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Predicting Swine Odour Concentrations

by

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in

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To Oladipo and Yejide Omotoso,
who gave more than I deserved,
and to
Kipkem, Ralph and Gloria Henry,
whose love and support have been powerful,
even across the seas

Without you, there is nothing.

ABSTRACT

Confined animal feeding operations are known to produce odours, which often lead to public complaints. Efforts to reduce the odour of confined animal feeding operations focus on changes in housing, manure storage and animal diet, but evaluation of these efforts and the development of enforcement tools require precise odour measurements. This experiment attempted to determine if swine odour concentrations could be calculated using Artificial Neural Networks and the results of measurements of ammonia and hydrogen sulphide gases and the output of an AromaScan™ electronic nose. It was found that a recurrent network with, Symmetric Logistic activation of the hidden layer and Logistic of the output layer could be used to predict odour concentrations to account for 79% of the variation of the concentration measurements.

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LIST OF ABBREVIATIONS

°C	degrees Celsius
%	percent
µg	microgram
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AOPA	Agricultural Operations Practices Act
ASTM	American Society for Testing and Materials
CEN	Comité Européen de Normalisation
CFO	Confined Feeding Operation
EROM	European Reference Odour Mass
g	gram
g/mol	grams per mole
GC	Gas Chromatography
GC/MS	Gas Chromatography / Mass Spectroscopy
GC/FID	Gas Chromatography / Flame Ionisation Detection
GC/FPD	Gas Chromatography / Flame Potentiometric Detection
GC-O	Gas Chromatography – Olfactometry
GDT	General Detection Threshold
IDT	Individual Detection Threshold
L	Litres
Log	logarithm
m^2	square metre
m^3	cubic metre
mL	millilitres

MS	Mass Spectroscopy
NRCB	Natural Resources Conservation Board
NH_3	Ammonia
OU	Odour Unit
OU_E	European Union Odour Unit
OU_E/m^3	European Union Odour Unit per cubic metre
OU/m^3	Odour Unit per cubic metre
PCA	Principal Component Analysis
ppb	parts per billion
ppb-v	parts per billion by volume
ppm	parts per million
r	Pearson's correlation coefficient
R^2	Coefficient of Determination / Coefficient of Multiple Determination
s	second
SS	sum of squares of residuals
VOC	Volatile Organic Compound

1.0 INTRODUCTION

Livestock operations are increasing in size, and in Alberta they tend to be concentrated in the southern part of the province, near Lethbridge and Red Deer (NRCB, 2003). With large livestock operations come complaints about dust, noise, water quality degradation, and, most particularly, odour. Odour complaints need to be addressed, and odour-reducing methods are being researched and developed, but they need to be evaluated in a consistent and objective manner.

In Alberta, air quality objectives are measured in terms of weighted averages of specific gases (Alberta, 2004). Canadian regulations and enforceable standards (rather than objectives, which are not as easily enforced) govern gases based on the concentrations in air that are known to cause detrimental health effects (CCME, 1999). With odour, however, the concentrations of the constituent gases may be well below health criteria when nuisance effects are being observed. Alberta criteria for ammonia and hydrogen sulphide are directed towards odour nuisance, averaged over one or 24 hours (Alberta, 2004), although the criteria are stated in terms of analytical concentrations. However, livestock operations emit a variety of gases, and odour nuisance may occur before the levels based on a single gas have been reached.

The standard method of odour measurement is the use of olfactometry, but this method can be time and personnel-intensive. In olfactometry, a sample of the odour is presented to qualified odour panellists at successively greater concentrations / lower dilutions. The extent of dilution required is a measure of the odour's level above its detection threshold, or the odour concentration. However, there are drawbacks to the use of this method. Finding and retaining qualified panellists, time constraints and expenses of this method work against its ease of application. Thus, systems are being developed that do not require the large time investment of human subjects, but will retain the use their perceptions as the standard.

The electronic nose has been used for many odour-detecting applications, and best results are obtained when the odour-source is simple, consisting of one or two

odorous chemicals. However, livestock odours are caused by a mixture of odorous constituents, so that each instrument's results need to be calibrated and validated with human subjects and the particular odour source type before the instrument can be used to replace the human panels. This research project attempts to do that for swine odours using an electronic nose, and additional input data – ammonia and hydrogen sulphide concentrations. The project will use statistical analysis methods, and Artificial Neural Networks to relate odour concentrations as determined by an odour panel with the results obtained from an electronic nose and the gas measurements.

It is hoped that the models derived from this research can be applied to swine manure odour samples so that quick field measurements can be taken of odour, with occasional validation and recalibration using odour panels. If odour assessment is simplified and made less time-consuming than olfactometry, it is possible that regulations may be developed and made enforceable regarding swine odour sources, and research into reducing odours from these specific sources may proceed with greater ease.

In this thesis, the need for research on odour measurement and a description of the different techniques used in the past are in Section 2, Review of Literature. The Review of Literature also describes the data analysis methods that have been used in the past for odour measurement. Section 3 describes the Objectives of this work and the hypotheses to be tested. Methods (Section 4) describes the sampling procedure and data analysis methods selected, along with a rationale for the methods of each chosen. This section also describes the instrumentation and equipment used, and the criteria used for determining success of the experiment. Data Collection (Section 5) summarise the data obtained from olfactometry, the electronic nose and the gas meters, and describe criteria for data that were removed from further analysis. In Results and Discussion (Section 6), the methods and the results of the detailed analyses are presented. Section 7 discusses ANN Refinement, or the steps taken to improve the network design for predicting odour concentrations. In Conclusions (Section 8) is a summary of the conclusions that can be drawn from this experiment. Section 9 contains Recommendations for future experimentation. Section 10 contains References.

2.0 REVIEW OF LITERATURE

This section provides an overview of the literature as it pertains to the current study. A description of the current state of swine odour issues in Alberta is presented. This is followed by a description of how odour is perceived, and of several odour measurement methods. The final portion of this section describes the methods of analysing data that have been used and how they may affect the conclusions that can be drawn.

2.1 Swine Production in Alberta

In Alberta, the majority of swine are raised in Confined Feeding Operations (CFOs) (AAFRD, 2003). CFOs are "An activity on land that is fenced or enclosed or within buildings where livestock are confined for the purpose of growing, sustaining, finishing or breeding by means other than grazing, but does not include seasonal feeding and bedding sites." as defined by the *Agricultural Operations Act* (Alberta, 2001) (AOPA). CFOs are governed by AOPA, and administered by the Natural Resources Conservation Board (NRCB) and Alberta Agriculture, Food and Rural Development.

In 2002, the NRCB was given the responsibility for approvals and enforcement regarding CFOs in Alberta. Applications to the NRCB for new confined feeding livestock operations numbered 169 (approvals, registrations and authorizations) in 2002 (NRCB, 2003) and 36 in the first quarter of 2003 (NRCB, 2004). Approximately half the applications in each year were for approvals as opposed to registrations, meaning that they were for facilities that housed large numbers of animals (NRCB, 2003).

The NRCB's administrative regions in Alberta are shown below. They are, from North to South, Fairview, Barrhead, Red Deer and Lethbridge, as shown in Figure 1. From the inception of the AOPA and for the first quarter of 2003, the last period for which figures are available, applications for new facilities tended to be in Southern

Alberta, with Lethbridge region having the most. In 2002 - 2003, 47 % of applications were for the Red Deer region of the NRCB's 4 regions. In that fiscal year 91 of the 116 applications received in the province were for swine facilities.

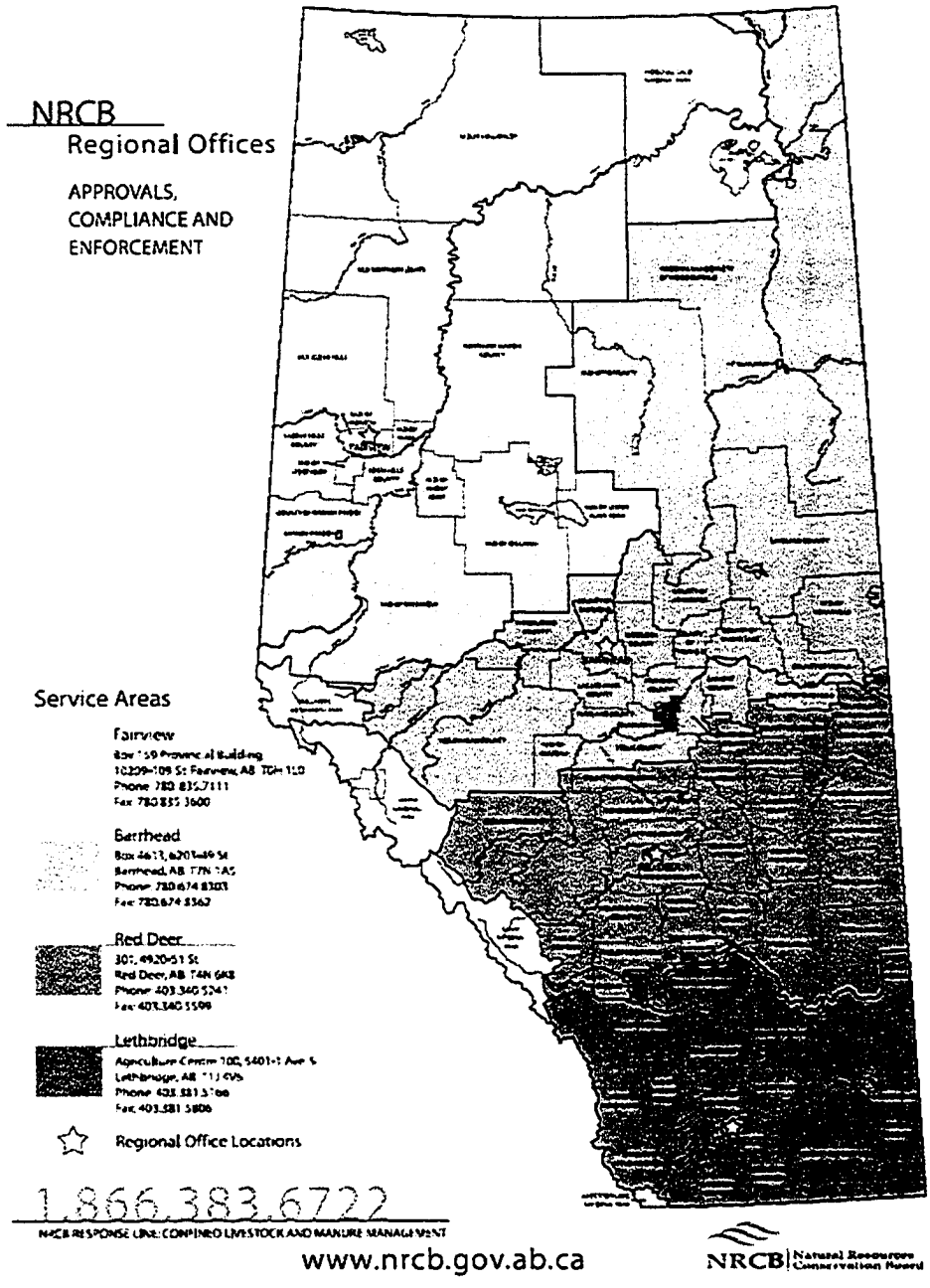


Figure 1: Regions of the Alberta Natural Resources Conservation Board

(Reprinted with permission from the NRCB)

Canada's hog inventory grew from 5.2 million head in 1975 to 13.96 million head in 2001 (AAFRD, 2003). At the same time, the number of farms with swine declined from 26,000 in 1976 to 2,677 in 2001, indicating a 10-fold rise in the average size of hog operations. Between 1996 and 2001 alone, the swine population of Alberta rose by 17%. The distribution of swine populations also changed, so that while areas from Camrose and north lost swine, areas near Lethbridge, Medicine Hat, Drumheller and Wainwright experienced swine population increases of 20, 67, 47, 94 percent, respectively (using Environment Canada census areas) (AAFRD, 2003).

In 2003, approximately 50% of Alberta's swine population were in the Red Deer, Drumheller and Lethbridge areas and 82% of the animals were in operations that have more than one thousand (1127) pigs. Farms with less than 20 pigs are located predominantly from Edmonton and northwards to Peace River (AAFRD, 2003). In 2004, Alberta's swine population stands at just over 3 million animals (Alberta, 2004).

Of applications for new and expanding facilities received by the NRCB, swine facilities account for 54% of the total received in 2002 – 2003, with dairy operations a distant second at 17% (NRCB, 2004). Thus, the swine population of Alberta appears set to continue to increase for the foreseeable future, again with most of the growth expected to be in Southern Alberta.

The NRCB is also the body which receives complaints lodged regarding confined feeding operations. In the first year of administering AOPA the NRCB received 981 complaints about CFOs (Alberta, 2003). Compliance reports for NRCB-governed operations indicate that odour complaints are most common (NRCB, 2003). Of the complaints, more than 75% were regarding southern Alberta facilities, with NRCB Regions Red Deer and Lethbridge accounting for 52 and 25% respectively, and 249 complaints generated by a single facility. Complaints regarding facilities (as opposed to development permits and non-compliance, livestock disposal and other complaints) numbered 431, with 31% of these relating to swine facilities. Odour complaints accounted for 42% of all facility complaints.

Swine odour as a nuisance in Alberta has been clearly established by the above statistics. Research is currently underway in Alberta and in other jurisdictions with high swine populations on methods of reducing swine facility odours. Methods under consideration include feed management, housing improvements and manure handling methods. However, the success of any measure must be evaluated before large scale implementation of potentially expensive changes. Farmers' reluctance to make changes for the purpose of reducing odours can be inferred from a Statistics Canada study which found that Alberta's implementation of odour reduction strategies on livestock operations was highest in the country at a dismal 34% of operations (Beaulieu, 2004). The most common methods of odour management were the planting of shelter-belts, and housing improvements. Feed management was also conducted for odour reduction. All methods were found to be more in use at swine operations than at any other type of livestock operation (Beaulieu, 2004).

Producers make efforts to reduce the odour emissions from their facilities, but without a simple method of measuring odours, the efficacy of these measures and the impact of their failure on downwind residents may not be quantifiable. If a field method of measuring odours can be shown to be consistent and reliable, measuring the nuisance impacts and the benefits of mitigation measures would become simpler.

2.2 Odour

2.2.1 Human perception of Odour

Odour perception is the result of chemicals interacting with nerve receptors (Ohloff, 1994). When an individual inhales, volatile molecules travel to olfactory receptor cells (neurones) high in nose and cross a 20 μm thin aqueous mucous layer to get to receptor surface, the olfactory epithelium, which is 6 cm^2 in size and approximately at level with the eyes (Gardner and Bartlett, 1999). The molecule reacts with proteins in the olfactory epithelium. A signal is generated, and travels down the nerve axon to the olfactory bulb of brain. The olfactory bulb processes the signal, and passes it to the olfactory cortex of cerebral cortex. It is estimated that there are 100 million receptor cells. A simplified diagram of the olfactory system is shown in Figure 2.

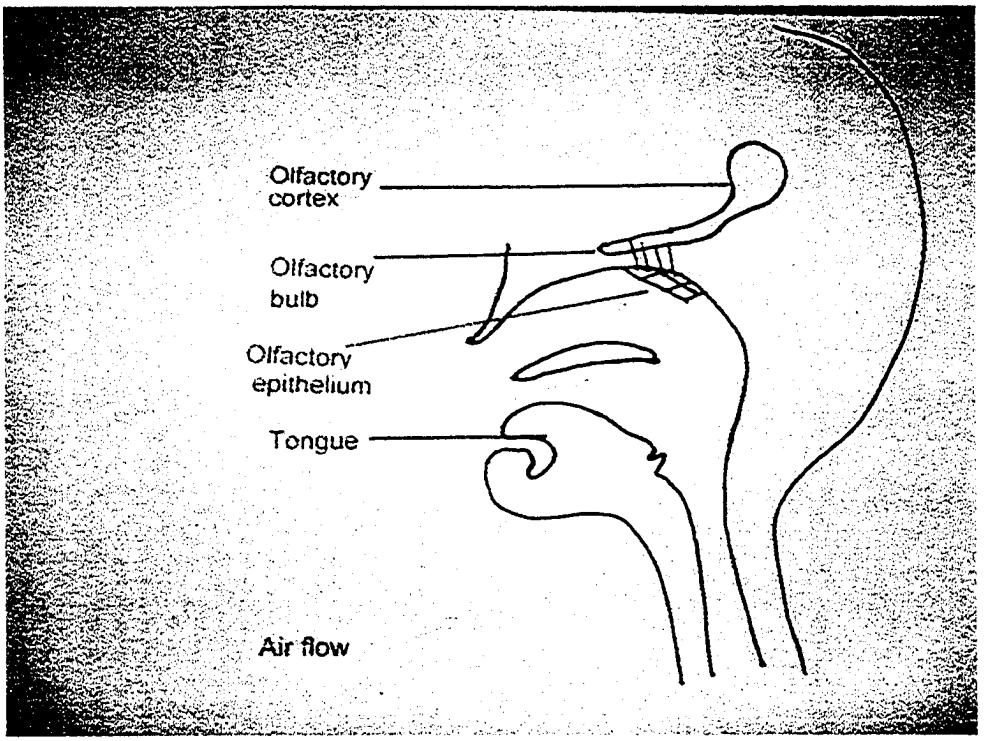


Figure 2: Simplified diagram of the olfactory system

(adapted from Markert, 2002 and Ohloff, 1994)

The Trigeminal nerve also reacts to odours. The reaction is processed as "mouth feel" or other physical reactions, such as a warming, burning, tingling or cold sensation. However, the response of the trigeminal nerve are processed in a different part of the brain from the olfactory nerve, and the trigeminal nerve receptors may be less sensitive than are olfactory receptors (Ohloff, 1994). An example of this is that Schiffman *et al.* (2001) found that if an odour sample was supplied to a subject one nostril at a time, the subject could not identify which nostril had received the odour, but could identify which nostril received the *irritant* – which is processed as a trigeminal response.

Moncrieff (1970) states that non-polar molecules are reflected off the olfactory epithelium, producing no signals and therefore are not detected. Moncrieff (1970) also stated that it is the adsorption and desorption of odorous molecules that causes

the energy changes in the olfactory epithelium which are translated into nerve signals. Molecules that are not adsorbed are not detected as odorous.

Additionally, air must be moving for odour to be perceived (Moncrieff, 1970). If the subject holds his or her breath, or plugs their nose, even with odourous molecules already in nostrils, perception of odour is diminished.

The sensitivity of the nose to an odorous compound is partially only a function of the volatility and vapour pressure of the molecule, which affect its mobility. However, musk is a molecule with very low volatility, but human sensitivity to very small quantities of this molecule are very high (Moncrieff, 1970).

Murphy *et al.* (2002) and Ohloff (1994) indicated that olfactory impairment was more prevalent as people age. They also found that being a current smoker, and illnesses such as epilepsy and nasal and respiratory tract infections affected olfactory abilities. Ohloff (1994) also indicated that females are more sensitive to odours than males.

The individual's previous exposure to an odour also has an effect on current perception. Adaptation is the phenomenon in which a person's response to an odour is affected by previous exposure. Adaptation can cause a decrease in sensitivity to the odour (specific anosmia) or increased sensitivity (Smeets and Dalton, 2002).

Odorous compounds have been found to range between 30 and 300 g per mole (Bauer, *et al.,* 1990). Heavier compounds tend to not be volatile enough to be inhaled and carried high up into the nose to encounter the olfactory epithelium. Compounds that are lighter than 30 g per mole are usually non-polar, and thus not reactive enough with the epithelial lining to be detected as odours. Odourous compounds also tend not to have more than 2 polar functional groups. A larger number of functional groups would reduce the volatility of the molecules, which makes them non-detectable (Gardner and Bartlett, 1999).

Chemical structures can impart general odour characteristics (Bauer *et al.*, 1990). Aliphatic esters are the characteristic odours of fruits and flowers. Ketones are nutty in tone, and unsaturated alcohols are associated with "intensely green" odours.

However, the relationship between odour and chemical structure is not always straightforward, and small changes in structure can cause very different odours. Enantiomers are molecules which are chemically identical, except that the molecules are non-superimposable mirror images of each other. The enantiomers of limonene smell like turpentine and oranges, while enantiomers of carvone have odours of caraway and spearmint (Ohloff, 1990). Some ammonia-containing compounds such as amines and amides have a slight ammonia-like odour, while others in these groups do not, or have other, more overwhelming odour characteristics (Dravnieks, 1985). Thus, chemical structure alone cannot be used as a method of determining an odour's potential effect on the receptor.

2.2.2 Odour Mixtures

While individual chemicals have their characteristic odours, in nature we encounter many odorous mixtures. Le Guen *et al.* (2000) detected 42 odour-active compounds in cooked mussels using Gas Chromatography-Olfactometry (GC-O) to separate the compounds for detection by trained odour panellists. Although 42 odour-causing compounds were detected by the trained odour panellists, only 28 were identified using Mass Spectroscopy in a separate output stream – the others were in concentrations too low to be properly identified by the instrument. Schiffman *et al* (2001) conducted a literature search and identified 411 different compounds associated with swine facility odours, but were able to identify only 311 in their own samples by instrumental methods.

Without the use of Gas Chromatography (GC) to separate the odorous compounds, outside of the laboratory situation, exposure to odours is generally exposure to a mixture of chemicals. However, it is not necessarily a mixture of all the present component compounds, and the proportions of each of the chemicals in the odour would change over the exposure period. In aroma research (generally for the manufacture of pleasant odour-active compounds), fragrances are described as having three notes – a top note, consisting of the first chemicals to be detected by the observer, a middle note which is perceived next, and an end-note or dry-out, perceived last (Bauer *et al.*, 1990). The top note tends to contain the more volatile components of the aroma, but not exclusively. The bottom note also consists of those odorous compounds with the greatest persistence – decreasing the actual

concentration of the odourant does not produce a noticeable decline in the perceived concentration.

The perception of an odorous compound is related to its concentration. For single compound odours, the relationship tends to be linear, as illustrated in the graph below, adapted from Cain and Moskowitz (1974). As illustrated in Figure 3, the relationship is not the same for all compounds. The different slopes of the two compounds indicate the differences in their odour persistence. For the compounds described as top notes in perfumery (represented by 1-propanol in Figure 3), the slope of this graph is steep, where a small increase in concentration leads to a large perceived increase or response to stimulus. For bottom notes, or less volatile compounds, the increase is slower, with a large increase in concentration leading to a somewhat smaller increase in perceived concentration (represented by 1-octanol). Top note compounds include citrus oils, and bottom notes include musk (Gardner and Bartlett, 1999).

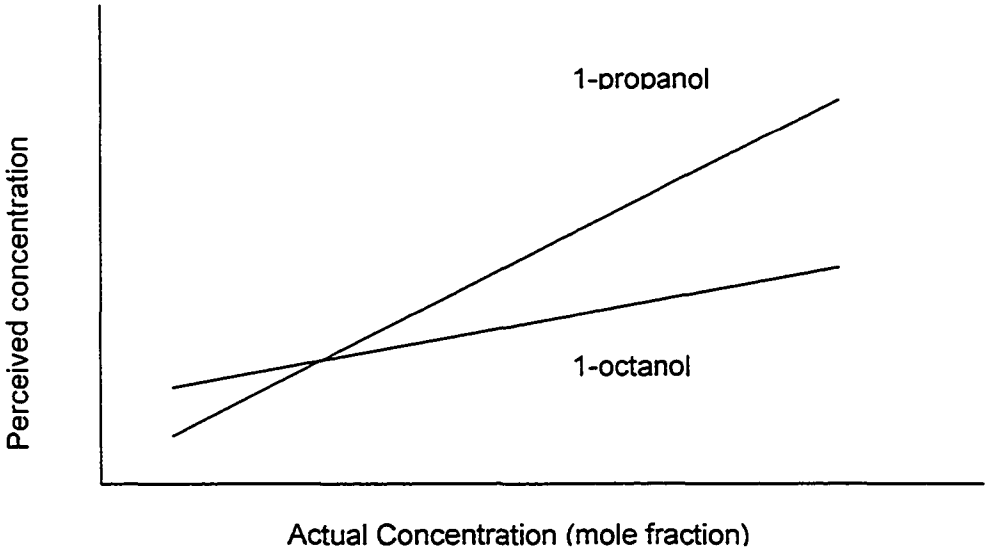


Figure 3: Perceived and Actual Concentrations of Odour Sources

(adapted from Cain and Moskowitz, 1974)

The relationship may not be as clear for mixtures of compounds, as they will contain both top and bottom note components. Schiffman *et al.* (2001) used GC/MS, GC/FID and GC/FPD to identify 331 odorous compounds in hog manure. However, the researchers found that most of the compounds were well below their published odour detection thresholds. It was considered that in a mixture of compounds such as in manure, there may be additive, synergistic and cumulative interactions among the chemicals, affecting their perception by human subjects, although Gardner and Bartlett (1999) stated that synergistic effects are probably rare, and are related to low concentrations and competition for non-specific odour receptors. Additionally, among this chemical mixture are other, non-odorous compounds, such as methane, which may act as carrier gases and increase the mobility of other compounds in the mixture.

The sense of taste and the sense of smell are linked (Rothe, 1988). Additionally, a person's perception of a taste or odour may also be affected by visual clues such as food colouring (Rothe, 1988), and, by extension, the sight of a large livestock housing facility or manure lagoon. Powers *et al* (2000) stated that removal of odour panels from the source of the odour reduces bias in odour detection (due to influences such as wind speed, and visual effects), but that this makes the process of odour measurement slower and reduces the possible applicability of a response.

Most exposures to animal odours occurring outside the laboratory also include particulate matter, such as dust, dried fecal matter and dried feed. Schiffman *et al.* (2000) found that many odorous compounds were adsorbed onto the sampling bags and dust that would be filtered out of collected samples. In un-controlled exposures to odour, these would be present to contribute to the subject's experience of the odour source.

The standard method for measuring an odour is by olfactometry. This method is accepted by the European Union (CEN 13725:2003) and standardised by ASTM (E 679-91). Other methods are often used as surrogates for this time and resource intensive method, including different methods that depend on human detectors.

2.3 Odour Measurement Methods

As odour detection is an organic response to varied stimuli, the standard methods of odour measurement make use of human subjects in olfactometry. The human nose has been found to be able to detect many odorous compounds at levels below instrumental detection limits (Le Guen *et al.*, 2000; Schiffman *et al.*, 2001). Human panels are not always easily available, however, and so several instrumental methods are often used as a surrogate for the panels.

2.3.1 Olfactometry

Olfactometry consists of the instrument that delivers the odour sample to the human observer, and the observers or panellists. Standards for olfactometry govern the instrument and the qualifications of a person to be a panellist. The word "olfactometer" is used at times to refer to the instrument, and at times to the entire system consisting of the instrument and the panellists using it.

The olfactometer must be constructed of materials that do not retain odours. Stainless steel and Teflon are the materials of choice for most instrument parts that come into contact with the odours. The instrument is designed to provide the odour to the panellists at pre-determined dilutions in fresh air, and for the dilution to be controlled by an operator.

Cain and Moskowitz (1974) stated that odour concentration cannot be separated from hedonic tone in reporting, as a substance that is pleasant at a low concentration may be very unpleasant at a higher concentration. This is somewhat accounted for by determining the odour's hedonic tone at or slightly above its detection threshold, the minimum concentration at which it is distinguishable from background. The substance's concentration in the odour sample above this threshold can then be taken into account in further examination of the odour.

As there is variation among humans in odour detecting-capability, olfactometry makes use of the observations of a panel, or group of individuals, rather than a single odour observer. In the European Union odour measurement standard (CEN, 2003) panellists must also be able to consistently detect n-butanol at a concentration

between 20 ppb-v and 80 ppb-v – usually expressed as 40 ppb (the geometric mean of the two concentrations). A concentration of 40 ppb-v of n-butanol is equivalent to 123 µg of n-butanol evaporated in $1m^3$ of a neutral gas. This mass of n-butanol is considered 1 European Reference Odour Mass, or EROM. A European Odour Unit (OU_E) is the amount of an odourant that when evaporated into $1m^3$ of a neutral gas at standard conditions elicits a physiological response from a panel equivalent to that elicited by 1 EROM. Thus, when the odour detection threshold of a substance is identified by a panel selected to detect n-butanol at 1 EROM, the two can be compared.

Olfactometry is used to determine the detection threshold for an odour as a measure of its strength. If the odour can be detected when it is very dilute, it has a low detection threshold and is considered a strong odour. Odours that can only be detected when not diluted or with a low number of dilutions have a high detection threshold and are considered weak.

Odour samples that are collected for analysis in a laboratory, either by olfactometry or by other instrumental methods, are generally filtered to remove particulate matter. Filtering the sample alters the humidity of the sample, as well as removing some nuclei on which odourous molecules may be adsorbed (Schiffman *et al.*, 2001). Although this is the standard practice, it must be acknowledged that this further removes the odour measurement from the experience in the environment.

Rothe (1988) and Powers *et al.* (2000) noted the influence of visual cues such as sample colour on perception of odour and taste. Odour measurement in olfactometry seeks to remove these other cues by removing the different visual stimulations provided by the different sources, and make the measurement as objective as something based on human perception can be.

The instrument delivers the odorous sample to the panellist at a predetermined low concentration (very diluted), and the panellist reports if the odour was detected or not. The concentration of the odorant is then increased by a factor of two and presented to the panellist again. In this stepwise manner, the threshold concentration of detection of the odour is determined.

Drawbacks of using olfactometry include the difficulty of finding qualified panellists, time constraints of this systematic and therefore slow exposure of the sample to panellists. Qu *et al.* (2001) found that only approximately 30% of the population met the CEN (2003) (at the time in draft form) standard for being able to detect n-butanol at 40ppb. Most olfactometers test one panellist at a time, using the results of all the people to whom the odour was exposed to determine the odour concentration. The University of Alberta's olfactometer has been developed to reduce the time constraints by making it possible to test up to eight panellists at a time.

2.3.2 Gas Chromatography and associated methods

Chromatography is a method of separating mixtures into their different components. Gas chromatography (GC) is conducted using either helium, hydrogen or nitrogen gas to separate the compounds in a gas mixture. The different components of the gas have different affinities for the carrier or solvent phase, and so are eluted from the mixture and sent to the detection system at different times. The individual compounds may then be identified or further characterised by using Mass Spectrometry (MS), Photoinisation Detection (PID), Flame Ionisation Detection (FID), Flame Potentiometric Detection (FPD) or whatever method is appropriate for the particular mixture.

Gas Chromatography–Olfactometry (GC-O) is a method whereby a portion of the eluted gas is sent to a port for detection by odour panellists. This presents the compounds to the panellists in a purer form, so that the odour character of a mixture can be broken down into its distinctive notes. Another stream of the eluted chemicals is sent to a Mass Spectrometer (MS) for identification of the compounds. Using this method, LeGuen et al (2000) were able to determine that the characteristic odour of cooked mussels comes from the presence of 6 specific compounds. GC-O has been found to be useful if analysis of a particular odourous component of a mixture is desired. Ferriera et al (2001) used GC-O to determine which of over 60 identifiable odourous compounds were most responsible for the characteristic odours of high-quality aged red wines.

