odorant profile and its relationship to olfactory description

Gas chromatography can obtain a profile of odorant concentration and provide useful information, which is directly related to human olfactory response. However, a means is needed to transform the odour expressed as odorant composition into one that expresses olfactory response.

In early stage of odour research, some researchers have attempted to find a relationship between odour concentration and the concentration of a single or a couple of components in the air sample to simplify odour measurements (Darling, 1977; Schaefer, 1977). However, it was revealed that establishing an indicative relationship between odour concentration and any component might be difficult or impossible because of the variation of odour measurements and emissions for the main. Livermore & Laing (1998) suggest that odours are recognised as an object from an emission source even though the odorants are complex mixtures of chemicals. Studies using 1-butanol, 2-pentanone and n-butyl acetate have demonstrated that sensitivity to, and stability of the odour was enhanced by composites of the three components rather than the presence of a single component (Patterson *et al*., 1993). In the study, mixtures could exhibit an additive effect on odour and in some cases hyper and hypo addition where the results were above addition and below addition of their threshold levels respectively.

In a recent research regarding the odorant compounds which are made from the decay process of piggery manure (Hobbs *et al*., 2001), hydrogen sulphide, acetic acid and ammonia are present. And, as expected, hydrogen sulphide was found to be the primary odorant. The result showed that the acid-base balance gave no effect to the odour concentration. Furthermore, 4-methyl phenol gave a negative odour concentration effect with increasing concentration.

Consequently, GC-MS can give information of the concentration of a lot of volatile compounds presented in odorous air samples. However, the concentration of different odorous compounds found in odour emission sources is still unknown because many compounds are present at very low concentrations under the detection limit of GC. Furthermore, the concentration of each component is continuously changed. Work has been performed trying to correlate odour to concentrations of the single component such as ammonia and hydrogen sulphide (Livestock and poultry odour workshop I, University of Minnesota, 2000). However, it was concluded that there might be no correlations between the concentration of single component and odour.

A. 4 Choice of chromatography column and detectors

In the odour measurement using Gas chromatography, the selection of appropriate column and detector for specific air samples can be difficult as there are several options or combinations necessary to obtain the best information about odour components. The choice of column will affect those odorants that are observable and detectable. Often two columns may be used especially during method development and possibly with different detectors to obtain the required sensitivity.

Typically, some columns will be able to analyse sulphides but may not be able to separate volatile fatty acids and a sample splitter should be used with a dual column system. Choice of column will be limited by the gas volume to be analysed, as well as considering the flow capacity of the detector. Overall a balancing act has to be performed to ensure that sample introduction, gas chromatographic separation and detector specifications are compatible.

Capillary columns have dimensions between 0.05 and about 1 mm internal diameter and operate with gas flows lower than I ml/min, so a small volume of sample is required for analysis. Here the packed columns have an advantage over the capillary columns in determining low concentrations chiefly because the FID response is a function of the mass of the analyte ionised in the detector. However, peak separation for packed columns becomes a problem with complex mixtures and there are difficulties with materials used. Sulphur-containing compounds will readily disappear into silica or metal or porous polymer surfaces.

From the analytical point of view, the important factors are that the odour sample or its components are not decomposed or lost on the instrument surfaces due to adsorption. This primarily dictates the choice of column, fittings and sampling method. As sulphides are relatively unstable and often present in malodours, then consideration should focus around minimising oxidation, adsorption and chromatographic column choice. Low concentrations of odorants

means a high sample volume and column size unless samples can be pre-concentrated onto an adsorbent and adequately retrieved for analysis. Samples obviously have to be volatile and increasing volatility means they are more likely to be eluted quickly from the column.

With regarding to the choice of detector, the limit of Gas chromatography systems and the characteristics of detector are main factors to consider. Generally, odours and more certainly malodours are mostly polar in behaviour and are flammable. Therefore, Flame Ionisation Detectors (FID) would be a good choice.

Flame Ionisation Detectors (FID)

Maybe, the most commonly used detector for the measurement of odorous compounds. The principal process of FID is that the measurement of the ionisation current of the analyte after combustion. In detail, the process of ionisation which occurs in organic compounds when the carbon-carbon bond is broken via a thermal process in the flame that results in the formation of carbon ions. These ions are collected in the flame by applying a positive potential to the FID jet and the ions are pushed to the collection electrode where the current is measured. The response (current) is proportional to the concentration and is measured with an electrometer/amplifier.

The sensitivities of FID in the low ng range are lower than the Mass Spectrometry systems for most compounds by a factor of 2 or 3. The dynamic range of FID is 106. FID is a good choice as odorants are mostly composed of hydrogen and carbon. However, sensitivity to sulphur containing compounds can be less for the FID for the same reason.

Mass spectrometry (MS)

Although Mass Spectrometry (MS) is expensive, it should be the detector of choice because it has the additional capacity to identify unknown compounds

from the air samples. There are limitations to gas flows of often up to 1 ml/min. Therefore, it is compatible with capillary columns. Normally, MS systems operate in the *ng* range when scanning the full mass scale of 10 to 600 mass units but this can be improved by single ion monitoring.

One of the limitations is that the sensitivity increases with lower gas flows into the MS, because there are less gas molecules to impede travel of ions to the detector. Additional problems include the inflow of oxygen into the ion source from the sample volume especially if it requires desorption from a solid adsorbent after odour sampling in air. Oxygen will react with the hot surfaces of the ion lens reducing the sensitivity by the build up of electrostatic charges on these oxidised surfaces.

A. 5 Odour measurement using gas chromatography

As Gas chromatography is a major instrumental method in the field of analytical chemistry, the sampling and analysis techniques of Gas chromatography for odorous components have been rapidly developed. Although there are a lot of research data using Gas chromatography, the works related to the odour issues in livestock operations are reviewed in this dissertation.

In terms of the sampling methods for Gas chromatography analysis, Solid Phase Micro Extraction (SPME) is a solvent-less extraction method for gaseous and liquid phases. The schematic diagram of SPME device is presented in *Fig A.1*.

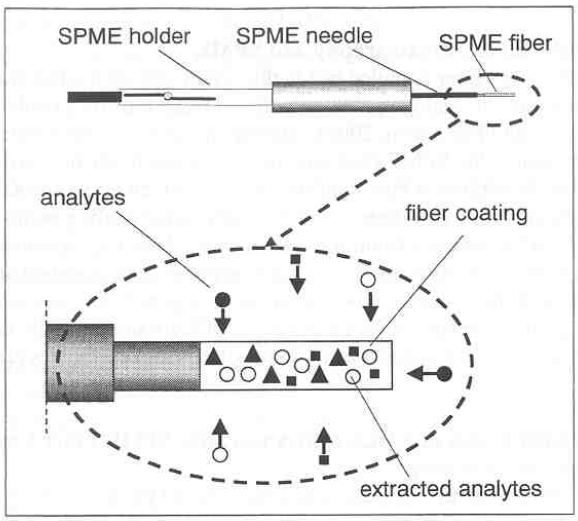


Fig A. 1 Schematic diagram of SPME device, fiber coating is exposed to airborne VOCs (reproduced from Koziel, 2001)

SPME is an alternative to conventional sampling and sample preparation for determining complex VOC mixtures in both air and liquid. SPME has been successfully applied in numberous environmental, food, flavour, pharmaceutical, clinical, and forensic applications. Recently, it has also been applied to detect

VOC compounds emitted from animal housings and manure storages (Auvermann *et al*., 2002).

The usages of Gas chromatography have concentrated mostly on the emissions of ammonia from livestock in terms of animal housing (Hartung, 1992), from storage facilities (Petersen *et al*., I998b) and land spreading of liquid slurry (Pain *et al*., 1990) and total emission rates have been used to produce an inventory for the UK of ammonia emissions (Pain *et al*., 1998).

Some work involving VOCs have been performed on livestock wastes, and 27 VOCs have been identified (Zahn *et al*., 1997). These VOCs decrease the air quality near the livestock operations. The VFAs C_2-C_9 demonstrated the greatest potential for decreased air quality, since these compounds exhibited the highest transport coefficients and highest airborne concentrations. Flux measurements suggested that the total rate of VOC emissions from the deep-basin swine waste storage system was 500 to 5700 fold greater than established VOC fluxes from natural sources. The emission rates were positively correlated with wind velocity between 0.2 and 9.4 m/s and a maximum concentration of VOCs present in the air was observed to occur at a wind velocity of 3.6 m/s.

Biofilters have been evaluated for controlling animal rendering odours using an odour port Gas chromatography and a Gas chromatography coupled with Mass Spectrometry system and compared with a forced choice olfactometric response from an odour panel. About 300 compounds were identified and 40 were recognised as odorous. Some compounds originated from the biofilter (Luo & van Oostrom, 1997). An unusual compound, 3-hydroxy-4,5-dimethyl-2(5H)-furanon, was detected during composting especially when high temperatures were reached (Krauss *et al*., 1992).

APPENDIX B

Contouring Plots for the USQ Wind Tunnel

B. 1 Contouring plots over the solid surface

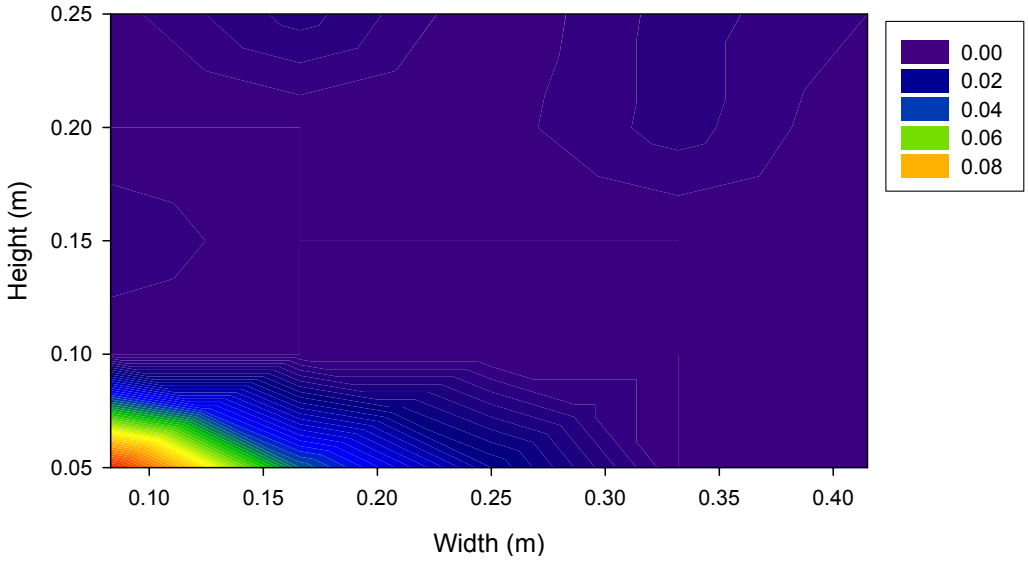


Fig B. 1Cross-sectional wind speed profile over the solid surface, airflow rate $0.001m^3/s$

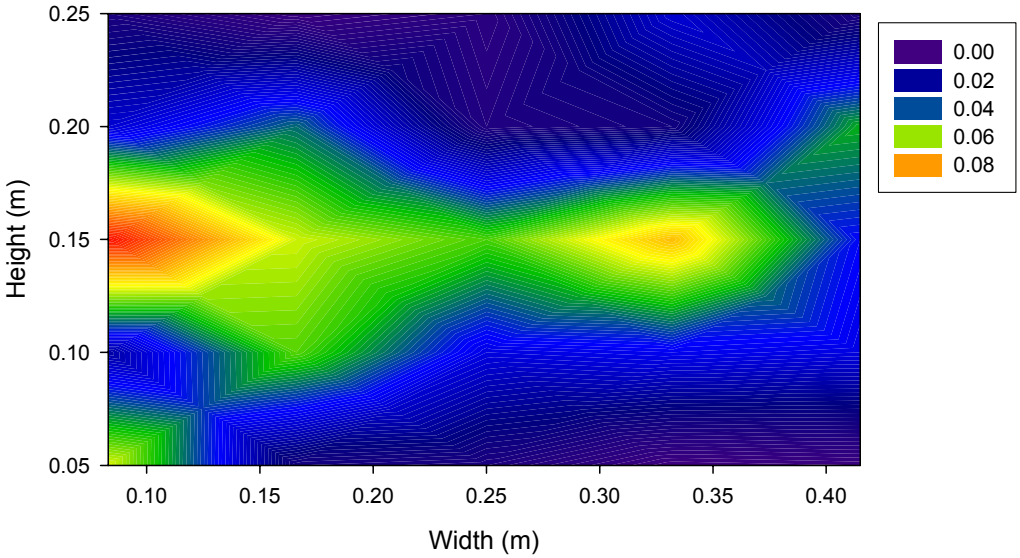


Fig B. 2 Cross-sectional wind speed profile over the solid surface, airflow rate $0.005m^3/s$

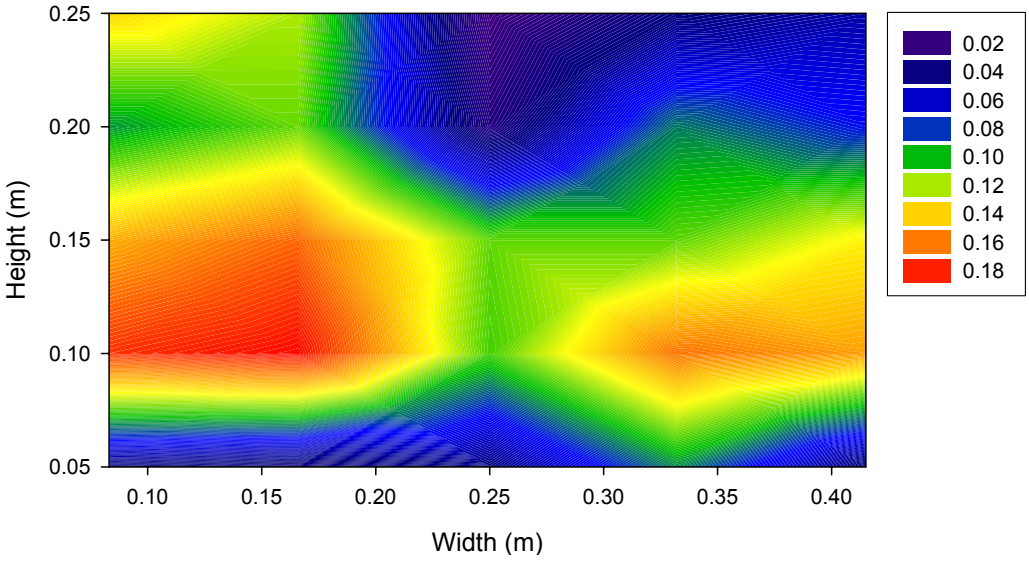


Fig B. 3 Cross-sectional wind speed profile over the solid surface, airflow rate $0.015m^3/s$

