Single-component Modelling of Pig Farm Odour with Statistical Methods and Neural Networks

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Pork farm odour has become an increasingly important problem for the pork industry because non-farming rural residents object to the odours coming from pig facilities and insist that it disrupts enjoyment of their properties. The pork industry has thus faced strong opposition to farm expansion or the creation of new pork farms. Reducing pork farm odour requires an understanding of what causes the odour and the ability to measure the odour. The pork industry and researchers have attempted to model pork farm odour using single-component odour indicators, such as ammonia and hydrogen sulphide, with statistical models. Single-component analysis refers to only one odour indicator being used to predict odour levels. In this paper, a neural network approach to the pork farm odour using single-component analysis with the consideration of other relevant factors, such as measurement location is proposed. Neural network models and statistical models for pork farm odour have been developed and compared for single-component models to determine which method produces superior results. In general, the use of neural networks to model the pork farm odour yields more accurate and precise odour intensity predictions than the statistical models. The measurement location for the pork farm odour was considered in several model comparisons. The neural network models significantly outperformed the statistical models in this comparison because the statistical models are not able to consider the measurement location. This indicates that measurement location is a relevant factor for modelling pork farm odour. This also demonstrates that factors other than odour components should be considered during modelling. It is hypothesised that a multiple-component (odour components) and multiple-factor (environmental conditions and other human expert knowledge) analysis approach to the modelling of pork farm odour using neural networks and other intelligent systems techniques will yield increased accuracy for odour prediction and a thorough understanding of this significant problem.

1. Introduction

The pork industry in Canada and many other developed countries has been experiencing significant public relations problems due to odourous emissions emanating from swine operations. These public relations issues are primarily with non-farming rural residents who are not familiar with modern agricultural practices and are not accepting of farm odours (Schiffman et al., 1995). Pork producers through the development and deployment of odour reducing technologies and methods are attempting to address this odour issue (Zhang et al., 2002a). Odour quantification is necessary to evaluate the effectiveness of odour reduction efforts. Odour quantification is very expensive and time-consuming because odour intensity is traditionally measured using olfactometry or gas chromatography (Gralapp et al., 2002). Odour intensity is the relative perceived psychological strength of an odour above its odour detection threshold. Odour intensity represents the increase in sensation intensity experienced by an individual as the chemical concentration increases. Researchers have investigated the possibility of identifying a major component in the pork farm odour that would serve as an indicator for the odour intensity (Barth et al., 1974; Guo et al., 2000; Williams, 1984). This would simplify pork farm odour measurement and reduce costs through the development of a convenient...
method for measuring the air-phase concentration of the indicator and then generating an odour intensity based on a developed algorithm. There are over 200 different air-phase components in pork farm odour (Schiffman et al., 2001). Hydrogen sulphide (H₂S) and ammonia (NH₃) are the two components that have drawn the most attention as possible odour indicators because they are easily measured and considered to be large contributors to the odour. Statistical models have been the primary tools used to predict odour intensities based on the air-phase concentration of an odour indicator (Guo et al., 2000).

Researchers have used the method of least squares extensively for the development of pork farm odour models, because it is simple to use and the experimental information is paired data sets (odour indicator concentration and corresponding odour intensity). A limitation of this model is that a linear relationship is forced on the system being modelled (Johnson, 1994). When the system being modelled exhibits non-linear behaviour, the accuracy of the linear least-squares model will be reduced. Previous research studies that have used the linear least-squares model for modelling the pork farm odour has consistently demonstrated that the linear model is inadequate for this application. Pork farm odour is a very complex system that has many different components that interact with each other (Zahn et al., 2000). Many of these components have low odour thresholds, making them easily detected by humans. There are many factors that are reported to affect odour intensity, including, but not limited to: temperature, relative humidity, odour source, season and time of day (Zhang et al., 2002a). Many of these factors are considered to be human expert knowledge of the pork farmers, which cannot be incorporated into a statistical model. Statistical single-component analysis of the pork farm odour has been shown to be insufficient for predicting pork farm odour intensities (Guo et al., 2000). Researchers have only considered the pork farm odour in one dimension because it is a simple approach. However, pork farm odour is very complex with many components, emission sources and other contributing factors. It is proposed that the consideration of factors that contribute to the pork farm odour, other than the odour components, will also improve the accuracy and precision of odour predictions. The odour source (pig building or pig manure storage) is the contributing factor considered in this paper. The odour source can be included in a neural network model, but not statistical models.