These methods of using chemical identification to identify odours have their limitations. As stated in the section on odours, small differences in chemical structure can cause great differences in the perceived odour's intensity and characteristics. Additionally, in the use of GC, the chosen detection method may not identify odorous but inorganic substances such as ammonia and hydrogen sulphide, which are important components of livestock odours (Bockreis and Jager, 1999, Hobbs *et al.*, 2000). Schiffman *et al.* (2000) hypothesised that synergistic and additive reactions among the numerous chemicals in odourous manure samples could account for the disparity among detection by instrument and by humans. MS and other instrumental detection methods require that each individual compound is in a quantity great enough and is eluted sufficiently distantly in time from compounds with a similar measurement profile for confident identification. However, for example, many ammonia-containing compounds (such as amines, amides, skatole, indole, pyridines) have an ammonia-like odour to some degree (Dravnieks, 1985) but would be eluted at different times from the GC. Some may be at levels that are too low to be identified by MS. Although all would contribute to the perception of ammonia in the sample, the recipient of the data would then have to examine the data and attempt to come up with relationships among the different compounds that contribute to the character of the odour. This is an approach that is being used by several researchers (Powers, 2003).

While instrumentation may provide an objective measure of the odour, it is the reaction of human receptors that is of interest in odour research. Instrumentation methods of measuring odours need to be correlated with human perception of those odours in order to be of value.

2.3.3 Electronic Noses

An electronic nose is a device containing an array of sensors which react to the presence of the odorant in a consistent manner. Odour sensing devices can be created which react by changes in mass, heat generation, changes in optical properties (adsorption, reflectivity, fluorescence), and, most commonly, by changes in electrical properties (capacitance, resistance, voltage) (Gardner and Bartlett, 1999). The commercially available electronic noses of most interest here are those

which react to odorous compounds by a change in the electrical resistance of the different sensors.

Whatever the response method of the sensor array, the change is measured, and the variety of changes in the different sensors can be used to create a profile for the specific odour. The responses of the different sensors are characteristic to and depend on the specific properties of each sensor, and how they react to the different components of an odour.

The sensors in an electronic nose are usually metal oxide or conducting polymers. Metal oxide sensors are usually of tin oxide doped with catalytic metals and metal oxides such as platinum, palladium, zinc oxide, titanium oxide, or tungsten oxide. Metal oxide sensors are effective at 300°C to 550°C, requiring lots of power to operate (Gardner and Bartlett, 1999). Conducting polymer sensors, however, can operate at room temperature, although they may not be as sensitive as are metal oxide sensors (Gardner and Bartlett, 1999). Because of the difference in operating temperatures, electronic noses are not currently made to take advantage of the properties of both polymer and metal oxide sensors.

The different sensors in an array have different specificities. For repeated uses in an environment that is not expected to vary greatly, sensors and operating temperatures can be chosen to maximise the value of the information they provide. Wilson *et al.* (2000) used 3 different metal oxide sensors operating at 10 different temperatures to create a model that was adequate for discriminating among 7 different chemical odours.

The pattern of response of an electronic nose can be added to a library of odours detected, and used to discriminate among odours. Electronic noses have been used to measure fruit ripeness (Brezmes *et al.*, 2001; Brezmes *et al.*, 2000), dairy produce freshness (Capone *et al.*, 2001; Goodner *et al.*, 2001), to discriminate among different types of cheeses, coffees and alcohols (Gardner and Bartlett, 1999) and for identifying pesticide residues (Baby *et al.*, 2000).

Wilson *et al.* (2000) and Hudon *et al.* (2000) found that a longer sample time improved the results of the electronic nose sampling. Wilson *et al.* (2000) especially found that the data clusters were better (more similarity within, more differences among clusters) when the sample time was longer.

Brezmes, *et al.* (2000, 2001), in their experiments on fruit ripeness measurement found that the use of electronic nose data was enhanced by the use of other data that could be gathered about the samples, such as fruit weight and average surface characteristic. In their work, electronic nose data were compared with traditional fruit-ripeness measurement techniques in a successful attempt to determine if the electronic nose data could be used in place of destructive methods.

Misselbrook *et al.* (1997) found that an AromaScan electronic nose's sensor response could be transformed to a linear relationship with odour concentration with approximately 60% variance.

The response of the electronic nose alone is not significant unless it can be related to other data. Olfactometry produces a measure of at what concentration an odour can be detected. GC and associated measures identify the concentrations of individual constituents in an odour. An electronic nose produces a response to the complex mixtures of odours so that the presence of more than 300 odorous compounds in a swine odour sample is reduced to 32 numbers indicating the change in resistance of 32 sensors. The value of those numbers produced must be determined by the instrument's user.

The AromaScan electronic nose contains built-in software that can be used to create an odour library, so that one can identify if the odour source is manure, cheese or fruit. However, more information can be obtained if the electronic nose is dedicated to a specific type of sample for producing more refined data.

Work on an electronic nose often deals with a specific sample type – fruit at different stages of ripeness (Brezmes *et al.*, 2001; Brezmes *et al.*, 2000), to discriminate among different types of cheeses (Gardner and Bartlett, 1999), or to estimate the strength of odours of different livestock operations (Qu, 2001). The instrument's

output is usually analysed and a model created to relate the sensor responses to a specific piece of information in which the user is interested about the type of samples being analysed. An electronic nose's use can be made simple or complex as desired.

2.3.4 Other Surrogates for Olfactometry

Stuetz *et al* (1999) attempted to see if H_2S data or an electronic nose would produce a better surrogate of the odour concentrations at different wastewater treatment plants. They found that the relationships that could be derived were best for data points within an individual wastewater treatment plant, but that the different plants had such different source waters that comparison among them was useless. In particular, the H_2S was too greatly affected by oxidation and the presence of metals in the water to be of use in the data analysis.

Powers et al (2000) used GC/MS and olfactometry data to train an electronic nose. They found that regression analysis and the GC/MS data were enough to predict panellist response only to an accuracy with an R^2 value of 0.23. Twenty-two different odourous compounds were identified in the GC/MS. The poor success of the data analysis was attributed to the presence of un-quantified compounds and the variation among panellists. Between the two instrumental measures – the GC/MS and the electronic nose, the R^2 value was as good as 0.81. However, only 8 samples were used for this experiment, and the compounds which can be detected by GC/MS do not include important manure compounds such as ammonia and hydrogen sulphide.

2.4 Data Analysis Methods

Electronic noses have been known to respond to different odorous samples in measurable ways. Attempts are being made to use the response of an electronic nose to sample properties, such as fruit ripeness (Brezmes *et al.*, 2001; Brezmes *et al.*, 2000), dairy product freshness (Capone *et al.*, 2001) and swine odour concentrations (Powers, 2003; Qu *et al.*, 2001).

Different experimenters have used different data analysis methods to predict odour concentrations using electronic nose data. The value of the responses of different sensors, data pre-processing methods, and additional data that can be used along with electronic nose data need to be determined for each particular application.

Brezmes *et al.* (2001) found that fruit ripeness could be predicted using the electronic nose and additional data, such as surface character and fruit weight. However, the data analysis methods that gave the best predictions of the fruit ripeness depended on the particular fruit, and the sensors used. It was also found that only two sensors, if they were the right ones, could be used for predicting the fruit ripeness to within 93% success. Data analysis methods that were successful included Partial Least Squares with an unsupervised neural network. These researchers found that Principal Component Analysis of electronic nose data was useful for predicting the ripeness of peaches and pears, but not useful for predicting the ripeness of pinklady apples.

Qu *et al.* (2001) found success pre-processing electronic nose data by use of Principal Component Analysis (PCA) before using a supervised artificial neural network program. PCA reduced the 32 inputs (from each of the sensors) to 3 inputs, accounting for 99% of the sample variation. Using this method, the researcher was able to predict the olfactometry results with a Mean Absolute Percentage Error (MAPE) of less than 20%. Goodner *et al.* (2001), however, caution against the use of PCA. They found that PCA, as a measure of the variability of the data, was not useful in their experiment with simple concoctions and artificially derived electronic nose data. However, Goodner's experiment used six simple artificial odour mixtures, which may be far from representative of natural complex odours such as those of manure.

Hanumantharaya *et al.*(1999) used 524 data points to create an ANN using an AromaScan™ electronic nose and olfactometry data. They found that using PCA to reduce the size of the dataset reduced the time required for training of the backpropagation network, and gave a better prediction of the output that did the ANN created using raw data. Their experiment reduced 32 sensor inputs to 10 Principal Components, discarding eigenvalues that were less than 1% of the variation.

Stuetz *et al.* (1999) felt that the response of no individual sensor in the array was significant – rather, it was the pattern of response of all the sensors that was important. Canonical discriminant analysis was conducted in order to maximise the correlations among the sensors, rather than the variance.

Polikar *et al.*(2001) also felt that PCA was not particularly useful for analysis of the electronic nose data and identifying the most useful sensors. They found that it would reduce the dimensionality of the data but not identify which sensors were most relevant. The authors used two different approaches to identify which of the 20 sensors used would provide the most relevant information, and eliminated those sensors which did not appear to provide additional information. In an experiment in which they used 12 different volatile organic compounds at 7 different concentrations, they noted that each sensor's response was linear within the range tested, so that an increase in the concentration of the odorant produced an increase in the response of the sensor that could be described in a linear fashion. The authors used this linear relationship to interpolate the responses of the sensors to increase the number of concentrations to which the model was applied, without actually testing it at each concentration. Again, however, this may not be quite applicable to complex odours such as manure, which are mixtures of chemicals, unlike Polikar's single chemical system.

From the literature reviewed, the method of analysing electronic nose data cannot be pre-determined based on the sample type. Brezmes *et al.* (2000, 2001) found that a single approach did not work for similar types of fruit (apples and pears). Several researchers (Goodner *et al.*, 2001) discount PCA, while Qu (2001) and Hanumantharaya *et al.* (1999) found it was a useful tool. Polikar *et al.* (2001) and Brezmes *et al.* (2000, 2001) found value in selecting specific sensors for use in data analysis, while Stuetz *et al.* (1999) and Qu *et al.* (2001) found that the pattern of response was more important than any specific sensor. As each electronic nose needs to be calibrated for the odour source, the optimal data analysis methods may need to be determined for different odour sources.

2.4.1 Principal Component Analysis

Principal Component Analysis (PCA) is a method of reducing large numbers of variables (such as the output of each of the electronic nose's 32 sensors) to a smaller number of broader concepts, or factors (Cody and Smith, 1997). The first new variable is a combination of all the others that is highly correlated with the original. The second new variable is created after the correlations of the first have been accounted for (Cody and Smith, 1997), and is correlated with the remainder of the dataset. Each of these new variables is called a Principal Component, and is the sum of each of the variables multiplied by the eigenvector. The value of the eigenvectors indicates the importance of that particular input variable in creating the first Principal Component. In a dataset with 32 variables, the sum of all the eigenvalues is 32, and the magnitude of each eigenvalue explains the proportion of the sample set's variance that is explained by that factor or Principal Component.

2.4.2 Artificial Neural Networks

Artificial Neural Networks (ANNs) are software programs for creating models of complex processes. ANNs are useful when the relationships among inputs and outputs are not well understood, and some relevant data are unavailable for developing a model (Hopgood, 2001). ANNs are also useful when it is not known if the data are related in a linear fashion or a nonlinear fashion (such as logarithmic, or trigonometric relationships).

In unsupervised networks, outputs are categories which the network identifies. The method is described as unsupervised or self-organising, and the network is trained to recognise patterns in the dataset (Zahner and Micheli-Tzanakou, 2000). The AromaScan AS32 (Osmetech, Crewe, UK) (AromaScan™) electronic nose has an internal ANN software package that is an example of an unsupervised ANN. The patterns of response of the 32 sensors in the AromaScan are called odour fingerprints, and they are used to build up a library of odours. The AromaScan™ can then be used to identify different odours. In the work of Brezmes *et al.* (2000, 2001), unsupervised networks were used to put the fruit into different classes of ripeness.

In supervised ANNs, output data are numerical values. Supervised ANNs have been used successfully to predict treated water quality (Baxter *et al.*, 2002) and odour

concentrations (Qu *et al.*, 2001). Hanumantharaya *et al.* (1999) used an AromaScan™ electronic nose and a backpropagation neural network to correlate swine odour concentrations to the electronic nose output.

Artificial Neural Networks are simple imitations of biological nervous systems in their organisation (Zahner and Micheli-Tzanakou, 2000). In the "hidden layer" of an ANN, which is where calculations occur, each neuron processes all the inputs it receives and sums them to create an output which it passes on to the next hidden layer neuron, or the output layer (as determined by the user). Each neuron processes the inputs it receives by applying a weighting factor to each and summing them. The neuron then applies a mathematical activation or transfer function to the sum of its inputs (Hopgood, 2001). Successive training iterations are used to adjust the weights applied to each connection to produce the desired outcome of the network. The transfer functions applied may be chosen by the user depending on the ANN software used. Transfer functions are usually non-linear, and among the most commonly applied transfer functions are tangent hyperbolic and logistic (Diamantaras, 2002; Hanumantharaya *et al.*, 1999; Hopgood, 2001; Zahner and Micheli-Tzanakou, 2000).

In supervised learning, the data are commonly divided into three groups – learning, production and testing data sets (Baxter *et al.*, 2002). The ratios of the sets can be selected by the user. The majority of the data is the learning or training set, which is used to create the model. The production set is used to modify the models created by the training set by back-propagation. Some papers describe the data set only in terms of what data were used to train the network, meaning both production and training sets. At a specified number of iterations, the calibration interval, the model is tested against the production set, and the results used to modify the model, which remains based on the training set. Training is usually run until a specified condition has been reached – the test set error reaches a minimum, or a number of training eras has passed, or the number of training errors since the minimum error has been reached. The testing set is the last set, and is used to test the model but does not influence its formation. The success of the model can be estimated by the results of applying it to the test dataset. Tests of the predictive ability of a ANN include

determination of the value of the coefficient of determination (R^2), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

According to Baxter *et al.* (2002), it is best to use a simple model. The best model for water treatment plants was found by experience to be a 3 layer multilayer perceptron, with a linear scaling input layer, logistic functions in the hidden layer, and a logistic output layer. The experimenters then changed the number of neurons in the hidden layer to optimise the predictive ability of the network. In their experiment, with a dataset of 80 cases, with 8 input parameters, it was found that 32 hidden layer neurons produced the best model. Zahner and Micheli-Tzanakou (2000), however, state that the number of neurons in the hidden layer should number no more than one less than the number of elements in the dataset, which would have limited the number of hidden layer neurons used by Baxter *et al.* (2002) to 7.

When a model has been found that yields predictions that are satisfactory, the model must be tested to ensure that it has not over-learned the data. This can be done using the same dataset. The dataset is re-sorted so that the training, production and test data sets are not the same. When the model is run using this reassigned data, a robust model will continue to give acceptable predictions. If the model's predictive capability declines significantly, the model is not stable and cannot be applied.

Some reduction of the inputs may be considered necessary. Goodner *et al.* (2001) proposed that the ratio of data cases to input variables should be no less than 6 to avoid over-fitting of noisy data in ANN. For a data set that includes electronic nose data and the input of 32 sensors, this would mean that the data set should contain at least 192 cases. In some cases, however, this size of data set is not attainable. Instead, the number of the input variables can be reduced. Hanumantharaya *et al.* (1999) and Diamantaras (2002) recommend doing this by PCA.

Hanumantharaya *et al.* (1999) found that a feed-forward backpropagation ANN to analyse the output of an AromaScan™ could successfully predict odour concentrations. These experimenters used 90% of the data for training, and 10% for validation (or testing) of the network. In determining the best network architecture for the dataset, simulations were carried out for at least 50000 iterations on the dataset

of 524 cases. Simulations using hyperbolic tangent and logistic activation functions in the hidden layers were found to give the lowest value of mean squared error.

Hopgood (2001) also cautioned that neural networks can be used reliably for interpolation, but are poor at extrapolating beyond the range of data on which they have been trained.

The extent to which an experiment refines an ANN depends on the dataset. El-Din *et al.* (2004) refined their network by systematically determining the best network transfer functions, the minimum number of training epochs and hidden-layer neurons required. The selections were based on the minimum number of training epochs and hidden-layer neurons that produced a satisfactory prediction. R^2 values that are close to 1 are considered evidence of good predictions. The lower the value of R^2, (the coefficient of determination) the poorer the predictive ability of the model. This is explained further in Section 4.6.

3.0 OBJECTIVES

The objective of this experiment is to determine if swine odour concentrations can be predicted using other methods. The methods to be tested are hydrogen sulphide concentrations, ammonia gas concentrations, and the response of an AromaScan electronic nose. This experiment will seek to determine if alone, or used together, these measures can be used for predicting the response of an odour panel. The hypotheses to be tested are stated below:

1. Odour concentration can be predicted from ammonia data.
2. Odour concentration can be predicted from hydrogen sulphide data.
3. Odour concentration can be predicted from hydrogen sulphide and ammonia data.
4. Odour concentration can be predicted from electronic nose data.
5. Odour concentration can be predicted from electronic nose data with ammonia and hydrogen sulphide data

4.0 METHOD

4.1 Sample Collection

The samples used in this experiment are the swine odour samples analysed at the University of Alberta's Odour Laboratory. Their sources were different, although the method of sample collection is essentially the same.

Samples are collected in a bag made of Tedlar, which is a material that will not retain or alter the odours of the sample. The bag is placed in a chamber such as the one below so that the outlet is exposed to the atmosphere via a particulate filter (Figure 4). The bag is sealed in the chamber, and a vacuum is applied to the chamber. This creates a negative pressure that causes the outside air sample to be drawn into the sample bag. Air samples collected in Tedlar bags were presented within 24 hours of collection to odour panels at the University of Alberta's Odour Laboratory. Within 48 hours of collection, samples were analysed using an electronic nose, a hydrogen sulphide gas meter, and an ammonia gas meter.

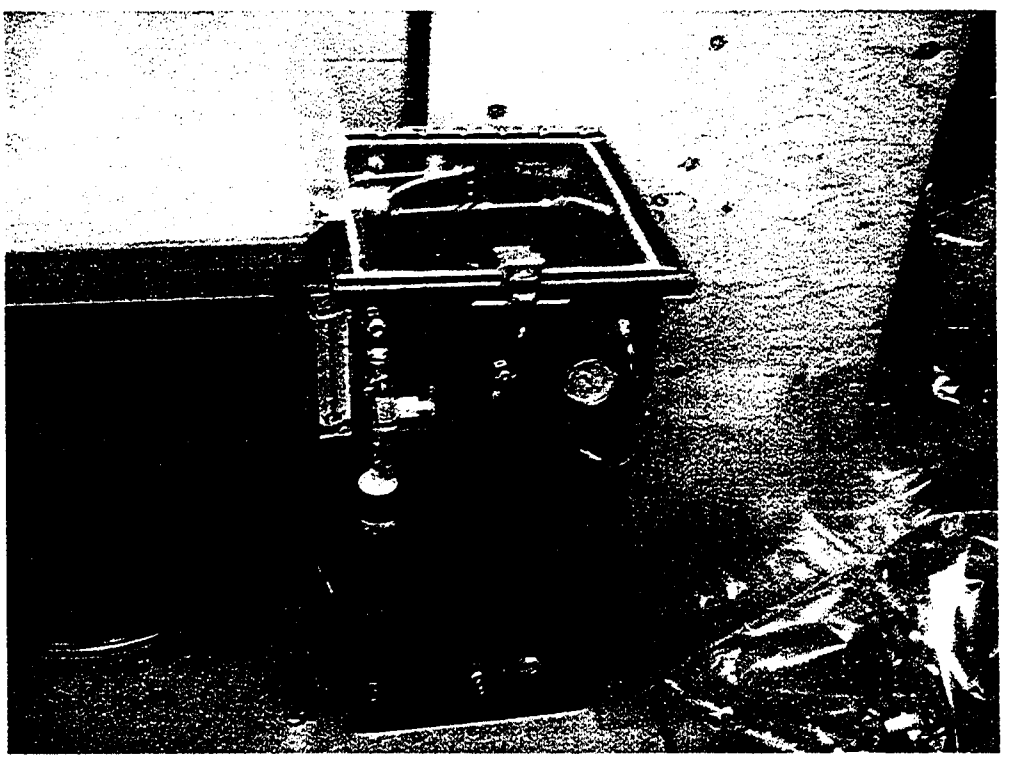


Figure 4: Odour Sample Lung

4.2 The University of Alberta's Olfactometer

The University of Alberta's olfactometer was designed using the European Union Standard (CEN, 1998), and modified and upgraded to allow for eight panellists to be exposed to the odour simultaneously (Feddes *et al.*, 2001). Panellists are recruited each year in September or as needed, and are generally students at the University of Alberta. They are compensated for their time, and are also reimbursed for parking costs to attend sessions. Panellists must be able to detect n-butanol at a concentration of 40 ppb (by volume) to be qualified under the European Union standard (CEN, 1998). At the University of Alberta, panellists are tested before each session to ensure that they consistently detect n-butanol at a concentration between 20 ppb and 80 ppb. The panellists are assigned to different ports at random for each panel session in which they participate to allow for some slight variations in the instrument's odour delivery. The instrument is operated with a minimum of 5 panellists at a time.

Figure 5 shows a typical panel station at the University of Alberta's olfactometer. The panellists are able to listen to music using the headphones provided, and are also permitted to read during the panel. They must not smoke, eat or drink during a panel session.

The sample in a Tedlar bag is placed in a sealed chamber and connected to an outlet that leads to the olfactometer's intake valve. Pressure is applied to the chamber to compress the sample bag and push the sample out at a rate determined by the desired dilution range.

At the individual stations, control valves deliver a mixture of the odour sample and fresh air to the panellists. The fresh air is provided by the building air supply (pumped directly to the laboratory). The unit is considered a dynamic unit, meaning that the air is flowing constantly to the panellist area. An indicator light at each panel station indicates to the panellist that the sample presentation period has begun. The panellist has 15 seconds from presentation of the sample to identify which selector presents the sample.

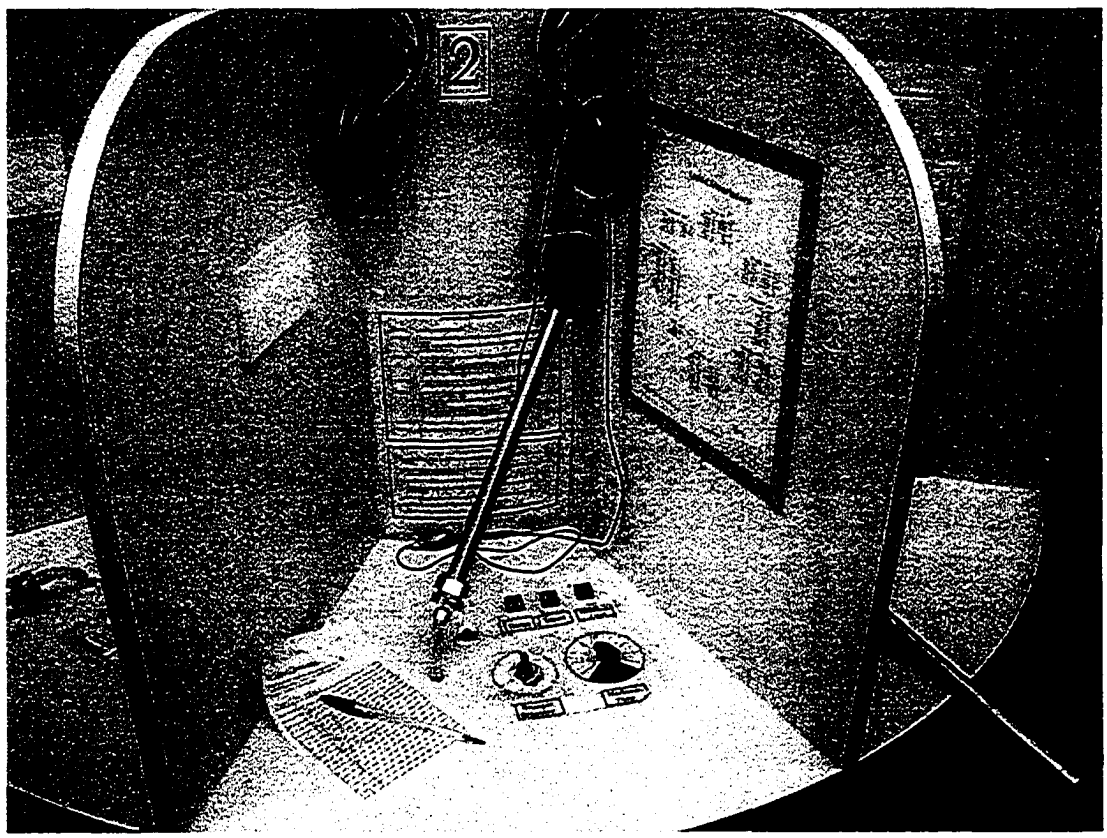


Figure 5: Odour Panellist Station at the University of Alberta's Olfactometer

At the first exposure, a low dose of the sample (diluted 16,000 times) is delivered to panellists with a larger quantity of air. The airflow of the air/odour mixture is kept constant (20L per minute) as the proportion of the odorous sample is increased stepwise throughout the experiment. The panellist sniffs at a single outlet port, but must rotate the dial among three selectors supplying air to that port. Two of the selectors will provide fresh air, while the third provides air diluted with the sample (or n-butanol during panellist calibration). The panellist must state which of the three choices is the odour sample. It is a forced-choice method of panellist reporting, meaning that the panellist must choose in accordance with ASTM standards (ASTM, 1991). If the panellist is certain, they select the button marked "Detect". If they are uncertain, they can select the button marked "Guess". If no choice is made after 15 seconds, a non-response is recorded. The light to the left of the panellist's controls flashes to indicate that sample presentation has begun (Figure 6).

When all panellists have made their choice, the concentration of the odorant is doubled in the next sample, and panellists must again choose among the three possible streams. The location of the odorous sample in the panellists' selection is changed with each successive concentration presented. When a panellist has correctly identified the odorous sample twice in a row, the panellist is considered to have detected the sample. The next highest concentration is then presented for the panellist to determine the sample's hedonic tone. The square knob labelled "Hedonic Tone" in Figure 6 lights up to indicate to the panellist that the sample has been identified and that hedonic tone is to be selected. Hedonic tones were not used for this current experiment, although the data were collected.

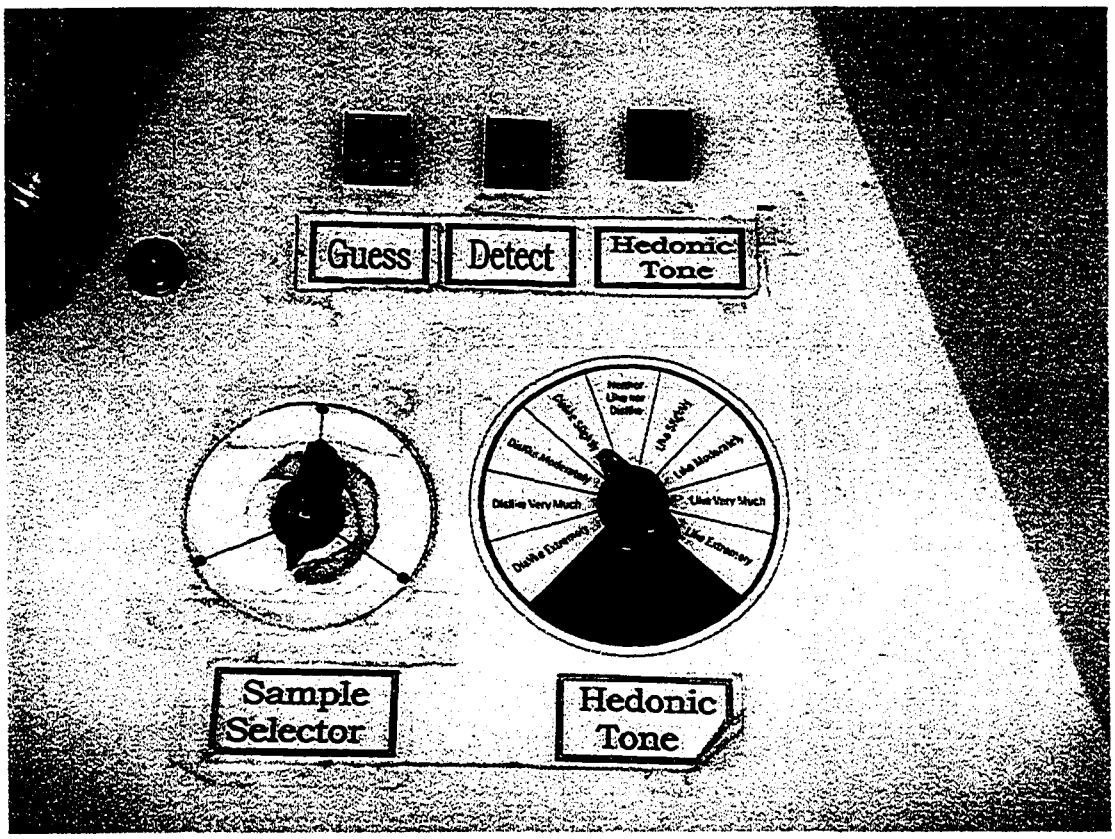


Figure 6: Odour Panellist Selection Controls

Between samples, the ports are flushed with fresh air for 130 to 300 seconds to remove residual odours. The system is then "primed" for 90 seconds so that the odour sample is present at the correct concentration at each port when panellists are

asked to make their selections. The machine is pre-set with 12 dilution levels, from 16000 to 8, with the concentration of the odourant being doubled with each successive presentation to the panel.

The instrument is tested and the fittings and valves checked frequently to ensure that the instrument continues to operated as designed. A panel's results are as shown in Table 1.

Each panellist's individual detection threshold (IDT) is calculated as the geometric mean of the concentration at which the sample was first correctly identified and the panellist was certain (D+) and the concentration immediately preceding it. The level of correct identification is validated by a successive correct identification at the next highest concentration. In the example, panellist CR correctly detected the sample at dilutions of 1000 and 500. The IDT is calculated as follows:

$$IDT = (2000 * 1000)^{1/2}$$
$$IDT = 1414\ OU/m^3$$

It can also be seen from the table that panellist MB correctly identified the sample at 500 dilutions, but was unable to validate that detection at the succeeding dilution level of 250. This panellist was presented with the sample again, until two successively correct identifications had been made. This panellist's IDT is therefore higher than that of the others, although the first correct detection was the same as for panellists SO, RG and OF.

The panel's detection threshold (General Detection Threshold, or GDT) is the geometric mean of the response of all the panellists:

$$GDT = (1414 * 707 * 177 * 707 * 707)^{1/5}$$
$$GDT = 616\ OU/m^3$$

Table 1: Example of an Odour Panel's Response to One Sample

Port	Dilution / Panellist	16000	8000	4000	2000	1000	500	250	125	63		IDT
1	CR	*	G-	G+	G-	D+	D+	*	*	*	*	1414
2	SO	*	C-	C-	C+	G+	D+	D+	*	*	*	707
3	MB	*	C+	G+	C+	G+	D+	D-	D+	D+	*	177
4	RG	*	C-	G-	C+	C-	D+	D+	*	*	*	707
5	OF	*	C-	C-	C-	C-	D+	D+	*	*	*	707
										OU/m^3 =		616

Sample M167 date 9 September, 2003

D =certain, G =guess, + =correct, - = incorrect, C = no response within 15 seconds (computer guess), * = panellist not tested at this level,
IDT = Individual Detection Threshold. Panellists' initials are changed for their privacy.

The panel leader's experience with the particular sample is used to reduce the sampling time by not always beginning the procedure at 16,000 dilutions, as shown in the example. For this particular odour sample, the panel's detection threshold was 616 OU/m^3.