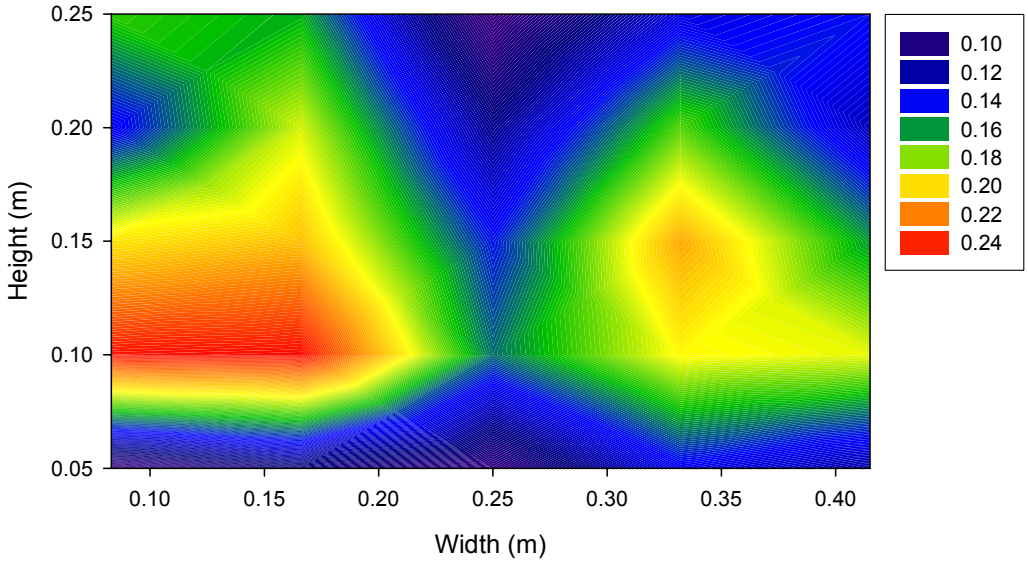


Fig B. 4 Cross-sectional wind speed profile over the solid surface, airflow rate $0.024m^3/s$

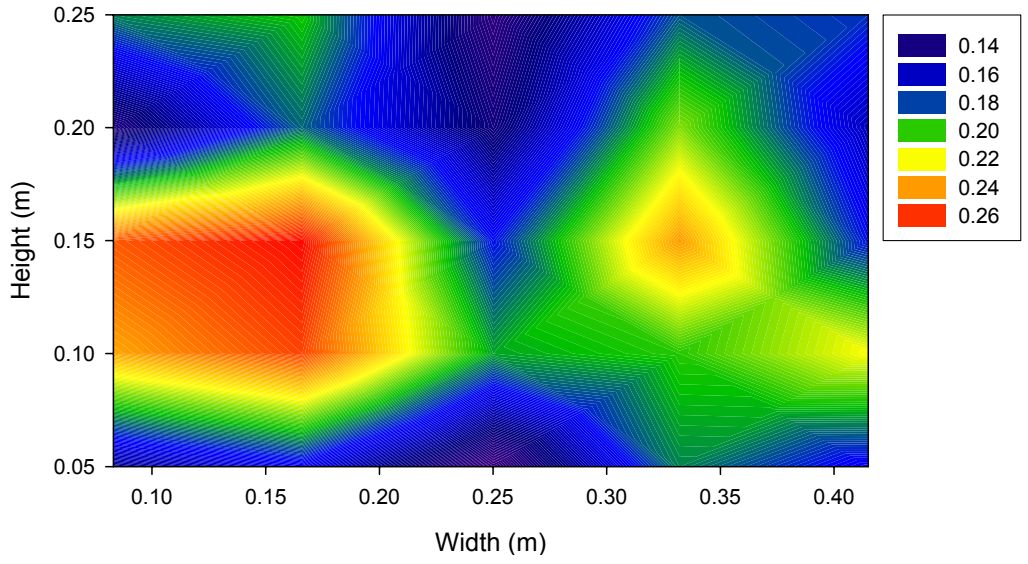


Fig B. 5 Cross-sectional wind speed profile over the solid surface, airflow rate $0.028m^3/s$

B. 2 Contouring plots over the liquid surface

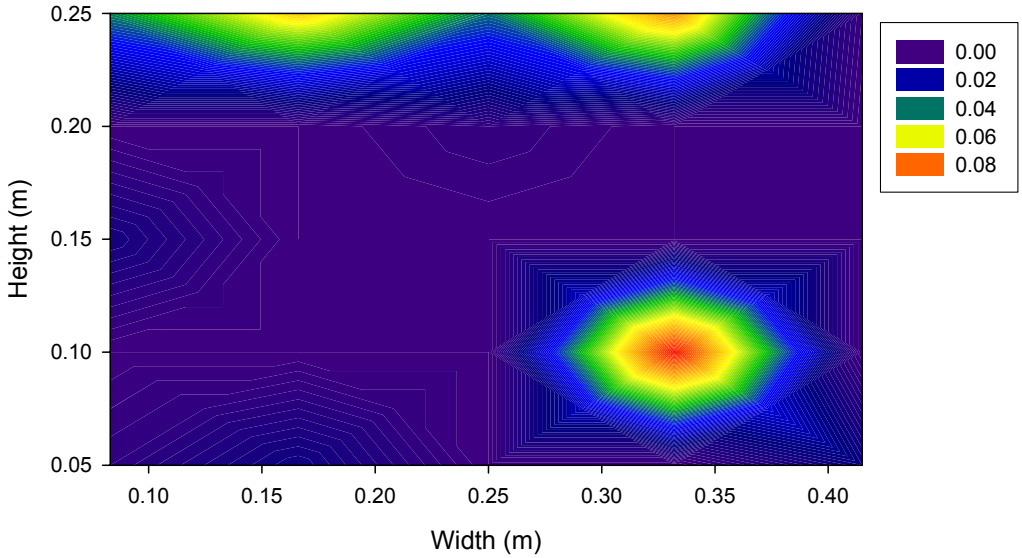


Fig B.6 Cross-sectional wind speed profile over the liquid surface, airflow rate $0.002m^3/s$

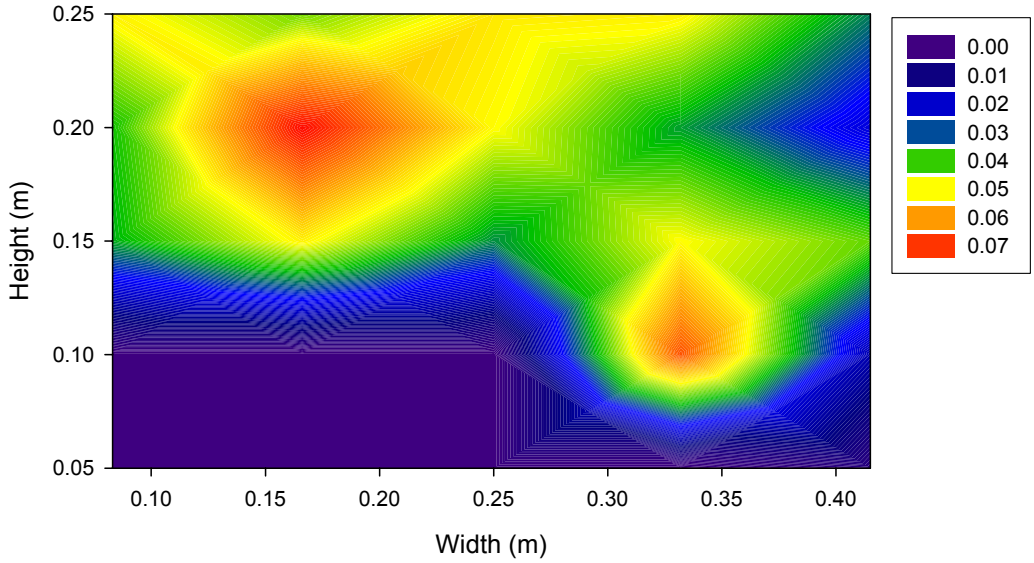


Fig B.7 Cross-sectional wind speed profile over the liquid surface, airflow rate $0.005m^3/s$

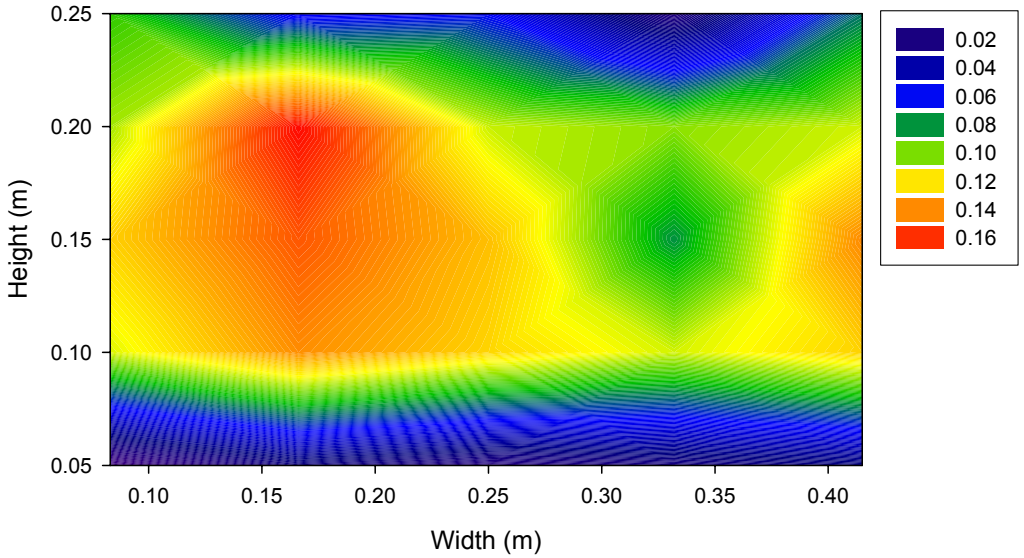


Fig B.8 Cross-sectional wind speed profile over the liquid surface, airflow rate $0.013m^3/s$

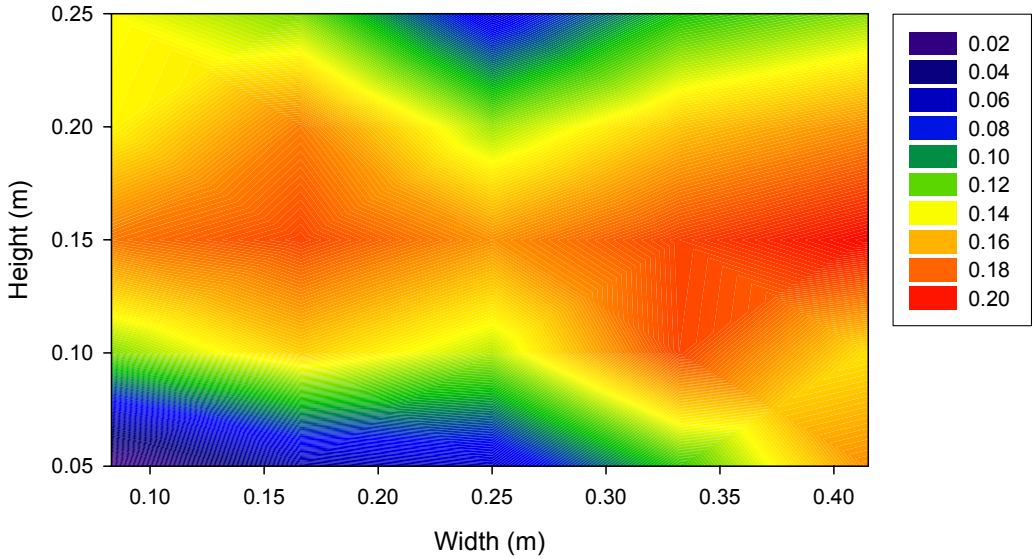


Fig B.9 Cross-sectional wind speed profile over the liquid surface, airflow rate $0.021m^3/s$

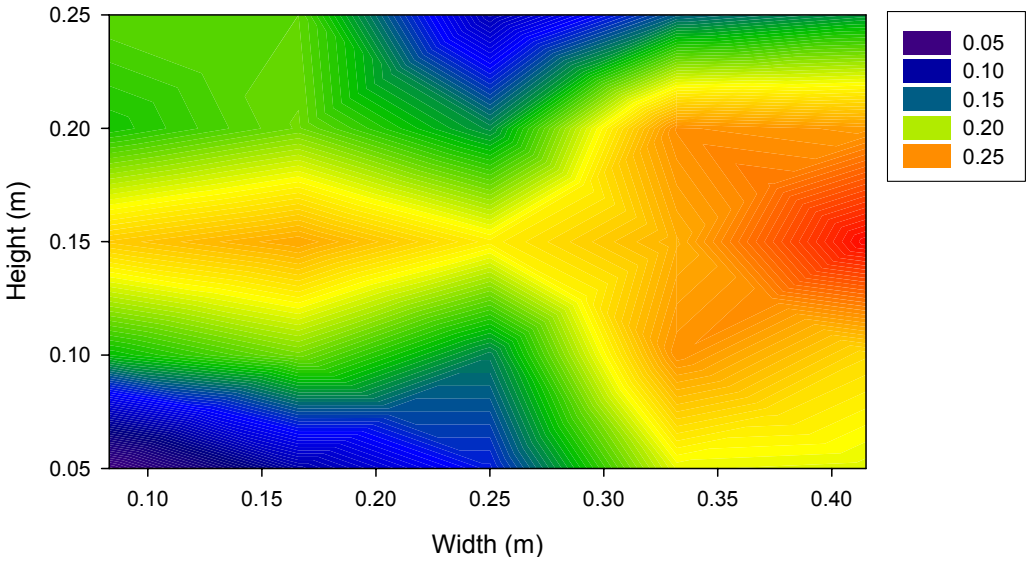


Fig B.10 Cross-sectional wind speed profile over the liquid surface, airflow rate $0.028m^3/s$

APPENDIX C

Physical and Chemical Analysis Results in the Pond Experiment 1

C. 1 Overview of the experiment 1

Experiment 1 had been conducted for 12 months from 8th August 2001 to 14th August 2002. Reactor vessel 2 operated the organic loading rate (OLR) of 72g VS/m^3·day was used as a control reactor to compare the results from the other reactor vessels. Reactor 1, 3,4 and 5 had been operated with the OLR of 36, 108, 144, and 180g VS/ m^3·day respectively. Averaged detention time was 128days.

In analysing the data, paired samples Student's T-test with 95% or 99% confidence had been applied to find out the difference of physical and chemical parameters between each reactor vessels. And then, the correlation between raw feeding effluent and liquid sample collected from the reactor vessel are analysed. Non-linear regression statistical method has been used to develop a simple empirical model to predict the effect of feeding effluent on the chemical constituent of the piggery effluent pond.