Neural networks are used for modelling complex systems that exhibit linear or non-linear behaviour (Jang et al., 1997). Neural networks are developed and trained for specific applications that require predictions to be performed. Neural networks are capable of automatically learning the relationship that exists between an odour indicator and odour intensity. Neural networks do not need any previous knowledge of the system being studied to determine the relationship that exists between the inputs and outputs (Zhang et al., 2002b).

It is proposed that single-component analysis of the problem using neural network modelling techniques will improve the accuracy and precision of odour intensity predictions when compared to non-linear statistical models. The neural network models of the odour will be compared against non-linear statistical models because the linear models of the odour have already
been proven to be insufficient, and the odour appears to be a non-linear system. The first objective of this paper is to demonstrate that intelligent systems modelling techniques, specifically neural networks, will provide better overall performance than statistical models for pork farm odour when considering single-component analysis (one odour indicator, such as ammonia). This will be achieved by comparing the performance of neural network models and non-linear statistical models using single-component analysis for NH$_3$ and H$_2$S. The second objective is to demonstrate that consideration of external factors, like season or odour source; in pork farm odour models will improve performance of the models and indicate which external factors are relevant to this complex system. This will be achieved by combining the pig building and pig manure storage data sets for H$_2$S and NH$_3$, so that the odour source can be included as a factor in neural network pork farm odour models.

2. Methods

Statistical models and neural network models have been developed to demonstrate the performance differences of these two methods for predicting pork farm odour intensity. This section discusses the data sets used for model development and testing, and the statistical tools used to compare the results. In addition, the specific models proposed in this paper are outlined.

2.1. Data sets

Researchers at the Department of Biosystems and Agricultural Engineering at the University of Minnesota provided the pork farm odour data used in this paper from the Farmstead Odour Database. Each data set has the air-phase concentration of a single indicator (NH$_3$ or H$_2$S) with an odour intensity generated by human assessors (olfactometry). The data sets include NH$_3$ and H$_2$S measurements from swine barn sources and swine manure storage sources. The odour samples were collected using a vacuum box and pump to draw the air into 10-L Tedlar bags. The odour dilution threshold was determined within 48 h of sampling using eight trained human panellists and a dynamic olfactometer. The odour dilution thresholds for all samples are reported in odour units (OU) (Guo et al., 2000). The H$_2$S concentration in parts per billion or NH$_3$ concentration in parts per million was measured for a sample within 48 h of sampling. The air samples were taken from pig building sources and pig manure storage facilities on Minnesota pig farms in 1998 and 1999.

The odour indicator concentrations and odour intensities of each data set were checked for correlation to demonstrate the need to use non-linear statistical models for comparison against the developed neural networks. The correlation coefficient of each data set never exceeded 0.78 (Table 1) and thus the use non-linear statistical models is appropriate. The measurements taken from pig manure storage sources indicate a stronger correlation than measurements taken at pig building sources. The NH$_3$ measurements generally show a stronger correlation than the H$_2$S measurements. The relatively low to medium correlation of all the data sets indicates that neither, H$_2$S or NH$_3$, can be used as a single indicator for pork farm odour. This result was expected and confirms the results of other researchers (Barth et al., 1974; Lunn et al., 1977; Guo et al., 2000; Williams, 1984).

Each data set used for model development has had approximately 20% of its data points randomly selected for testing and the other 80% of the data points were used for model development. There are a total of ten models that have been developed for this paper, four non-linear statistical models and six neural network models. The performance of each statistical model is compared against the performance of the corresponding neural network model. The data sets have been broken down into six different categories in Table 1. The