4.3 The University of Alberta's Electronic Nose

The University of Alberta's Olfactometry Laboratory contains an AromaScan A32S electronic nose (Osmetech, Crewe, UK). The AromaScan A32S electronic nose (AromaScan™) has 32 conducting polymer sensors which are housed inside the unit for controlled air-flow, and each connected to a computer output system. When the sensors are exposed to an odorous samples, the polymers adsorb and desorb different molecular components, altering the resistance of the sensors. It is this change in resistance which is measured by the instrument's internal computers and reported. As the polymers are different, their responses differ, and the pattern of response of all the sensors is characteristic of the odour sample. Additionally, some work has shown that changing the concentration of the odour sample can increase or decrease the magnitude of the response of the sensors, although this change is not necessarily linear (Misselbrook, 1997).

The sample is connected to the AromaScan™ as shown in Figure 7. The sample is drawn into the instrument at a rate of 726mL/minute. The sample passes through a solution of 2% isopropanol and then to the chamber housing the sensors. This isopropanol stage adjusts the moisture content so that it is similar for each sample. The response of polymer sensors can be affected by changes in humidity, and air of low humidity can damage the sensors.

The sensor output is sent to a computer, where AromaScan™ software displays the measured change in resistance for each sensor, along with the temperature and humidity of the sample. The response of the sensors for the entire sampling period is recorded at intervals as determined by the operator. In this case, data were saved every second during sampling period.

Figure 7: Setup of the Electronic Nose, Single Gas Meter, Sample and Computer

After each sample was run, the AromaScan™ was run through a cleaning cycle by passing air containing the isopropanol solution over the samples. The length of cleaning cycle found to be effective ranged from 10 minutes to 2 minutes, depending on the samples. The efficacy of the cleaning cycle was verified by running a reference cycle after each wash. In the reference cycle, fresh air is passed across the sensors, and they do not register a change. Each sampling cycle began with a 20 second reference, then a 20 second wash, followed by the 600 second sampling phase. A typical response is shown below, using sensors 1, 10, 20 and 30 (sample JP193, September 2003). These sensors were chosen in order to illustrate the similarity of response of the sensors, as well as the differing magnitudes of the response.

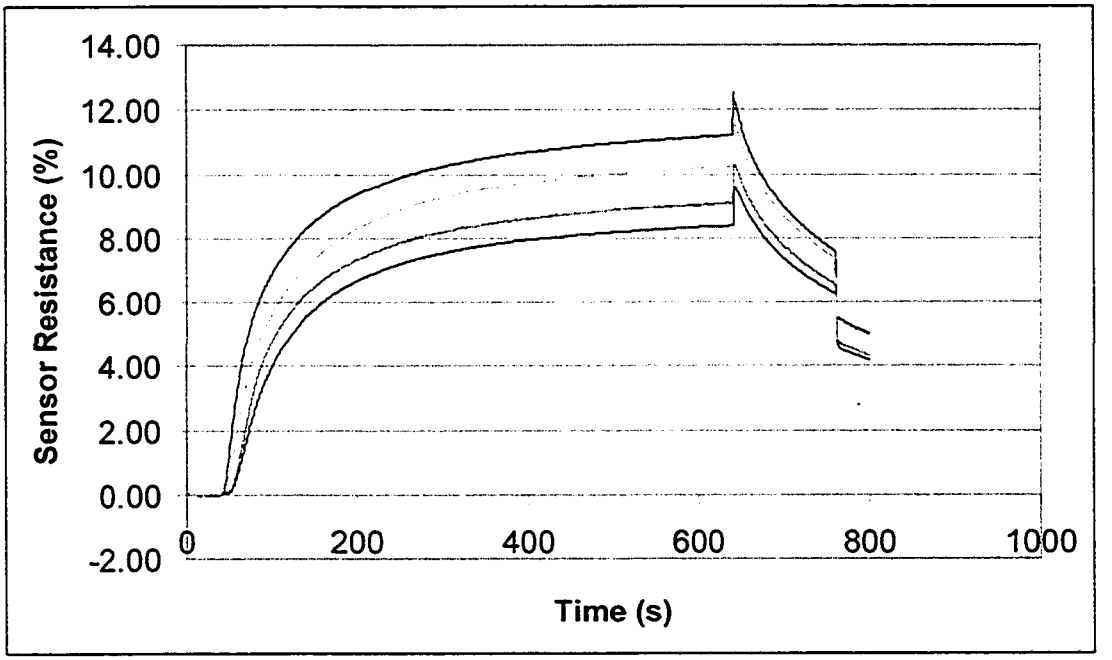


Figure 8: Response of Typical Electronic Nose Sensors to an Odour

At the end of the sampling period another wash cycle is begun, appearing as a peak on the chart above after 640 seconds.

The sample period for the electronic nose was chosen to be 600 seconds. From the literature review it was felt that a longer period of sampling would provide a better data set for this calibration exercise. Initial sampling in June of 2003 found that the change in resistance of the sensors continued to increase beyond the initially chosen period of 120 seconds. The sampling period was increased to 300 s, then to 600 s when it was seen that the resistance continued to increase. It was seen that the meter response in a few cases was continuing to increase at 600 s of sampling. However, the rate of increase by that time was slow, and it was felt that approximately 90% of the total increase may have been reached by that time. Some researchers (Qu, 2002) have used periods as short as 120 seconds and achieved satisfactory relationships with olfactometry data. The 600 s sampling period chosen was a compromise between getting the absolute value of the change and an acknowledgement that in field samples would probably not provide a steady air concentration for such a period.

The AromaScan™'s sensors are known to have different sensitivities to different compounds. From the manufacturer's information, sensor 17 is known to be very sensitive to long chained esters, sensor 18 is known to be strongly sensitive to aromatics, long-chained alcohols and carboxylic acids. Various other sensors exhibit other sensitivities. If an odour source has been characterised so that it is known that these components may be significant, future use of the electronic nose could specify that the input of these sensors is not agglomerated with other sensors' responses if data pre-processing is conducted.

The AromaScan™ contains software for Artificial Neural Networks. However, this is an example of unsupervised networks, which are most useful for categorising data. The AromaScan™'s internal library can be built up so that the instrument can distinguish among different odour sources, such as manures, foods and perfumes. Other data, such as odour concentrations and the concentrations of gases like hydrogen sulphide, cannot be added to the network. In the current situation, supervised artificial neural networks will be used to predict odour concentration as currently measured by olfactometry, using gas meter and electronic nose data as inputs.

4.4 Other Instruments

The hydrogen sulphide (H_2S) was measured using a Toxi Ultra® Single Gas Detector (Biosystems Inc., Middletown, Connecticut, USA). The instrument measures H_2S in concentrations from 0 ppm to 10 ppm, and records values in its internal data logger every 10 seconds. Alarms on the instrument were disabled.

Ammonia (NH_3) was measured using a Dräger PAC III® Single Gas Ammonia Meter (Draeger Safety Inc., Mississauga, Ontario, Canada). The instrument was set to alarm when ammonia concentrations are greater than 150 ppm. It has a range of 0 to 200 ppm, and indicates when the concentration is greater than 200 ppm by showing three plus signs (+ + +).

The data results from these instruments were recorded manually as the maximum reading obtained during a 120 s sampling period, where the value displayed did not change for at least 20 seconds.

The electronic nose was connected to the meters as illustrated in Figure 7 above. For hydrogen sulphide, the readings obtained by the Toxi Ultra® detector were observed for the first 180 s of the sampling period during which the electronic nose measurements were also being taken.

For each sample, the AromaScan™ was run a second time, with the ammonia measuring Dräger® unit replacing the Toxi Ultra®. A 120 s sampling cycle was run on the AromaScan. The ammonia meter's alarm was not disabled, and would sound at 150 ppm. Sampling was halted if the ammonia reading reached 200 ppm during that time period, as this is the meter's maximum. At a reading of 200 ppm, the meter would show three plus signs rather than a value (+ + +). In such cases, the ammonia concentration was recorded as 250 ppm, as it is known to be greater than the maximum 200 ppm.

The electronic nose readings collected during the ammonia measurement period were discarded – the AromaScan™ was used merely to obtain consistent air-flow through the gas meter.

4.5 Data Set

The samples used for this analysis are the swine odour samples that were analysed by the University of Alberta's olfactometry laboratory in the period June 2003 to July 2004. The laboratory analyses samples from municipal solid waste, wastewater treatment plants, and animal rearing operations. Swine odours are the bulk of the samples analysed by the laboratory. As each odour type gives a characteristic profile, it was felt best that only one type of odour should be used for this experiment – different types of odour are easily identified by electronic noses, but it is difficult to compare them.

The swine odour samples came from two different farms in Alberta, one farm in Saskatchewan and one farm in Quebec. Air samples were taken from the headspace of barrels in which manure was stored, manure storages, swine housing exhausts, and within the housing. Housing unit samples were collected from farrowing sows, weiner piglets, growers, finishers, and the nursery. This provided a wide range of swine odour sources.

As olfactometry was conducted first, and the leftover material used for electronic nose analysis, there is a slight bias in the data set towards the stronger samples. If a sample could be identified by the panellists with a great deal of dilution, only a few runs would be required to determine the detection threshold and hedonic tone, and very little of the sample would be used. With samples that had a higher detection threshold, too much of the sample may be consumed to leave an adequate sample for use in the electronic nose. When the sample bag appeared small (less than 2L remaining), the sample was not put through the electronic nose.

Initial data collection did not include ammonia and hydrogen sulphide data. Thus, the first 3 months of data are only useable for analyses that do not include these gas measurements.

4.6 Hypotheses and Statistical Analysis

The hypotheses to be tested are listed in Section 3.0 Objectives. In order to determine the value of the data collected, the hypotheses are tested in a systematic fashion.

The hypotheses to be tested are restated below:

1. Odour concentration can be predicted using ammonia data only.
2. Odour concentration can be predicted using hydrogen sulphide data only.
3. Odour concentration can be predicted from hydrogen sulphide and ammonia data.
4. Odour concentration can be predicted from electronic nose data.

5. Odour concentration can be predicted from electronic nose data with ammonia and hydrogen sulphide data
6. Odour concentration can not be predicted using electronic nose, ammonia and/or hydrogen sulphide data.

Each of the data sets represented by hypotheses was analysed as presented in Figure 9.

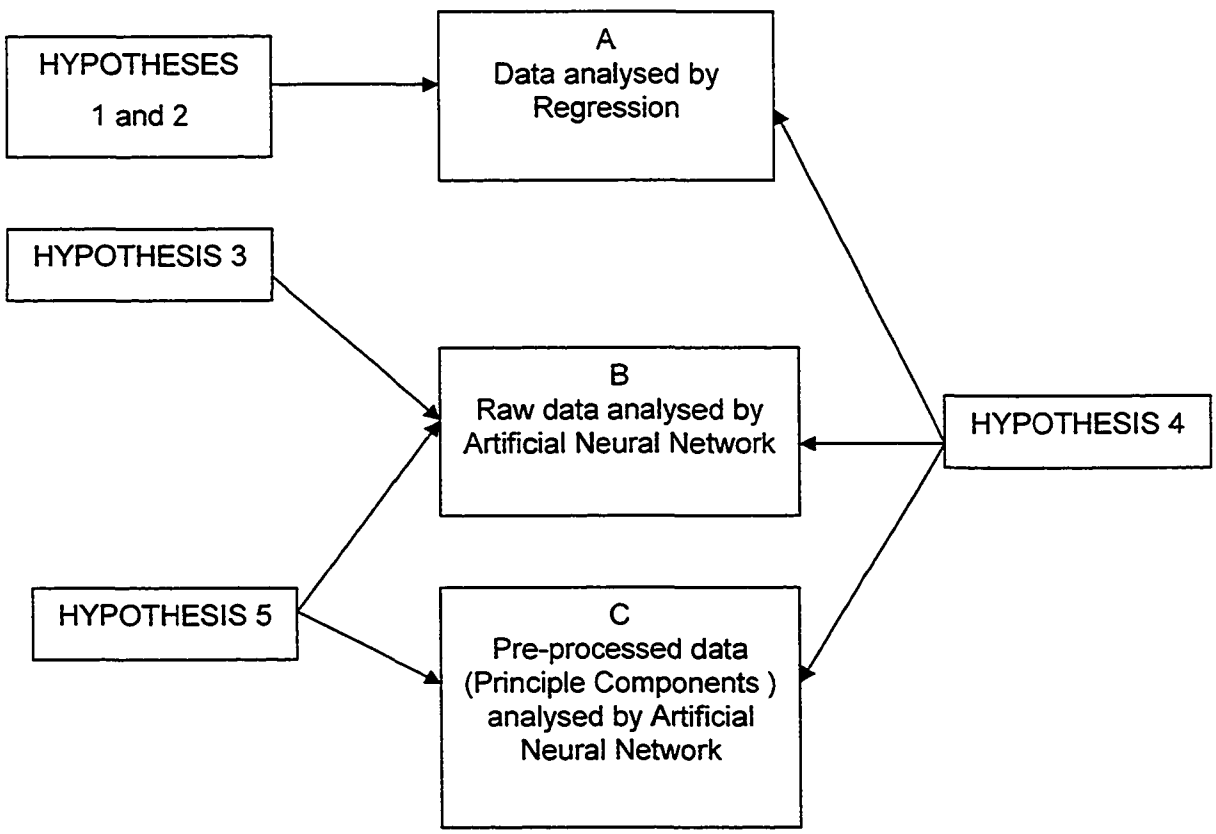


Figure 9: Analysis Methods for the Different Input Data

Data analysis methods A, B and C are the three methods of processing the data used to determine the relationships.

- Method A is linear regression, which can be determined by charting the data on Microsoft Excel and finding the equation and multiple coefficient of regression (R^2) value this way.
- Method B is to enter the raw data into Artificial Neural Network software. The value of R^2 is calculated, and the output of the Network (predictions) can be compared to the actual values of the odour concentrations measured.
- Method C is to pre-process the raw data by Principal Component Analysis (PCA), and then process as for Method B.

Hypotheses 1 and 2, using only the gas meter data, are tested using linear regression only. Hypothesis 3 uses the data of 2 gas meters. An Artificial Neural Network is used for the raw data here, Analysis method B. With only 2 inputs, no pre-processing of the data is needed. The small number of different inputs and the large dataset would help give the user confidence that a valid relationship can be determined.

For Method C, the data from the electronic nose is pre-processed for input into an ANN. This is to reduce the number of inputs into the network. This option was considered because of the size of the dataset (less than 100 cases) and the large number of inputs provided by the electronic nose (32). For future research, attempts could be made to make use of only the responses of specific sensors, identified to provide the most information, or known (by the AromaScan™'s manufacturer) to have affinities to specific components of the odour source.

When the electronic nose data are analysed using linear regression (Method A), some pre-processing is also conducted. This is done systematically as follows:

a) Each sensor's response is plotted against the odour concentration;
b) The average response of all the sensors is plotted against the odour concentration; and
c) Principal Components 1, 2, 3 and 4 are plotted against the odour concentration.

The use of this stepped approach is an attempt to determine the minimum amount of data required to predict odour concentrations, and the relative value of increased data collection and more complicated data analysis methods.

For Hypothesis 5 which uses electronic nose data and the gas meter data, the different combinations of data input into ANN are as follows:

a) Raw sensor and gas meter data are entered into ANN;
b) 5 Principal Components are determined using the data set from a) and the 5 Principal Components form the ANN input data; and
c) the first 3 Principal Components from electronic nose data and the raw data from the single gas meters form 5 inputs into the ANN.

Each method of data analysis listed above provides a prediction of the odour concentration based on the inputs. Linear regression is an attempt to create a straight-line model relating input data to odour concentration. Linear Regression using Microsoft Excel to find the equation of the line and predict the R^2 value was conducted for Method A. Principal Component Analysis was conducted using SAS for Method B. ANN using NeuroShell™ was used for methods B and C. ANN also produces a model of the output and a value of R^2.

For multiple regression determined using Microsoft Excel, the following applies:

$$R^2 = SS_{Regression} / SS_{Total}$$

Where R^2 is the coefficient of multiple determination, $SS_{Regression}$ is the Sum of the squared residuals from the model and SS_{Total} is the sum of the squared residuals from the data set's mean. R^2 is the proportion of the variance that is explained by the model. When the model is perfect, R^2 is one.

When ANN is used to determine the relationships, the value of R^2 is given by the following equation:

$$R^2 = 1 - (SSE / SS_{YY})$$

Where

$SSE = \sum (y - \hat{y})^2$

$SS_{YY} = \sum (y - \ddot{y})^2$

And

y is the actual value of y;

$\hat{y}$ is the predicted value of y; and

$\ddot{y}$ is the mean of the values of y.

NeuroShell 2™'s help file advocates that this is the best value for determining the fit of the model for supervised networks. As with linear regression, a value of R^2 close to 1 indicates a good model fit. In this calculation of the value of R^2, negative values can be obtained. These indicate a very poor fit of the model, and are shown as "error" in the results sections of this work. The dataset and model with the value of R^2 closest to 1 are selected as the best for predicting odour concentrations.

In using ANN, the model can be refined further. After determining the best data set from initial testing, the best network design can be determined through further refinement, by systematically testing the different network types, transfer functions, and number of hidden layer neurons.

4.7 Artificial Neural Networks Using NeuroShell 2™

The software used for Artificial Neural Networks is NeuroShell 2™ (NeuroShell™), created by Ward Systems Group Inc. NeuroShell™ permits the user to apply supervised or unsupervised learning models, choose the network architecture, the number of neurons in the hidden layers, their activation functions, and the output activation type.

Unsupervised learning is used for outputs that are categories. In this experiment, the desired output was a numeric value, so supervised networks were used. The default network type for the data was a Ward 2 network, containing 3 slabs in the hidden layer, each containing 4 neurons. The activation functions of the slabs were left at their defaults: Gaussian, Gaussian Complement and Tangent-hyperbolic functions.

The three datasets to be tested using ANN were made into different spreadsheet files for entry into NeuroShell™. Each file was entered into the NeuroShell™ Batch Processor. The number of input slabs was determined by the dataset. If the dataset to be used contained only 2 inputs (example, hydrogen sulphide and ammonia measurements), there were 2 neurons in the input slab. When the raw data from all measurements were used, there were 35 neurons in the input slab. NeuroShell™'s test set extraction module was used to set up the training, testing and production files, which split the datasets in the ratio 3:1:1. The software was also used to create the maximum/minimum files, and the data scaled so that data from outside the training range can be scaled into the model and will not be set to one of the extremes.

The network was set so that the training dataset was checked against the testing dataset after every 200 events (the calibration interval was set at 200, which worked out to approximately every 2 to 3 epochs, depending on the input dataset), and this used to update the weights applied to the training. At the end of the 100 epoch, or full runs of the entire training dataset, the network would stop training, and the model it created was applied to the production set. The value of R^2 for the production set was used to determine the best input dataset.

ANNs can be refined to determine the optimal architecture, number of hidden layer neurons, their activation functions, and the optimal number of training epochs. This first round of ANN was used to determine the optimal dataset. Section 7.0, ANN Refinement describes the further refinements conducted to create a more optimal network.

5.0 DATA COLLECTION

Over one hundred samples were collected over period of approximately 1 year. For the first 3 months, ammonia and hydrogen sulphide data were not collected. The data collected from these first few months are still used in the analyses that do not use the gas measurement data (hypothesis 4). Additionally, some scheduled sample measurement was lost due to operating problems with the electronic nose – a blown fuse in December, and difficulty in scheduling the gas analysis in January. The raw sample data are presented in Appendix A.

Outlier analysis was conducted on the dataset to determine if any values should be discarded. This was done for hydrogen sulphide data and olfactometry measurements. The mean and standard deviation of these values was determined for the entire dataset. Values that were more than twice the standard deviation away from the mean were considered outliers and the data were discarded.

Odour concentrations for the experiment ranged from 96 OU / m^3 to 11313 OU/ m^3. This largest value is more than twice the next nearest value (5040 OU/m^3). Outlier analysis identified it to be an outlier, and so it was discarded from further data analysis.

For samples collected after the first three months of the experiment, the complete data set consists of 36 items – olfactometry results, 2 gas measurements (NH_3 and H_2S) and 33 sensors after discarding the data from 2 sensors. The two discarded measures (temperature and base temperature) were found to not vary significantly among the samples. This approach was also used by Qu (2002). For samples collected before October of 2003, the data set contains only electronic nose data. Odour panels also report hedonic tone for each sample. Hedonic tone was reported as verbal descriptors or as a number from -4 to +4 during different parts of the experiment. Hedonic tone data were not retained for this current data analysis, although in future work it could be used. The hedonic tone values noted for manure samples when the –4 to +4 scale was used were all negative values. The data collection results are summarised in Table 2.

Table 2: Data Collection Results Summary

Variable	Odour Concentration	Ammonia concentration	Hydrogen Sulphide Concentration	Electronic nose change in resistance
Number of Measurements	119	95	95	119 for 35 sensors
Minimum	96	0	0.2	-5.5
Maximum	11313	>200*	8.3	56.8
Mean	1563	69	0.9	Not applicable
Number discarded	1	none	2	none
New maximum	5040	Not applicable	3.7	Not applicable

* ammonia concentrations that appeared to be greater than 200 ppm were assumed to be 250 ppm for further calculations.

Sixty of the samples were from manure storage barrels and 2 from earthen manure storages. The remainder of the samples were collected from housing units containing swine of different developmental.

5.1 Sensor and Meter Response

Visual analysis of the data as they were collected showed that the samples did differ from each other. Ammonia concentrations ranged from undetectable to over 200 ppm (the upper limit of the instrument). Samples that had ammonia readings that were higher than 200 ppm were recorded as having concentrations of 250 ppm to distinguish them from those that were close to 200 ppm. As there are several values of ammonia concentration that are listed at 250 ppm, it was decided that removing these would be un-representative of the data-set. Removing these high values would have reduced the dataset by 26 data points. Outlier analysis was conducted by determining the distance of each data point from the mean of all the data. Data

that were beyond 2 standard deviations of the mean were determined to be outliers. For ammonia measurements, no outliers were detected.

Hydrogen sulphide concentrations ranged from 0.2 to 8.2 ppm (the instrument had an upper limit of 10.0 ppm). This upper value, and the second highest concentration of hydrogen sulphide (6.0 ppm) were both identified to be outliers (beyond 2 standard deviations away from the mean of the data), and were removed from further data analysis. Once these two values were removed, the maximum concentration of hydrogen sulphide used was 3.7 ppm.

The AromaScan gives a continuous display of the sensor response. In this experiment, sample detection commenced after 40 seconds (20 s reference period and 20 s wash). For the different samples, the magnitude of the sensor response could be seen to vary, as did the time it took for the sensor responses to stabilise at their maximum. No electronic nose data were discarded prior to data analysis.

Removal of all outliers reduced the dataset so that for analyses requiring ammonia and hydrogen sulphide data there were 94 samples. For analyses not using the gas meter data, there were 119 samples.

5.2 Principal Component Analysis

Principal Component Analysis (PCA) is used to reduce the number of variables used to a smaller number for ease of further analysis and manipulation. PCA was conducted on the different datasets used in the different hypotheses. The tables of eigenvalues and the principal components are in Appendix B.

The first step in conducting Principal Component Analysis to determine the eigenvalues is to analyse the data and determine correlation coefficients. It was found that the electronic nose sensors were highly correlated with eachother ($r>0.8$). When ammonia and hydrogen sulphide measurements were added to the dataset, it was seen that some sensors were positively correlated with ammonia while most were negatively correlated with it. Sensors 15, 16,21 and 32 were most strongly

correlated with ammonia, but even this correlations were poor ($r<0.4$). All sensors were positively and weakly correlated with hydrogen sulphide ($r\approx0.1$).

It was found that when PCA was conducted on all the electronic nose data, the first eigenvalue would account for 94% of the variation, and that this eigenvalue was almost an average of the responses of all the different sensors (except relative humidity). This indicates that there were no sensors that were ineffective for this data analysis, and, conversely, that a few sensors could not be isolated and used for this data analysis (with data from the others discarded). The second eigenvalue, accounting for 5% of the sample variance, was positively related to the response of some sensors, and negatively to that of others. The third eigenvalue accounted for 1% of the variance, and was largely related to the sample humidity.

When PCA was conducted using gas meters as well as electronic nose sensor data, it was found that 88% of the variance could be explained by the first eigenvalue, which again appeared to be the average sensor response. The second eigenvalue accounted for 7% of the variance, and appeared to be largely related to ammonia measurements, and the sensors which were somewhat correlated with ammonia. The third eigenvalue was related to hydrogen sulphide concentrations, and accounted for 3% of the sample variance. Eigenvalue 4 accounted for 1% of the sample variance, and was related to relative humidity. Only eigenvalues accounting for 99% of the sample variance were used in further data analysis.

6.0 RESULTS AND DISCUSSION

Data analysis in this experiment was systematically conducted to find the simplest relationships among the data collected (using the hydrogen sulphide and ammonia meters and the electronic nose) and the olfactometry results.

The data were analysed according to the 5 tested hypotheses presented in section 4.6 Hypotheses and Statistical Analysis. The first hypotheses to be tested are hypotheses 1, 2 and 3, using gas measurement data to attempt to predict olfactometry results / odour concentration by linear regression.

The next hypotheses to be tested are hypotheses 3, 4 and 5 using regression. When the electronic nose data are used in regression, there was some pre-processing of the data, which is also described in Section 4.6.

When ANN is used to process the data (Methods B and C), the data are sorted into three sets for training, production and testing. The ratios of the three sets are chosen to be 3:1:1 (most of the data are used for training). NeuroShell's Test Set Extraction module was used to sort the data into the different groups, by assigning 20% of the data to each of the Production and Testing sets.

6.1 Hypothesis 1

When the samples were connected to the Dräger meter for ammonia measurement, it was clear that there were large variations among the samples. Some samples caused the alarm on the meter to sound within seconds, as they had ammonia concentrations in excess of 150 ppm. Other samples had ammonia readings of zero. It was hoped that simple linear regression would indicate clear relationships among the data.

Hypothesis 1 is restated as follows:

1. Odour concentration can be predicted from ammonia data.

This was tested by using simple data plots and linear regression. The odour concentrations were plotted against the Dräger meter readings and the coefficient of determination (R^2) value found.

When the ammonia data are plotted against the odour concentrations, no relationship could be determined, and the value of R^2 was found to be 0.04. This is illustrated in Figure 10, which indicates that ammonia concentrations cannot be used to predict odour concentration.

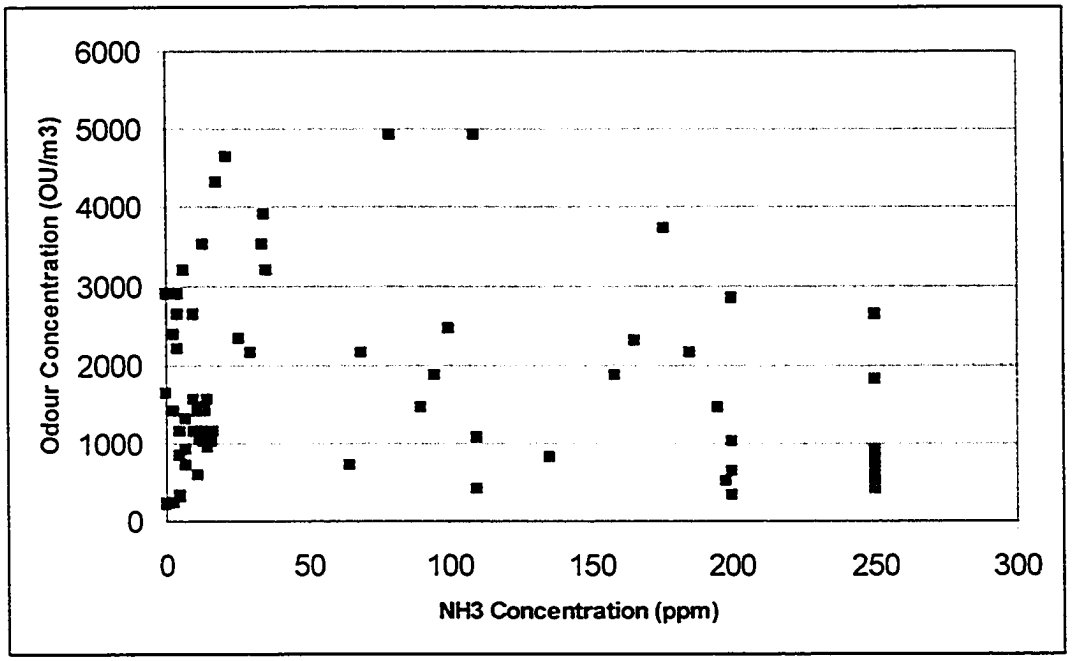


Figure 10: Odour Concentration versus Ammonia Concentrations

Powers *et al.* (2000) also found that ammonia concentrations were a poor predictor of manure odour concentrations. This may be in part because a high measured concentration of ammonia may indicate that the manure is slightly aged, so that the ammonia-containing compounds (amines, amides) may have degraded into ammonia and less reactive carbon-containing compounds. The relationship between

ammonia concentrations and manure odour concentrations is difficult to predict because along with the degradation of ammonia-containing compounds, will also be the degradation of other (non-ammonia-containing) odourous compounds in the sample. The human nose, however, will often detect compounds with ammonia as a functional group as smelling "ammonia-like" (Dravnieks, 1985; Schiffman *et al.*, 2001). Ammonia-containing compounds in manure samples include skatoles, amines, amides, pyridines. Hobbs *et al.* (2000) also stated that the detection of some compounds by olfactometry can be suppressed by the presence of other compounds. This may also in part explain the lack of a relationship between ammonia concentrations and odour concentrations.

6.2 Hypothesis 2

Hypothesis 2 is as restated below:

2. Odour concentration can be predicted from hydrogen sulphide data.

Hypothesis 2 uses hydrogen sulphide data only to predict the odour concentration. This yielded a positive relationship and a better R^2 value (0.51) than did use of ammonia as a measure, as shown in Figure 11.

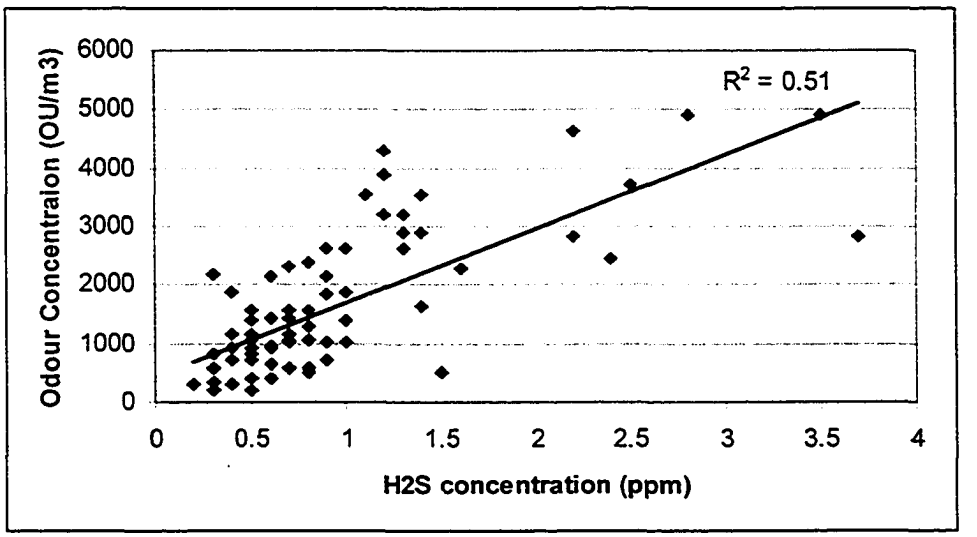


Figure 11: Odour Concentrations versus Hydrogen Sulphide Concentrations

It can be seen from the graph that the hydrogen sulphide concentrations are positively related to odour concentrations. The value of R^2, and the spread of the data about the trend line show that hydrogen sulphide concentrations are somewhat useful as a predictor of odour concentrations, but more data may be needed to better define the relationship. Hobbs *et al.* (2000) found that hydrogen sulphide is a compound whose detection is not suppressed by the presence of other odorous compounds.