C. 2 Total Solid and Volatile Solid Analysis

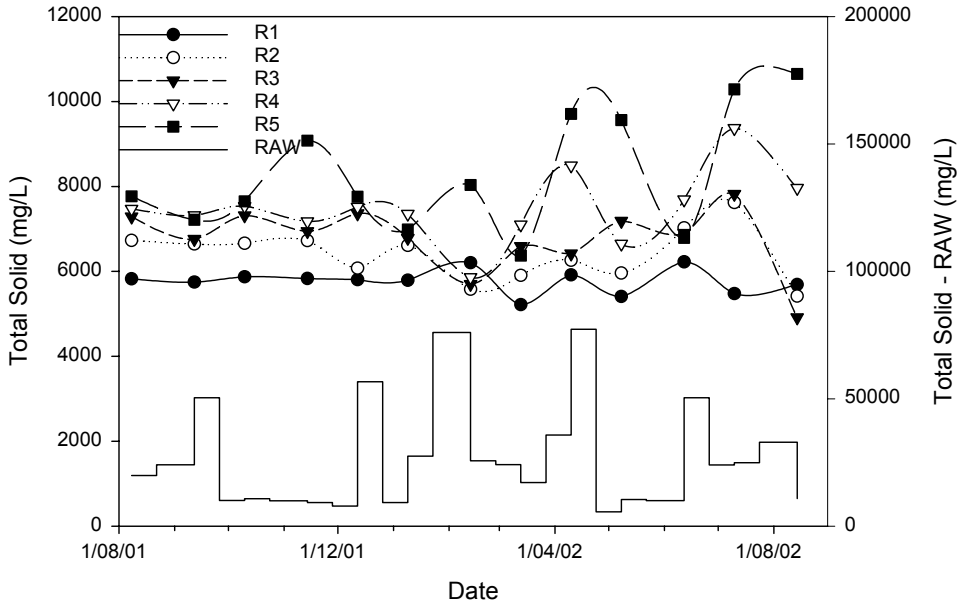


Fig C. 1 Course of the Total Solid values in five reactor vessels and raw feeding effluent in time

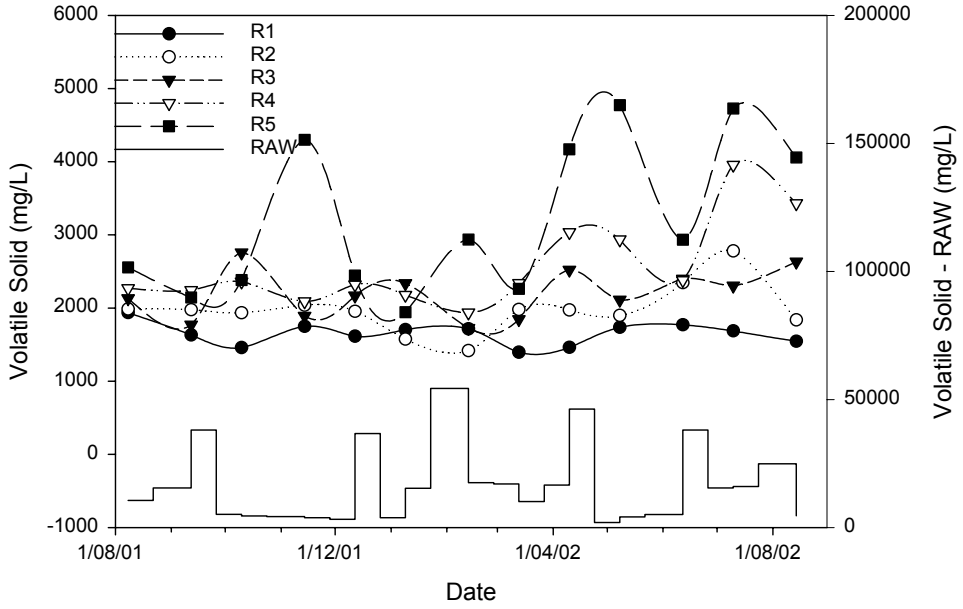


Fig C. 2 Course of the Volatile Solid values in five reactor vessels and raw feeding effluent in time

Table C. 1 Total Solid T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-631.54	659.49	-3.453	12	0.005**
R3 × R2	-367.08	504.79	-2.622	12	0.022*
R4 × R2	-1098.69	696.81	-5.685	12	0.000**
R5 × R2	-1898.00	1576.34	-4.341	12	0.001**

1. *: 95% Probability (P<0.05)
2. **: 99% Probability (P<0.01)

Table C. 2 Volatile Solid T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-330.69	351.01	-3.397	12	0.005**
R3 × R2	-221.77	414.47	-1.929	12	0.078
R4 × R2	-597.54	475.06	-4.535	12	0.001**
R5 × R2	-1224.77	960.24	-4.599	12	0.001**

1. **: 99% Probability (P<0.01)

C. 3 pH and Alkalinity

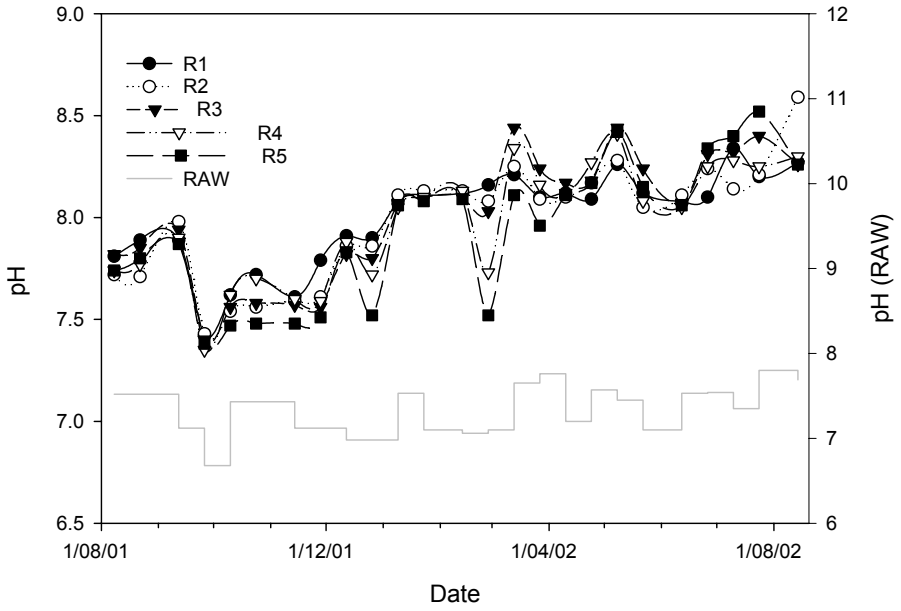


Fig C. 3 Course of the pH in five reactor vessels and raw feeding effluent in time

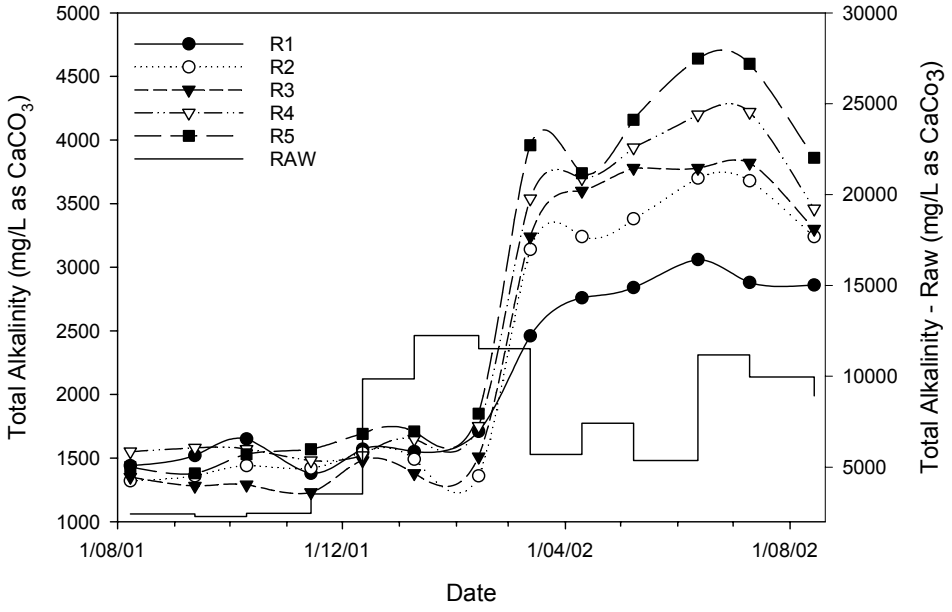


Fig C. 4 Course of the total alkalinity in five reactor vessels and raw feeding effluent in time

Table C. 3 pH T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	0.015	0.111	0.684	24	0.501
R3 × R2	-0.029	0.118	-1.236	24	0.228
R4 × R2	0.006	0.119	0.252	24	0.803
R5 × R2	0.048	0.181	1.337	24	0.194

Table C. 4 pH correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw	*R1*	*Raw*	R2	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	7.33	8.00	7.33	7.98	7.33	8.01	7.33	7.96	7.33	7.93
	SD	0.287	0.232	0.287	0.286	0.287	0.307	0.287	0.288	0.287	0.344
	N	25	25	25	25	25	25	25	25	25	25
Correlations	*Pearson Cor.*	0.467*[2]		0.476*		0.547**[3]		0.584**		0.529**	
	Sig (2-tailed)	0.019		0.016		0.005		0.002		0.007	
	N	25		25		25		25		25	

1. Organic Loading Rate (g VS /m^3·day)
2. *: 95% Probability (P<0.05)
3. **: 99% Probability (P<0.01)

Table C. 5 Total alkalinity T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-202.3	393.6	-1.853	12	0.089
R3 × R2	-56.2	180.8	-1.120	12	0.285
R4 × R2	-296.2	190.4	-5.609	12	0.000**
R5 × R2	-446.9	341.9	-4.713	12	0.001**

1. **: 99% Probability (P<0.01)

Table C. 6 Total alkalinity correlation analysis

		Trial 1 (36g)[1]		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	16.61	2.13	33.23	2.33	49.84	2.39	66.45	2.63	83.06	2.78
	SD	13.44	0.67	26.88	1.04	40.32	1.17	53.76	1.19	67.20	1.36
	N	13	13	13	13	13	13	13	13	13	13
Correlations	Pearson Cor.	0.319		0.283		0.269		0.251		0.290	
	Sig. (2-tailed)	0.288		0.349		0.374		0.409		0.337	
	N	13		13		13		13		13	

1. Organic Loading Rate (g VS /m^3·day)
2. Total akalinity loading rate(g Alkalinity/m^3·day)

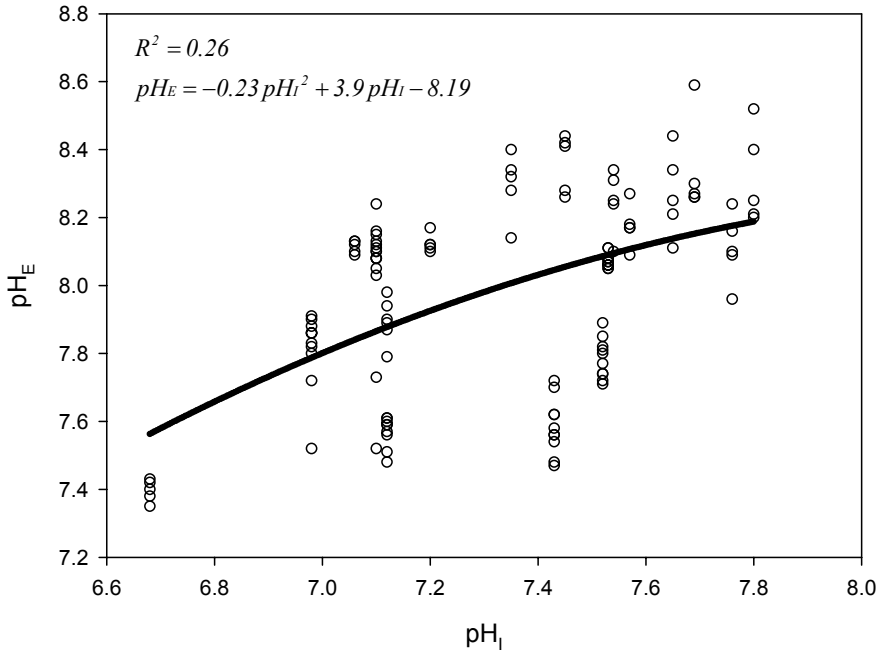


Fig C. 5 pH non-linear regression between input pH and expected pH values

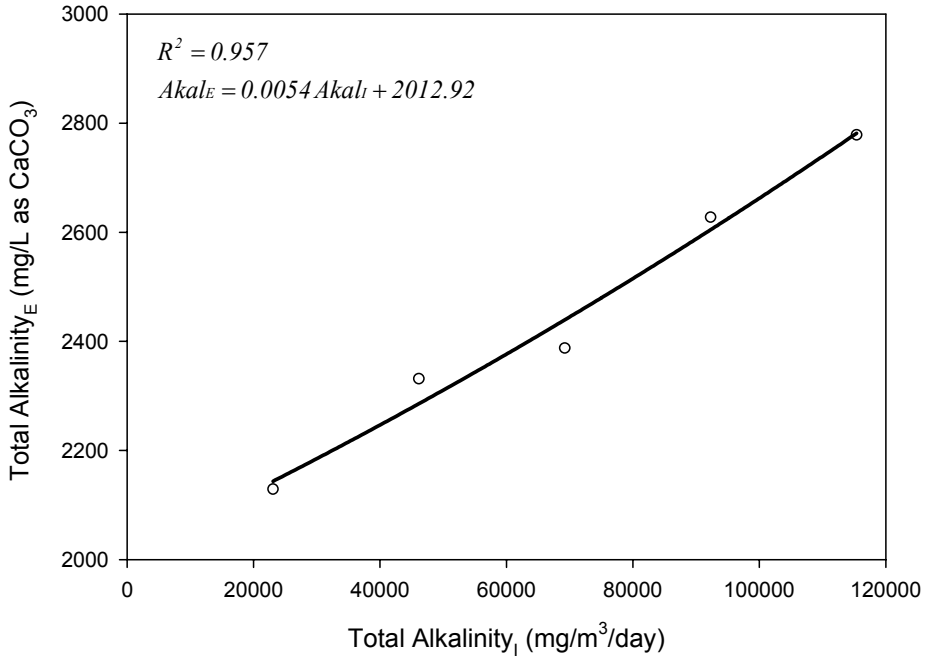


Fig C. 6 Total alkalinity linear regression between input and expected total alkalinity values

C. 4 Electrical Conductivity

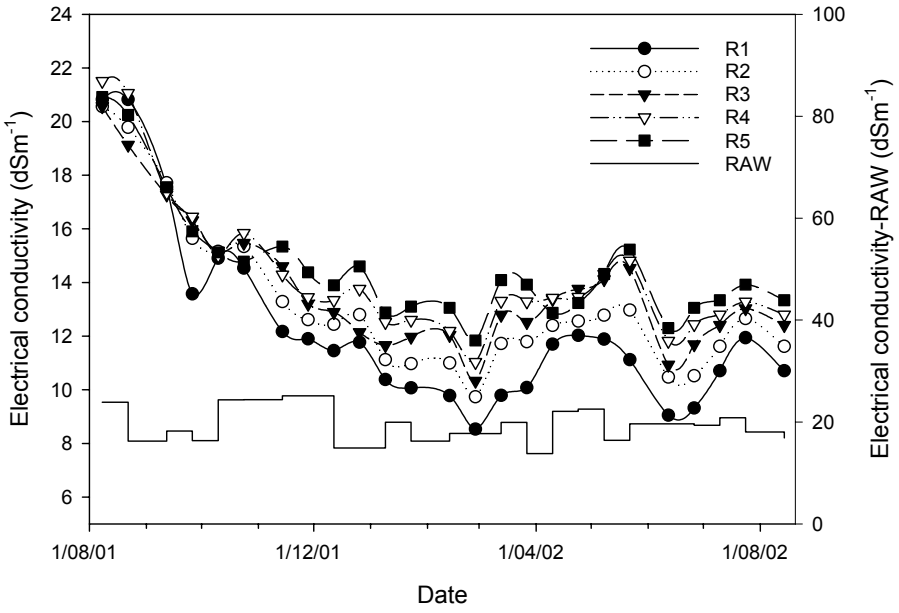


Fig C. 7 Course of the EC values in five reactor vessels and raw feeding effluent in time