<table>
<thead>
<tr>
<th>Data set</th>
<th>Odour indicator</th>
<th>Odour source</th>
<th>Associated models</th>
<th>Correlation coefficient (R)</th>
<th>Number of samples</th>
<th>Model development</th>
<th>Model testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>NH$_3$</td>
<td>Pig building</td>
<td>S1, N1</td>
<td>0.69</td>
<td>34</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>NH$_3$</td>
<td>Manure storage</td>
<td>S2, N2</td>
<td>0.739</td>
<td>33</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>H$_2$S</td>
<td>Pig building</td>
<td>S3, N3</td>
<td>0.239</td>
<td>42</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>H$_2$S</td>
<td>Manure storage</td>
<td>S4, N4</td>
<td>0.779</td>
<td>28</td>
<td>7</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>NH$_3$</td>
<td>Combined</td>
<td>N5</td>
<td>0.686</td>
<td>67</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>H$_2$S</td>
<td>Combined</td>
<td>N6</td>
<td>0.477</td>
<td>67</td>
<td>17</td>
<td></td>
</tr>
</tbody>
</table>
number of samples used for model development and testing has been presented in Table 1.

The data used for developing the various models have been normalised on the interval [0 1]. The largest positive number was found in a given data set and then all data was divided by the maximums found, to achieve normalisation along [0 1].

2.2. Statistical analysis tools

The data and results from this study have been analysed using several statistical tools. The correlation coefficient is a measure of the strength of a linear relationship between two variables. The correlation coefficient $R$ ranges on the interval $[0, 1]$, where 0 indicates that there is random or non-linear relationship between the variables (Banks et al., 2001). A value of 1 or $-1$ indicates a linear relationship. The correlation coefficient $R$ was used to determine the correlation between the air-phase odourant concentration and the odour intensity for all data sets. The correlation coefficient was also used to determine the correlation between the predicted values and observed values of the test sets.

The mean absolute error $E_a$ measures the mean of the absolute difference between the observed and predicted values (Zhang et al., 2002b). The value for $E_a$ was used as the primary performance comparison between the neural network models and non-linear statistical models. The closer the value of $E_a$ is to zero, the higher the level of performance for the model. The standard deviation of the mean absolute error $\sigma$ is also used to analyse the precision of the results. The lower the standard deviation is, the more precise the odour intensity prediction is. Both the $E_a$ and $\sigma$ are presented as percentages to allow easier interpretation and comparison of the magnitudes.

2.3. Statistical models

Pork farm odour researchers performing single-component analysis of the odour have generally used the method of least squares for modelling. Since this linear model has been shown to be insufficient to model the odour, it was decided to use a non-linear statistical model. The third-order inverse polynomial statistical model is given as

$$y = a + \frac{b}{x} + \frac{c}{x^2} + \frac{d}{x^3}$$  (1)

where: $a$, $b$, $c$ and $d$ are constant parameters for the third-order inverse polynomial.

The input variable $x$ for the non-linear statistical models is the air-phase concentration of a single odourant, NH$_3$ or H$_2$S. The H$_2$S is measured in parts per billion (ppb) and the NH$_3$ is measured in parts per million (ppm). The output variable $y$ is the odour intensity measured in odour units, and $N$ is the number of samples. These statistical models are not capable of incorporating non-numeric or subjective human expert knowledge, such as the location of the odour measurement. The parameters for the statistical models are presented in Table 2.

2.4. Neural network models

The six neural network models have been designed with an input layer, hidden layer and output layers. A three-layer neural network is theoretically able to learn any non-linear relationship at a desired level of precision with sufficient number of hidden neurons in the network architecture and through sufficient learning. All the neural networks developed for this application have a single output neuron for the odour intensity measured in odour units. The air-phase concentration of ammonia has been used as the single input for neural networks models N1 and N2. While the air-phase concentration of H$_2$S is the single input for models N3 and N4, neural networks N5 and N6 have a second input for the location of the odour source; this network architecture is presented in Fig. 1. Many other factors, such as temperature and relative humidity, which contribute to the pork farm odour, could also be used in the neural network as the inputs if that information were available.

<table>
<thead>
<tr>
<th>Model</th>
<th>Odour indicator</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$a$</td>
</tr>
<tr>
<td>S1</td>
<td>NH$_3$</td>
<td>2 867.9</td>
</tr>
<tr>
<td>S2</td>
<td>NH$_3$</td>
<td>2 021.9</td>
</tr>
<tr>
<td>S3</td>
<td>H$_2$S</td>
<td>1 743.6</td>
</tr>
<tr>
<td>S4</td>
<td>H$_2$S</td>
<td>2 012.2</td>
</tr>
</tbody>
</table>
because neural networks are capable of modelling multiple input–multiple output systems (Yang, 2003).