6.3 Hypothesis 3

Neither of the gas meters when used alone provides a satisfactory measure of odour concentration, but hydrogen sulphide appears to provide a significantly better measure than does ammonia.

Hypothesis 3 attempts to make use of the data of both measurements, and is restated below.

3. Odour concentration can be predicted from hydrogen sulphide and ammonia data.

Attempts to use data from both gas meters to predict odour concentration are hampered by the fact that they are in different ranges. Ammonia concentrations go higher than 200 ppm while hydrogen sulphide values only up to 3.7 ppm are retained for this dataset.

The gas meter data were entered into NeuroShell2™'s ANN. A Ward 2 network is the default network chosen for this experiment. This network produced a prediction of odour concentrations as shown in Figure 12.

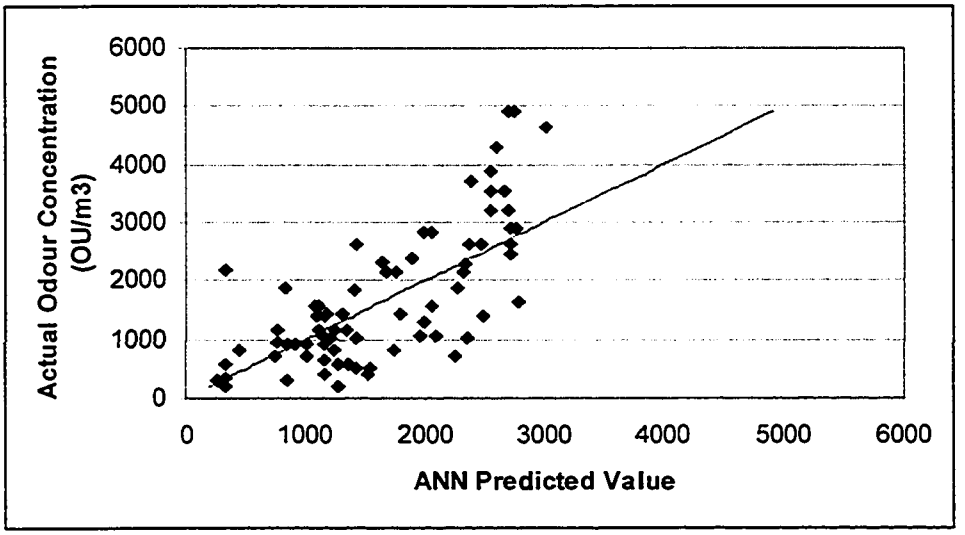


Figure 12: Odour Concentration Prediction Using Ammonia and Hydrogen Sulphide Gas Meters and ANN

The straight line on Figure 12 represents a perfect relationship between predicted and measured odour concentrations. The better the ANN predictions, the closer the values would be to the line. Figure 12 shows that when ANN is used to determine a relationship between measured ammonia and hydrogen sulphide concentrations and odour concentrations as determined by olfactometry, the predictive ability of the network is poor. The value of R^2 determined for this outcome is 0.58.

Visual examination of the output data also show that the predictive capability of the network was poor for the upper, middle and lower ranges of odour concentrations, with a tendency to over-predict odour concentrations towards the upper end of the range of data provided.

6.4 Hypothesis 4

Hypothesis 4 is restated below:

4. Odour concentration can be predicted from electronic nose data.

The response of the electronic nose to samples varied, with some samples producing high peaks that appeared to continue climbing even after 10 minutes of sampling, and others peaking within 2 minutes, or climbing very slowly.

In order to relate the odour concentration to the electronic nose data, several approaches were taken. They are restated below:

a) Each sensor's response is plotted against the odour concentration;
b) The average response of all the sensors is plotted against the odour concentration; and
c) Principal Component 1 is plotted against the odour concentration.

After these approaches are explored, the data are systematically tested using ANN to determine if this will produce a better predictor of odour concentration than would simple linear methods.

For using ANN, the data are tested as follows:

a) Raw sensor data are entered into the ANN; and
b) The data are analysed using PCA, and Principal Components 1, 2, and 3 are entered into the ANN (accounting for over 99% of the dataset variance).

6.4.1 Linear Regression

When the responses of the individual sensors were plotted against the odour concentration, the results were similar to that seen in Figure 13 – no discernible relationship. The value of R^2 for a trend line for this graph was 0.01.

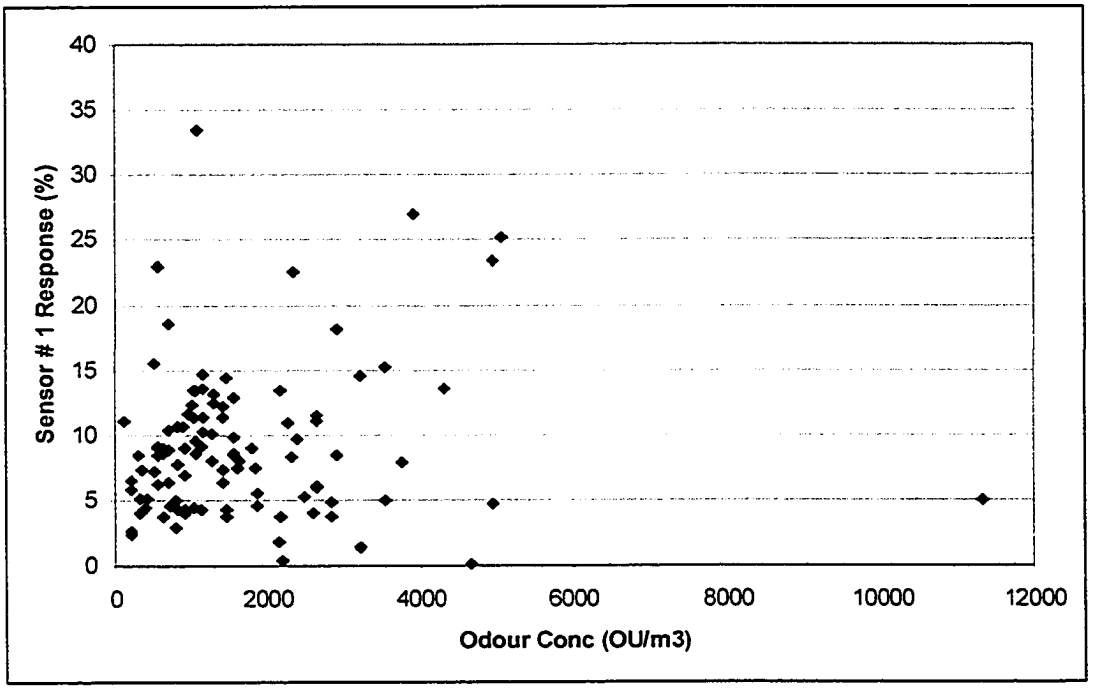


Figure 13: Electronic Nose Sensor #1 Response with Odour Concentrations

The second approach is to take the average sensor response and compare it to the odour concentrations. The average sensor response was also plotted against odour concentrations (Figure 14). The value of R^2 was found to be less than 0.01.

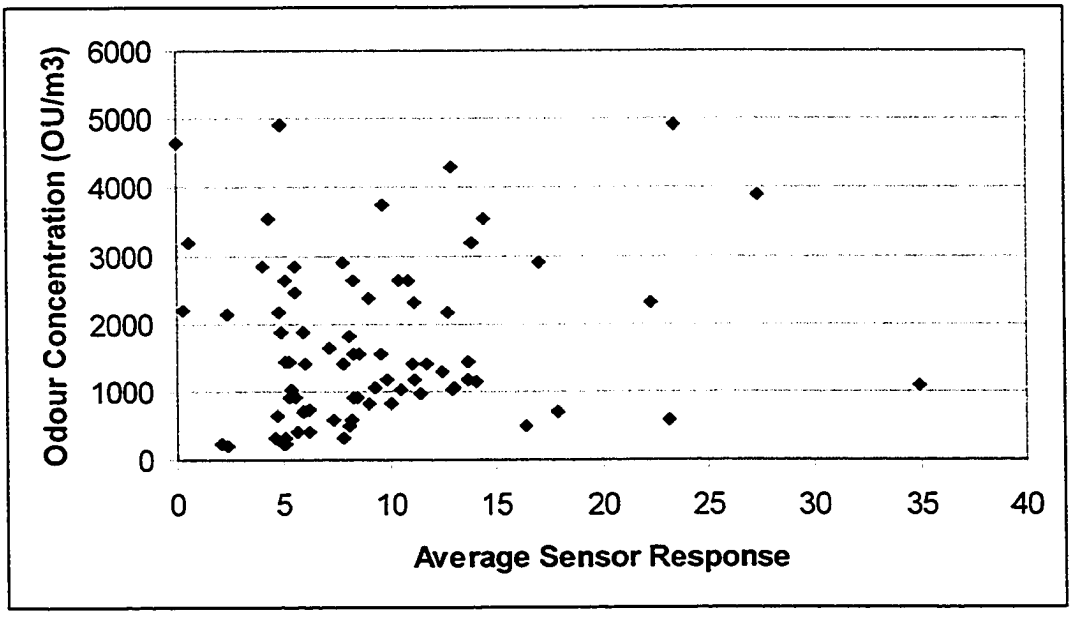


Figure 14: Odour Concentrations and Average of Electronic Nose Sensor Responses

Qu (2002) took the logarithm of the olfactometry data before plotting it against the electronic nose data. Taking the log of the olfactometry results in this resulted in an R^2 value of 0.01, which was not a significant improvement over the previous case. The results of this transformation are shown in Figure 15.

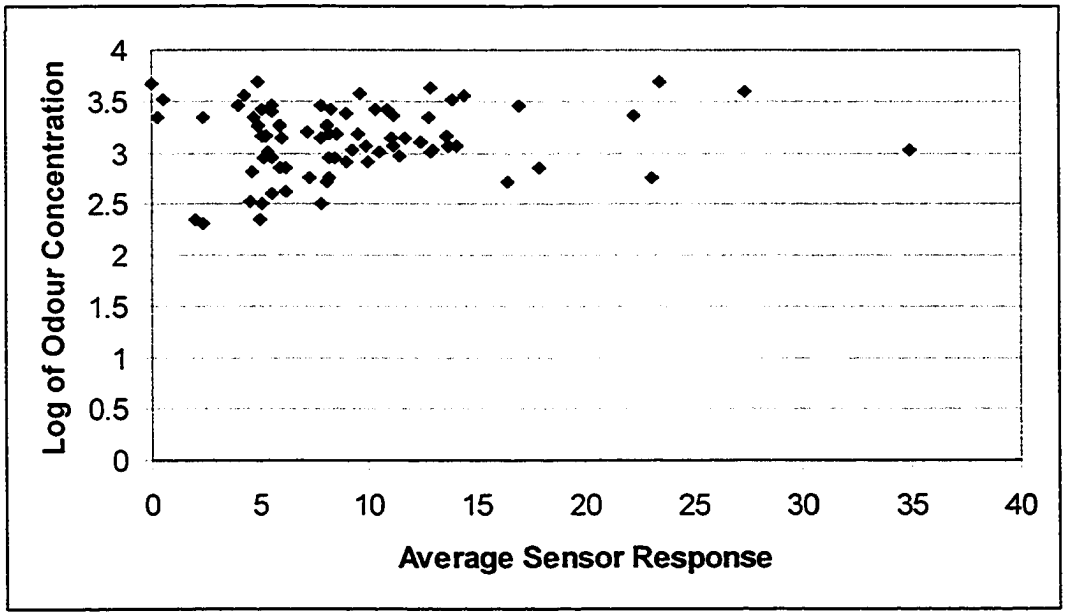


Figure 15: Log of Odour Concentrations and Average Sensor Response

The value of the data from sensor averages is not expected to be high as the sensors vary in their ranges of response. The data were normalised, by converting each sensor's response to a ratio of that sensor's response for the particular sample, and its response for all the samples. The resultant data are plotted in Figure 16, which indicates no linear relationship (the value of R^2 was 0.004).

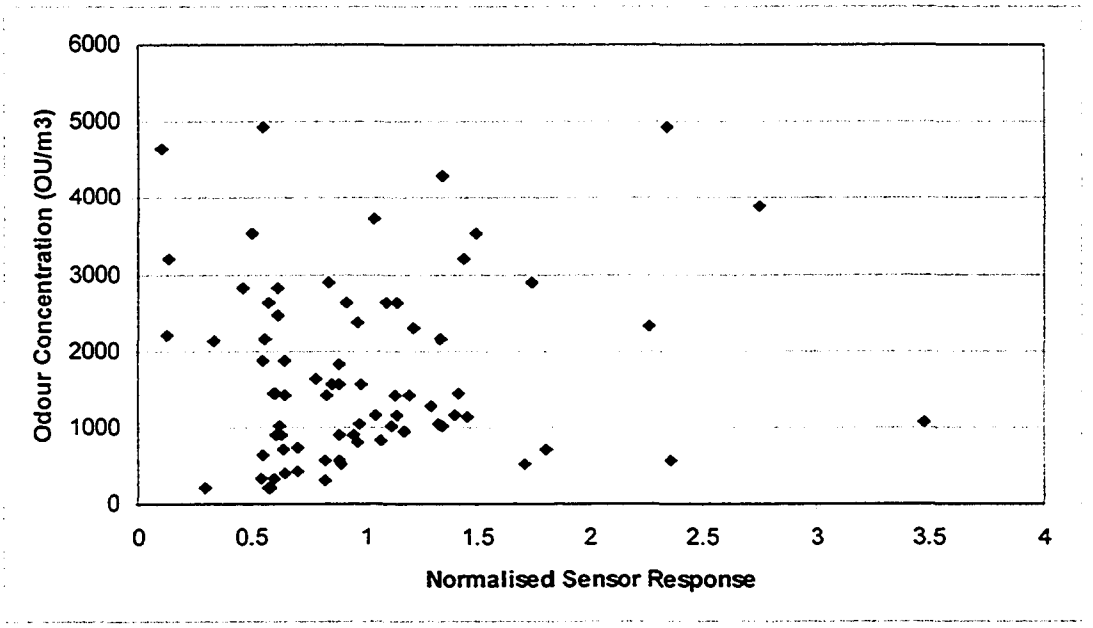


Figure 16: Odour Concentrations and Normalised Sensor Response

6.4.2 Principal Component Analysis

When electronic nose data are analysed by Principal Component Analysis (PCA), the first three eigenvalues account for more than 99% of the variation in the data. Table 3 shows the first 15 eigenvalues calculated using SAS – a software program for statistical analysis.

The AromaScan gathers 35 measures for each sample – the odour responses of 32 different polymer sensors, the relative humidity of the sample, the sample temperature and the sensor temperature. The last two measures are found to be fairly constant for the duration of each sampling period, and do not vary among samples. The relative humidity of the samples does vary, and is added to the output of the 32 sensors so that PCA makes use of 33 inputs.

Table 3 shows the eigenvalues used in determining the Principal Components for further analysis. Only the first three Principal Components are used in further analysis, accounting for 99.6% of the variation. The full tables of eigenvalues and the eigenvectors (used to calculate the value of each principle component) are in Appendix B.

Table 3: Eigenvalues of Correlation Matrix for Electronic Nose Data

	Eigenvalue	Difference	Proportion	Cumulative
1	29.94	28.33	0.94	0.936
2	1.60	1.29	0.05	0.986
3	0.31	0.24	0.01	0.996
4	0.08	0.06	0.00	0.998
5	0.02	0.00	0.00	0.999
6	0.02	0.01	0.00	0.999
7	0.01	0.01	0.00	1.000
8	5.57E-03	2.19E-03	2.00E-04	1.000

Each sensor's input into the Principal Components is determined by the eigenvectors, which are also calculated by SAS. The table showing the eigenvectors for each sensor (contributing to Principal Components 1 to 3) are in Appendix B. For each sensor, the value of the eigenvector is multiplied by the value of the resistance when the particular sample is connected to the electronic nose. For each sample, instead of 33 inputs from the electronic nose, the input into the ANN is 3 Principal Components, each consisting of the 33 values compressed according to the eigenvectors.

Principal Component 1 can be plotted against the odour concentration. Principal Component 1 appeared to be an average sensor response, with approximately equal inputs from each sensor. This accounts for 93% of the variation in the data, and so may be able to provide a simple measure of how the electronic nose data relate to the odour concentrations. From Figure 17, however, it can be seen that this is not quite a useful linear measure, yielding an R^2 value of 0.04. This indicates that variation among the sensors is not the best linear measure of odour concentration, although this may be a good measure for use in ANN. Summing the first 3 Principal Components produced a similarly poor relationship.

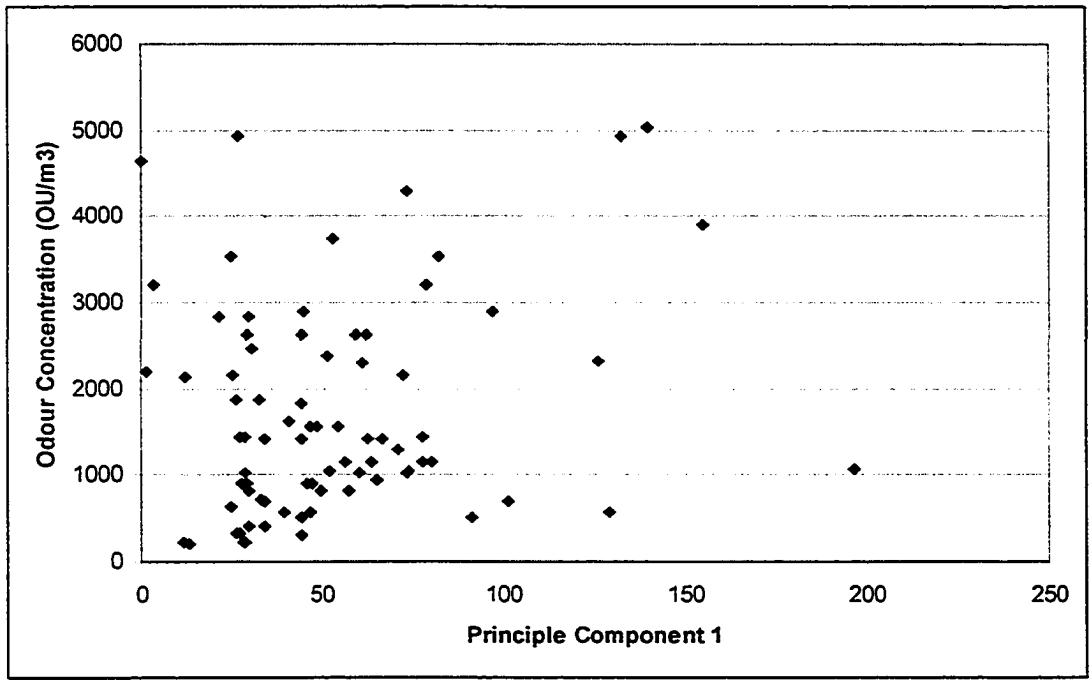


Figure 17: Odour Concentration and Principal Component #1 for Electronic Nose Data

6.4.3 Artificial Neural Networks

The electronic nose data were entered into NeuroShell using the Ward 2 network with 9 neurons in the hidden layer. The 9 neurons and their activations are:

- 3 tanh
- 3 Gaussian
- 3 Gaussian Complement

The network was run for 100 epochs (complete tests of the training dataset). The network prediction was then plotted against the actual data (Figure 18).

In Figure 18, the straight line represents a perfect relationship between predicted and measured odour concentrations. The scatter plot shows the predictions from the ANN. From Figure 18 it can be seen that the electronic nose produced a worse prediction than did the use of gas meter data in ANN. The network predictions all seemed to be in the mid-range of odour concentrations, not capturing either higher or lower values, and with a great deal of scatter about the mid-range. This measure did

not produce a good prediction of odour concentration. The value of R^2 for this network prediction was 0.45.

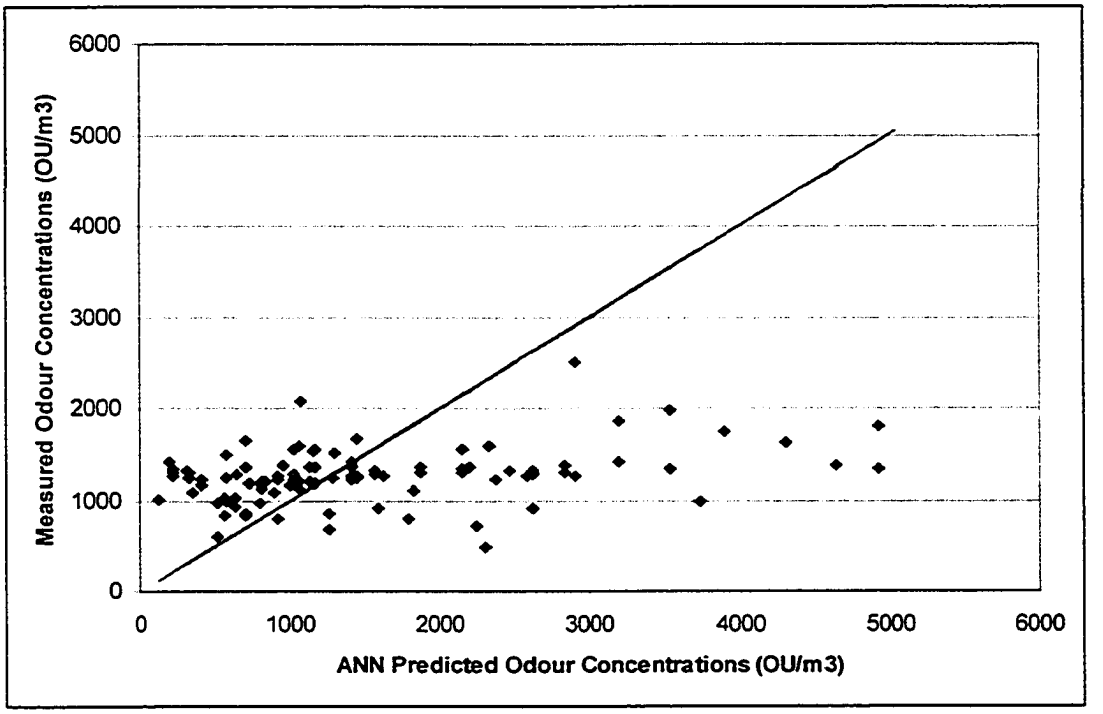


Figure 18: ANN Prediction of Odour Concentrations Using Electronic Nose Data

Principal Components were then used as input data for the ANN. The same network type was run. The results are shown in Figure 19, and did not improve significantly from the un-processed data entered into the ANN. The value of R^2 for this prediction is 0.46.

In Figure 19 the straight line again represents a perfect relationship between predicted and measured data. The scatter of data around that line shows the ANN's tendency to predict odour concentrations above or below the measured values.

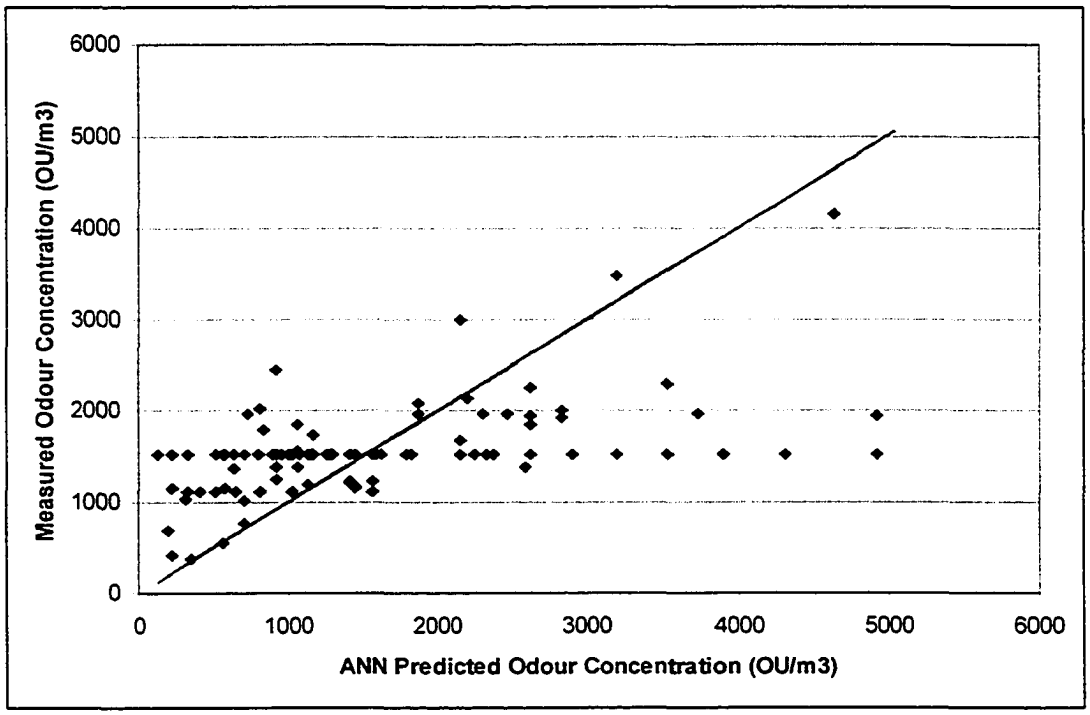


Figure 19: ANN Prediction of Odour Concentration Using Pre-Processed Electronic Nose Data

Principal Component Analysis did not significantly improve the performance of the network. Hanumantharaya *et al.* (1999) found that PCA was useful, but mostly for reducing the time to train the network, not for improving predictive ability. With this current data set, training time was not a significant factor. Qu *et al.* (2001), using the same electronic nose and input data type (swine manure odours) found that pre-processing data by PCA was essential in improving the performance of the ANN. This disparity may be due to the different software package used by Qu *et al.* (2001), (Adaptive Logic Network) and activation functions of the neurons in the network. Those researchers also used an un-trained olfactometry panel whose results were then normalised. This dataset may have contained more noise, which PCA helped to reduce.

6.5 Hypothesis 5

Hypothesis 5 is restated below:

5. Odour concentration can be predicted from electronic nose data with ammonia and hydrogen sulphide data

In order to test this hypothesis, ANN must be used. The dataset to be entered into ANN consists of 35 values – the two gas measurements and the 33 electronic nose sensor responses. The data analysis follows a similar pattern to testing of Hypothesis 4, except that no linear regression is used.

The raw data as received were processed by ANN, as was the dataset reduced to 5 Principal Components using PCA. A third dataset type was also created. This consisted of the ammonia and hydrogen sulphide data and the first 3 Principal Components from the electronic nose sensor responses as calculated for Hypothesis 4.

6.5.1 Principal Component Analysis

This data set contains 94 cases, each with 35 input variables. According to Goodner *et al.* (2001), with 35 input variables there should be a dataset containing at least 210 cases (or six times the number of input variables). Because the data set contains only 94 cases, it could be considered preferable to reduce the number of input variables, by a method such as PCA, before entering the information into the network.

PCA yielded the results in Table 4, which shows eigenvalues for the first 5 Scores as calculated using SAS. The full table of eigenvalues is found in Appendix C. The first 5 eigenvalues, accounting for 99.7% of the variation are used in the analyses for this dataset. The full set eigenvectors is in Appendix C.

Table 4: Eigenvalues of Correlation Matrix Using Electronic Nose Data and Ammonia and Hydrogen Sulphide Measures

	Eigenvalue	Difference	Proportion	Cumulative
1	30	28	0.88	0.88
2	2.31	1.35	0.07	0.95
3	0.95	0.58	0.03	0.98
4	0.37	0.20	0.01	0.99
5	0.18	0.11	0.01	1.00

6.5.2 Artificial Neural Networks

The method of using ANN is the same as for Hypothesis 4. A Ward 2 network with 9 neurons in the hidden layer was used to determine the general value of each data set in predicting the odour concentration. The activation functions used were Tanh, Gaussian and Gaussian Complement (three of each). The network was run for 100 epochs.

When the data set without pre-processing are entered into the ANN, the value of R^2 was calculated to be 0.45 when the network was applied to the production dataset. In Figure 20, the straight line represents perfect predictions of odour concentration by the ANN. The scatter of the data around the line show the ANN's predictive ability when applied to the dataset.

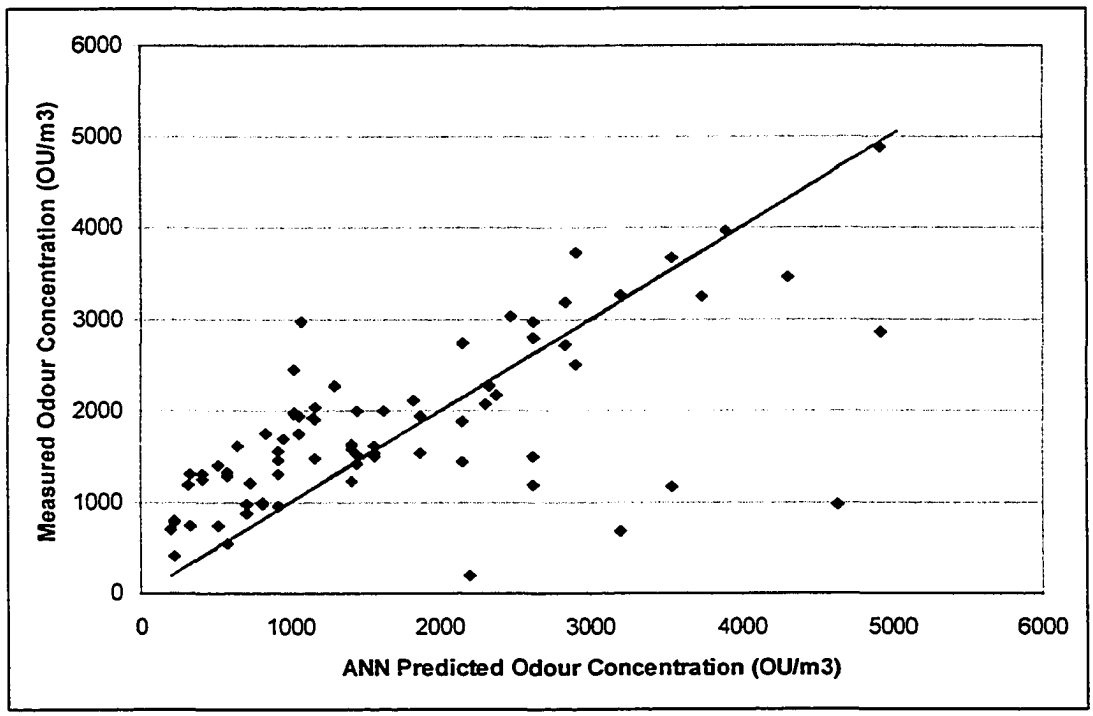


Figure 20: ANN Prediction of Odour Concentration Using Electronic Nose and Gas Meter Data

When PCA was done on the data set and Principal Components calculated based on the responses of the gas meters and the electronic nose, 5 Principal Components were used as input data to the ANN. Figure 21 indicates a poor prediction, which is confirmed by an R^2 value of 0.47. This indicates that pre-processing the data using PCA did not improve the predictive ability of the network significantly.