Table C. 7 Electrical Conductivity T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-0.906	0.674	-6.723	24	0.000**
R3 × R2	-0.600	0.606	-4.945	24	0.000**
R4 × R2	-1.074	0.538	-9.971	24	0.000**
R5 × R2	-1.360	0.894	-7.603	24	0.000**

1. **: 99% Probability (P<0.01)

Table C. 8 Electrical conductivity correlation statistical analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	72.7	12.3	145.3	13.2	218.0	13.8	290.7	14.3	363.3	14.5
	SD	72.0	3.3	144.0	2.8	216.1	2.5	288.1	2.6	360.1	2.2
	N	25	25	25	25	25	25	25	25	25	25
Correlations	Pearson Cor.	0.083		0.085		0.140		0.047		0.025	
	Sig. (2-tailed)	0.692		0.685		0.504		0.824		0.906	
	N	25		25		25		25		25	

1. Organic loading rate (g VS /m^3·day)

2. Feeding electrical conductivity value (EC dsm^{-1}/m^3·day)

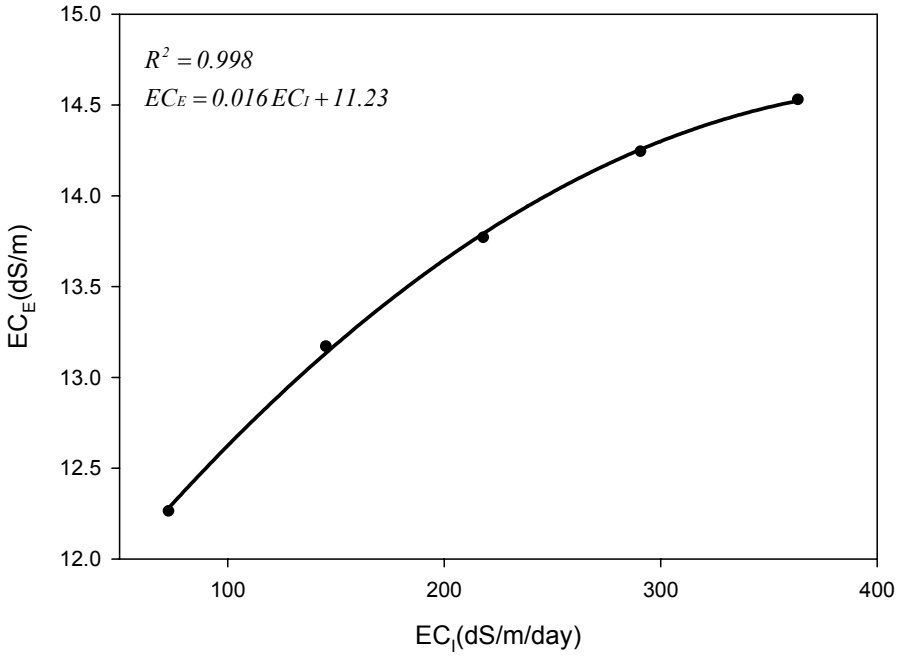


Fig C. 8 EC linear regression between input and expected EC values

C. 5 Chemical Oxygen Demand

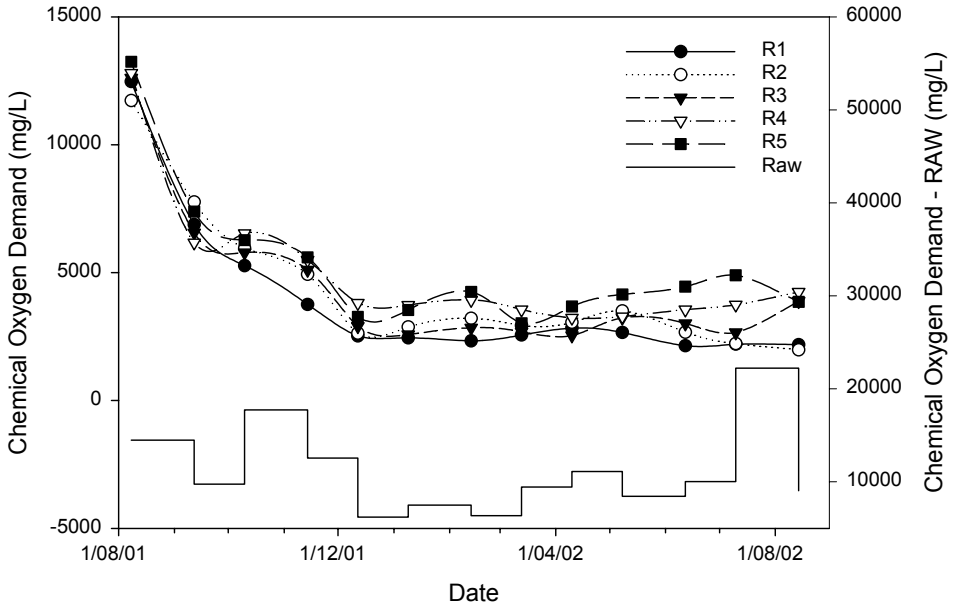


Fig C. 9 Course of the COD values in five reactor vessels and raw feeding effluent in time

Table C. 9 Chemical oxygen demand T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-399.23	522.80	-2.753	12	0.017*
R3 × R2	-72.31	753.48	-0.346	12	0.735
R4 × R2	-663.08	909.00	-2.630	12	0.022*
R5 × R2	-938.46	826.75	-4.093	12	0.001**

1. *: 95% Probability (P<0.05)

2. **: 99% Probability (P<0.01)

Table C. 10 Chemical Oxygen Demand correlation analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	33123	3865	66247	4264	99370	4336	165616	4927	165616	5202
	SD	31527	2945	63053	2780	94579	2820	157632	2603	157632	2722
	N	13	13	13	13	13	13	13	13	13	13
Correlations	Pearson Cor.	0.144		0.190		0.257		0.254		0.195	
	Sig. (2-tailed)	0.638		0.535		0.397		0.403		0.523	
	N	13		13		13		13		13	

1. Organic Loading Rate (g VS /m^3·day)
2. COD loading rate (COD mg/m^3·day)
3. COD value in reactor vessel (mg/L)

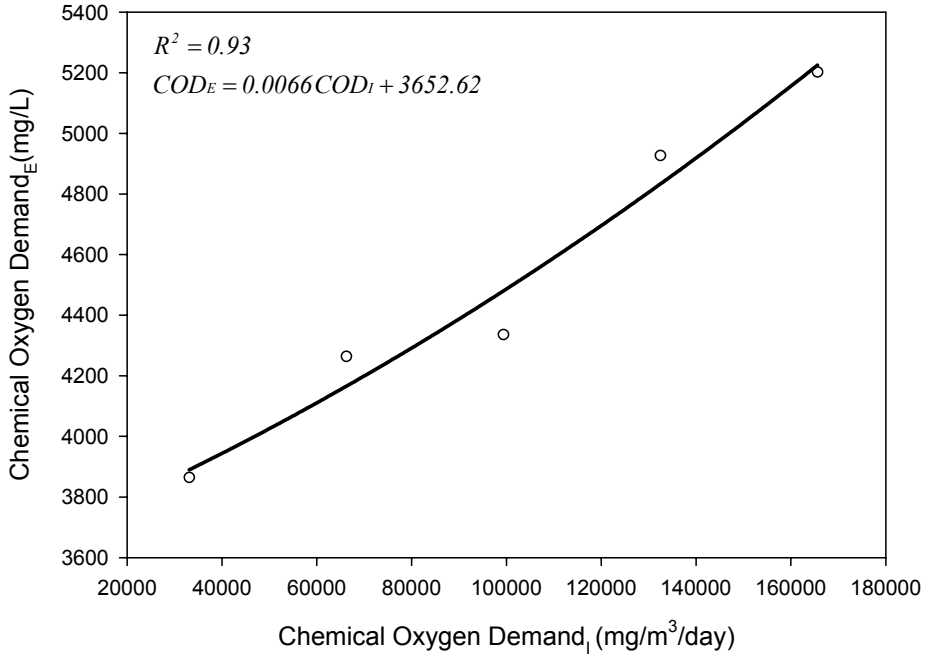


Fig C. 10 COD linear regression between input and expected COD values

C. 6 Total Nitrogen and Ammonia Nitrogen Compounds

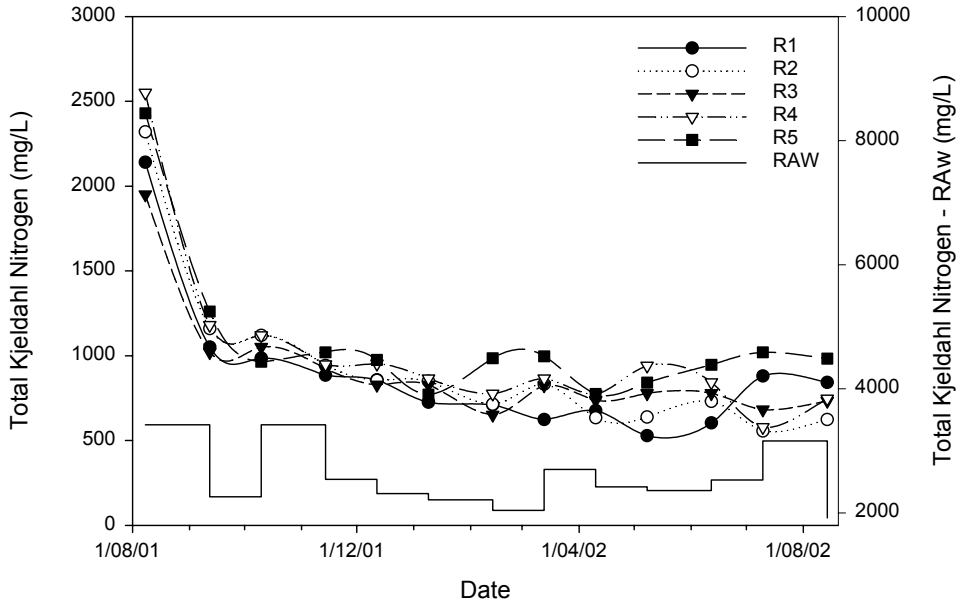


Fig C. 11 Course of the TKN values in five reactor vessels and raw feeding effluent in time

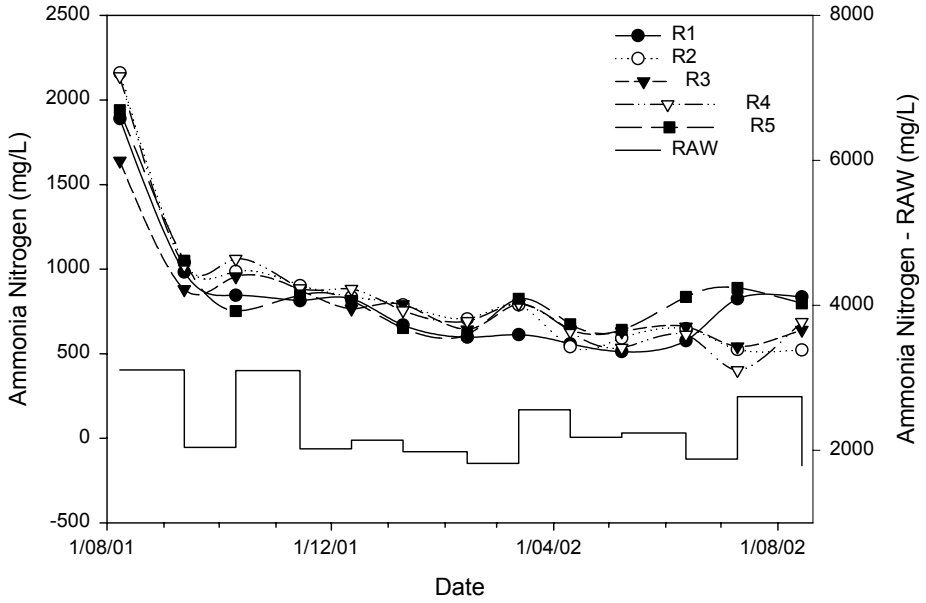


Fig C. 12 Course of the NH_3_N values in five reactor vessels and raw feeding effluent in time

Table C. 11 Total Kjeldahl Nitrogen T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-36.00	155.56	-0.834	12	0.420
R3 × R2	14.77	136.64	0.390	12	0.704
R4 × R2	-89.39	92.51	-3.484	12	0.005**
R5 × R2	-153.39	163.20	-3.389	12	0.005**

1. **: 99% Probability (P<0.01)

Table C. 12 Ammonia Nitrogen T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-37.69	169.17	-0.803	12	0.437
R3 × R2	44.08	160.07	0.993	12	0.340
R4 × R2	-4.92	73.66	-0.241	12	0.814
R5 × R2	-22.62	181.67	-0.450	12	0.661

1. *: 95% Probability (P<0.05)
2. **: 99% Probability (P<0.01)

Table C. 13 Total Kjeldahl Nitrogen correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw[2]	*R1[3]*	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	7341	885	14683	921	22024	906	29365	1010	36707	1074
	SD	6320	407	12640	460	18960	335	25279	488	31600	426
	N	13	13	13	13	13	13	13	13	13	13
Correlations	*Pearson Cor.*	0.104		0.136		0.192		0.140		0.036	
	Sig. (2-tailed)	0.735		0.657		0.530		0.649		0.907	
	N	13		13		13		13		13	

1. Organic Loading Rate (g VS /m^3·day)
2. TKN loading rate (TKN mg/m^3·day)
3. TKN value in reactor vessel (TKN mg/L)

Table C. 14 Ammonia Nitrogen correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw[2]	*R1[3]*	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	6561	811	13122	849	19683	805	26244	854	32805	871
	SD	5619	355	11237	430	16856	279	22474	429	28093	343
	N	13	13	13	13	13	13	13	13	13	13
Correlations	*Pearson Cor.*	0.096		0.119		0.205		0.148		-0.003	
	Sig. (2-tailed)	0.755		0.698		0.501		0.629		0.993	
	N	13		13		13		13		13	

1. Organic Loading Rate (g VS /m^3·day)
2. NH_3-N loading rate (NH_3-N mg/m^3·day)
3. NH_3-N value in reactor vessel (NH_3-N mg/L)