The inputs to the neural network and target during training have been normalised on the interval [0 1]. The largest positive number was found in a given data set for the inputs and targets. All inputs and targets are divided by the maximums found to achieve normalisation along [0 1]. The linear scalar function for the output of the networks is simply the largest target value in a given data set.

A three-layer neural network normally has a non-linear activation function for the hidden layer and linear or non-linear activation function for the output layer. A non-linear activation function was used for the hidden layer,

\[ y = \frac{1}{(1 + e^{-x})} \] (2)

The linear activation function,

\[ y = x \] (3)

was used for the output layer of all developed neural networks.

The neural network models are all feed-forward networks that have been trained using the fast back-propagation (fast BP) learning algorithm proposed by Karayiannis and Venetsanopoulos (1993). The predicted output is \( y \), the target output is \( y_t \), and \( x \) is a network input. The fast BP algorithm is based on minimising squared errors, whose error function \( E \) is defined as:

\[ E = \sum_{k=1}^{N} (e_k)^2 = \sum_{k=1}^{N} (y_{tk} - y_k)^2 \] (4)

where: \( k \) is an index number and \( N \) is the total number of data samples. The fast BP learning algorithm modifies the weights between neurons by the following formulae (Karayiannis & Venetsanopoulos, 1993):

\[ v_j = v_j + \alpha e_o h_j \] (5)

\[ w_{ji} = w_{ji} + \alpha e_h x_i \] (6)

where: \( i \) and \( j \) are index values for the neurons, \( \alpha \) is the learning rate, \( v \) is a connection weight from the input layer to the hidden layer, and \( w \) is a connection weight from the hidden layer to the output layer. Variable \( e_o \) is the error of an output neuron, \( e_h \) is the error of a hidden neuron, and \( \lambda \) is a modification factor. These parameters are calculated by (Karayiannis & Venetsanopoulos, 1993):

\[ e_o = \lambda e_o + (1 - \lambda) \tanh(\beta e_o) \] (7)

\[ e_h = (1 - h_j^2)e_o v_j \] (8)

\[ \lambda = e^{-n/E^2} \] (9)

where: \( \beta \) and \( \mu \) are positive constants.

The trial number of hidden neurons for the six neural networks was calculated using the equation below, where \( N_i \) is the number of input neurons, \( N_o \) is the number of output neurons, \( N_t \) is the number of data points for training, and \( N_{tm} \) is the trial number of hidden neurons for the network (Zhang et al., 2002b).

\[ N_m = 0.5(N_i + N_o) + \sqrt{N_t} \] (10)

The trial number of neurons was used as a starting point to determine the number of hidden neurons \( N_h \) for each network. Relevant information regarding the neural network models has been presented in Table 3.

### 3. Results and discussion

The number of hidden neurons is very important to the performance of a neural network, which is discussed in the next section. The first set of models developed and
compared considers only a single-component as an odour indicator with no other factors, such as temperature or measurement location. The second set of models consider the odour source (pig manure storage or pig housing), in addition to a single-component odour indicator.

### 3.1. Number of hidden neurons

The ability of the neural network to learn the relationship that exists between input and output data is dependent on the number of hidden neurons in the neural network. An insufficient number of hidden neurons will not be able to achieve the desired level of precision from the network, which is known as the ‘under-fitting’ problem (Zhang et al., 2002b). Using an excessive number of hidden neurons will not allow the generalisation of the relationship due to memorisation of the data set, which is the so-called ‘over-fitting’ problem (Zhang et al., 2002b). Although a neural network model with an excessive number of hidden neurons would produce a smaller error over the training data sets, it is not able to accurately predict for any conditions outside of the training set. Therefore, it is very important that the appropriate number of hidden neurons be used in the neural network models. Equation (14) was used to determine a trial number of hidden neurons \( N_m \). Many neural network models were developed and the number of hidden neurons was varied around \( N_m \). The number of hidden neurons was varied about \( N_m \) on a range of negative five to positive five hidden neurons with an increment of one. The number of hidden neurons \( N_h \) for each neural network model was determined through the comparison of performance measures for each neural network model by trial and error. The appropriate number of hidden neurons \( N_h \) for each neural network model is presented in Table 3.