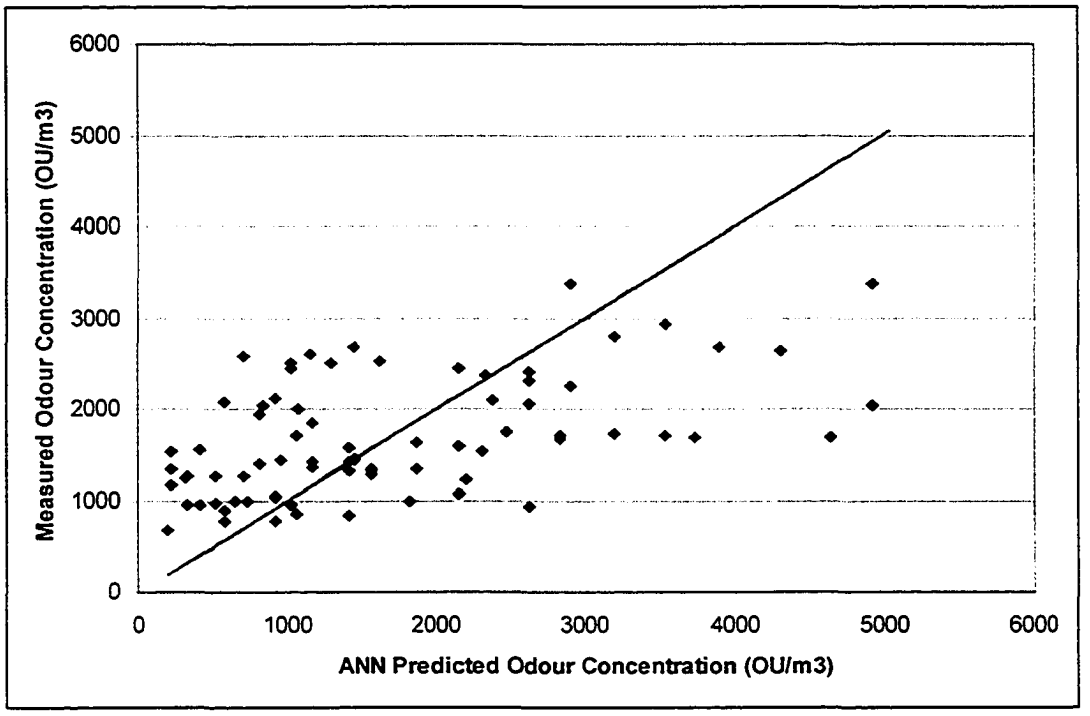


Figure 21: ANN Prediction of Odour Concentrations Using Pre-Processed Electronic Nose and Ammonia and Hydrogen Sulphide Measurements

The third method of entering the data for this set used the values from both gas meters and the PCA processed data from the electronic nose. The prediction is plotted against the actual values in Figure 22. The value of R^2 was calculated to be 0.75, which is a better value than calculated for previous networks using the same data.

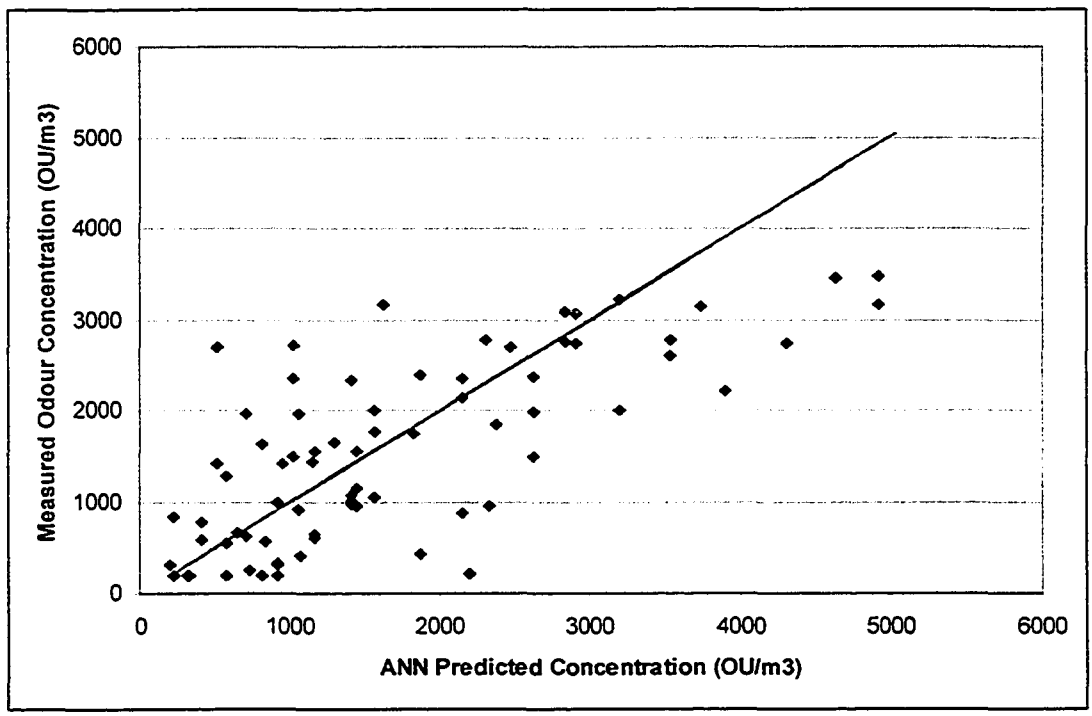


Figure 22: ANN Prediction of Odour Concentration Using Ammonia and Hydrogen Sulphide Measurements and Pre-Processed Electronic Nose Data

6.6 Summary of Results

For the different hypotheses and analyses, the values of R^2 for the predictions are as shown in Table 4. The values of R^2 range from 0.04 to 0.75 for the different methods of predicting odour concentrations.

Table 5 shows that data from the electronic nose and from the single gas meters are useful in predicting the odour concentrations of samples. Using measurements of ammonia and hydrogen sulphide alone provided better predictions of odour concentrations than did the use of the electronic nose alone. In combination, the three measures produced a network with a predictive ability of 0.75. The use of Principal Component Analysis to pre-process the data actually decreased the predictive ability of the networks used for the above datasets if ammonia and hydrogen sulphide measurements were included in the PCA. Using the ammonia and hydrogen sulphide measurements with PCA-processed electronic nose data produced the best prediction of odour concentrations.

Table 5: Summary of Results

Hypothesis	Input Data	Pre-Processing	Method	R^2
1	NH_3	None	Linear Regression	0.04
2	H_2S	None	Linear Regression	0.51
3	NH_3 and H_2S	None	ANN	0.58
4	Electronic nose	None	Linear Regression	0.01
4	Electronic Nose	None	ANN	0.45
4	Electronic nose	PCA	ANN	0.46
5	Electronic Nose, H_2S and NH_3	None	ANN	0.67
5	Electronic Nose, H_2S and NH_3	PCA of all input data	ANN	0.47
5	Electronic Nose, H_2S and NH_3	PCA of electronic nose data, no pre-processing of H_2S and NH_3 inputs	ANN	0.75

Once the best dataset has been determined, the network may be refined in order to determine the optimal network architecture, activation and output functions, the number of neurons in the hidden layers, and the number of training epochs (El-Din *et al.*, 2004).

In this experiment, over one third of the ammonia values were assumed – the ammonia meter could only read values up to 200 ppm, but some samples were clearly above this level, and were set at 250 ppm in further analyses. Data analysis later showed that ammonia measurements were valuable in predicting odour

concentrations when combined with hydrogen sulphide measurements, or with hydrogen sulphide measurements and electronic nose data. It is possible that with more accurate measurements of ammonia concentrations even better relationships could have been derived. Keeping the ammonia concentrations at the instrument's maximum would have reduced the sensitivity possible for this dataset.

The samples collected for this experiment were from a variety of sources, encompassing different ages of swine in their housing, and stored manure (in barrels and in earthen manure storages). Swine housing is associated with ammonia odours (Harper *et al.*, 2004) while lagoons are more associated with hydrogen sulphide and sulphide odours

Electronic nose measurements were analysed using PCA for the best prediction of odour concentrations. PCA of the sensor data yielded eigenvectors that showed that the first Principal Component was essentially an average of the responses of all sensors. Ammonia and hydrogen sulphide measurements were the second and third most important input variables in PCA of data that contained those measurements. The relative humidity of the samples was another significant contributor to the variance among measurements. This indicates that the entire range of sensors in the electronic nose responded to the different samples to which it was exposed in this experiment.

The weakness of PCA as a method of reducing the dataset can be seen in the fact that when ammonia and hydrogen sulphide measurements are included in the PCA, the predictive value of the dataset decreases. PCA for the dataset found that the most important inputs constituted an average of the electronic nose sensor responses, with ammonia and hydrogen sulphide accounting for less than 20% of the variance. However, this input dataset gave a prediction with an R^2 value of only 0.47, which is less than that achievable using ammonia and hydrogen sulphide data alone (R^2=0.67). PCA was useful in reducing data that were already highly correlated with each other, such as the readings of the 32 different sensors of the electronic nose.

7.0 ANN REFINEMENT

Artificial Neural Network data analysis proceeds in several stages. The different data sets as described in Hypotheses and Statistical Analysis (Section 4.6) are entered into the network. The network is run with different architectures and different input and output types to determine which data set provides the best values of R^2. When the best architecture and activation functions have been found, the network is again run in order to optimise the number of hidden neurons and number of training epochs. In Section 6 it was determined that the optimal input data was a combination of ammonia and hydrogen sulphide measurements along with PCA pre-processed electronic nose data. Section 7 discusses the steps taken to optimise the network, and the results of these steps.

The maximum/minimum, training, testing and production files from network trials of Hypothesis 5 in Section 6 were used in the continued testing of the network to determine the optimal architecture, activation functions, number of training epochs, and number of neurons in the hidden layers. The network uses the training files to create a model, which is updated at user-specified intervals using the testing files. At the end, the model is applied to the production dataset, to which the network has not yet been exposed. The prediction (value of R^2) determined using the production dataset is a measure of the model's success.

When the best architecture was determined, the network was further optimised by determining the activation and output functions. This is done by first, systematically varying the output type and hidden-layer activation functions. Then, the number of hidden layer neurons and training epochs were determined by changing those in a systematic manner as well.

7.1 Network Architecture Choice

NeuroShell™ allows the three different supervised network architectures illustrated in Figure 23. A Ward 2 network was used in Section 6 to determine the optimal data set for predicting odour concentrations.

In Figure 23, each "box" represents a slab. The input slabs contain the number of input neurons. In the data set where there are 4 parameters in the model (4 Principal Components), the input slab has 4 neurons. In the data set where 35 inputs are used (33 electronic nose inputs and 2 single gas meters), there are 35 neurons in the input slab. In this experiment, a single output is required – the value of the Odour Concentration (OU/m^3). This is represented by a single neuron in the output layer. Each hidden layer slab contains a number of neurons that can be selected by the software, or determined by the user. The number and arrangement of the hidden layer slabs can be selected by the user, within the software's boundaries.

In a Ward network, data from different areas of the dataset can be processed by different hidden layer slabs, using different activation functions. The user can specify whether 2 or 3 hidden layer slabs are used. For Section 6, 3 hidden layer slabs are used, meaning that the high, low and medium values of the data set can be processed using different activation functions. In the standard feed-forward network, each slab is connected to the one immediately preceding it and the one immediately following it, and no other. NeuroShell™ allows 1, 2 or 3 slabs in the hidden layer of standard networks. The network's speed can be increased or decreased by changing the number of neurons in each hidden layer slab. In recurrent networks, the response of the network to a given data pattern is affected by the inputs to which it has been previously exposed. The user is allowed to specify whether the update in processing is determined by the output of the input layer, by the activity in the hidden layer, or by the output layer. At this stage of testing, for each architecture type, the default activation and output functions were retained and not altered by the user.

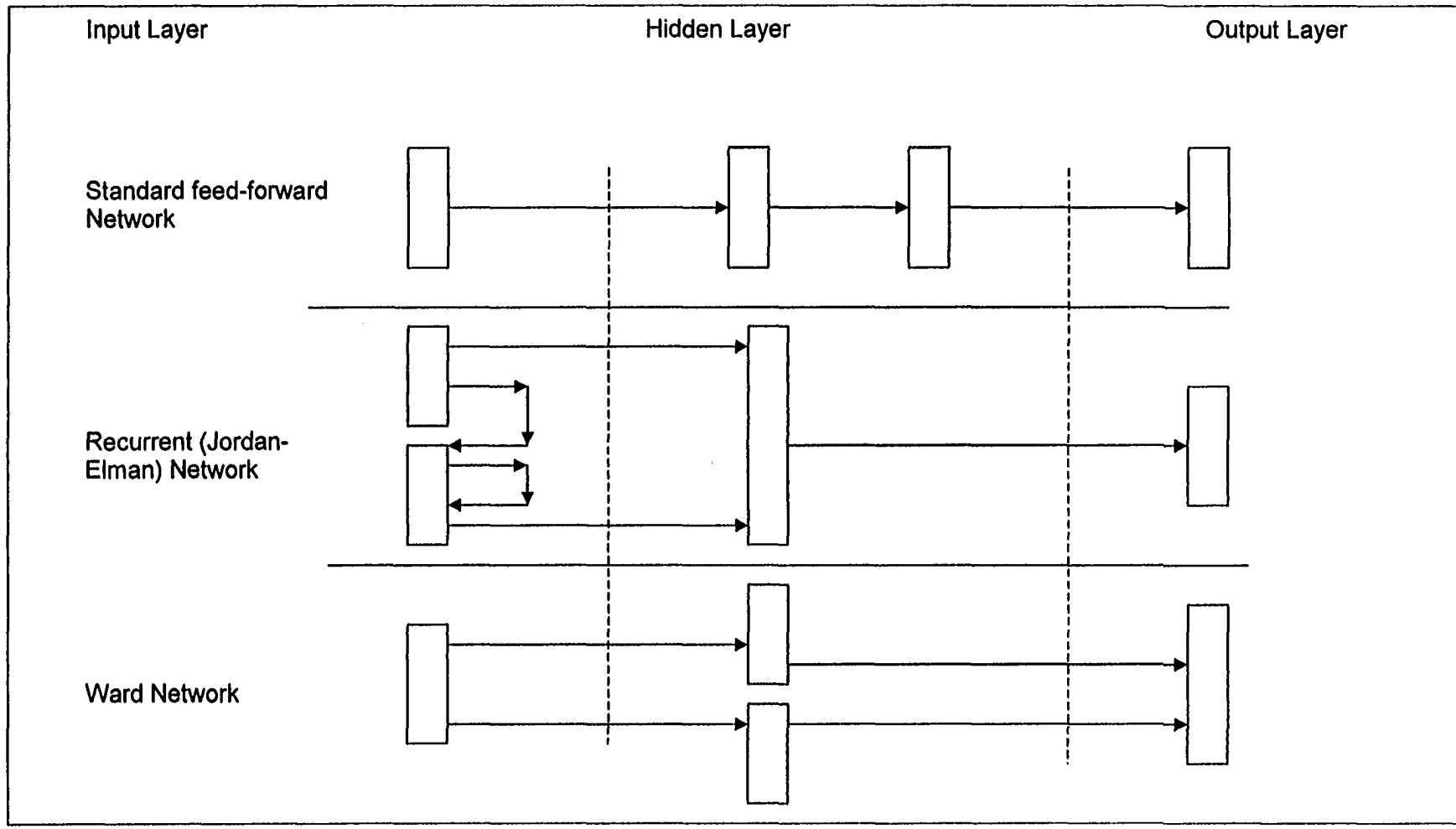


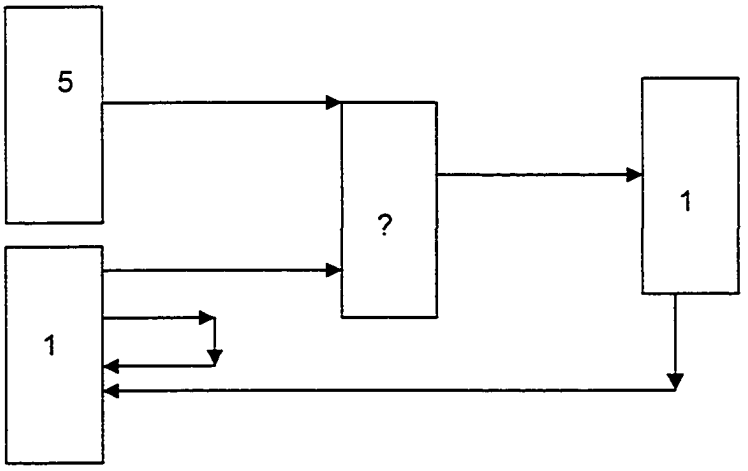
Figure 23: Different Types of Networks Available in NeuroShell 2™

The different architectures were tested with the user-selected number of 12 neurons in the hidden layer. Each network was run until 2000 events after the test set error minimum had been reached. The calibration interval was set to 200, and the data were saved on the best test set. The results are as shown in Table 6.

Table 6: Results for Different ANN Network Types

Network Type	R^2 Value
Feed-forward type 1	0.19
Feed-forward type 2	0.26
Feed-forward type 3	0.01
Recurrent type 1	0.60
Recurrent type 2	0.69
Recurrent type 3	0.74
Ward 1	0.19
Ward 2	0.30
Ward 3	0.32

From the results shown in Table 5, the best network was a Recurrent Network. The arrangement of the neurons is illustrated in Figure 24, which shows an output layer with dampened feedback. The input layer contains 5 neurons as there are 5 input items. The recurrent layer contains 1 neuron. There were 12 neurons in the hidden layer, as set by the user (in a single slab), although the number of hidden layer neurons was to be refined in a subsequent stage. The immediate stage of refinement, however, is to determine the optimal activation and output functions.



Numbers represent number of neurons in each slab

Figure 24: Chosen Artificial Neural Network Architecture

7.2 Activation and Output Function Choice

The architecture chosen for future analysis of the dataset was a Recurrent network as illustrated in Figure 24. For this network, the default input is scaled linearly, and the hidden layer and output neurons are scaled logistically. In order to optimise the network, it is required to determine which of the possible activation function was best for the dataset.

The possible activation functions in the hidden layer are Linear, Logistic, Gaussian, Gaussian Complement, Symmetric Logistic, Tan-Hyperbolic, Tan-Hyperbolic 150, and Sine. Each requires a specific input type, ranging from 0 to 1 (Logistic, Gaussian, Symmetric Logistic and Gaussian Complement functions) or from -1 to +1 (other possible functions). For each network run, the input was scaled according to the requirements of the hidden layer's activation function. The number of hidden layer neurons was kept at 12.

The training was kept at 100 epochs with a calibration interval of 200 events for determining the optimal activation functions. The Batch Processor was then set up to use the same maximum/minimum, training, testing and production files as used in previous sections with this dataset, with different hidden layer and output layer activation functions. The completed networks were then applied to the production files, which are not used for training, and the values of R^2 recorded. These values are shown in Table 7.

Table 7: R^2 Values Using Different Activation and Output Functions

Activation / Output	Logistic	Tanh	Gaussian	Sine	Tanh15	Symmetric Logistic	Gaussian Complement
Logistic	0.74	0.69	0.32	error	0.78	0.85	0.16
Linear	0.38	error	0.32	error	0.09	error	error
Tanh	0.45	error	0.31	error	0.28	0.56	0.07
Gaussian	0.81	0.59	0.81	error	error	0.27	error
Sine	0.43	error	0.26	error	error	error	0.03
Tanh15	0.47	error	0.48	error	0.60	error	0.11
Symmetric Logistic	0.18	error	error	error	error	0.44	error
Gaussian Complement	0.60	error	0.23	0.32	0.83	0.14	0.26

The best value of R^2 was obtained by using a Symmetric Logistic activation function with a Logistic output function. These activation functions will be used in the further refinement of the network.

7.3 Hidden Layer Neurons and Training Epochs.

The optimal activation function and output function were selected in Section 7.2. The next stage of network optimisation is to determine the number of hidden layer neurons and training epochs. Previous runs of the network had been set at 200 epochs with 12 hidden layer neurons. Twelve hidden layer neurons were selected

initially because in testing of all the different networks, this was a common multiple of 1, 2 and 3, the number of hidden layer slabs permitted by the different network architectures. Preliminary testing had found that 6 hidden layer neurons provided poor predictions for all network types, so 12 was chosen as the interim standard. As the selected architecture has only 1 slab in the hidden layer, the distribution of hidden layer neurons is not a concern, and any number of hidden layer neurons can be selected. The number of hidden layer neurons selected is shown in Table 8, along with the results of running the network with these numbers of hidden layer neurons for different numbers of training epochs.

Table 8: Value of R^2 Using Different Numbers of Hidden Layer Neurons and Training Epochs

Training Epochs / Hidden Layer Neurons	20	50	75	100	200	300
5	0.41	0.41	0.41	error	0.38	0.55
8	error	0.34	0.79	0.71	0.57	0.46
10	0.47	0.59	0.49	0.52	0.51	0.52
12	0.09	0.79	0.49	0.51	0.22	error
15	0.31	0.34	0.34	0.41	0.27	0.27
20	0.17	0.55	0.74	0.71	0.60	0.43
25	0.19	0.43	0.37	0.68	0.55	0.43

It was found that the best value of R^2 was obtained using 8 hidden layer neurons and 75 training epochs, or 12 hidden layer neurons and 50 training epochs. It is only with these training criteria that the value of R^2 reached 0.79, while the next highest value of R^2 was 0.74, attained with 20 hidden layer neurons and 75 training epochs. The results in Table 8 are reproduced in Figure 25, where the shaded areas show the different values of R^2.

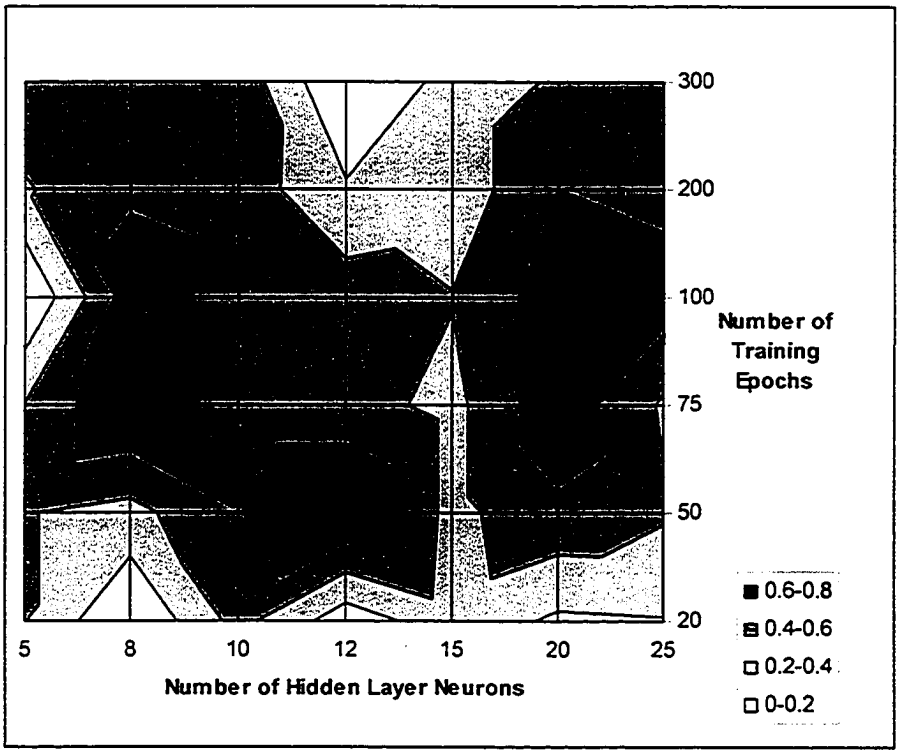


Figure 25: Optimal Number of Hidden Layer Neurons and Training Epochs

As the purpose of the network refinement is to determine the minimum number of hidden layer neurons and training epochs required to produce a reasonable value of R^2, the final choice is to use 8 hidden layer neurons, trained for 75 epochs.

The final network selected is a Recurrent Network with a dampened feedback link, 8 neurons in the hidden layer, and a single neuron in the feedback layer. The hidden layer activation function is Symmetric Logistic, and the output function is Logistic. The network should be trained for 75 epochs before being applied to the new data.

When new data are collected, the network can be trained again, using the optimal architecture and functions determined from this experiment. As this dataset contained less than 100 values, a longer training time (because of a higher number of training epochs) is acceptable. For larger datasets, a smaller number of training epochs may be preferable, in which case the operator should choose the architecture with 12 hidden layer neurons and 50 training epochs.

8.0 CONCLUSIONS

This experiment has shown that the use of ammonia and hydrogen sulphide gas measurements with an electronic nose and supervised Artificial Neural Networks can be used to predict swine odour concentrations. This model is improved by pre-processing the electronic nose data using Principal Component Analysis.

Using NeuroShell 2™ ANN software, the best network architecture for Artificial Neural Networks for predicting the odour concentrations using these measures was found to be a Recurrent Network with a dampened feedback. The optimal activation functions were found to be Symmetric Logistic activation in the hidden layer and Logistic activation of the output layer. The optimal number of hidden-layer neurons was found to be 8 when the network was run for 75 training epochs. This produced an R^2 value of 0.79. With a larger dataset, where training time may become an issue, the same architecture can produce good results with 12 hidden layer neurons and 50 training epochs.

9.0 RECOMMENDATIONS

It was shown in this experiment that Artificial Neural Networks and the inputs described above can be used to predict odour concentrations. It is possible that a larger dataset would provide a better prediction. Ammonia data used in this experiment contained a large number of values that were assumed, because the upper limit of the instrument was below the concentrations of ammonia in several samples. An instrument with a larger detection range could also assist in producing better predictions.

Future work could use the same data, analysed differently – by being selective about which of the AromaScan™'s sensors' responses are used as inputs into the models, or by using different methods of reducing the data set (using Cannonical Discriminant Analysis or other factor analysis methods in place of Principal Component Analysis). For some of the samples, ammonia and hydrogen sulphide were also measured in the field, and could provide better input data than laboratory measurements taken hours later. Methane concentrations were also collected for some samples, and could potentially be a good input into odour models. Hedonic tone information was recorded but not used in this experiment. The sample source (housing or manure storage) was recorded, but not taken into account in the models. As a model input, sample source could alter the relative value of ammonia and hydrogen sulphide measurements. The measure of the model's success in this experiment was the value of R^2, which compares the predictions to the mean of all samples. Other researchers have used Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE) and other statistics to measure the predictive ability of a model, and it is possible that using these other measures would provide a different evaluation of the dataset and the model's predictive ability. There is a great deal of work that can be done with the data already collected, and different statistical analysis methods may be all that are required to determine the value of the data in predicting swine odour concentrations as measured using olfactometry.

In this experiment, a model was created for swine odours using an electronic nose and ammonia and hydrogen sulphide gas concentrations. For other odour sources, different model may need to be created. The value of ammonia and hydrogen

sulphide measurements in for other odour sources may be lower than they are for swine odour. It is expected that the ability of the model to predict odour concentrations from other types of livestock operations will be less than for swine odours. One potential use of this dataset may be to add the odour source type as a model input, and expand the dataset and improve the model using other livestock operations. As it exists at this point, however, the model is best applied to swine operations, and its utility for other types of operations would need to be investigated before this can be applied.

Ammonia and hydrogen sulphide data were found to be the most valuable contributors to the model, with the electronic nose providing less information on its own than the use of these two together. Ammonia and hydrogen sulphide are simple measures to obtain, with widely available and inexpensive meters. The value of the electronic nose for predicting swine odour concentrations in this case is potentially not worth the expense. However, for other odour types, which are not as heavily characterised by these two easily measured gases, the electronic nose's usefulness may be increased. It is also worth noting that ammonia and hydrogen sulphide gases were not above health criteria in the odours with the greatest concentrations. Odour-derived concentrations limits will not necessarily be the same as those devised based on health criteria for the individual gases.

10.0 REFERENCES

AAFRD. (2003). "Alberta Agriculture, Food and Rural Development. Alberta's Pork Production Industry." Agri-Facts: Practical Information for Alberta's Agriculture Industry.

Alberta. (2001). "Province of Alberta, Agricultural Operation Practices Act." Alberta Queen's Printer.

Alberta. (2003). "Alberta Agriculture, Food and Rural Development. Alberta's Pork Production Industry." Agri-Facts: Practical Information for Alberta's Agriculture Industry.

Alberta. (2004). "Alberta Ambient Air Quality Objectives." Alberta Environment (online resource, http://www3.gov.ab.ca/env/protenf/approvals/factsheets/ABAmbientAirQuality.pdf). Accessed September 2004.

Alberta. (2004). "Pigs on Farms in Alberta." Alberta Agriculture, Food and Rural Development online resource (http://www1.agric.gov.ab.ca/$department/deptdocs.nsf/all/sdd1510#top) accessed December, 2004.

ASTM. (1991). "Standard Practice for Determination of Odor and Taste Thresholds By a Forced-Choice Ascending Concentration Series Method of Limits." Annual Book of ASTM Standards, Vol 11.01, Annual Book of ASTM Standards, Vol 15.07.

Baby, R. E., M. Cabezas, and E. N. Walsoe de Reca. (2000). "Electronic nose: a useful tool for monitoring environmental contamination." *Sensors and Actuators B: Chemical*, 69(3), 214-218.

Bauer, K., D. Garbe, and H. Surburg. (1990). *Common fragrance and flavor materials: preparation, properties, and uses*, VCH Verlagsgesellschaft; VCH Publishers, Weinheim, Federal Republic of Germany, New York, N.Y., USA.

Baxter, C. W., S. J. Stanley, Q. Zhang, and D. W. Smith. (2002). "Developing artificial neural network models of water treatment processes: a guide for utilities." *Journal of Environmental Engineering and Science*, 1, 201 - 211.

Beaulieu, M. S. (2004). "Farm Environmental Management in Canada: Manure Management in Canada." *Vol 1, No. 2*, Statistics Canada.

Bockreis, A., and J. Jager. (1999). "Odour monitoring by the combination of sensors and neural networks." *Environmental Modelling and Software*, 14(5), 421-426.

Brezmes, J., E. Llobet, X. Vilanova, J. Orts, G. Saiz, and X. Correig. (2001). "Correlation between electronic nose signals and fruit quality indicators on shelf-life measurements with pinklady apples." *Sensors and Actuators B: Chemical*, 80(1), 41-50.

Brezmes, J., E. Llobet, X. Vilanova, G. Saiz, and X. Correig. (2000). "Fruit ripeness monitoring using an Electronic Nose." *Sensors and Actuators B: Chemical*, 69(3), 223-229.

Cain, W. S., and H. R. Moskowitz. (1974). "Psychophysical Scaling of Odor." Human Responses to Environmental Odors, Academic Press Inc, New York and London, 2 - 32.

Capone, S., M. Epifani, F. Quaranta, P. Siciliano, A. Taurino, and L. Vasanelli. (2001). "Monitoring of rancidity of milk by means of an electronic nose and a dynamic PCA analysis." *Sensors and Actuators B: Chemical*, 78(1-3), 174-179.

CCME. (1999). *Canadian Environmental Quality Guidelines*, Canadian Council of Ministers of the Environment, Winnipeg, MB, Canada.

CEN. (1998). "Air quality - Determination of odour concentraion by dynamic olfactometry." Comité Européen de Normalisation / Europeran Committee for Standardisation.

CEN. (2003). *Air quality - Determination of odour concentration by dynamic olfactometry*, Comité Européen de Normalisation / European Committee for Standardisation, Brussels, Belgium.

Cody, R. P., and J. K. Smith. (1997). *Applied Statistics and the SAS Programming Language*, Prentice Hall, Upper Saddle River, New Jersey.

Diamantaras, K. I. (2002). "Neural Networks and Principle Component Analysis." Handbook of Neural Network Signal Processing, Hu, Y. H. and J.-N. Hwang, eds., CRC Press, Boca Raton, FL, USA.