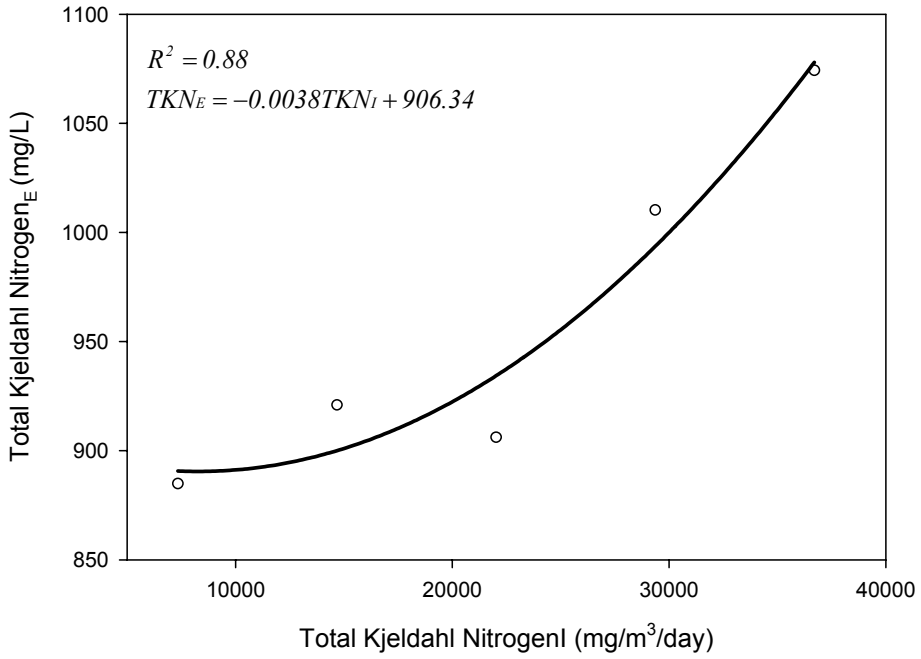


Fig C. 13 TKN linear regression between input and expected TKN values

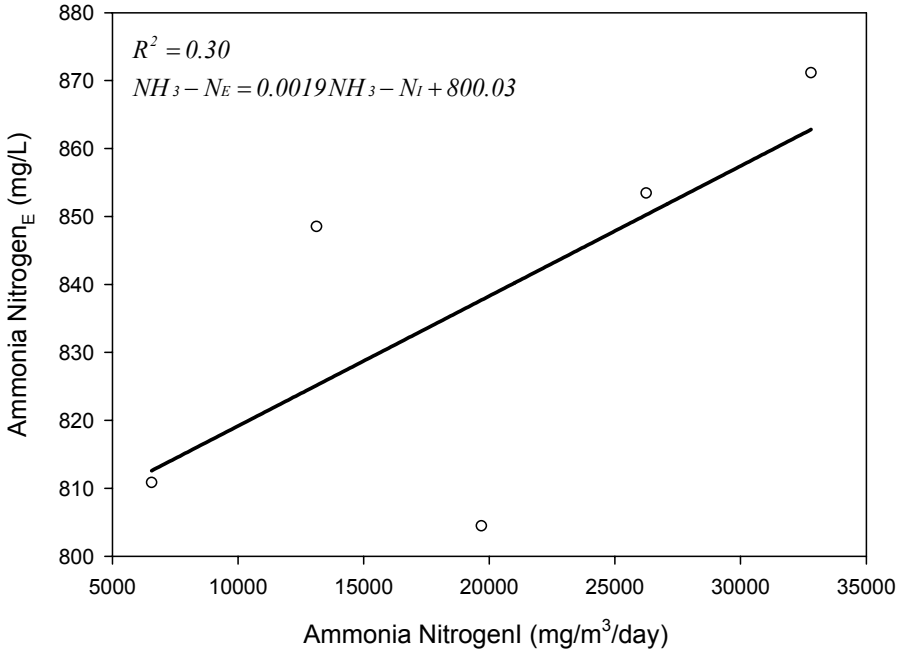


Fig C. 14 NH_3-N linear regression between input and expected NH_3-N values

APPENDIX D

Physical and Chemical Analysis Results in the Pond Experiment 2

D. 1 Overview of the experiment 2

After conducting experiment 1, reactor vessels were allowed to equilibrate for experiment 2 with same VS loading rate of 72g/m^3·day for 60 days. Experiment 2 had been conducted for 6 months from 13th November 2002 to 26th March 2003.

Canter & Englande (1970) estimated the mean hydraulic retention time (HRT) values of 31days for anaerobic effluent ponds used in the warmer southern states in USA (Martin, 1991). Therefore, HRT of 30 days was applied in experiment 2 as a standard HRT.

The same VS loading rates used in experiment 1 were applied in experiment 2. In addition to the chemical parameters analysed in experiment 1, more chemical parameters including total phosphorus, potassium, sulphide and sulphate were analysed to find out the relationship between odour emission rates and chemical parameters.

In analysing the data, paired samples Student's T-test with 95% or 99% confidence, correlation and regression statistical analysis were applied in this research work.

D. 2 Total Solid and Volatile Solid Analysis

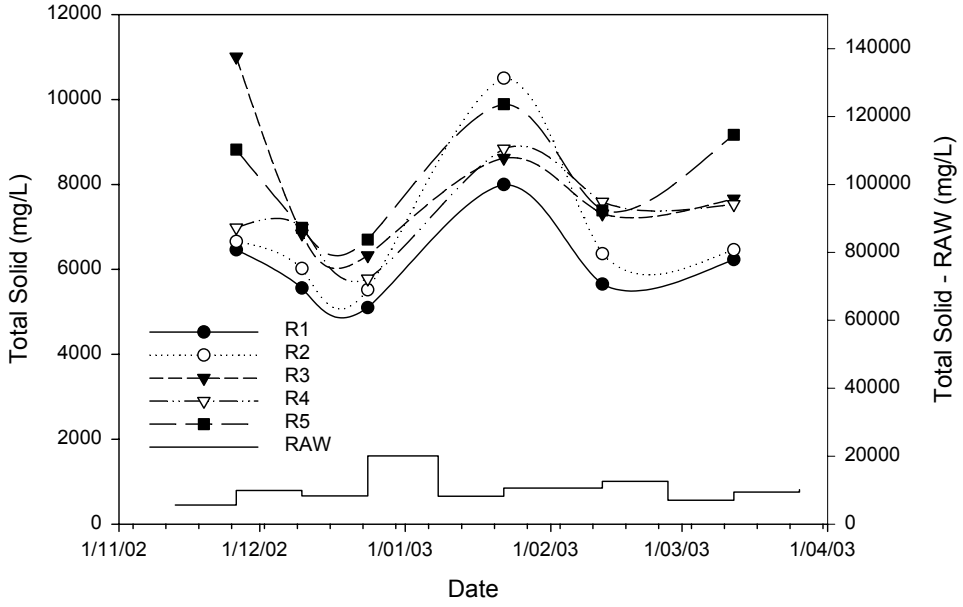


Fig D. 1 Course of the Total Solid values in five reactor vessels and raw feeding effluent in time

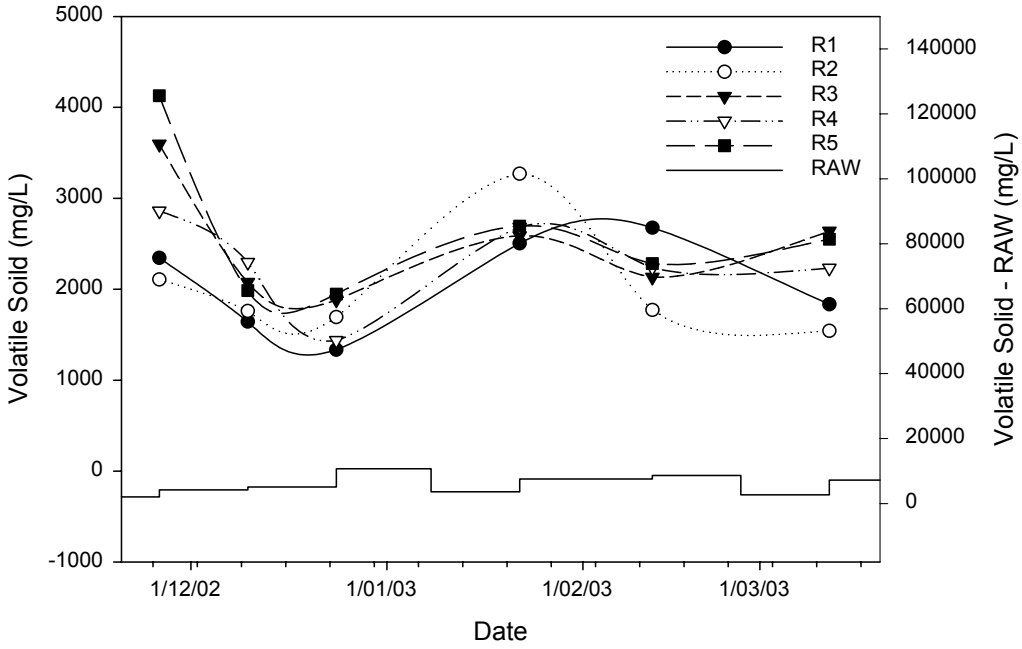


Fig D. 2 Course of the Volatile Solid values in five reactor vessels and raw feeding effluent in time

Table D. 1 Total Solid T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-754.17	875.75	-2.109	5	0.089
R3 × R2	-1040.17	1981.21	-1.286	5	0.255
R4 × R2	-362.67	1067.26	-0.832	5	0.443
R5 × R2	-1237.67	1146.41	-2.644	5	0.046*

1. *: 95% Probability (P<0.05)

Table D. 2 Volatile Solid T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	32.00	579.64	0.135	5	0.898
R3 × R2	-461.67	758.02	-1.492	5	0.196
R4 × R2	-266.67	553.36	-1.180	5	0.291
R5 × R2	-573.83	875.53	-1.605	5	0.169

D. 3 pH and Alkalinity

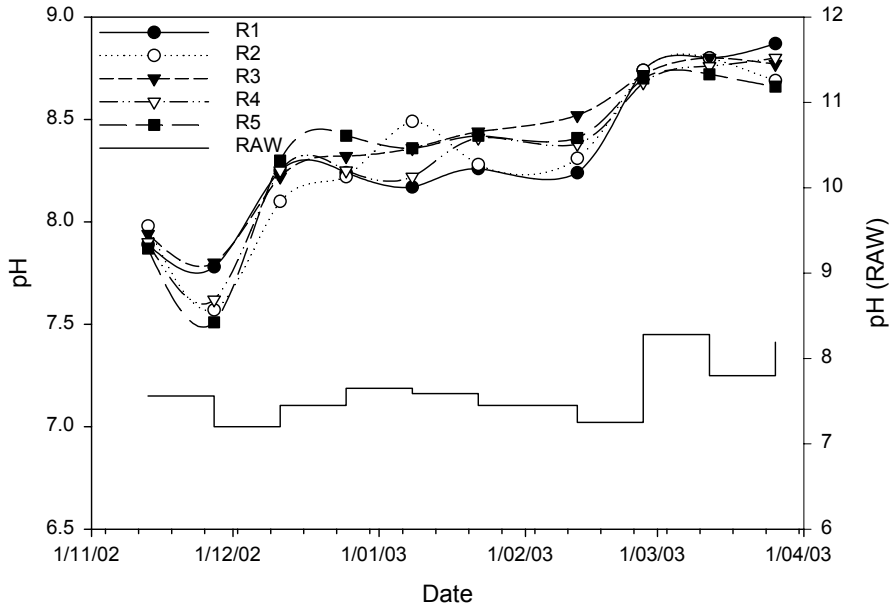


Fig D. 3 Course of the pH in five reactor vessels and raw feeding effluent in time

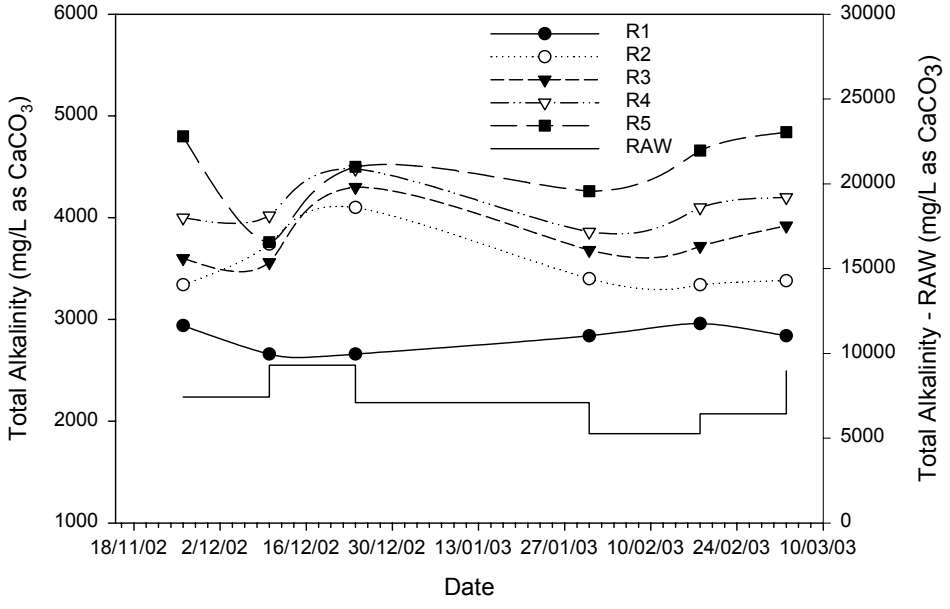


Fig D. 4 Course of the total alkalinity in five reactor vessels and raw feeding effluent in time

Table D. 3 pH T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	0.006	0.155	0.123	9	0.905
R3 × R2	-0.071	0.116	-1.929	9	0.086
R4 × R2	-0.009	0.126	-0.225	9	0.827
R5 × R2	-0.019	0.128	-0.469	9	0.650

Table D. 4 pH correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw	*R1*	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	7.64	8.32	7.64	8.32	7.64	8.39	7.64	8.33	7.64	8.34
	SD	0.36	0.37	0.36	0.38	0.36	0.34	0.36	0.37	0.36	0.38
	N	10	10	10	10	10	10	10	10	10	10
Correlations	*Pearson Cor.*	0.821**		0.769**		0.690*		0.732*		0.677*	
	Sig. (2-tailed)	0.004		0.009		0.027		0.016		0.032	
	N	10		10		10		10		10	

1. Organic Loading Rate (g VS /m^3·day)
2. *: 95% Probability (P<0.05)
3. **: 99% Probability (P<0.01)

Table D. 5 Total alkalinity T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-733.3	429.6	-4.181	5	0.009**
R3 × R2	-246.7	240.6	-2.512	5	0.054
R4 × R2	-560.0	218.4	-6.282	5	0.002**
R5 × R2	-920.0	604.5	-3.728	5	0.014*

1. *: 95% Probability (P<0.05)
2. **: 99% Probability (P<0.01)

Table D. 6 Total alkalinity correlation analysis

		Trial 1 (36g)[1]		*Trial 2 (72g)*		Trial 3 *(108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw[2]	*R1*[3]	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	29.9	2.82	59.8	3.6	89.7	3.8	119.5	4.1	149.4	4.5
	SD	13.8	0.1	27.7	0.3	41.5	0.3	55.3	0.2	69.2	0.4
	N	6	6	6	6	6	6	6	6	6	6
Correlations	*Pearson Cor.*	-0.056		-0.159		-0.577		-0.316		-0.215	
	Sig. (2-tailed)	0.916		0.763		0.231		0.541		0.683	
	N	6		6		6		6		6	