### 3.2. Single-component models with no external factors

The neural network models, N1, N2, N3 and N4, all performed better than their corresponding non-linear statistical models (S1–S4) for single-component analysis using \( \text{NH}_3 \) or \( \text{H}_2\text{S} \) with no other factors considered in terms of mean absolute error. The performance comparison of the neural network models and statistical models is based on the mean absolute error of the observed odour intensity values and predicted odour intensity values for the test sets. The test sets represent 20% of the available data and are randomly selected.

The largest performance increase was a reduction in the value of \( E_a \) from 74.00% with the statistical model S4 to 22.30% with the neural network model N4. This significant decrease in the value for \( E_a \) was achieved with the \( \text{H}_2\text{S} \) measurements from pig manure storage facilities. The smallest performance increase was attained with the \( \text{H}_2\text{S} \) measurements from pig buildings. The mean absolute error for statistical model S3 is 21.22% and for the neural network model N3 it is 14.42%, showing a modest difference of 6.80%.

The lowest value for \( E_a \) of 13.00% realised by the single-component models with no external factors considered was achieved for the neural network model N2, while the corresponding statistical model S2 resulted in a value for \( E_a \) of 43.90%. This is expected due to the strong correlation, 0.86, of the observed values and predicted values for model N2, and the weak correlation, 0.62, for model S2.

The highest value of \( E_a \) for a single-component model without external factors considered was 74.00%, achieved by statistical model S4, which was trained using \( \text{H}_2\text{S} \) measurements from a pig manure storage facility. The corresponding neural network model N4 has a lower value for \( E_a \) of 22.30%.

Each of the neural network models (N1–N4) has performed better than the corresponding statistical models (S1–S4) in terms of \( E_a \) as the comparative performance indicator; this is summarised in Table 1.

With the exception of models S2 and N2, the correlation between the predicted odour intensities and observed odour intensities were very similar between the statistical models and the neural network models (Table 4) indicating that there is no significant increase in correlation from the use of neural networks for single-component models that do not consider other contributing factors. The standard deviation for the neural network models was lower than that of the statistical models for all four-model comparisons, as shown in Table 4. This generally lower standard deviation shows that the neural network models provide more precise predictions than the non-linear statistical models.

The neural network models have improved the accuracy and precision of the odour intensity predictions compared to the predictions of the non-linear statistical models. The pork farm odour problem has benefited from analysis using the intelligent systems.
modelling technique of neural networks. However, the neural network models still exhibit unacceptably high values of \( E_a \) and \( \sigma \), indicating that H\(_2\)S and NH\(_3\) are not suitable as single-component odour indicators. However, the performance of the single-component neural network models might be improved through the introduction of external factors like odour source, season, and time of day.

The literature survey performed indicates that there are currently no other pork farm odour components that are being considered as possible single-component indicators for the odour. Current pork farm odour research has shifted to the development of multiple-component statistical models using multiple regression statistics (Zahn et al., 2001). Zahn et al. (2001) of Iowa State University have developed a nine-component statistical pork farm odour model. The components were selected based on their odour thresholds and olfactory properties. This multi-component analysis of pork farm odour using a statistical model showed strong correlation of observed odour intensities and predicted odour intensities, where the value for the coefficient of determination \( R^2 \) is 0.88 (Zahn et al., 2001).

It has been demonstrated that the accuracy and precision of the single-component models for pork farm odours can be improved through the use of neural networks over statistical models. Based on our investigation and literature survey, it is hypothesised that multiple-component pork farm odour models could also be improved upon through the use of neural networks and other intelligent system modelling techniques.

### 3.3. Single-component neural network models with odour source as a factor

The pig-building source and pig manure storage source odour data sets were combined for both H\(_2\)S and NH\(_3\) to allow the inclusion of odour source in the modelling. The statistical models are not able to incorporate the measurement location because it is a form of human expert knowledge, whereas the neural network models are able to incorporate this knowledge. A second input neuron was added to the neural network models to accommodate measurement location as an input, as demonstrated in Fig. 1. The odour source locations are either pig buildings or pig manure storage facilities.