Dravnieks, A. (1985). "Atlas of Odor Character Profiles." ASTM publication code number 05-06100-36, Philadelphia, PA.

El-Din, A. G., D. W. Smith, and M. Gamal El-Din. (2004). "Application of artificial neural networks in wastewater treatment." *Journal of Environmental Engineering and Science*, 3, S81 - S95.

Feddes, J. J. R., G. Qu, C. A. Ouellette, and J. J. Leonard. (2001). "Development of an eight-panellist single port, forced-choice, dynamic dilution olfactometer." *Canadian Biosystems Engineering*, 43, 6.1 - 6.5.

Ferreira, V., M. Aznar, R. Lopez, and J. Cacho. (2001). "Quantitative Gas Chromatography-Olfactometry Carried out at Different DIlutions of an Extract. Key Differences in the Odor Profiles of FOur High-Quality Spanish Aged Red Wines." *Journal of Agricultural and Food Chemistry*, 49, 4818 - 4824.

Gardner, J. W., and P. N. Bartlett. (1999). *Electronic noses: principles and applications*, Oxford University Press, New York.

Goodner, K. L., J. G. Dreher, and R. L. Rouseff. (2001). "The dangers of creating false classifications due to noise in electronic nose and similar multivariate analyses." *Sensors and Actuators B: Chemical*, 80(3), 261-266.

Hanumantharaya, U., J. Leis, and N. Hancock. (1999). "Quantitative Odour Modelling Using Electronic Nose Information." Fifth International Symposium on Signal Processing and its Applications (ISSPA 99), Brisbane, Australia.

Harper, L. A., R. R. Sharpe, T. B. Parkin, A. De Visscher, O. van Cleemput, and F. M. Byers. (2004). "Nitrogen Cycling through Swine Production Systems: Ammonia, Dinitrogen, and Nitrous Oxide Emissions." *Journal of Environmental Quality*, 33, 1189-1201.

Hobbs, P. J., T. H. Misselbrook, M. S. Dhanoa, and K. C. Persaud. (2000). "Relationship between olfactory response and major odorants from livestock wastes." Proceedings of the 2nd International Conference on Air Pollution Agricultural Operations., ASAE:St. Joseph, MI., Des Moines, Iowa.

Hopgood, A. A. (2001). *Intelligent Systems for Engineers and Scientists*, CRC Press, Boca Raton, FL, USA.

Hudon, G., C. Guy, and J. Hermia. (2000). "Measurement of odor intensity by an electronic nose." *Journal Of The Air & Waste Management Association (1995)*, 50(10), 1750-1758.

Le Guen, S., C. Prost, and M. Demaimay. (2000). "Critical Comparison of Three Olfactometric Methods for the Identification of the Most Potent Odorants in Cooked Mussels (*Mytilus edulis*)." *Journal of Agricultural and Food Chemistry*, 48(1307), 1314.

Misselbrook, T. H., P. J. Hobbs, and K. C. Persaud. (1997). "Use of an Electronic Nose to Measure Odour Concentration Following Application of Cattle Slurry to Grassland." *Journal of Agricultural Engineering Research*, 66(3), 213-220.

Moncrieff, R. W. (1970). *Odours*, William Heinemann Medical Books, London, England.

Murphy, C., Clara R. Shcubert, Karen J. Cruikshanks, Barbara E. Klein, Ronald Klein, David M. Nondahl. (2002). "Prevalence of Olfactory Impairment in Older Adults." *JAMA*, 288(18), 2307 - 2312.

NRCB. (2003). "Natural Resources Conservation Board Applications, Program Summary For The Agricultural Operation Practices Act For The Year 2002." Alberta Natural Resources Conservation Board.

NRCB. (2003). "Natural Resources Conservation Board Compliance and Enforcement program Summary for the Agricultural Operation Practices Act for the Year 2002."

NRCB. (2004). "Year in Review." Alberta Natural Resources Conservation Board.

Ohloff, G. (1994). *Scent and Fragrances: The fascination of odors and their chemical perspectives*, Lawrence, W. P. a. B. M., translator, Springer-Verlag.

Polikar, R., R. Shinar, L. Udpa, and M. D. Porter. (2001). "Artificial intelligence methods for selection of an optimized sensor array for identification of volatile organic compounds." *Sensors and Actuators B: Chemical*, 80(3), 243-254.

Powers, W. (2003). "Characterization of air in and around poultry and livestock facilities." Gaseous and Odour Emissions from Animal Production Facilities, Horsens, Denmark.

Powers, W. J., T. v. Kempen, D. S. Bundy, A. Sutton, and S. J. Hoff. (2000). "Objective measurement of odors using gas chromatography/mass spectrometry and instrumental technologies." Proceedings of the 2nd International Conference on Air Pollution Agricultural Operations., ASAE:St. Joseph, MI., Des Moines, Iowa.

Qu, G., J. J. R. Feddes, W. W. Armstrong, R. N. Coleman, and J. J. Leonard. (2001). "Measuring Odor Concentration with an Electronic Nose." *Transactions of the ASAE*, 44(6), 1807 - 1812.

Rothe, M. (1988). *Introduction to aroma research*, Reidel; Distributors for the U.S.A. and Canada Kluwer Academic, Boston Hingham, MA, U.S.A.

Schiffman, S. S., J. L. Bennett, and J. H. Raymer. (2001). "Quantification of odors and odorants from swine operations in North Carolina." *Agricultural and Forest Meteorology*, 108(3), 213-240.

Smeets, M., and P. Dalton. (2002). "Perceived odor and irritation of isopropanol: a comparison between naive controls and occupationally exposed workers." *International Archives of Occupational and Environmental Health*, 75(8), 541 - 584.

Stuetz, R. M., R. A. Fenner, and G. Engin. (1999). "Assessment of odours from sewage treatment works by an electronic nose, H2S analysis and olfactometry." *Water Research*, 33(2), 453-461.

Wilson, D. M., T. Roppel, and R. Kalim. (2000). "Aggregation of sensory input for robust performance in chemical sensing microsystems." *Sensors and Actuators B: Chemical*, 64(1-3), 107-117.

Zahner, D. A., and E. Micheli-Tzanakou. (2000). "Artificial Neural Networks: Definitions, Methods, Applications." Supervised and Unsupervised Pattern Recognition: Feature Extraction and Computational Intelligence, Micheli-Tzanakou, E., ed., CRC Press, Boca Raton, FL, USA.

APPENDIX A – Raw Data from Olfactometry, Gas Measurements and Electronic Nose

Table 9A: Raw Data from Gas Meters and Electronic Nose Measurements (sensors 1 – 18)

date olfact / bag number	sample info	H2S	NH3	OU	# 1	# 2	# 3	# 4	# 5	# 6	# 7	# 8	# 9	# 10	# 11	# 12	# 13	# 14	# 15	# 16	# 17	# 18
2003-07-30JH141	lagoon 15 min			126	11.03	10.39	13.08	13.25	9.92	8.38	10.52	10.26	8.10	7.99	8.84	9.06	8.84	10.61	7.13	7.44	9.17	7.12
28-NovJP251	inlet fresh	0.3	0	203	2.35	2.46	2.43	2.45	1.88	1.89	1.95	2.15	2.32	2.22	2.36	2.48	2.20	1.89	2.74	2.88	2.94	3.60
2004-04-21CH5-2	Quebec	0.5	0	221	6.50	6.92	7.99	7.73	5.06	3.80	5.89	5.46	4.51	4.45	4.30	4.46	4.68	5.89	2.30	2.43	4.99	4.58
2004-04-21CH5-2	Quebec	0.3	0	221	2.59	2.65	3.04	2.94	2.05	1.68	2.26	2.12	1.72	1.68	1.72	1.77	1.82	2.26	1.44	1.46	1.92	1.82
2004-04-21CH9	Quebec	0.3	3	221	5.75	6.55	6.96	6.85	4.50	3.67	5.62	5.44	5.05	4.98	4.64	4.83	4.96	5.71	2.94	3.08	5.58	5.22
06-NovCO#2	control	0.2	5	315	8.49	9.80	11.11	11.34	7.11	5.72	8.97	8.35	7.76	7.63	6.76	7.05	7.36	9.01	4.50	4.78	8.86	8.98
06-NovCO#2	Control 2	0.2	5	315	8.49	9.80	11.11	11.34	7.11	5.72	8.97	8.35	7.76	7.63	6.76	7.05	7.36	9.01	4.50	4.78	8.86	8.98
2004-04-15SCH87	barrel	0.4	250	323	3.97	3.32	4.93	5.45	4.89	5.56	4.93	4.93	4.05	3.92	4.63	4.64	4.21	4.90	7.58	7.39	4.29	4.00
2004-04-21CH7	Quebec	0.3	5	328	5.14	5.78	6.08	6.01	4.10	3.48	4.94	4.87	4.69	4.62	4.34	4.51	4.55	5.01	3.02	3.15	5.25	5.09
2003-08-22JP333	grower			354	7.29	7.22	9.18	9.33	6.60	5.43	7.38	6.89	5.56	5.51	5.51	5.66	5.76	7.28	4.00	4.16	6.07	5.34
2004-04-01SCH142	barrel	0.6	250	406	4.43	3.66	5.41	5.99	5.47	6.34	5.25	5.32	4.28	4.12	5.04	5.04	4.50	5.16	8.96	8.70	4.38	3.74
2004-04-01SCH142	barrel	0.6	250	406	4.43	3.66	5.41	5.99	5.47	6.34	5.25	5.32	4.28	4.12	5.04	5.04	4.50	5.16	8.96	8.70	4.38	3.74
2004-03-31SCH110	barrel	0.5	110	416	5.07	4.55	6.02	6.54	5.72	6.42	5.54	5.69	4.95	4.76	5.73	5.81	5.14	5.47	9.77	9.70	5.28	4.88
2004-03-31SCH110	barrel	0.5	110	416	5.07	4.55	6.02	6.54	5.72	6.42	5.54	5.69	4.95	4.76	5.73	5.81	5.14	5.47	9.77	9.70	5.28	4.88
2004-03-31SCH251	barrel	1.5	250	512	15.48	16.35	19.80	20.88	15.26	14.84	16.96	16.09	14.41	14.24	14.58	14.94	14.97	17.57	15.57	15.57	15.78	12.72
2004-03-31SCH251	barrel	1.5	250	512	15.48	16.35	19.80	20.88	15.26	14.84	16.96	16.09	14.41	14.24	14.58	14.94	14.97	17.57	15.57	15.57	15.78	12.72
2004-03-31SCH94	barrel	0.8	198	512	7.16	6.72	8.35	8.90	7.46	8.13	7.46	7.64	6.87	6.64	7.83	7.93	7.09	7.38	12.08	12.20	7.25	6.41
2004-03-31SCH94	barrel	0.8	198	512	7.16	6.72	8.35	8.90	7.46	8.13	7.46	7.64	6.87	6.64	7.83	7.93	7.09	7.38	12.08	12.20	7.25	6.41
2003-08-06JH175	finisher			561	8.50	7.95	10.30	10.40	7.83	6.57	8.38	8.06	6.18	6.09	6.73	6.90	6.82	8.41	5.44	5.63	6.97	5.31
2003-08-08J27	grower			562	9.19	8.43	11.00	11.20	8.73	7.49	9.26	8.92	6.80	6.69	7.57	7.76	7.65	9.26	6.26	6.44	7.81	5.76
16-JanM130	finisher	0.3	11	575	9.05	11.04	13.29	13.73	7.58	5.76	9.78	8.76	7.95	7.83	6.82	7.14	7.62	9.70	3.69	3.96	8.90	8.24
2004-03-31SCH165	barrel	0.7	250	575	22.99	23.51	26.53	27.62	21.40	20.39	24.02	23.82	22.60	22.27	22.90	23.52	22.73	24.17	22.52	23.02	24.95	24.02
2004-03-31SCH165	barrel	0.7	250	575	22.99	23.51	26.53	27.62	21.40	20.39	24.02	23.82	22.60	22.27	22.90	23.52	22.73	24.17	22.52	23.02	24.95	24.02
2004-03-	barrel	0.8	250	575	6.20	5.66	7.65	8.37	6.94	7.80	8.98	6.97	5.91	5.74	6.75	6.78	6.24	6.98	10.26	10.05	6.19	4.53

31SCH250																					
2004-03-31SCH250	barrel	0.8	250	575	6.20	5.66	7.65	8.37	6.94	7.80	6.98	6.97	5.91	5.74	6.75	6.78	6.24	6.98	10.26	10.05	6.19	4.53
2003-08-08JH182	pregrower			630	8.62	8.01	10.50	10.60	7.99	6.66	8.51	8.17	6.13	6.05	6.79	6.96	6.91	8.52	5.14	5.35	7.00	5.07
2003-08-06J14	grower			630	9.05	8.24	10.60	10.80	8.42	7.22	8.79	8.54	6.56	6.44	7.34	7.52	7.32	8.82	6.42	6.62	7.46	5.63
2004-04-15TD7	barrel	0.6	250	645	3.69	3.10	4.62	5.13	4.54	5.12	4.60	4.57	3.72	3.61	4.24	4.23	3.87	4.58	6.73	6.52	3.92	3.63
05-NovJ71	biofilter	0.4	7	707	6.43	8.13	9.10	9.31	5.23	3.96	7.08	6.48	6.24	6.12	4.98	5.23	5.64	7.06	2.39	2.63	7.11	7.63
06-NovJP262	barrel	0.9	65	707	18.56	20.65	23.11	23.75	16.29	14.29	19.44	18.46	17.48	17.17	15.93	16.56	16.81	19.62	13.59	14.05	20.23	20.50
2003-08-08JH184				707	8.92	8.27	10.70	10.90	8.42	7.17	8.97	8.61	6.59	6.49	7.29	7.47	7.40	8.98	5.94	6.12	7.54	5.57
2003-08-22JP244	finisher			707	10.40	9.64	12.10	12.50	9.68	8.55	10.10	9.78	7.91	7.80	8.37	8.58	8.37	10.00	8.14	8.29	8.78	7.70
2004-04-01J91	barrel	0.5	250	724	4.54	3.81	5.63	6.34	5.87	7.03	5.62	5.76	4.70	4.51	5.50	5.50	4.89	5.54	10.09	9.80	5.00	4.83
2004-04-01J91	barrel	0.5	250	724	4.54	3.81	5.63	6.34	5.87	7.03	5.62	5.76	4.70	4.51	5.50	5.50	4.89	5.54	10.09	9.80	5.00	4.83
2003-08-08JH147	weaner			794	4.93	4.89	6.63	6.73	4.61	3.55	5.10	4.63	3.39	3.36	3.42	3.50	3.70	5.02	1.69	1.77	3.69	2.59
2003-08-22JP205	lagoon 15 min			794	2.91	2.86	3.61	3.74	2.71	2.45	3.06	3.05	2.59	2.54	2.55	2.64	2.53	3.02	2.25	2.36	2.82	2.78
28-NovSCH15	barrel	0.3	136	813	7.70	7.52	8.55	8.99	7.91	8.96	7.57	7.86	7.53	7.24	8.28	8.53	7.63	7.55	13.65	13.67	8.98	9.53
2004-04-15GRANT2	barrel	6	250	813	4.31	3.41	5.31	5.98	5.41	6.29	5.50	5.56	4.41	4.30	5.13	5.13	4.65	5.48	8.04	7.82	4.63	3.93
16-JanSCH96	farrowing	0.5	5	832	10.67	12.96	15.37	15.84	9.13	7.43	11.23	10.22	9.41	9.23	8.37	8.73	9.13	11.23	5.92	6.17	10.84	10.19
2003-08-15JP316	dry sow			891	10.70	9.58	12.20	12.50	9.85	8.53	10.20	9.86	7.63	7.50	8.48	8.67	8.42	10.00	7.39	7.63	8.38	6.41
16-JanSCH93	farrowing	0.6	7	912	9.01	11.10	13.35	13.80	7.57	5.86	9.69	8.68	7.89	7.76	6.77	7.08	7.56	9.61	3.82	4.08	8.92	8.28
2004-03-31SCH256	barrel	0.6	250	912	6.93	7.54	8.86	9.48	7.06	8.33	7.36	7.14	6.61	6.40	6.98	7.11	6.81	7.34	8.86	8.76	7.92	7.01
2004-03-31SCH256	barrel	0.6	250	912	6.93	7.54	8.86	9.48	7.06	8.33	7.36	7.14	6.61	6.40	6.98	7.11	6.81	7.34	8.86	8.76	7.92	7.01
2004-04-01SCH151	barrel	0.4	250	912	4.29	3.74	5.49	6.15	5.41	6.28	5.43	5.45	4.35	4.22	4.87	4.88	4.48	5.39	7.67	7.39	4.60	4.30
2004-04-01SCH151	barrel	0.4	250	912	4.29	3.74	5.49	6.15	5.41	6.28	5.43	5.45	4.35	4.22	4.87	4.88	4.48	5.39	7.67	7.39	4.60	4.30
2004-04-01SCH163	barrel	0.5	250	912	4.03	3.52	5.19	5.77	5.08	5.92	5.03	5.05	4.03	3.89	4.55	4.55	4.17	4.98	7.46	7.20	4.33	4.13
2004-04-01SCH163	barrel	0.5	250	912	4.03	3.52	5.19	5.77	5.08	5.92	5.03	5.05	4.03	3.89	4.55	4.55	4.17	4.98	7.46	7.20	4.33	4.13
09-DecSCH44	finisher	0.6	15	952	11.65	14.51	15.55	15.80	9.58	7.99	12.16	11.25	11.34	11.09	9.53	10.01	10.38	12.18	7.15	7.42	13.74	15.60
2003-09-19JP205	dry sow			1000	12.28	12.36	14.84	15.12	11.04	9.67	12.30	11.76	10.22	10.09	9.83	10.10	10.17	12.36	9.01	9.18	11.43	11.24
16-JanJH146	finisher	0.9	16	1024	11.34	13.65	16.17	16.76	9.66	7.77	12.13	11.04	10.16	9.99	8.96	9.35	9.82	12.10	5.75	6.05	11.47	10.63
16-JanSCH76	gestation	0.7	13	1024	13.39	17.57	19.84	20.57	10.85	8.70	14.04	12.74	12.68	12.42	10.64	11.21	11.83	14.12	6.69	7.09	15.14	16.10
2004-03-31SCH174	barrel	1	250	1024	4.49	3.83	5.57	6.12	5.29	5.95	5.21	5.24	4.24	4.14	4.88	4.88	4.43	5.19	7.92	7.70	4.19	3.41
2004-03-31SCH174	barrel	1	250	1024	4.49	3.83	5.57	6.12	5.29	5.95	5.21	5.24	4.24	4.14	4.88	4.88	4.43	5.19	7.92	7.70	4.19	3.41
2003-09-19JH106	dry sow			1051	9.56	9.81	11.75	11.86	8.19	6.77	9.24	8.80	7.58	7.48	7.17	7.40	7.49	9.18	5.56	5.83	8.51	8.50
05-NovJ67	biofilter	0.8	12	1051	13.39	15.84	17.65	18.14	11.40	9.67	14.04	13.22	12.71	12.45	11.18	11.65	12.01	14.21	8.88	9.27	15.04	15.96
06-NovJ67S	biofilter	0.5	12	1051	8.56	9.83	10.00	10.30	7.43	7.18	8.54	8.85	9.48	9.21	8.75	9.15	8.79	8.64	8.57	8.94	11.88	14.06

05-NovJP371	barrel	0.7	110	1072	33.46	39.80	42.20	43.37	28.63	26.79	33.24	32.21	32.38	31.54	29.71	31.04	30.98	33.97	29.08	29.94	41.46	48.04
06-NovJP731	barrel	0.7	110	1072	33.43	39.80	42.20	43.37	28.63	26.77	33.24	32.18	32.36	31.54	29.71	31.04	30.98	33.95	29.08	29.94	41.46	48.04
2003-08-15JP331	grower			1122	9.09	8.47	10.70	10.70	8.21	7.00	8.58	8.27	6.50	6.40	7.03	7.21	7.10	8.54	5.90	6.11	7.13	5.73
2003-08-15JP330	pregrowe r			1123	4.33	4.52	5.77	5.72	3.68	2.68	4.15	3.71	2.79	2.77	2.66	2.74	2.98	4.07	1.03	1.12	2.99	2.39
16-JanSCH92	gestation	0.7	10	1149	14.70	19.09	21.52	22.30	11.92	9.57	15.36	14.03	13.95	13.66	11.85	12.47	13.07	15.43	7.65	8.10	16.58	17.30
17-OctSCH18	biofilter	0.5	5	1160	10.29	12.56	13.98	14.26	8.59	6.93	11.00	10.24	9.94	9.77	8.37	8.75	9.22	11.11	5.51	5.86	11.49	12.95
09-Dec#34	gestation	0.4	14	1160	11.30	14.23	15.27	15.52	9.30	7.71	11.86	10.93	11.04	10.79	9.20	9.66	10.06	11.86	6.80	7.05	13.44	15.57
09-DecSCH72	finisher	0.7	17	1160	13.58	17.04	17.94	18.19	11.27	9.76	13.69	12.75	13.05	12.76	11.10	11.63	11.96	13.72	9.51	9.73	16.23	19.86
2003-08-08J21	dry sow			1260	8.03	7.46	9.79	9.98	7.67	6.50	8.14	7.72	5.90	5.81	6.46	6.61	6.61	8.13	5.10	5.23	6.72	4.92
2003-08-08JH183	farrowing			1260	10.10	8.75	11.50	11.90	9.95	8.62	9.99	9.77	7.38	7.25	8.67	8.86	8.50	9.90	7.96	8.15	8.63	6.02
2003-09-19JP217	grower			1281	12.49	12.50	15.01	15.23	11.13	9.66	12.56	12.01	10.43	10.32	10.11	10.41	10.46	12.64	8.91	9.16	11.68	11.33
16-JanCAO9	farrowing	0.8	7	1290	13.12	16.97	19.23	19.92	10.61	8.42	13.72	12.52	12.34	12.09	10.47	11.02	11.58	13.76	6.58	7.00	14.59	15.02
2003-09-19JP211	dry sow			1414	12.16	12.33	14.83	15.08	10.78	9.25	12.29	11.72	10.17	10.05	9.74	10.03	10.13	12.37	8.38	8.64	11.35	11.06
05-NovJP219	biofilter	0.5	11	1414	12.15	14.43	16.13	16.61	10.29	8.60	12.91	12.08	11.60	11.39	10.05	10.49	10.88	13.04	7.49	7.86	13.64	14.39
06-NovJP219E	biofilter	0.5	11	1414	7.30	8.31	8.45	8.73	6.28	6.07	7.24	7.51	8.04	7.80	7.44	7.78	7.45	7.29	7.19	7.52	10.04	11.84
06-NovJP219S	biofilter	0.5	11	1414	7.30	8.31	8.45	8.73	6.28	6.07	7.24	7.51	8.04	7.80	7.44	7.78	7.45	7.29	7.19	7.52	10.04	11.84
09-DecJP369	nursery	1	3	1414	6.39	8.39	9.06	9.10	4.97	3.73	6.60	5.99	6.06	5.91	4.73	4.99	5.32	6.46	2.51	2.70	7.25	9.10
09-DecSCH73	gestation	0.5	14	1414	11.32	14.12	15.20	15.45	9.27	7.64	11.86	10.95	11.01	10.78	9.22	9.67	10.06	11.89	6.77	7.03	13.29	15.12
16-JanSCH108	gestation	0.7	12	1448	14.44	18.43	21.16	21.95	11.89	9.50	15.13	13.77	13.40	13.14	11.51	12.08	12.68	15.18	7.48	7.90	15.64	15.84
2004-04-01SCH13	barrel	0.6	90	1448	4.34	3.99	5.37	5.71	4.98	5.46	4.73	4.80	4.08	3.92	4.69	4.75	4.21	4.67	8.12	8.02	4.34	4.22
2004-04-01SCH13	barrel	0.6	90	1448	4.34	3.99	5.37	5.71	4.98	5.46	4.73	4.80	4.08	3.92	4.69	4.75	4.21	4.67	8.12	8.02	4.34	4.22
2004-04-15SCH254	barrel	0.7	195	1448	3.80	2.92	4.56	5.13	4.90	5.81	4.79	4.90	3.92	3.78	4.68	4.68	4.13	4.72	8.32	8.09	4.21	3.78
2003-09-19J12	grower			1561	12.89	12.97	15.57	15.86	11.52	10.06	13.01	12.43	10.80	10.67	10.41	10.72	10.78	13.08	9.24	9.48	12.10	11.81
09-DecCAO2	farrowing	0.8	10	1561	8.63	11.06	11.85	12.06	7.04	5.72	9.23	8.43	8.53	8.35	6.94	7.29	7.67	9.18	4.70	4.92	10.32	12.17
09-DecJ90	gestation	0.5	15	1561	9.82	12.17	13.14	13.33	8.09	6.65	10.33	9.52	9.50	9.32	7.98	8.36	8.73	10.36	5.78	6.00	11.38	12.67
09-DecJH98	farrowing	0.7	10	1561	8.41	10.63	11.48	11.68	6.86	5.54	8.95	8.20	8.23	8.06	6.77	7.11	7.47	8.93	4.61	4.83	9.92	11.30
2003-08-08J51	dry sow			1587	7.44	6.99	9.21	9.36	6.99	5.78	7.54	7.11	5.39	5.32	5.83	5.98	6.02	7.52	4.24	4.39	6.09	4.44
16-JanSCH87	nursery	1.4	0	1625	7.97	10.70	12.76	13.21	6.33	4.44	8.63	7.58	7.12	7.01	5.65	5.99	6.56	8.56	2.26	2.55	8.17	8.24
2003-08-08JH171	farrowing			1782	8.93	8.13	10.70	10.90	8.59	7.38	9.07	8.73	6.62	6.53	7.38	7.54	7.45	9.05	5.97	6.15	7.58	5.46
2004-04-01JP304	barrel	0.9	250	1824	7.52	8.43	8.81	9.16	6.76	6.55	7.88	8.16	8.72	8.50	8.18	8.50	8.10	7.90	7.61	7.90	10.10	10.30
2004-04-01JP304	barrel	0.9	250	1824	7.52	8.43	8.81	9.16	6.76	6.55	7.88	8.16	8.72	8.50	8.18	8.50	8.10	7.90	7.61	7.90	10.10	10.30
28-NovJ25	barrel	0.4	159	1866	4.63	4.40	4.94	5.12	4.51	4.94	4.24	4.30	3.99	3.89	4.44	4.55	4.18	4.25	6.96	6.91	4.71	4.81
28-NovN121	barrel	1	95	1866	5.47	5.44	5.88	6.10	5.19	5.64	5.03	5.16	5.01	4.85	5.41	5.58	5.08	4.99	8.23	8.27	6.03	6.42
28-NovN33	barrel	0.6	69	2143	1.84	1.28	1.14	1.21	2.04	3.13	0.89	1.48	1.59	1.43	2.47	2.49	1.83	0.90	6.05	6.00	1.98	2.14
21-JanSCH45	finisher	0.9	30	2152	13.48	14.58	17.19	17.73	12.02	10.42	14.30	13.51	12.20	11.99	11.62	12.05	12.17	14.24	9.31	9.64	13.75	12.53
2004-04-	barrel	0.9	185	2152	3.77	3.28	4.79	5.27	4.65	5.26	4.51	4.50	3.63	3.50	4.13	4.12	3.72	4.45	7.19	6.99	3.78	3.59

01SCH244																					
2004-04-01SCH244	barrel	0.9	185	2152	3.77	3.28	4.79	5.27	4.65	5.26	4.51	4.50	3.63	3.50	4.13	4.12	3.72	4.45	7.19	6.99	3.78	3.59
16-JanJ91	farrowing	0.3	4	2195	0.46	1.26	2.00	2.08	0.19	-0.33	0.69	0.34	0.13	0.13	-0.39	-0.36	-0.13	0.54	-1.18	-1.15	0.25	0.61
2003-08-06JH96	PG compost vessel			2245	11.00	10.10	11.80	12.20	10.70	10.30	11.00	11.20	9.38	9.19	10.50	10.80	10.20	11.10	11.60	11.80	10.70	8.95
2004-04-15SCH145	barrel	1.6	166	2299	8.30	6.69	9.07	10.01	10.07	12.54	9.34	9.86	8.69	8.36	10.34	10.47	9.00	9.25	19.60	19.28	9.63	9.92
17-OctJH97	biofilter	0.7	26	2320	22.50	25.66	28.45	29.16	19.28	17.23	22.63	21.87	21.09	20.66	19.31	20.11	20.25	23.10	17.80	18.42	25.81	27.89
21-JanSCH118	farrowing	0.8	3	2376	9.74	11.09	13.30	13.68	8.48	6.85	10.46	9.65	8.61	8.46	7.89	8.21	8.47	10.39	5.45	5.73	9.68	8.83
28-NovJH154	barrel	2.4	100	2462	5.22	5.05	5.48	5.72	4.97	5.42	4.76	4.92	4.73	4.58	5.13	5.28	4.79	4.74	7.91	7.93	5.65	5.94
2004-04-15SCH163/193	barrel			2580	4.03	3.52	5.19	5.77	5.08	5.92	5.03	5.05	4.03	3.89	4.55	4.55	4.17	4.98	7.46	7.20	4.33	4.13
21-JanSCH116	weaner	1.3	4	2623	5.92	6.97	8.68	8.81	4.93	3.48	6.43	5.68	4.85	4.81	4.17	4.36	4.73	6.34	1.73	1.93	5.42	4.90
21-JanSCH123	farrowing	1	10	2623	11.14	13.34	15.52	16.05	9.43	7.57	11.91	10.97	10.20	10.00	8.97	9.37	9.75	11.78	5.78	6.14	11.77	11.21
21-JanSCH48	farrowing	0.9	10	2623	11.52	13.32	15.56	16.12	10.05	8.33	12.44	11.61	10.62	10.43	9.71	10.11	10.37	12.33	6.97	7.31	12.11	11.12
2004-04-01SCH148	barrel	1	250	2623	6.06	4.89	7.00	7.87	7.68	9.60	7.00	7.25	6.02	5.77	7.36	7.33	6.39	6.89	14.72	14.30	6.31	5.93
2004-04-01SCH148	barrel	1	250	2623	6.06	4.89	7.00	7.87	7.68	9.60	7.00	7.25	6.02	5.77	7.36	7.33	6.39	6.89	14.72	14.30	6.31	5.93
28-NovN120	barrel	3.7	250	2828	4.84	4.32	5.36	5.84	5.25	6.13	4.93	5.03	4.41	4.29	4.96	4.97	4.60	4.95	7.99	7.78	5.42	4.43
28-NovN68	barrel	2.2	250	2828	3.73	3.22	4.08	4.36	3.98	4.48	3.74	3.76	3.23	3.17	3.68	3.68	3.44	3.79	5.51	5.34	3.73	3.10
16-JanSCH94	nursery	1.3	0	2896	18.08	22.83	26.25	27.07	14.71	11.67	18.89	17.58	16.81	16.40	14.65	15.45	15.98	18.90	8.94	9.63	19.92	19.20
21-JanSCH124	weaner	1.4	4	2896	8.51	9.85	11.80	12.11	7.31	5.76	9.20	8.45	7.56	7.44	6.78	7.09	7.36	9.08	4.25	4.54	8.59	7.83
21-JanSCH114	weaner	1.3	6	3198	1.38	1.96	2.85	2.78	0.70	-0.40	1.64	1.06	0.50	0.57	-0.05	0.00	0.43	1.55	-2.23	-2.12	0.55	0.56
21-JanSCH119	grower	1.2	36	3198	14.56	16.46	19.19	19.86	12.85	10.98	15.57	14.61	13.44	13.20	12.46	12.95	13.19	15.51	9.58	9.94	15.24	14.00
21-JanSCH125	grower	1.4	34	3530	15.16	17.31	20.05	20.75	13.29	11.35	16.20	15.19	14.13	13.85	12.99	13.51	13.78	16.12	9.88	10.28	16.12	14.76
21-JanSCH34	gestation	1.1	13	3531	5.02	5.55	6.88	7.01	4.25	3.22	5.32	4.71	3.90	3.90	3.53	3.66	3.94	5.27	1.94	2.05	4.41	4.12
28-NovJH116	barrel	2.5	176	3732	7.96	7.86	8.50	9.11	8.20	9.85	7.47	7.85	7.76	7.39	8.56	8.79	7.81	7.37	15.26	15.18	9.75	10.65
21-JanSCH117	grower	1.2	35	3898	27.03	31.59	35.49	36.70	23.40	21.16	27.61	26.45	25.74	25.16	24.23	25.25	25.10	27.89	22.11	22.83	31.27	31.67
21-JanSCH121	gestation	1.2	18	4304	13.57	15.53	18.14	18.75	11.87	10.02	14.46	13.55	12.50	12.25	11.51	11.98	12.22	14.39	8.71	9.08	14.32	13.24
17-OctJ25	biofilter	2.2	22	4641	0.08	0.23	0.34	0.37	0.08	-0.04	0.21	0.12	0.06	0.05	-0.08	-0.08	-0.01	0.13	-0.27	-0.27	0.01	-0.06
05-NovSCH7	barrel	3.5	80	4925	23.39	27.35	30.19	31.27	20.22	17.97	24.48	23.31	22.70	22.19	20.35	21.20	21.58	24.77	17.51	18.13	27.75	29.00
28-NovN61	barrel	2.8	109	4925	4.69	4.60	5.03	5.20	4.40	4.74	4.27	4.37	4.19	4.06	4.49	4.62	4.22	4.24	6.72	6.73	5.02	5.11
28-NovJP300 – outlier	barrel	1.4	192	11313	5.01	4.77	5.41	5.67	5.00	5.55	4.69	4.76	4.43	4.30	4.92	5.03	4.60	4.70	7.94	7.85	5.25	5.26
2004-04-15GRANT2 outlier	barrel	6	250	813	4.31	3.41	5.31	5.98	5.41	6.29	5.50	5.56	4.41	4.30	5.13	5.13	4.65	5.48	8.04	7.82	4.63	3.93
06-NovJP264 – outlier	barrel	8.3	180	5040	25.13	27.70	31.31	32.50	22.30	20.34	26.35	25.36	23.96	23.55	21.98	22.75	23.02	26.84	20.15	20.67	28.47	28.10