1. Organic Loading Rate (g VS /m³·day)
2. Total alkalinity loading rate(g Alkalinity/m³·day)

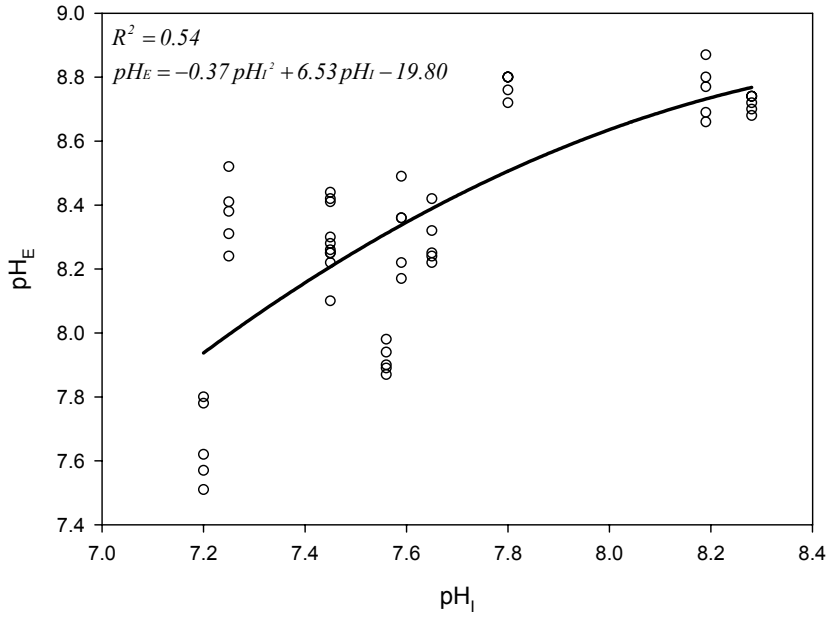


Fig D. 5 pH non-linear regression between input pH and expected pH values

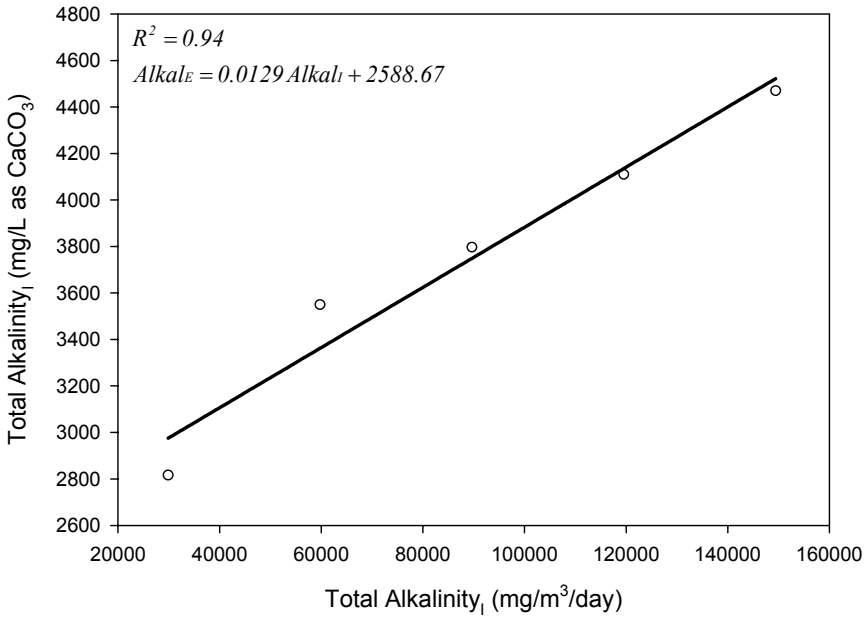


Fig D. 6 Total alkalinity linear regression between input and expected total alkalinity values

D. 4 Electronic Conductivity

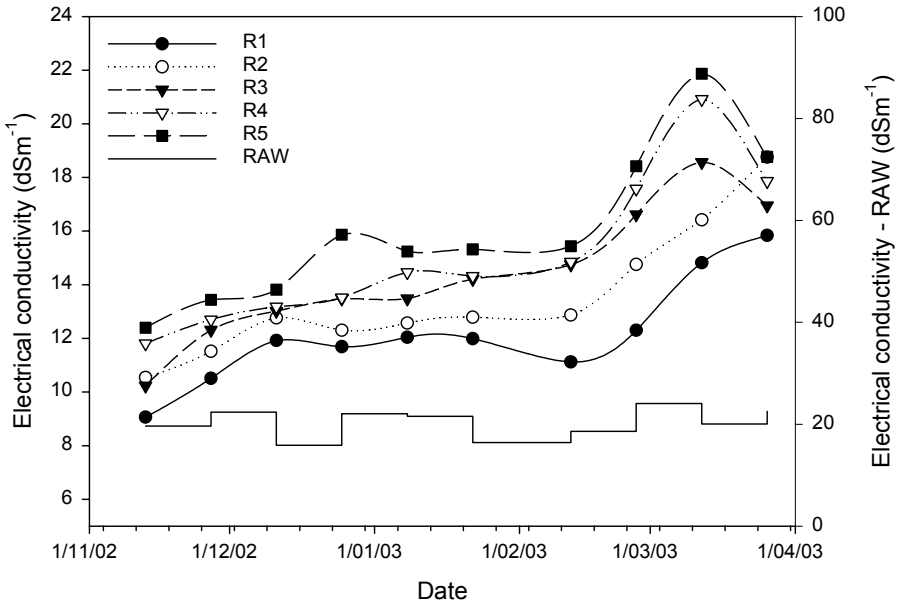


Fig D. 7 Course of the EC values in five reactor vessels and raw feeding effluent in time

Table D. 7 Electrical Conductivity T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-1.40	0.80	-5.510	9	0.000**
R3 × R2	-0.83	1.20	-2.194	9	0.056
R4 × R2	-1.59	1.42	-3.538	9	0.006**
R5 × R2	-2.53	1.50	-5.335	9	0.000**

1. **: 99% Probability (P<0.01)

Table D. 8 Electrical Conductivity correlation statistical analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	120.4	12.1	240.7	13.5	361.1	14.4	481.5	15.1	601.8	16.1
	SD	72.5	2.0	145.0	2.5	217.5	2.5	290.0	2.8	362.5	2.9
	N	10	10	10	10	10	10	10	10	10	10
Correlations	Pearson Cor.	-0.362		-0.190		-0.303		-0.151		-0.218	
	Sig. (2-tailed)	0.304		0.599		0.395		0.678		0.545	
	N	10		10		10		10		10	

1. Organic loading rate (g VS /m^3·day)

2. Feeding electrical conductivity value (EC dsm^{-1}/m^3·day)

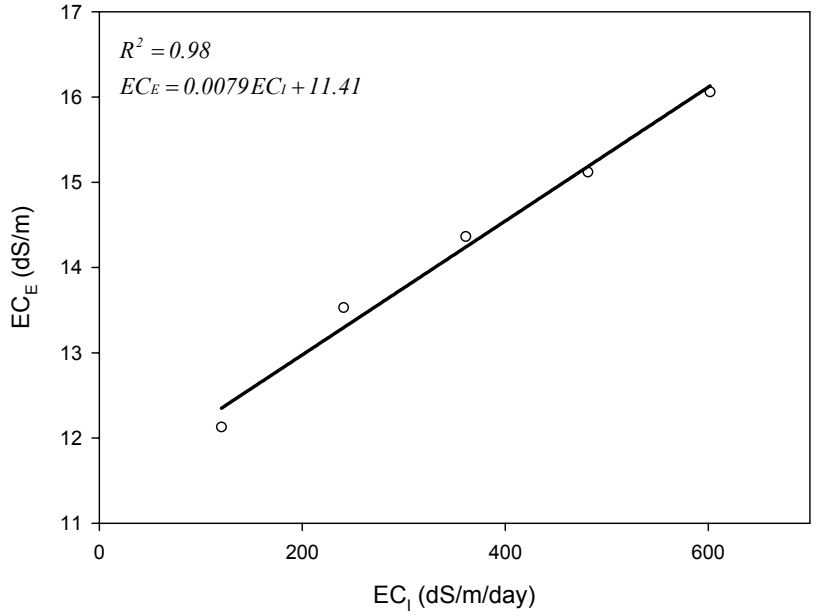


Fig D. 8 EC linear regression between input and expected EC values

D. 5 Chemical Oxygen Demand

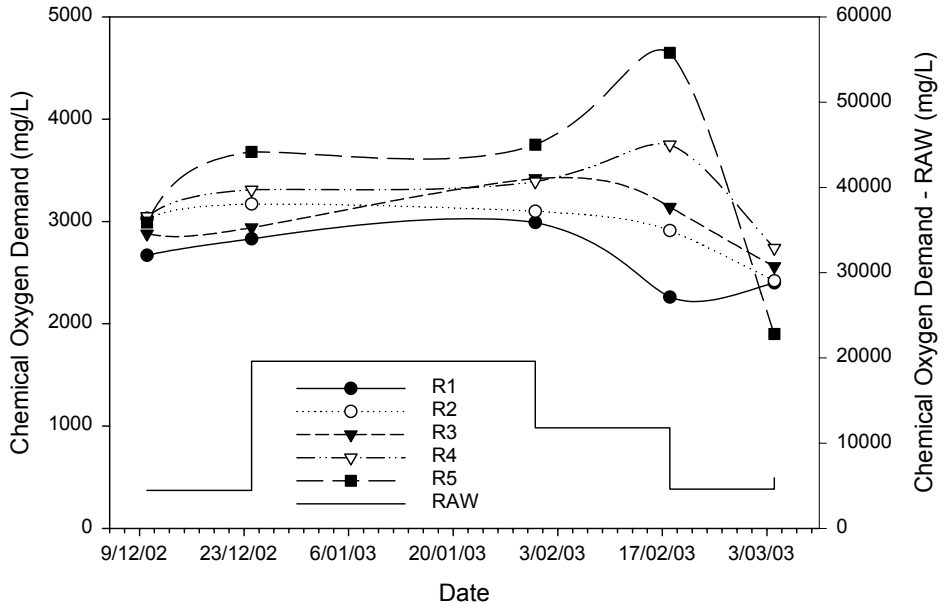


Fig D. 9 Course of the COD values in five reactor vessels and raw feeding effluent in time

Table D. 9 Chemical Oxygen Demand T-test

	Mean	*SD*	*T*	*df*	*Sig.(2-tailed)*
R1 × R2	-296	246.0	-2.690	4	0.055
R3 × R2	-62	240.4	-0.577	4	0.595
R4 × R2	-322	313.7	-2.295	4	0.083
R5 × R2	-468	849.6	-1.232	4	0.285

1. *: 95% Probability (P<0.05)

2. **: 99% Probability (P<0.01)

Table D. 10 Chemical Oxygen Demand correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw[2]	*R1[3]*	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	29110	2630	58221	2926	87332	2988	116442	3248	145554	3394
	SD	14153	300	28306	299	42458	319	56611	379	70764	1022
	N	5	5	5	5	5	5	5	5	5	5
Correlations	*Pearson Cor.*	0.877		0.586		0.315		0.013		0.073	
	Sig. (2-tailed)	0.051		0.299		0.606		0.984		0.908	
	N	5		5		5		5		5	

1. Organic Loading Rate (g VS /m^3·day)
2. COD loading rate (COD mg/m^3·day)
3. COD value in reactor vessel (mg/L)

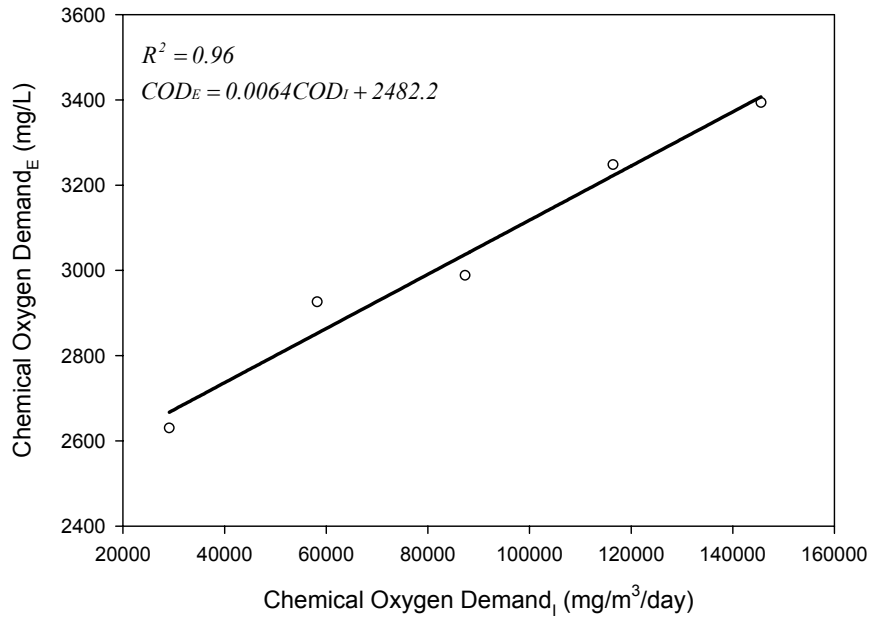


Fig D. 10 COD linear regression between input and expected COD values

D. 6 Total Nitrogen and Ammonia Nitrogen Compounds

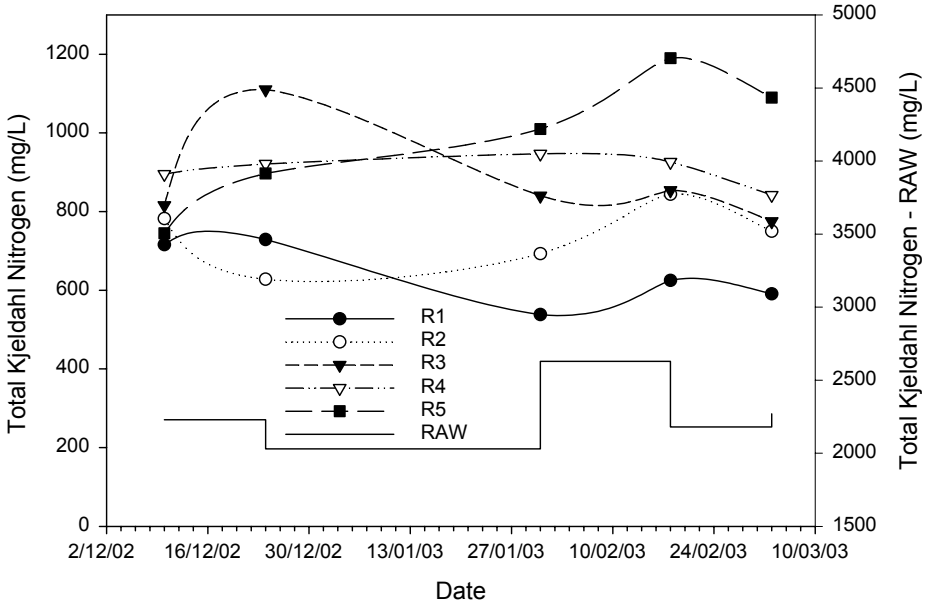


Fig D. 11 Course of the TKN values in five reactor vessels and raw feeding effluent in time