The neural network models N5 and N6 for the NH\(_3\) and H\(_2\)S combined data sets respectively, outperformed their neural network model counterparts N1–N4 in terms of the results for \( E_a \), \( \sigma \) and \( R \) (Table 4). The performance gains in terms of mean absolute error and standard deviation have only been slight, but have been achieved. Model N5 used ammonia as the odour indicator and produced the best results overall with a very low \( E_a \) of 11.68\%, standard deviation \( \sigma \) of 11.75\%, and a high correlation coefficient \( R \) of 0.94 between the observed and predicted odour intensities. Model N6, which used H\(_2\)S as the odour indicator, produced results very comparable to model N5: \( E_a \) value of 12.51\%, standard deviation \( \sigma \) of 13.22\%, and the highest correlation coefficient \( R \) at 0.96.

The statistical and neural network models for single-component analysis with no external factors considered generally only have marginal differences for the correlation coefficient, as shown in Table 4, whereas the single-component neural network models, N5 and N6, which consider odour source, have shown notable gains for correlation in favour of the neural network models (see Table 4). The stronger correlation achieved by the neural network models is at least partially attributable to the inclusion of the external factor, odour source, in the neural network models. Odour source is clearly a relevant factor that contributes to the pork farm odour, and it is a limitation of statistical models that are unable to include odour source, a form of human expert knowledge, for system modelling. There are many other factors than odour source that contribute to the pork farm odour. These factors include temperature, relative humidity, season, and time of day. The inclusion of these and other relevant factors could possibly increase the accuracy of pork farm odour models.

The inclusion of the odour source in the neural network models N5 and N6 has allowed those models to surpass the results of all non-linear statistical models and other neural network models presented. All of these performance gains for models N5 and N6 cannot only be attributed to the inclusion of the external factor, odour source, in the neural network models. The previous single-component odour models (S1–S4, N1–N4) for NH\(_3\) and H\(_2\)S have shown that simply
using a neural network to model the pork farm odour will generate modest performance gains.

It has been demonstrated that including external contributing factors, such as odour source, and the use of intelligent modelling tools, such as neural networks, will increase the accuracy and precision through lower errors and standard deviation. Zahn et al. (2001) have shown that multiple-component analysis of the pork farm odour is superior to single-component analysis, through the development of a nine-component statistical model (Zahn et al., 2001). The use of a single odour indicator for measuring pork farm odour is clearly insufficient and the pork farm odour should be treated as a complex system.

Combining multiple-component, multiple-factor analysis with neural network modelling techniques will likely increase the accuracy and precision of odour intensity prediction. The development of a large-scale neural network model that considers multiple-components and multiple-factors of the odour problem will enable the ranking of those factors using the ‘learning with forgetting’ neural network method (Ishikawa, 1996). This ranking of components and factors would allow the identification of significant odour components and major contributing factors. Odour reduction research for pork farms could then be directed towards the most significant components and factors. This would increase the efficiency of developing odour reduction technologies and methods for pork producers. A greater understanding of the pork farm odour will enable the accelerated deployment of effective odour control technologies, leading to improved public relations with non-farming rural residents.

4. Conclusion

Non-linear statistical and neural network models were developed and compared for single-component pork farm odour analysis using NH$_3$ and H$_2$S as odour indicators. The first set of models considered only a single-odour indicator and no other factors. In this case, the odour intensity predictions from the neural networks were generally better than the predictions produced by the non-linear statistical models. This indicates that neural network models provide better odour intensity prediction than the statistical models for predicting odour intensity with single-component odour analysis for the data sets used.

The second set of models considered a single-odour indicator (NH$_3$ or H$_2$S) and the odour source (pig building or pig manure storage). In this case, both of the developed neural network models N5 and N6 performed better than their corresponding neural network models (N1–N4) for every performance measure considered in this paper. The addition of an external factor to the neural network model slightly increased performance relative to the neural network models that did not consider an external factor, indicating that factors other than odour components are significant to the odour problem.

Overall, the neural network models have performed better than the non-linear statistical models. The neural network models are able to automatically learn the relationships that exist for pork farm odour and thus avoid the problem of selecting a relationship to represent the system. The neural network models can incorporate human expert knowledge, such as the odour source, which has the ability to increase the exactness of pork farm odour prediction. The use of neural networks and consideration of factors beyond the odour components can increase the accuracy and precision of pork farm odour predictions.

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