Table 10A: Raw Data from Gas and Electronic Nose Measurements (sensors 19 onwards)

date olfact / bag number	sample info	H2S	NH3	OU	# 19	# 20	# 21	# 22	# 23	# 24	# 25	# 26	# 27	# 28	# 29	# 30	# 31	# 32	Base Temp.	Relative Humidity	Base sensor Temp.
2003-07-30JH141	lagoon 15 min			126	11 27	9 16	8 99	7.14	6 25	4 84	9 32	9 54	10 69	11.04	10 12	11 77	13 23	6.78	25 23	37 21	35 16
28-NovJP251	inlet fresh	0 3	0	203	1 89	2 23	2 91	2.85	2.64	1.69	2 84	1.75	1.83	2.89	2.04	2 08	1.96	1.98	28.36	3.75	35.13
2004-04-21CH5-2	Quebec	0 5	0	221	6 60	5 53	3 13	4.05	3 31	1 81	4 03	5 61	6.13	5.63	4.96	7.44	7.84	2.77	23.57	33.08	35.16
2004-04-21CH5-2	Quebec	0 3	0	221	2 54	2.10	1 75	1.71	1 56	1.07	1.74	2 18	2.36	2 26	2.00	2 78	2 88	1.57	24.19	31.85	35.16
2004-04-21CH9	Quebec	0 3	3	221	6.36	6.18	3 70	4 54	3 69	2 19	4 48	5 29	5 46	5.61	4 48	6 03	6 30	2 85	26 05	26 66	35.13
06-NovCO#2	control	0 2	5	315	9 94	8 61	5 81	7 26	6 03	3 74	6 92	8 43	8 85	8 76	6 82	9 90	10 65	4 14	29 00	4 11	35 12
06-NovCO#2	control	0 2	5	315	9 94	8 61	5 81	7 26	6 03	3 74	6 92	8 43	8 85	8 76	6 82	9 90	10 65	4 14	29 00	4 11	35 12
2004-04-15SCH87	barrel	0 4	250	323	5 53	4 34	7 75	4 64	5 44	7 10	5 35	4 80	4 98	5 09	4 74	4 71	5 70	5 34	26 68	23 32	35 13
2004-04-21CH7	Quebec	0 3	5	328	5 47	5 65	3 75	4 39	3 64	2 37	4 26	4 62	4 76	5 12	4 11	5 31	5 47	2 93	25 60	27 90	35 13
2003-08-22JP333	grower			354	7 93	6 45	5 51	4 94	4 33	3 25	5 57	6 77	7 45	6 90	6 35	8 38	9 49	3 64	24 20	39 80	35 20
2004-04-01SCH142	barrel	0 6	250	406	5 63	4 23	9 10	4 57	5 74	8 11	6 05	5 06	5 34	5 64	5 39	5 15	6 02	6 85	25 70	22 66	35 14
2004-04-01SCH142	barrel	0 6	250	406	5 63	4 23	9 10	4 57	5 74	8 11	6 05	5 06	5 34	5 64	5 39	5 15	6 02	6 85	25 70	22 66	35 14
2004-03-31SCH110	barrel	0 5	110	416	6 07	5 07	9 84	5 48	6 15	7 45	7 09	5 47	5 71	6 60	5 79	5 63	6 31	7 54	27 05	23 54	35 14
2004-03-31SCH110	barrel	0 5	110	416	6 07	5 07	9 84	5 48	6 15	7 45	7 09	5 47	5 71	6 60	5 79	5 63	6 31	7 54	27 05	23 54	35 14
2004-03-31SCH251	barrel	1 5	250	512	19 46	15 52	18 07	13 05	14 43	17 07	16 34	17 34	18 33	18 22	15 80	19 68	21 47	14 55	24 98	33 98	35 15
2004-03-31SCH251	barrel	1 5	250	512	19 46	15 52	18 07	13 05	14 43	17 07	16 34	17 34	18 33	18 22	15 80	19 68	21 47	14 55	24 98	33 98	35 15
2004-03-31SCH94	barrel	0 8	198	512	7 99	6 83	12 16	6 89	7 70	9 01	9 25	7 26	7 42	8 59	7 42	7 47	8 18	8 81	26 42	27 52	35 13
2004-03-31SCH94	barrel	0 8	198	512	7 99	6 83	12 16	6 89	7 70	9 01	9 25	7 26	7 42	8 59	7 42	7 47	8 18	8 81	26 42	27 52	35 13
2003-08-06JH175	finisher			561	9 16	7 24	6 85	5 36	4 67	3 67	6 95	7 65	8 61	8 32	7 83	9 61	10 90	4 65	26 20	38 90	35 10
2003-08-08J27	grower			562	10 20	7 94	7 92	5 94	5 18	4 25	7 83	8 55	9 70	9 23	8 74	10 60	12 10	5 22	25 60	47 00	35 10
16-JanM130	finisher	0 3	11	575	11 18	9 35	5 04	6 52	4 96	2 73	6 98	9 56	10 34	9 37	7 27	11 80	12 60	3 23	27 61	27 58	35 12
2004-03-31SCH165	barrel	0 7	250	575	25 43	22 97	25 09	21 21	19 01	16 07	24 33	22 53	23 78	25 86	21 85	24 72	26 32	17 94	26 71	27 55	35 14
2004-03-31SCH165	barrel	0 7	250	575	25 43	22 97	25 09	21 21	19 01	16 07	24 33	22 53	23 78	25 86	21 85	24 72	26 32	17 94	26 71	27 55	35 14
2004-03-31SCH250	barrel	0 8	250	575	7 49	5 66	10 99	5 36	7 20	10 60	8 12	6 80	7 12	7 75	6 90	7 06	7 90	8 30	25 77	31 20	35 13
2004-03-31SCH250	barrel	0 8	250	575	7 49	5 66	10 99	5 36	7 20	10 60	8 12	6 80	7 12	7 75	6 90	7 06	7 90	8 30	25 77	31 20	35 13
2003-08-08JH182	pregrower			630	9 41	7 30	6 75	5 13	4 39	3 42	6 96	7 82	8 91	8 48	8 06	9 99	11 40	4 62	25 80	43 80	35 10
2003-08-	grower			630	9 44	7 39	7 90	5 85	5 15	4 18	7 76	8 00	9 03	9 05	8 51	10 00	11 30	5 46	25 90	37 40	35 10

06J14																				
2004-04-15TD7	barrel	0 6	250	645	5.13	3.97	6 96	4.14	4.91	6 46	4 81	4.45	4 65	4.62	4.36	4.43	5.37	4.73	26.80	22.76	35.13
05-NovJ71	biofilter	0.4	7	707	7.92	7.07	3 51	5.68	4 36	2.33	5.01	6.70	6.98	6.77	4.88	7.79	8 29	2 29	27.94	4.89	35.14
06-NovJP262	barrel	0.9	65	707	21.21	18.76	16.47	17.70	15.95	12.16	16.98	18.18	19.09	20.03	15.65	20.75	22.41	12.00	28.94	2.79	35.13
2003-08-08JH184				707	9.91	7.77	7 52	5 72	4.97	4.07	7.48	8 31	9.36	8.89	8.40	10 30	11.70	5.02	25.70	46.20	35.10
2003-08-22JP244	finisher			707	10.50	8 42	10 20	7.72	7.14	5.79	9.04	9 22	10 20	10 20	9.47	11 00	12.50	6.95	22.90	43.20	35.20
2004-04-01J91	barrel	0 5	250	724	6.04	4.72	10 24	5 82	7.16	9 81	6 64	5 38	5.74	6.17	5.75	5 38	6 34	7.52	27.05	20.79	35.14
2004-04-01J91	barrel	0 5	250	724	6.04	4.72	10.24	5 82	7.16	9 81	6 64	5.38	5.74	6.17	5.75	5.38	6 34	7.52	27.05	20.79	35.14
2003-08-08JH147	weaner			794	5.80	4.48	2 72	2 41	1.92	1.39	3 17	4 86	5.49	4.47	4.42	6 34	7.28	1.92	24.50	52.10	35.10
2003-08-22JP205	lagoon 15 min			794	3.12	2 81	2 94	2.57	2.35	1.78	2.87	2 73	2.93	3.20	2.84	3 06	3 52	1.86	25.00	41.70	35.20
28-NovSCH15	barrel	0 3	136	813	8 02	7.62	13.62	9 99	11.03	11.64	10 21	7 20	7.42	9.68	7.90	7.70	8 29	11.21	28.17	4.28	35.15
2004-04-15GRANT2	barrel	6	250	813	5.97	4.43	8 31	4.61	6.00	8.36	5.83	5 26	5.42	5.43	5 23	4 98	6.07	5.63	26.17	25.08	35.14
16-JanSCH96	farrowing	0.5	5	832	12.78	10.66	7.62	8 74	7.37	5 22	9.07	11.02	11.96	11.51	8.78	13.45	14.37	6.30	26.97	29.85	35.13
2003-08-15JP316	dry sow			891	10.70	8.43	9 63	6.50	5.75	4.66	8 92	9.18	10.40	10.50	9.86	11.40	13 00	7.03	24.10	32.50	35.10
16-JanSCH93	farrowing	0 6	7	912	11.01	9.23	5 23	6 67	5.23	3.30	7 08	9 50	10 29	9.43	7.25	11.73	12.53	3.75	27 23	29.37	35.12
2004-03-31SCH256	barrel	0 6	250	912	8.05	6.32	10 37	8 95	14.50	22.14	8.78	7.06	7.41	8 93	6.85	7.79	8 26	9.22	23.77	36.88	35.16
2004-03-31SCH256	barrel	0 6	250	912	8.05	6.32	10 37	8 95	14.50	22.14	8.78	7.06	7.41	8 93	6.85	7.79	8 26	9.22	23.77	36.88	35.16
2004-04-01SCH151	barrel	0 4	250	912	5 84	4.50	8 27	5 03	6 36	8 94	5 54	5 21	5 51	5 42	5 21	5 24	6 18	5.52	27.34	19.45	35.13
2004-04-01SCH151	barrel	0.4	250	912	5.84	4.50	8 27	5 03	6.36	8 94	5 54	5 21	5 51	5.42	5 21	5 24	6 18	5.52	27.34	19.45	35.13
2004-04-018CH163	barrel	0 5	250	912	5.48	4.13	7 94	4 91	6 01	8 23	5 24	4 83	5 16	5.15	4.92	4 98	5 89	5.37	27.48	18.95	35.13
2004-04-01SCH163	barrel	0 5	250	912	5.48	4.13	7.94	4 91	6.01	8 23	5 24	4 83	5 16	5.15	4.92	4 98	5 89	5.37	27.48	18.95	35.13
09-DecSCH44	finisher	0 6	15	952	13 81	12 67	8 59	13 29	11.81	8 28	10.16	11 75	12.15	12.76	9 25	13.62	14.59	6.88	28.17	1.68	35.13
2003-09-19JP205	dry sow			1000	12.98	10.77	11.10	10 42	9 69	7.77	10 36	11 29	12.12	11.93	10.40	13 13	14.78	8 28	23.26	28.02	35.17
16-JanJH146	finisher	0.9	16	1024	13.71	11.64	7.47	8 84	7.26	5 03	9.40	11 86	12.76	12.04	9 32	14.34	15 33	5.34	27.44	28.83	35.12
16-JanSCH76	gestation	0 7	13	1024	16.13	14.25	8 64	13.13	11.14	7.76	11.47	13 87	14 60	14.66	10 37	16.67	17 56	6.64	27.19	29.67	35.12
2004-03-31SCH174	barrel	1	250	1024	5.66	4.30	8 33	3 95	5.08	7.40	5.70	5.06	5 29	5.42	5.19	5 22	5 99	6.12	27.22	24.18	35.14
2004-03-31SCH174	barrel	1	250	1024	5.66	4.30	8.33	3.95	5.08	7.40	5.70	5.06	5.29	5.42	5.19	5 22	5.99	6.12	27.22	24.18	35.14
2003-09-19JH106	dry sow			1051	9.66	8.04	7.49	7.53	6.79	4 86	7.59	8.53	9.20	9.12	7.83	10.19	11.38	5.44	21.61	32.33	35.19
05-NovJ67	biofilter	0.8	12	1051	15.61	13.74	11.01	13.58	12.22	8.82	12.16	13.32	13.94	14.68	10.81	15.18	16.38	8.26	28.36	4.24	35.13
06-NovJ67S	biofilter	0.5	12	1051	8.75	9.30	10 11	11.59	11.07	8 24	10.32	7.86	8 10	10.80	7.38	8 20	8.46	7.23	28.36	4.25	35.13
05-NovJP371	barrel	0.7	110	1072	37 20	33 27	34.75	43.91	44.47	37.27	35 29	31.91	33.42	39.95	27.36	35.69	38.15	27.27	24.20	10.98	35.16
06-NovJP731	barrel	0.7	110	1072	37.20	33 27	34.75	43.91	44.47	37.27	35 29	31.88	33.42	39.95	27.36	35.69	38.15	27.27	24.20	10.97	35.16
2003-08-15JP331	grower			1122	9.18	7.42	7.67	5.61	4.99	4.03	7.31	7.80	8.79	8.72	8 14	9 89	11.10	5.72	25.90	25.80	35.10
2003-08-15JP330	pregrower			1123	4.62	3 60	1.95	2 00	1.60	1.05	2.40	3.80	4 31	3.64	3 39	5 29	5 83	1.57	25.20	26.00	35.20

16-JanSCH92	gestation	0.7	10	1149	17.65	15.66	9.74	14.03	11.60	7.69	12.77	15.18	15.94	16.16	11.51	18.09	18.96	7.19	27.54	29.11	35.13
17-OctSCH18	biofilter	0.5	5	1160	12.30	11.08	7.32	10.27	8.87	5.92	8.83	10.50	10.87	11.02	8.11	11.92	12.82	5.02	23.61	29.42	35.14
09-Dec#34	gestation	0.4	14	1160	13.51	12.41	8.19	13.20	11.80	8.27	9.80	11.50	11.87	12.42	8.94	13.32	14.19	6.58	27.30	2.70	35.14
09-DecSCH72	finisher	0.7	17	1160	15.60	14.61	11.34	17.80	16.54	12.26	12.24	13.34	13.87	15.12	10.81	15.57	16.50	9.92	25.17	6.15	35.18
2003-08-08J21	dry sow			1260	9.04	6.94	6.55	5.07	4.41	3.62	6.54	7.60	8.58	7.87	7.57	9.50	10.80	4.35	25.50	48.10	35.20
2003-08-08JH183	farrowing			1260	10.60	8.06	9.97	6.61	5.80	4.82	9.27	9.14	10.50	10.50	10.20	11.20	12.70	6.71	23.30	56.80	35.20
2003-09-19JP217	grower			1281	13.33	11.23	11.04	10.37	9.48	7.42	10.56	11.49	12.39	12.24	10.64	13.51	15.13	7.75	24.85	23.43	35.16
16-JanCAO9	farrowing	0.8	7	1290	15.73	13.97	8.45	12.02	9.73	6.10	11.23	13.52	14.24	14.34	10.24	16.19	16.94	6.12	27.69	27.84	35.12
2003-09-19JP211	dry sow			1414	13.10	10.95	10.47	10.08	9.14	7.04	10.16	11.27	12.10	11.89	10.30	13.26	14.85	7.39	24.63	24.94	35.16
05-NovJP219	biofilter	0.5	11	1414	14.35	12.64	9.47	11.96	10.57	7.41	10.75	12.18	12.74	13.16	9.72	13.96	15.03	6.86	28.64	3.90	35.14
06-NovJP219E	biofilter	0.5	11	1414	7.37	7.79	8.47	9.65	9.14	6.77	8.73	6.65	6.84	9.14	6.29	7.00	7.19	5.91	28.63	3.91	35.14
06-NovJP219S	biofilter	0.5	11	1414	7.37	7.79	8.47	9.65	9.14	6.77	8.73	6.65	6.84	9.14	6.29	7.00	7.19	5.91	28.63	3.91	35.14
09-DecJP369	nursery	1	3	1414	7.48	6.90	3.41	7.04	6.10	3.76	5.00	6.44	6.64	6.77	4.70	7.67	8.12	2.71	23.34	9.26	35.17
09-DecSCH73	gestation	0.5	14	1414	13.50	12.36	8.17	12.64	11.13	7.62	9.76	11.44	11.81	12.32	8.91	13.31	14.23	6.40	28.43	1.14	35.15
16-JanSCH108	gestation	0.7	12	1448	17.34	15.12	9.53	12.86	10.54	6.89	12.24	14.94	15.79	15.56	11.43	17.99	19.04	7.02	27.77	29.27	35.12
2004-04-01SCH13	barrel	0.6	90	1448	5.34	4.55	8.16	4.88	5.32	6.12	5.69	4.71	5.03	5.66	5.02	5.18	5.92	6.21	27.21	19.62	35.13
2004-04-01SCH13	barrel	0.6	90	1448	5.34	4.55	8.16	4.88	5.32	6.12	5.69	4.71	5.03	5.66	5.02	5.18	5.92	6.21	27.21	19.62	35.13
2004-04-15SCH254	barrel	0.7	195	1448	5.05	3.82	8.34	4.63	5.52	7.45	5.60	4.58	4.80	5.13	4.79	4.37	5.33	5.88	26.51	23.11	35.15
2003-09-19J12	grower			1561	13.76	11.49	11.45	10.84	9.94	7.87	10.93	11.93	12.82	12.63	10.94	13.91	15.67	8.06	24.19	23.47	35.16
09-DecCAO2	farrowing	0.8	10	1561	10.50	9.66	5.80	10.13	8.94	6.02	7.31	8.90	9.21	9.42	6.77	10.36	11.12	4.51	26.38	4.20	35.17
09-DecJ90	gestation	0.5	15	1561	11.76	10.67	6.98	10.71	9.38	6.46	8.37	9.95	10.30	10.59	7.80	11.62	12.47	5.51	28.54	0.90	35.15
09-DecJH98	farrowing	0.7	10	1561	10.18	9.30	5.64	9.43	8.20	5.51	7.10	8.64	8.92	9.13	6.61	10.08	10.79	4.37	27.80	2.05	35.14
2003-08-08J51	dry sow			1587	8.42	6.53	5.61	4.49	3.82	3.02	5.01	7.03	7.96	7.19	6.90	8.90	10.20	3.70	25.60	47.30	35.10
16-JanSCH87	nursery	1.4	0	1625	9.98	8.51	3.32	5.99	4.12	1.46	5.70	8.57	9.14	8.13	5.96	10.69	11.42	1.94	27.82	29.40	35.12
2003-08-08JH171	farrowing			1782	9.92	7.69	7.69	5.71	4.95	4.02	7.59	8.36	9.51	8.97	8.60	10.30	11.80	5.16	25.20	49.10	35.10
2004-04-01JP304	barrel	0.9	250	1824	8.31	9.06	8.91	8.59	7.36	5.24	9.06	7.42	7.54	9.42	7.09	7.55	7.89	6.53	26.73	26.52	35.12
2004-04-01JP304	barrel	0.9	250	1824	8.31	9.06	8.91	8.59	7.36	5.24	9.06	7.42	7.54	9.42	7.09	7.55	7.89	6.53	26.73	26.52	35.12
28-NovJ25	barrel	0.4	159	1866	4.64	4.31	7.07	5.02	5.66	6.11	5.17	4.04	4.21	5.20	4.41	4.58	4.90	6.01	28.81	3.43	35.15
28-NovN121	barrel	1	95	1866	5.34	5.12	8.32	6.45	6.88	6.81	6.48	4.79	4.93	6.42	5.21	5.33	5.60	6.79	27.70	4.36	35.14
28-NovN33	barrel	0.6	69	2143	0.73	1.23	5.84	2.83	3.77	4.66	3.31	0.82	0.77	2.45	2.13	0.64	0.43	5.30	28.76	23.51	35.16
21-JanSCH45	finisher	0.9	30	2152	15.76	13.75	11.34	11.02	9.22	6.69	12.27	13.63	14.69	14.64	12.00	16.03	17.21	8.12	26.73	23.68	35.11
2004-04-01SCH244	barrel	0.9	185	2152	5.07	3.99	7.42	4.27	4.98	6.46	4.86	4.44	4.72	4.86	4.56	4.71	5.51	5.39	27.40	19.08	35.12
2004-04-01SCH244	barrel	0.9	185	2152	5.07	3.99	7.42	4.27	4.98	6.46	4.86	4.44	4.72	4.86	4.56	4.71	5.51	5.39	27.40	19.08	35.12
16-JanJ91	farrowing	0.3	4	2195	0.82	0.37	-1.11	0.15	-0.23	-0.67	-0.31	0.67	0.89	0.33	0.01	1.35	1.69	-1.19	25.40	38.20	35.12
2003-08-06JH96	PG compost vessel			2245	11.40	9.93	13.20	9.62	9.18	8.09	11.70	9.88	10.70	12.20	10.90	10.80	12.10	9.29	24.90	43.50	35.20

2004-04-15SCH145	barrel	1.6	166	2299	9.53	8.06	19.05	11.69	14.34	18.52	12.88	8.72	8.87	11.05	10.08	8.17	9.68	16.11	25.79	24.73	35.14
17-OctJH97	biofilter	0.7	26	2320	24.93	21.63	21.98	24.56	23.46	18.55	22.39	21.53	22.53	25.31	18.40	23.91	25.91	16.52	22.94	29.33	35.16
21-JanSCH118	farrowing	0.8	3	2376	11.76	10.06	6.90	7.45	5.80	3.34	8.26	10.09	10.87	10.44	8.35	12.11	13.12	4.80	26.73	26.52	35.12
28-NovJH154	barrel	2.4	100	2462	5.00	4.77	8.02	5.96	6.41	6.45	6.12	4.52	4.67	6.06	4.96	5.00	5.31	6.55	28.21	3.66	35.15
2004-04-15SCH163/193	barrel			2580	5.48	4.13	7.94	4.91	6.01	8.23	5.24	4.83	5.16	5.15	4.92	4.98	5.89	5.37	27.48	18.95	35.13
21-JanSCH116	weaner	1.3	4	2623	7.33	6.01	2.61	3.69	2.36	0.53	4.06	6.21	6.79	5.88	4.71	8.03	8.68	1.30	26.75	23.61	35.13
21-JanSCH123	farrowing	1	10	2623	13.27	11.51	7.50	9.19	7.16	4.27	9.58	11.45	12.31	12.17	9.25	13.73	14.67	5.11	25.02	26.10	35.14
21-JanSCH48	farrowing	0.9	10	2623	13.87	12.11	8.72	9.38	7.29	4.29	10.30	11.96	12.82	12.79	10.01	14.07	15.05	6.06	26.72	23.45	35.12
2004-04-01SCH148	barrel	1	250	2623	7.26	5.63	14.50	7.56	10.70	16.00	9.30	6.53	6.89	8.11	7.46	6.45	7.47	11.78	24.66	24.11	35.15
2004-04-01SCH148	barrel	1	250	2623	7.26	5.63	14.50	7.56	10.70	16.00	9.30	6.53	6.89	8.11	7.46	6.45	7.47	11.78	24.66	24.11	35.15
28-NovN120	barrel	3.7	250	2828	5.10	3.97	8.24	5.47	6.74	8.74	5.90	4.65	4.84	5.73	5.09	4.82	5.46	6.91	25.45	8.13	35.16
28-NovN68	barrel	2.2	250	2828	3.99	3.28	5.82	3.45	4.17	5.50	4.12	3.53	3.70	4.11	3.83	3.81	4.29	4.97	28.69	3.35	35.14
16-JanSCH94	nursery	1.3	0	2896	21.63	19.04	11.59	15.64	12.24	6.90	16.15	18.69	20.10	20.58	14.84	22.23	23.10	9.00	26.76	30.46	35.13
21-JanSCH124	weaner	1.4	4	2896	10.29	8.80	5.56	6.35	4.65	2.23	7.09	8.81	9.59	9.17	7.21	10.76	11.52	3.61	26.75	22.82	35.12
21-JanSCH114	weaner	1.3	6	3198	2.11	1.37	-1.96	-0.37	-1.16	-2.40	-0.48	1.64	1.94	0.76	0.54	2.89	3.00	-2.31	26.73	24.28	35.13
21-JanSCH119	grower	1.2	36	3198	17.27	14.96	11.78	12.10	9.97	7.03	13.20	14.94	15.96	15.95	12.74	17.41	18.73	8.35	26.68	23.87	35.11
21-JanSCH125	grower	1.4	34	3530	17.91	15.60	12.18	12.79	10.53	7.47	13.82	15.54	16.64	16.69	13.17	18.14	19.31	8.64	26.47	24.42	35.12
21-JanSCH34	gestation	1.1	13	3531	6.04	4.79	2.71	3.33	2.57	1.48	3.54	5.09	5.65	4.89	4.03	6.62	7.10	1.62	26.73	23.85	35.12
28-NovJH116	barrel	2.5	176	3732	7.58	7.02	15.24	11.91	14.37	16.14	11.16	7.15	7.39	10.24	7.97	7.35	7.85	13.14	23.15	12.21	35.19
21-JanSCH117	grower	1.2	35	3898	30.94	27.27	25.71	29.27	26.72	20.76	28.16	26.73	28.46	32.09	23.41	30.68	32.89	21.66	23.72	28.03	35.16
21-JanSCH121	gestation	1.2	18	4304	16.03	14.01	10.77	11.35	9.16	5.96	12.34	13.89	14.89	15.03	11.82	16.33	17.55	7.65	26.64	23.19	35.12
17-OctJ25	biofilter	2.2	22	4641	0.18	0.09	-0.21	-0.17	-0.23	-0.26	-0.12	0.19	0.20	0.03	-0.02	0.23	0.26	-0.25	21.10	34.12	35.16
05-NovSCH7	barrel	3.5	80	4925	27.04	23.79	21.51	25.90	24.03	18.81	22.79	23.06	24.25	26.76	19.33	25.94	28.01	15.33	26.60	6.81	35.14
28-NovN61	barrel	2.8	109	4925	4.47	4.12	6.82	5.24	5.54	5.44	5.33	4.06	4.20	5.34	4.42	4.56	4.80	5.59	26.60	6.00	35.16
28-NovJP300 -- outlier	barrel	1.4	192	11313	5.02	4.64	8.03	5.56	6.30	7.03	5.80	4.48	4.65	5.74	4.87	4.98	5.38	6.77	28.54	3.57	35.14
2004-04-15GRANT2 -- outlier	barrel	6	250	813	5.97	4.43	8.31	4.61	6.00	8.36	5.83	5.26	5.42	5.43	5.23	4.98	6.07	5.63	26.17	25.08	35.14
06-NovJP264 - outlier	barrel	8.3	180	5040	28.61	24.41	24.23	25.24	23.72	19.99	24.17	24.69	25.90	27.66	21.28	27.33	29.93	17.50	28.82	3.21	35.13

APPENDIX B – Principal Component Analysis Of Electronic Nose Data

Table 11B: Eigenvalues of Correlation Matrix for Electronic Nose Sensor Data

	Eigenvalue	Difference	Proportion	Cumulative
1	29.94	28.33	0.94	0.936
2	1.60	1.29	0.05	0.986
3	0.31	0.24	0.01	0.996
4	0.08	0.06	0.00	0.998
5	0.02	0.00	0.00	0.999
6	0.02	0.01	0.00	0.999
7	0.01	0.01	0.00	1.000
8	5.57E-03	2.19E-03	2.00E-04	1.000
9	3.38E-03	1.75E-03	1.00E-04	1.000
10	1.63E-03	3.86E-04	1.00E-04	1.000
11	1.24E-03	4.04E-04	0.00E+00	1.000
12	8.40E-04	2.46E-04	0.00E+00	1.000
13	5.94E-04	9.97E-05	0.00E+00	1.000
14	4.94E-04	1.74E-04	0.00E+00	1.000
15	3.20E-04	9.19E-05	0.00E+00	1.000
16	2.28E-04	4.17E-05	0.00E+00	1.000
17	1.86E-04	2.61E-05	0.00E+00	1.000
18	1.60E-04	8.48E-05	0.00E+00	1.000
19	7.54E-05	1.30E-05	0.00E+00	1.000
20	6.25E-05	1.13E-05	0.00E+00	1.000
21	5.12E-05	1.05E-05	0.00E+00	1.000
22	4.07E-05	1.69E-05	0.00E+00	1.000
23	2.38E-05	4.20E-06	0.00E+00	1.000
24	1.97E-05	3.10E-06	0.00E+00	1.000
25	1.65E-05	4.40E-06	0.00E+00	1.000
26	1.22E-05	2.20E-06	0.00E+00	1.000
27	1.00E-05	2.50E-06	0.00E+00	1.000
28	7.50E-06	3.40E-06	0.00E+00	1.000
29	4.10E-06	1.10E-06	0.00E+00	1.000
30	2.90E-06	8.00E-07	0.00E+00	1.000
31	2.10E-06	9.00E-07	0.00E+00	1.000
32	1.20E-06		0.00E+00	1.000