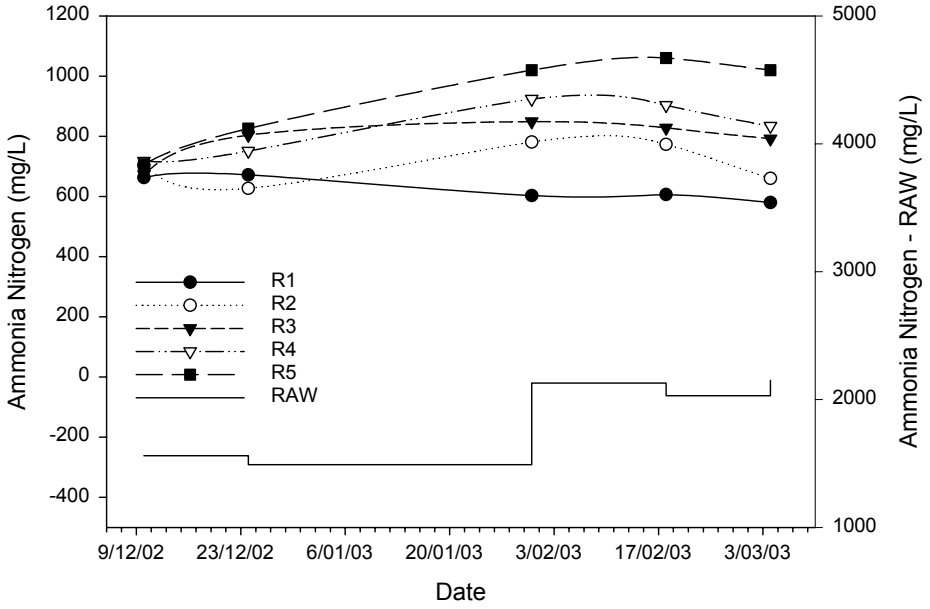


Fig D. 12 Course of the NH_3_N values in five reactor vessels and raw feeding effluent in time

Table D. 11 Total Kjeldahl Nitrogen T-test

	Mean	*SD*	*T*	*df*	*Sig.(2-tailed)*
R1 × R2	-99.6	124.7	-1.786	4	0.149
R3 × R2	-139.6	199.0	-1.569	4	0.192
R4 × R2	-166.8	99.0	-3.767	4	0.020*
R5 × R2	-247.0	161.6	-3.417	4	0.027*

1. **: 99% Probability (P<0.01)

Table D. 12 Ammonia Nitrogen T-test

	Mean	*SD*	*T*	*df*	*Sig.(2-tailed)*
R1 × R2	-84.0	92.6	-2.028	4	0.112
R3 × R2	-80.4	79.0	-2.275	4	0.085
R4 × R2	-117.2	60.3	-4.346	4	0.012*
R5 × R2	-217.8	133.7	-3.642	4	0.022*

1. *: 95% Probability (P<0.05)

Table D. 13 Total Kjeldahl Nitrogen correlation analysis

		Trial 1 (36g[1])		*Trial 2 (72g)*		*Trial 3 (108g)*		*Trial 4 (144g)*		*Trial 5 (180g)*	
		Raw[2]	*R1[3]*	*Raw*	*R2*	*Raw*	*R3*	*Raw*	*R4*	*Raw*	*R5*
Descriptive statistics	*Mean*	7.98	0.64	15.96	0.74	23.95	0.88	31.93	0.91	39.91	0.99
	SD	2.42	0.08	4.84	0.08	7.26	0.13	9.68	0.04	12.10	0.17
	N	5	5	5	5	5	5	5	5	5	5
Correlations	*Pearson Cor.*	-0.144		0.358		-0.732		-0.208		-0.462	
	Sig. (2-tailed)	0.817		0.555		0.159		0.738		0.434	
	N	5		5		5		5		5	

1. Organic Loading Rate (g VS /m^3·day)

2. TKN loading rate (TKN g/m^3·day)

3. TKN value in reactor vessel (TKN g/L)

Table D. 14 Ammonia Nitrogen correlation analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	6.52	0.62	13.05	0.71	19.57	0.79	26.10	0.83	32.62	0.93
	SD	1.78	0.04	3.55	0.07	5.33	0.07	7.11	0.09	8.88	0.15
	N	5	5	5	5	5	5	5	5	5	5
Correlations	Pearson Cor.	-0.517		0.413		-0.348		0.191		0.111	
	Sig. (2-tailed)	0.372		0.489		0.566		0.759		0.859	
	N	5		5		5		5		5	

1. Organic Loading Rate (g VS /m^3·day)
2. NH_3-N loading rate (NH_3-N g/m^3·day)
3. NH_3-N value in reactor vessel (NH_3-N g/L)

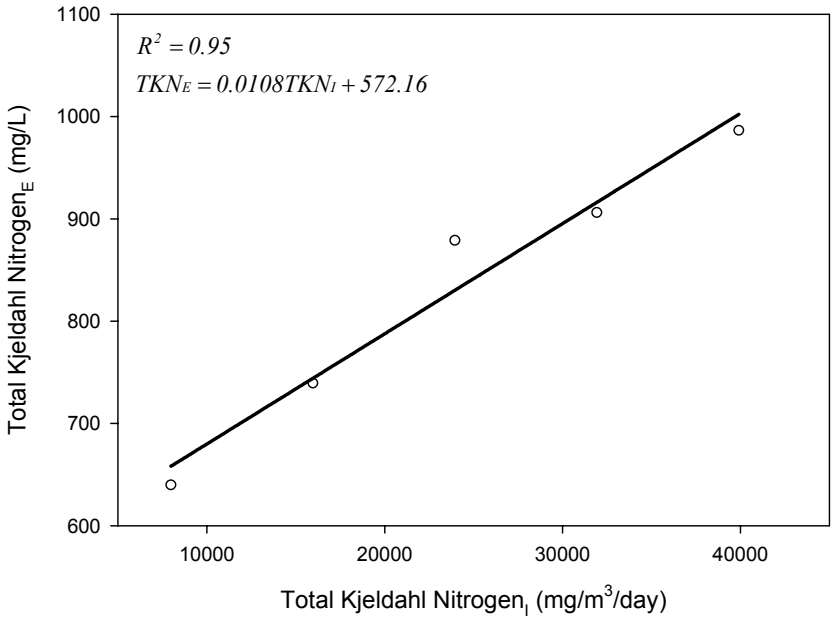


Fig. 10.32 TKN linear regression between input and expected TKN values

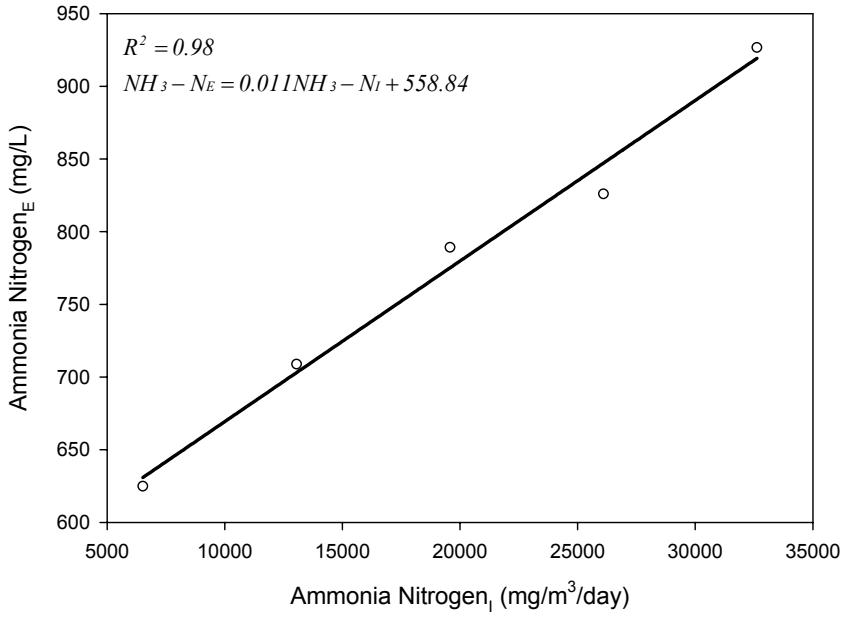


Fig D. 13 NH_3-N linear regression between input and expected NH_3-N values

D. 7 Total Phosphorus

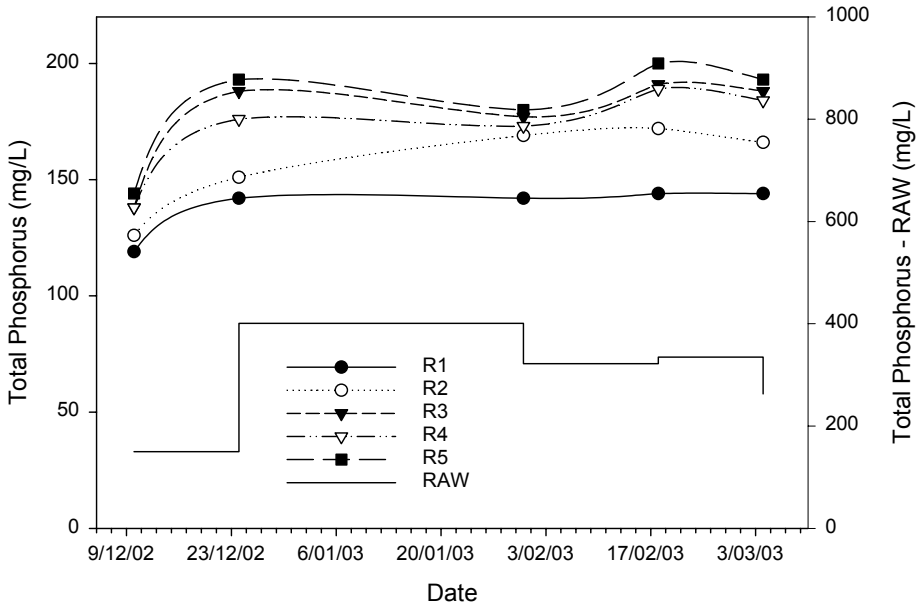


Fig D. 14 Course of the Total Phosphorus values in five reactor vessels and raw feeding effluent in time

Table D. 15 Total Phosphorus T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-18.6	9.97	-4.174	4	0.014*
R3 × R2	-19.6	11.19	-3.915	4	0.017*
R4 × R2	-15.2	7.79	-4.362	4	0.012*
R5 × R2	-25.2	11.69	-4.819	4	0.009**

1. *: 95% Probability (P<0.05)

2. **: 99% Probability (P<0.01)

Table D. 16 Total Phosphorus correlation analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	957	138	1914	157	2870	176	3827	172	4784	182
	SD	126	10.7	251	19.0	377	22.1	502	20.0	628	22.4
	N	5	5	5	5	5	5	5	5	5	5
Correlations	Pearson Cor.	0.855		0.884*		0.761		0.759		0.724	
	Sig. (2-tailed)	0.065		0.046		0.135		0.136		0.167	
	N	5		5		5		5		5	

1. Organic Loading Rate (g VS /m^3·day)
2. T-P loading rate (T-P mg/m^3·day)
3. T-P value in reactor vessel (T-P mg/L)

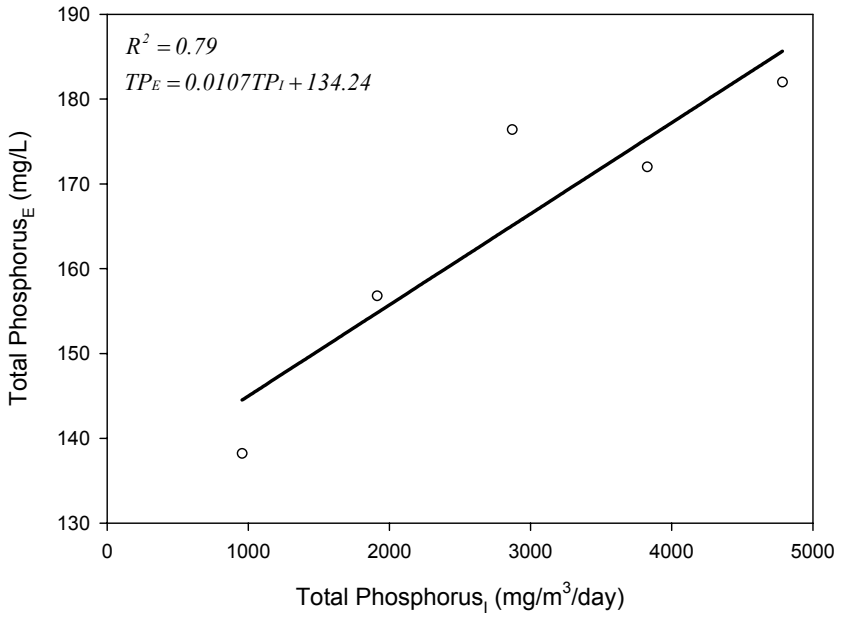


Fig D. 15 Total Phosphorus linear regression between input and expected T-P values

D. 8 Potassium

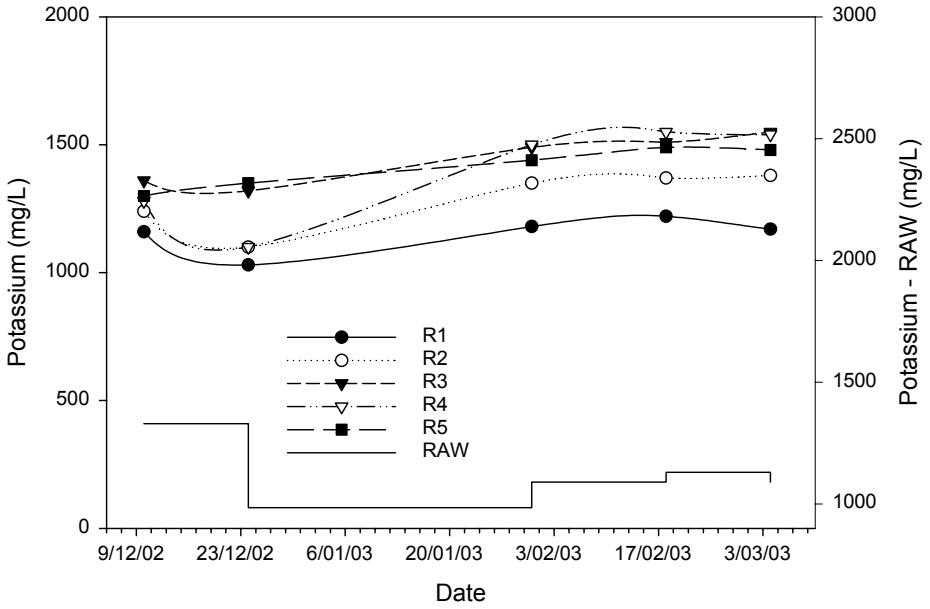


Fig D. 16 Course of the Potassium values in five reactor vessels and raw feeding effluent in time

Table D. 17 Potassium T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-136	59.83	-5.083	4	0.007**
R3 × R2	-158	38.99	-9.062	4	0.001**
R4 × R2	-106	80.50	-2.944	4	0.042*
R5 × R2	-124	73.69	-3.763	4	0.020*

1. *: 95% Probability (P<0.05)

2. **: 99% Probability (P<0.01)

Table D. 18 Potassium correlation analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	4.03	1.15	8.06	1.29	12.09	16.13	16.13	1.39	20.16	1.41
	SD	1.62	0.07	3.24	0.12	4.86	6.48	6.48	0.20	8.10	0.08
	N	5	5	5	5	5	5	5	5	5	5
Correlations	Pearson Cor.	0.362		0.129		-0.138		0.023		-0.491	
	Sig. (2-tailed)	0.549		0.837		0.824		0.971		0.401	
	N	5		5		5		5		5	