Table 12B: Eigenvectors of Sensor Data

Sensor #	Principal Component 1	Principal Component 2	Principal Component 3
sensor 1	0.1806	-0.11	-0.061
sensor 2	0.1773	-0.175	0.1645
sensor 3	0.1778	-0.175	0.0155
sensor 4	0.1785	-0.16	0.0049
sensor 5	0.1814	-0.013	-0.204
sensor 6	0.1779	0.1509	-0.214
sensor 7	0.1808	-0.111	-0.08
sensor 8	0.1819	-0.069	-0.097
sensor 9	0.1816	-0.068	0.0957
sensor 10	0.1815	-0.074	0.0882
sensor 11	0.1824	0.0172	-0.087
sensor 12	0.1825	0.0062	-0.065
sensor 13	0.1824	-0.048	-0.026
sensor 14	0.181	-0.108	-0.068
sensor 15	0.1555	0.3982	-0.168
sensor 16	0.1592	0.3719	-0.156
sensor 17	0.181	-0.06	0.1976
sensor 18	0.1761	-0.037	0.4443
sensor 19	0.1801	-0.131	-0.04
sensor 20	0.1796	-0.134	0.0808
sensor 21	0.1671	0.3072	-0.154
sensor 22	0.1781	0.0519	0.3717
sensor 23	0.1721	0.1854	0.4092
sensor 24	0.1488	0.4061	0.3
sensor 25	0.1817	0.0816	-0.026
sensor 26	0.1807	-0.115	-0.052
sensor 27	0.18	-0.125	-0.109
sensor 28	0.1827	-0.035	0.0179
sensor 29	0.1807	-0.008	-0.259
sensor 30	0.1777	-0.172	-0.089
sensor 31	0.1778	-0.159	-0.142
sensor 32	0.1643	0.3343	-0.064
Relative Humidity	-0.01765	-0.192535	0.902323

Table 13B: Input Data for ANN of Electronic Nose Data

date olfact bag number	olfact OU	PC1	PC2	PC3
2003-07-30 JH141	126	52.87652	-13.2442	35.28366
28-Nov JP251	203	13.12174	0.356435	3.234423
2004-04-21 CH5-2	221	28.12061	-13.2468	29.60439
2004-04-21 CH5-2	221	11.06578	-7.74837	28.87139
2004-04-21 CH9	221	27.94773	-10.0895	23.51035
06-Nov CO#2	315	44.3576	-8.67238	2.695148
06-Nov CO#2	315	44.3576	-8.67238	2.695148
2004-04-15 SCH87	323	28.10813	1.155568	23.27456
2004-04-21 CH7	328	25.56399	-8.85291	24.7013
2003-08-22 JP333	354	35.0873	-13.4033	36.45768
2004-04-01 SCH142	406	30.77015	3.186326	23.53653
2004-04-01 SCH142	406	30.77015	3.186326	23.53653
2004-03-31 SCH110	416	34.05704	3.003127	24.12866
2004-03-31 SCH110	416	34.05704	3.003127	24.12866
2004-03-31 SCH251	512	92.11801	-6.59644	34.22277
2004-03-31 SCH251	512	92.11801	-6.59644	34.22277
2004-03-31 SCH94	512	44.79162	2.624557	28.15612
2004-03-31 SCH94	512	44.79162	2.624557	28.15612
2003-08-06 JH175	561	40.90232	-12.9762	36.493
2003-08-08 J27	562	45.30391	-14.529	44.17366
16-Jan M130	575	46.28452	-17.4315	23.87693
2004-03-31 SCH165	575	130.4998	-7.68754	27.30497
2004-03-31 SCH165	575	130.4998	-7.68754	27.30497
2004-03-31 SCH250	575	40.24477	1.577721	31.66983
2004-03-31 SCH250	575	40.24477	1.577721	31.66983
2003-08-08 JH182	630	41.14988	-14.7008	41.01911
2003-08-06 J14	630	43.87194	-11.646	35.55459
2004-04-15 TD7	645	25.73995	0.333856	22.53682
05-Nov J71	707	33.92065	-9.29108	2.78137
06-Nov JP262	707	101.7587	-9.53327	1.57591
2003-08-08 JH184	707	43.7543	-14.4452	43.31817
2003-08-22 JP244	707	51.51802	-11.4428	40.8023
2004-04-01 J91	724	34.05982	5.452475	21.87706
2004-04-01 J91	724	34.05982	5.452475	21.87706
2003-08-08 JH147	794	22.29269	-16.2723	47.51026
2003-08-22 JP205	794	15.05744	-9.09044	37.85636
28-Nov SCH15	813	50.45144	10.79117	6.452685
2004-04-15 GRANT2	813	30.46091	1.437107	25.22195
16-Jan SCH96	832	56.59143	-15.8093	26.25652
2003-08-15 JP316	891	50.88708	-11.0505	31.64817
16-Jan SCH93	912	46.44133	-17.0599	25.54827
2004-03-31 SCH256	912	46.50376	4.494268	34.71865
2004-03-31 SCH256	912	46.50376	4.494268	34.71865
2004-04-01 SCH151	912	30.61103	2.33862	19.83375
2004-04-01 SCH151	912	30.61103	2.33862	19.83375

2004-04-01 SCH163	912	28.86228	2.335684	19.3026
2004-04-01 SCH163	912	28.86228	2.335684	19.3026
09-Dec SCH44	952	65.06569	-8.29522	-1.29179
2003-09-19 JP205	1000	62.95899	-10.0734	25.95483
16-Jan JH146	1024	59.58235	-17.7581	25.10862
16-Jan SCH76	1024	72.91825	-19.3091	23.74834
2004-03-31 SCH174	1024	29.53896	1.07536	24.62649
2004-03-31 SCH174	1024	29.53896	1.07536	24.62649
2003-09-19 JH106	1051	46.39123	-12.0798	29.20469
05-Nov J67	1051	73.86058	-8.97671	2.038616
06-Nov J67S	1051	52.13444	0.836863	2.287592
05-Nov JP371	1072	197.1363	-0.91258	4.287801
06-Nov JP731	1072	197.1094	-0.90232	4.276742
2003-08-15 JP331	1122	43.06293	-9.74801	24.86989
2003-08-15 JP330	1123	18.3539	-10.6588	23.56337
16-Jan SCH92	1149	79.75216	-20.4746	23.25336
17-Oct SCH18	1160	55.65774	-14.7498	24.36028
09-Dec #34	1160	63.45733	-8.4604	-0.5445
09-Dec SCH72	1160	77.59166	-6.38762	2.061138
2003-08-08 J21	1260	39.1985	-14.7934	44.83711
2003-08-08 JH183	1260	50.12143	-14.5651	53.97386
2003-09-19 JP217	1281	63.91298	-10.1117	21.74427
16-Jan CAO9	1290	70.38819	-19.4361	22.5348
2003-09-19 JP211	1414	62.09228	-10.9122	22.93503
05-Nov JP219	1414	66.54788	-9.56261	1.710733
06-Nov JP219E	1414	43.969	0.37032	2.236713
06-Nov JP219S	1414	43.969	0.37032	2.236713
09-Dec JP369	1414	34.04217	-8.64848	6.012679
09-Dec SCH73	1414	62.91878	-8.60367	-1.74076
16-Jan SCH108	1448	77.40223	-20.744	24.05912
2004-04-01 SCH13	1448	29.07593	1.951143	20.04615
2004-04-01 SCH13	1448	29.07593	1.951143	20.04615
2004-04-15 SCH254	1448	27.91768	2.85456	23.51709
2003-09-19 J12	1561	66.20601	-10.1728	21.77477
09-Dec CAO2	1561	48.41564	-8.01478	1.167576
09-Dec J90	1561	54.31538	-7.69401	-1.42586
09-Dec JH98	1561	46.71206	-7.55275	-0.43734
2003-08-08 J51	1587	35.69877	-15.1715	43.84172
16-Jan SCH87	1625	40.44463	-18.9543	24.62724
2003-08-08 JH171	1782	44.00047	-14.9222	46.08885
2004-04-01 JP304	1824	45.39587	-5.37841	23.5746
2004-04-01 JP304	1824	45.39587	-5.37841	23.5746
28-Nov J25	1866	27.42338	4.530496	4.557759
28-Nov N121	1866	32.90152	5.047336	5.25214
28-Nov N33	2143	12.37859	4.724612	23.09631
21-Jan SCH45	2152	72.30623	-13.7944	21.68885
2004-04-01 SCH244	2152	26.29091	1.667667	19.4596
2004-04-01 SCH244	2152	26.29091	1.667667	19.4596

16-Jan J91	2195	0.865946	-11.3106	33.67107
2003-08-06 JH96	2245	59.54667	-6.48738	41.9386
2004-04-15 SCH145	2299	61.60336	16.76618	27.8132
17-Oct JH97	2320	125.6576	-11.0235	24.34669
21-Jan SCH118	2376	50.93023	-15.0601	23.63502
28-Nov JH154	2462	31.11431	5.080009	4.697299
2004-04-15 SCH163/193	2580	28.86228	2.335684	19.3026
21-Jan SCH116	2623	28.68759	-14.1973	20.64593
21-Jan SCH123	2623	58.74938	-16.869	22.38845
21-Jan SCH48	2623	61.71687	-15.3271	20.69119
2004-04-01 SCH148	2623	45.32101	12.25766	26.58499
2004-04-01 SCH148	2623	45.32101	12.25766	26.58499
28-Nov N120	2828	30.77976	5.709599	9.479843
28-Nov N68	2828	22.44978	3.462103	4.681343
16-Jan SCH94	2896	96.6013	-25.7366	24.70513
21-Jan SCH124	2896	44.07905	-14.357	20.05895
21-Jan SCH114	3198	2.975107	-12.7944	20.86436
21-Jan SCH119	3198	78.54676	-15.8636	21.34291
21-Jan SCH125	3530	81.94867	-16.4922	21.63209
21-Jan SCH34	3531	24.26549	-11.0881	21.24341
28-Nov JH116	3732	53.67958	14.41701	13.64737
21-Jan SCH117	3898	154.554	-13.6534	23.68839
21-Jan SCH121	4304	73.06439	-15.6511	20.52644
17-Oct J25	4641	-0.42279	-7.46987	30.70953
05-Nov SCH7	4925	132.7813	-10.534	3.193932
28-Nov N61	4925	27.35835	3.309521	6.566942

APPENDIX C – Principal Component Analysis Of Electronic Nose, Ammonia And Hydrogen Sulphide Data

Table 14C: Eigenvalues of Correlation Matrix for Electronic Nose and Gas Meter Data

	Eigenvalue	Difference	Proportion	Cumulative
1	30.08	27.77	0.88	0.885
2	2.31	1.35	0.07	0.953
3	0.95	0.58	0.03	0.981
4	0.37	0.20	0.01	0.992
5	0.18	0.11	0.01	0.997
6	7.09E-02	5.65E-02	2.10E-03	0.999
7	1.44E-02	5.74E-03	4.00E-04	0.999
8	8.64E-03	3.69E-03	3.00E-04	1.000
9	4.94E-03	1.96E-03	1.00E-04	1.000
10	2.99E-03	7.79E-04	1.00E-04	1.000
11	2.21E-03	9.17E-04	1.00E-04	1.000
12	1.29E-03	5.42E-04	0.00E+00	1.000
13	7.48E-04	1.10E-04	0.00E+00	1.000
14	6.38E-04	2.60E-04	0.00E+00	1.000
15	3.79E-04	6.48E-05	0.00E+00	1.000
16	3.14E-04	7.91E-05	0.00E+00	1.000
17	2.35E-04	1.28E-04	0.00E+00	1.000
18	1.07E-04	3.79E-05	0.00E+00	1.000
19	6.88E-05	1.32E-05	0.00E+00	1.000
20	5.56E-05	1.41E-05	0.00E+00	1.000
21	4.15E-05	1.53E-05	0.00E+00	1.000
22	2.62E-05	3.20E-06	0.00E+00	1.000
23	2.30E-05	7.30E-06	0.00E+00	1.000
24	1.57E-05	4.70E-06	0.00E+00	1.000
25	1.10E-05	1.20E-06	0.00E+00	1.000
26	9.80E-06	2.20E-06	0.00E+00	1.000
27	7.70E-06	4.00E-07	0.00E+00	1.000
28	7.20E-06	3.80E-06	0.00E+00	1.000
29	3.40E-06	1.00E-07	0.00E+00	1.000
30	3.30E-06	1.10E-06	0.00E+00	1.000
31	2.20E-06	7.00E-07	0.00E+00	1.000
32	1.50E-06	6.00E-07	0.00E+00	1.000
33	9.00E-07	2.00E-07	0.00E+00	1.000
34	7.00E-07		0.00E+00	1.000

Table 15C: Eigenvectors of Sensor and Gas Meter Data

Sensor #	Principal Component 1	Principal Component 2	Principal Component 3
H2S	0.0061	0.1457	-0.107
NH3	-0.014	0.554	0.1447
sensor 1	0.1817	-0.084	0.0147
sensor 2	0.1775	-0.151	0.0012
sensor 3	0.1781	-0.138	0.0518
sensor 4	0.1788	-0.124	0.0598
sensor 5	0.183	0.0075	0.0395
sensor 6	0.1779	0.1448	0.0244
sensor 7	0.1815	-0.078	0.044
sensor 8	0.1827	-0.045	0.0317
sensor 9	0.1824	-0.062	-0.011
sensor 10	0.1823	-0.065	-0.007
sensor 11	0.1829	0.0213	0.0118
sensor 12	0.1831	0.0097	0.0076
sensor 13	0.183	-0.035	0.0134
sensor 14	0.1817	-0.075	0.0418
sensor 15	0.1505	0.3342	-0.044
sensor 16	0.1551	0.31	-0.045
sensor 17	0.1816	-0.068	-0.053
sensor 18	0.1773	-0.078	-0.141
sensor 19	0.1807	-0.094	0.0521
sensor 20	0.1804	-0.109	0.0086
sensor 21	0.1645	0.2626	-0.029
sensor 22	0.179	0.0028	-0.137
sensor 23	0.172	0.1209	-0.145
sensor 24	0.1406	0.3343	-0.074
sensor 25	0.1822	0.0652	-0.007
sensor 26	0.1812	-0.08	0.0585
sensor 27	0.1807	-0.085	0.0711
sensor 28	0.1833	-0.032	0.0031
sensor 29	0.1824	0.016	0.0559
sensor 30	0.1784	-0.125	0.0731
sensor 31	0.1789	-0.112	0.0767
sensor 32	0.1613	0.2761	-0.048
Relative Humidity	-0.006	0.0716	0.9235

Table 16C: Input Data for ANN Using PCA of Gas Meters and Electronic Nose Data

date olfact / bag number	olfact OU	PC1	PC2	PC3	PC4	PC5
28-Nov JP251	203	13.16557	1.172014	2.891401	0.068443	-2.17011
2004-04-21 CH5-2	221	11.43436	1.213248	29.96796	2.285654	-9.8898
2004-04-21 CH5-2	221	28.50776	-2.79346	32.58809	3.152144	-8.14006
2004-04-21 CH9	221	28.21725	-0.19771	26.25673	2.390707	-5.35227
06-Nov CO#2	315	44.34579	-3.00775	6.382912	1.712838	3.916363
06-Nov CO#2	315	44.34579	-3.00775	6.382912	1.712838	3.916363
2004-04-15 SCH87	323	24.97593	145.4099	57.38603	2.972399	130.4931
2004-04-21 CH7	328	25.81943	2.143618	27.24149	2.156116	-5.37275
2004-04-01 SCH142	406	27.62839	147.1192	56.72483	2.831715	130.4789
2004-04-01 SCH142	406	27.62839	147.1192	56.72483	2.831715	130.4789
2004-03-31 SCH110	416	32.82436	69.54601	37.10189	1.243026	52.00923
2004-03-31 SCH110	416	32.82436	69.54601	37.10189	1.243026	52.00923
2004-03-31 SCH251	512	89.11868	142.7222	70.07607	5.554542	129.3971
2004-03-31 SCH251	512	89.11868	142.7222	70.07607	5.554542	129.3971
2004-03-31 SCH94	512	42.40926	119.1119	53.64787	2.555558	100.1125
2004-03-31 SCH94	512	42.40926	119.1119	53.64787	2.555558	100.1125
16-Jan M130	575	46.46259	-1.24729	30.41406	3.969421	1.795899
2004-03-31 SCH165	575	127.4196	140.1969	63.73531	4.505963	133.7504
2004-03-31 SCH165	575	127.4196	140.1969	63.73531	4.505963	133.7504
2004-03-31 SCH250	575	37.201	147.9737	64.94484	3.41114	127.5769
2004-03-31 SCH250	575	37.201	147.9737	64.94484	3.41114	127.5769
2004-04-15 TD7	645	22.60375	144.6008	56.99535	3.335645	130.9593
05-Nov J71	707	33.8926	-2.41327	7.143423	2.055885	4.482103
06-Nov JP262	707	100.9233	29.75279	14.12087	2.725743	37.20933
2004-04-01 J91	724	30.89569	148.4778	54.4114	2.165226	129.7252
2004-04-01 J91	724	30.89569	148.4778	54.4114	2.165226	129.7252
28-Nov SCH15	813	48.64318	85.70593	21.4817	-0.76179	69.45472
2004-04-15 GRANT2	813	27.38292	146.9558	58.4856	8.416832	129.0986
16-Jan SCH96	832	56.87627	-2.63366	31.16583	3.6905	-3.73362
16-Jan SCH93	912	46.6956	-2.71967	31.27257	4.141953	-1.61906
2004-03-31 SCH256	912	43.53555	150.9828	67.80595	1.960408	116.8671
2004-03-31 SCH256	912	43.53555	150.9828	67.80595	1.960408	116.8671
2004-04-01 SCH151	912	27.43602	145.5152	53.75055	2.6581	131.0264
2004-04-01 SCH151	912	27.43602	145.5152	53.75055	2.6581	131.0264
2004-04-01 SCH163	912	25.68216	145.3787	53.23569	2.758537	131.2517
2004-04-01 SCH163	912	25.68216	145.3787	53.23569	2.758537	131.2517
09-Dec SCH44	952	64.89827	1.97739	4.360263	1.570494	6.894845
16-Jan JH146	1024	59.71056	1.746101	32.33615	4.586023	3.833249
16-Jan SCH76	1024	73.101	-1.47042	31.7468	4.193839	-0.82112
2004-03-31 SCH174	1024	26.41858	145.7951	58.50965	3.678065	130.7096
2004-03-31 SCH174	1024	26.41858	145.7951	58.50965	3.678065	130.7096
05-Nov J67	1051	73.76143	0.717315	7.016237	2.025655	5.799143
06-Nov J67S	1051	52.02505	8.172091	3.840868	-0.34875	1.305831
05-Nov JP371	1072	195.7957	62.42121	21.64679	-0.88596	41.41509
06-Nov JP731	1072	195.7687	62.42605	21.63408	-0.88877	41.40767

16-Jan SCH92	1149	79.96899	-4.11918	31.20263	4.386712	-1.38657
17-Oct SCH18	1160	55.94074	-2.33469	29.34361	3.145083	-5.81537
09-Dec #34	1160	63.31465	1.434783	5.0622	1.382296	5.707568
09-Dec SCH72	1160	77.45098	5.451192	7.374698	0.974635	2.86838
16-Jan CAO9	1290	70.63003	-5.18428	29.59863	4.374658	-2.16754
05-Nov JP219E	1414	66.45676	-0.45793	6.802923	1.924457	6.058005
06-Nov JP219S	1414	43.86902	7.206473	3.750525	-0.12395	1.733657
06-Nov JP219S	1414	43.86902	7.206473	3.750525	-0.12395	1.733657
09-Dec JP369	1414	34.1246	-3.27685	9.555745	2.295202	-1.64432
09-Dec SCH73	1414	62.75798	1.047883	3.894064	1.56454	6.984078
16-Jan SCH108	1448	77.59264	-3.01197	32.17306	4.622843	0.80317
2004-04-01 SCH13	1448	28.07392	56.62125	30.79516	1.30273	42.50804
2004-04-01 SCH13	1448	28.07392	56.62125	30.79516	1.30273	42.50804
2004-04-15 SCH254	1448	25.5296	116.3689	48.93358	2.371479	99.38243
09-Dec CAO2	1561	48.34512	-0.03984	5.83374	1.835654	3.461795
09-Dec J90	1561	54.13638	2.348332	3.898718	1.540738	8.060042
09-Dec JH98	1561	46.61521	-0.09024	4.073143	1.70878	4.739243
16-Jan SCH87	1625	40.8014	-8.24576	30.18443	5.177849	-5.41189
2004-04-01 JP304	1824	42.30736	140.4733	60.28147	4.377585	130.5426
2004-04-01 JP304	1824	42.30736	140.4733	60.28147	4.377585	130.5426
28-Nov J25	1866	25.3005	92.98143	25.39489	1.03667	85.5523
28-Nov N121	1866	31.6614	58.20453	16.56329	0.752377	48.80438
28-Nov N33	2143	11.70326	47.74214	29.80368	0.486396	27.17579
21-Jan SCH45	2152	72.18106	11.84247	29.3261	3.910944	13.47436
2004-04-01 SCH244	2152	23.99612	108.9231	44.11245	2.664691	95.6886
2004-04-01 SCH244	2152	23.99612	108.9231	44.11245	2.664691	95.6886
16-Jan J91	2195	1.255108	1.729103	36.64658	2.903322	-9.51759
2004-04-15 SCH145	2299	59.61928	112.5558	43.3911	-0.1013	76.18694
17-Oct JH97	2320	125.6557	12.63155	30.99156	2.045787	1.262498
21-Jan SCH118	2376	51.20479	-3.78611	27.91634	3.907794	-2.55732
28-Nov JH154	2462	29.80671	61.06042	16.57602	2.195617	51.91311
21-Jan SCH116	2623	28.91953	-3.3675	25.00242	4.321787	-1.38286
21-Jan SCH123	2623	58.92811	-1.56605	28.56637	4.36827	1.20154
21-Jan SCH48	2623	61.86188	-0.76536	26.22648	4.016065	2.635617
2004-04-01 SCH148	2623	42.19092	155.1103	56.2394	1.266161	125.2022
2004-04-01 SCH148	2623	42.19092	155.1103	56.2394	1.266161	125.2022
28-Nov N120	2828	27.49407	146.051	42.39039	5.042677	133.4912
28-Nov N68	2828	19.10219	142.846	38.82574	4.088866	137.1669
16-Jan SCH94	2896	96.9739	-13.192	32.7023	6.022576	-4.09858
21-Jan SCH124	2896	44.30156	-3.52778	24.41495	4.351026	-0.89684
21-Jan SCH114	3198	3.187557	-1.29047	25.15839	4.163134	-1.43404
21-Jan SCH119	3198	78.34595	13.54518	30.68449	4.607539	17.11157
21-Jan SCH125	3530	81.78305	12.06406	30.9195	4.862437	15.74077
21-Jan SCH34	3531	24.37476	4.129491	25.7616	3.590268	2.058021
28-Nov JH116	3732	51.43156	112.7836	32.74095	0.915772	84.70005
21-Jan SCH117	3898	154.4168	15.67164	32.36506	3.110481	8.51108
21-Jan SCH121	4304	73.10015	3.492099	27.27522	4.379286	7.128113
17-Oct J25	4641	-0.31741	14.23605	34.71866	4.186531	1.138655

05-Nov SCH7	4925	131.8102	38.18773	18.4551	4.982737	39.80615
28-Nov N61	4925	25.95917	65.16138	20.2723	3.089559	56.67246

Table 17C: ANN Input Data for Using Gas Measurements and PCA of Electronic Nose Data

date olfact / bag number	olfact OU	H2S	NH3	PC1	PC2	PC3
28-Nov JP251	203	0.3	0	13.12174	0.356435	3.234423
2004-04-21 CH5-2	221	0.5	0	11.06578	-7.74837	28.87139
2004-04-21 CH5-2	221	0.3	0	28.12061	-13.2468	29.60439
2004-04-21 CH9	221	0.3	3	27.94773	-10.0895	23.51035
06-Nov CO#2	315	0.2	5	44.3576	-8.67238	2.695148
06-Nov CO#2	315	0.2	5	44.3576	-8.67238	2.695148
2004-04-15 SCH87	323	0.4	250	28.10813	1.155568	23.27456
2004-04-21 CH7	328	0.3	5	25.56399	-8.85291	24.7013
2004-04-01 SCH142	406	0.6	250	30.77015	3.186326	23.53653
2004-04-01 SCH142	406	0.6	250	30.77015	3.186326	23.53653
2004-03-31 SCH110	416	0.5	110	34.05704	3.003127	24.12866
2004-03-31 SCH110	416	0.5	110	34.05704	3.003127	24.12866
2004-03-31 SCH251	512	1.5	250	92.11801	-6.59644	34.22277
2004-03-31 SCH251	512	1.5	250	92.11801	-6.59644	34.22277
2004-03-31 SCH94	512	0.8	198	44.79162	2.624557	28.15612
2004-03-31 SCH94	512	0.8	198	44.79162	2.624557	28.15612
16-Jan M130	575	0.3	11	46.28452	-17.4315	23.87693
2004-03-31 SCH165	575	0.7	250	130.4998	-7.68754	27.30497
2004-03-31 SCH165	575	0.7	250	130.4998	-7.68754	27.30497
2004-03-31 SCH250	575	0.8	250	40.24477	1.577721	31.66983
2004-03-31 SCH250	575	0.8	250	40.24477	1.577721	31.66983
2004-04-15 TD7	645	0.6	250	25.73995	0.333856	22.53682
05-Nov J71	707	0.4	7	33.92065	-9.29108	2.78137
06-Nov JP262	707	0.9	65	101.7587	-9.53327	1.57591
2004-04-01 J91	724	0.5	250	34.05982	5.452475	21.87706
2004-04-01 J91	724	0.5	250	34.05982	5.452475	21.87706
28-Nov SCH15	813	0.3	136	50.45144	10.79117	6.452685
2004-04-15 GRANT2	813	6	250	30.46091	1.437107	25.22195
16-Jan SCH96	832	0.5	5	56.59143	-15.8093	26.25652

16-Jan SCH93	912	0.6	7	46.44133	-17.0599	25.54827
2004-03-31 SCH256	912	0.6	250	46.50376	4.494268	34.71865
2004-03-31 SCH256	912	0.6	250	46.50376	4.494268	34.71865
2004-04-01 SCH151	912	0.4	250	30.61103	2.33862	19.83375
2004-04-01 SCH151	912	0.4	250	30.61103	2.33862	19.83375
2004-04-01 SCH163	912	0.5	250	28.86228	2.335684	19.3026
2004-04-01 SCH163	912	0.5	250	28.86228	2.335684	19.3026
09-Dec SCH44	952	0.6	15	65.06569	-8.29522	-1.29179
16-Jan JH146	1024	0.9	16	59.58235	-17.7581	25.10862
16-Jan SCH76	1024	0.7	13	72.91825	-19.3091	23.74834
2004-03-31 SCH174	1024	1	250	29.53896	1.07536	24.62649
2004-03-31 SCH174	1024	1	250	29.53896	1.07536	24.62649
05-Nov J67	1051	0.8	12	73.86058	-8.97671	2.038616
06-Nov J67S	1051	0.5	12	52.13444	0.836863	2.287592
05-Nov JP371	1072	0.7	110	197.1363	-0.91258	4.287801
06-Nov JP731	1072	0.7	110	197.1094	-0.90232	4.276742
16-Jan SCH92	1149	0.7	10	79.75216	-20.4746	23.25336
17-Oct SCH18	1160	0.5	5	55.65774	-14.7498	24.36028
09-Dec #34	1160	0.4	14	63.45733	-8.4604	-0.5445
09-Dec SCH72	1160	0.7	17	77.59166	-6.38762	2.061138
16-Jan CAO9	1290	0.8	7	70.38819	-19.4361	22.5348
05-Nov JP219E	1414	0.5	11	66.54788	-9.56261	1.710733
06-Nov JP219S	1414	0.5	11	43.969	0.37032	2.236713
06-Nov JP219S	1414	0.5	11	43.969	0.37032	2.236713
09-Dec JP369	1414	1	3	34.04217	-8.64848	6.012679
09-Dec SCH73	1414	0.5	14	62.91878	-8.60367	-1.74076
16-Jan SCH108	1448	0.7	12	77.40223	-20.744	24.05912
2004-04-01 SCH13	1448	0.6	90	29.07593	1.951143	20.04615
2004-04-01 SCH13	1448	0.6	90	29.07593	1.951143	20.04615
2004-04-15 SCH254	1448	0.7	195	27.91768	2.85456	23.51709
09-Dec CAO2	1561	0.8	10	48.41564	-8.01478	1.167576
09-Dec J90	1561	0.5	15	54.31538	-7.69401	-1.42586
09-Dec JH98	1561	0.7	10	46.71206	-7.55275	-0.43734
16-Jan SCH87	1625	1.4	0	40.44463	-18.9543	24.62724
2004-04-01 JP304	1824	0.9	250	45.39587	-5.37841	23.5746
2004-04-01 JP304	1824	0.9	250	45.39587	-5.37841	23.5746
28-Nov J25	1866	0.4	159	27.42338	4.530496	4.557759
28-Nov N121	1866	1	95	32.90152	5.047336	5.25214

28-Nov N33	2143	0.6	69	12.37859	4.724612	23.09631
21-Jan SCH45	2152	0.9	30	72.30623	-13.7944	21.68885
2004-04-01 SCH244	2152	0.9	185	26.29091	1.667667	19.4596
2004-04-01 SCH244	2152	0.9	185	26.29091	1.667667	19.4596
16-Jan J91	2195	0.3	4	0.865946	-11.3106	33.67107
2004-04-15 SCH145	2299	1.6	166	61.60336	16.76618	27.8132
17-Oct JH97	2320	0.7	26	125.6576	-11.0235	24.34669
21-Jan SCH118	2376	0.8	3	50.93023	-15.0601	23.63502
28-Nov JH154	2462	2.4	100	31.11431	5.080009	4.697299
21-Jan SCH116	2623	1.3	4	28.68759	-14.1973	20.64593
21-Jan SCH123	2623	1	10	58.74938	-16.869	22.38845
21-Jan SCH48	2623	0.9	10	61.71687	-15.3271	20.69119
2004-04-01 SCH148	2623	1	250	45.32101	12.25766	26.58499
2004-04-01 SCH148	2623	1	250	45.32101	12.25766	26.58499
28-Nov N120	2828	3.7	250	30.77976	5.709599	9.479843
28-Nov N68	2828	2.2	250	22.44978	3.462103	4.681343
16-Jan SCH94	2896	1.3	0	96.6013	-25.7366	24.70513
21-Jan SCH124	2896	1.4	4	44.07905	-14.357	20.05895
21-Jan SCH114	3198	1.3	6	2.975107	-12.7944	20.86436
21-Jan SCH119	3198	1.2	36	78.54676	-15.8636	21.34291
21-Jan SCH125	3530	1.4	34	81.94867	-16.4922	21.63209
21-Jan SCH34	3531	1.1	13	24.26549	-11.0881	21.24341
28-Nov JH116	3732	2.5	176	53.67958	14.41701	13.64737
21-Jan SCH117	3898	1.2	35	154.554	-13.6534	23.68839
21-Jan SCH121	4304	1.2	18	73.06439	-15.6511	20.52644
17-Oct J25	4641	2.2	22	-0.42279	-7.46987	30.70953
05-Nov SCH7	4925	3.5	80	132.7813	-10.534	3.193932
28-Nov N61	4925	2.8	109	27.35835	3.309521	6.566942