1. Organic Loading Rate (g VS /m³·day)
2. K loading rate (K g/m³·day)
3. K value in reactor vessel (K g/L)

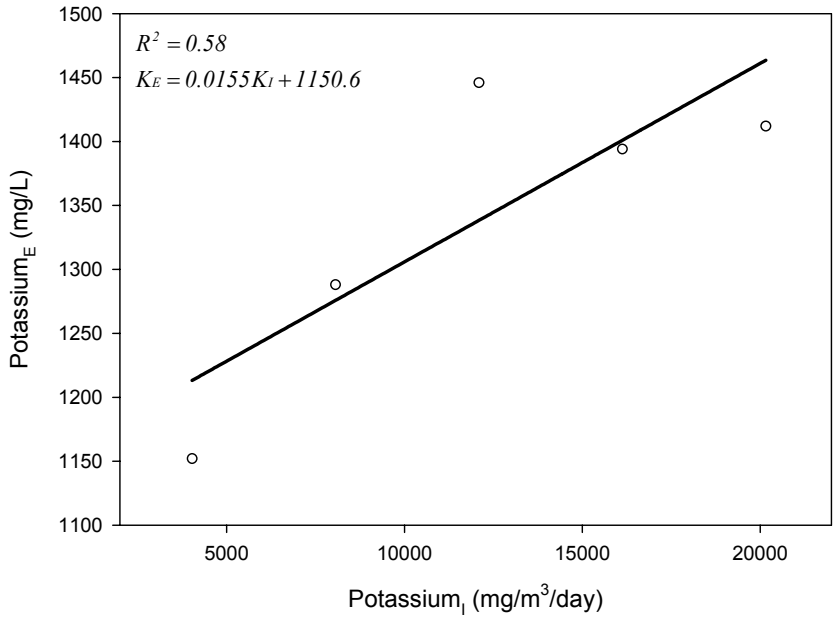


Fig D. 17 Potassium linear regression between input and expected K values

D. 9 Sulphide and Sulphate

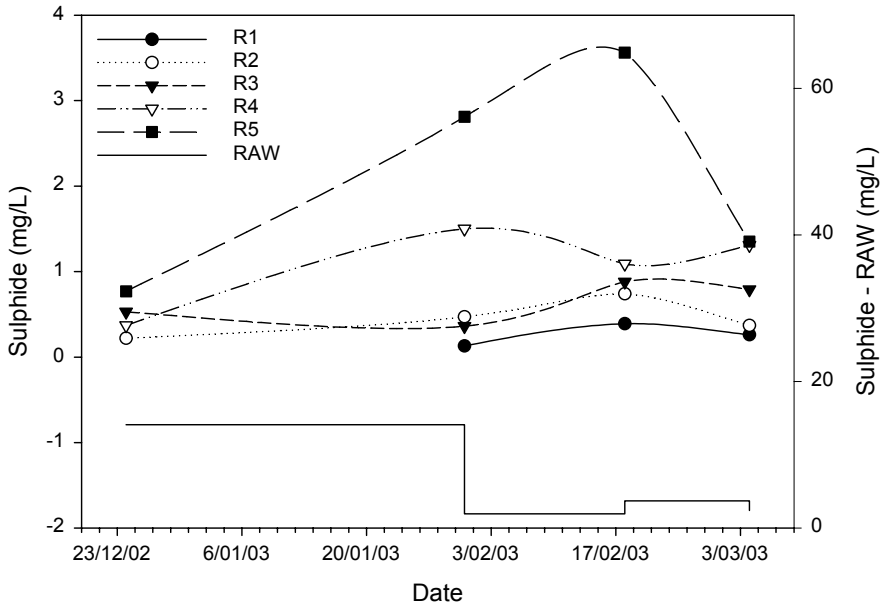


Fig D. 18 Course of the Sulphide values in five reactor vessels and raw feeding effluent in time

Table D. 19 Sulphide T-test

	Mean	*SD*	*t*	*df*	*Sig.(2-tailed)*
R1 × R2	-0.27	0.14	-3.402	2	0.077
R3 × R2	-0.19	0.23	-1.646	3	0.198
R4 × R2	-0.62	0.43	-2.848	3	0.065
R5 × R2	-1.67	1.08	-3.096	3	0.053

1. *: 95% Probability (P<0.05)

2. **: 99% Probability (P<0.01)

Table D. 20 Sulphide correlation analysis

		Trial 1 (36g[1])		Trial 2 (72g)		Trial 3 (108g)		Trial 4 (144g)		Trial 5 (180g)	
		Raw[2]	R1[3]	Raw	R2	Raw	R3	Raw	R4	Raw	R5
Descriptive statistics	Mean	15.25	0.26	30.00	0.45	45.25	0.64	60.75	1.07	75.75	2.12
	SD	12.60	0.13	25.60	0.22	38.20	0.24	51.31	0.49	64.19	1.29
	N	4	3	4	4	4	4	4	4	4	4
Correlations	Pearson Cor.	1.000		-0.616		-0.183		-0.978*		-0.651	
	Sig. (2-tailed)	.		0.384		0.817		0.022		0.349	
	N	3		4		4		4		4	

1. Organic Loading Rate (g VS /m^3·day)
2. Sulphide loading rate (S^{2-} mg/m^3·day)
3. Sulphide value in reactor vessel (S^{2-} mg/L)

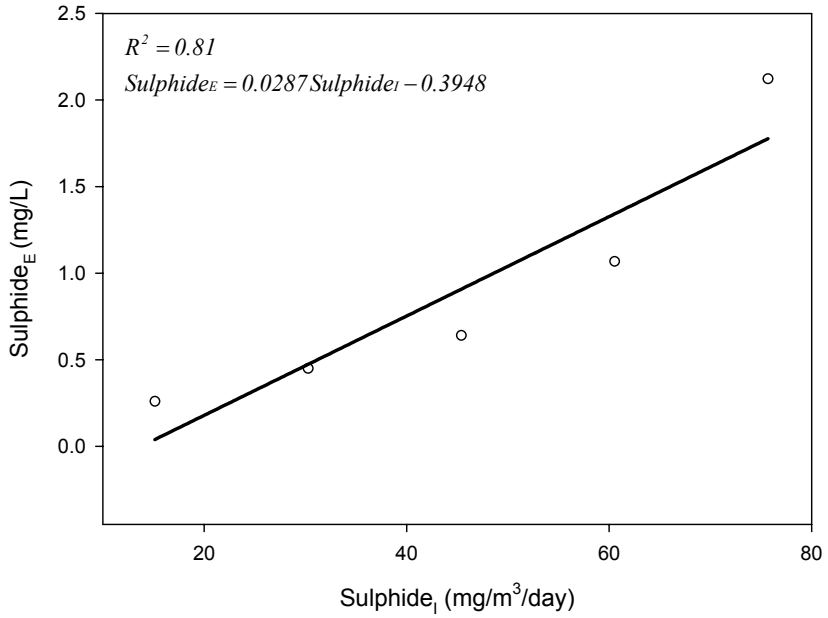


Fig D. 19 Sulphide linear regression between input and expected Sulphide values

Table D. 21 Sulphate Analysis Result

Date	*RAW*	*R1*	*R2*	*R3*	*R4*	*R5*
26/11/02	-	-	-	-	-	-
10/12/02	8.2	5.2	5.1	-	6.8	13.8
24/12/02	11	-	-	-	-	-
31/01/03	-	-	-	-	-	-
18/02/03	-	-	-	20.2	17.3	19.1
04/03/03	34.8	8.3	6.2	15.5	28.7	11.9
MEAN	18.00	6.75	5.65	17.85	17.60	14.96
SD	14.62	2.19	0.78	3.32	10.95	3.73

APPENDIX E

The Comparison of Odour Emission Rate between Olfactometry and the AromaScan in Experiment 2

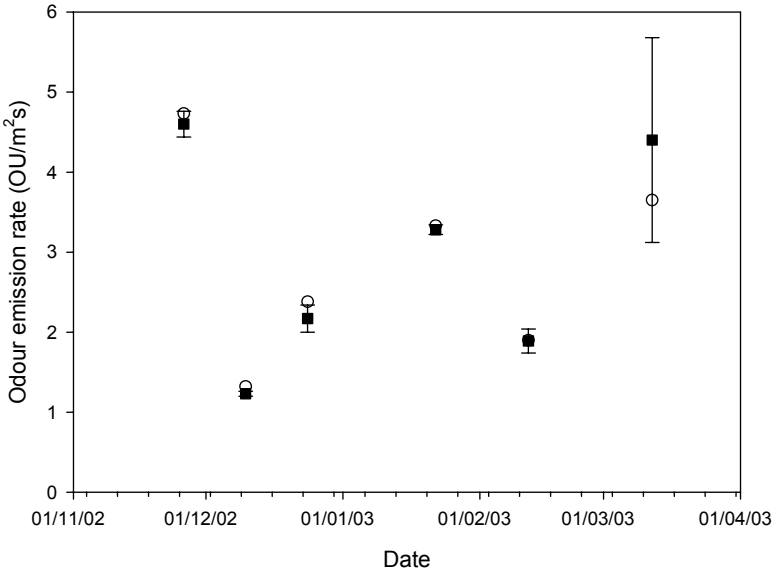


Fig E. 1 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 1 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN

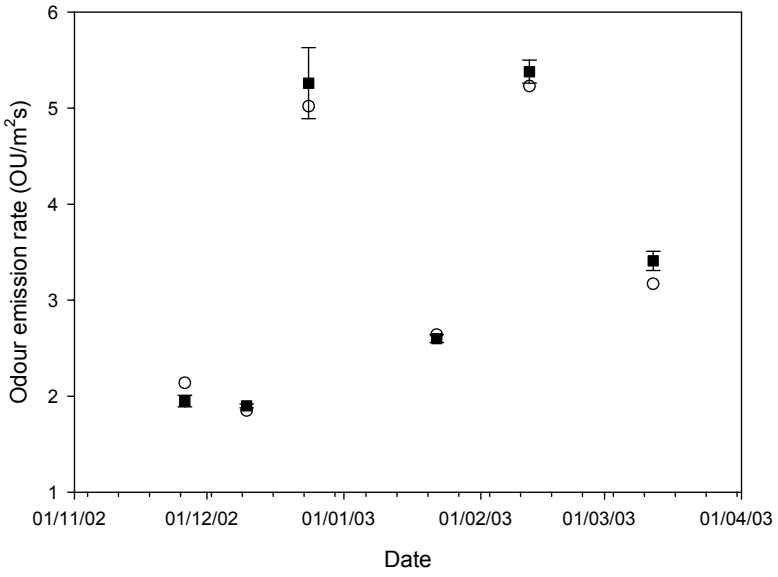


Fig E. 2 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 2 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN

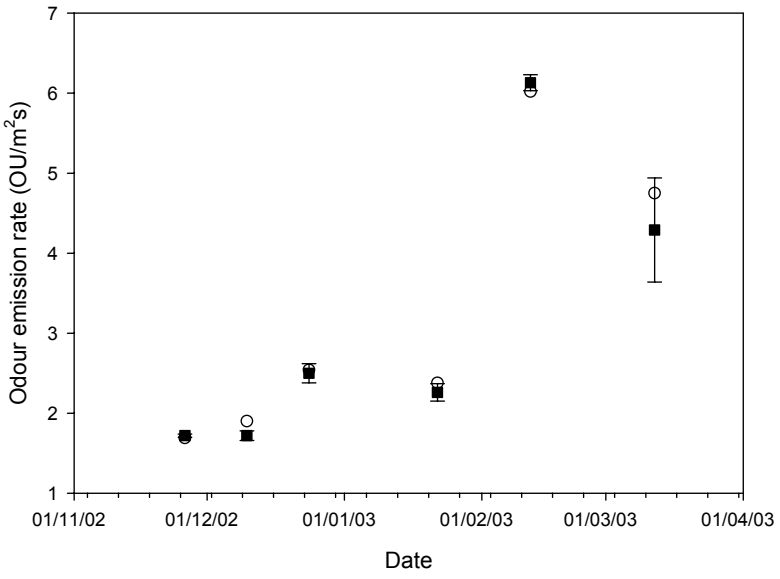


Fig E. 3 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 3 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN

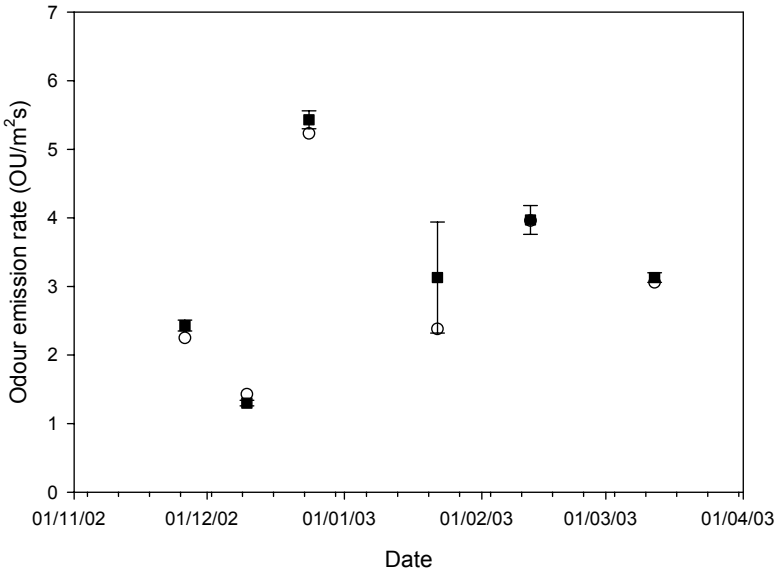


Fig E. 4 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 4 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN

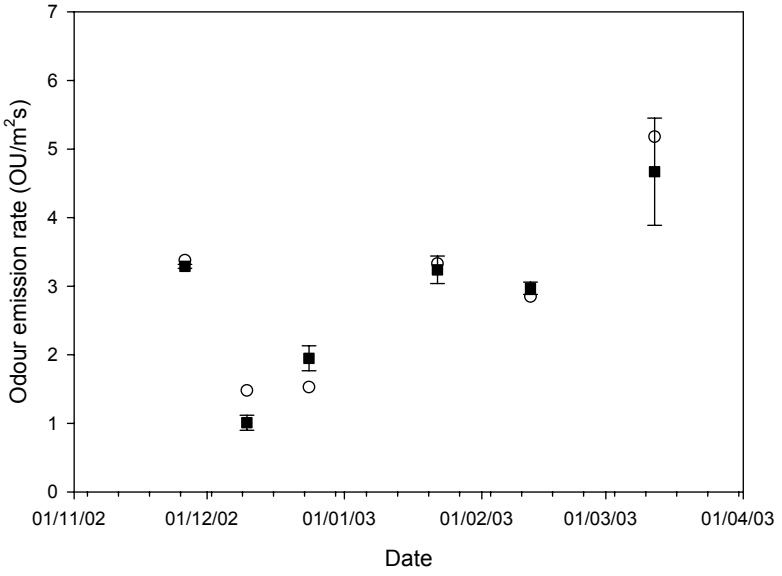


Fig E. 5 The comparison of odour emission rate between olfactometry and the AromaScan in Reactor 5 over experiment 2: ○, odour emission rate measured by olfactometry; ■, odour emission rate predicted by the Aromascan and ANN