Prediction of health of dairy cattle from breath samples using neural network with parametric model of dynamic response of array of semiconducting gas sensors

J.W.Gardner, E.L.Hines, F.Molinier, P.N.Bartlett and T.T.Mottram

Abstract: The authors report on the use of a sampling device to collect the breath from individual members of a herd of dairy cattle during a two-week period. The response of an array of six semiconducting oxide gas sensors to the breath samples has been recorded and subsequently modelled by a time-dependent, linear, second-order system. Four characteristic sensor parameters have been estimated using a neural network, and these parameters have been used to train a predictive multilayer perceptron network. The results show that either a static response parameter (based on the difference in the signal from zero time) or a single time constant can be used to predict reasonably well the health of the cow as judged against blood samples. In both cases, the identification rate of unknown samples being about 76%. Further improvements may be possible through the use of network compensation of variations in sample temperature and humidity.

1 Introduction

Ketosis, or acetonaemia, is a condition associated with the inefficient use of cattle feed in the dairy industry. It not only compromises the health of the cow, but is also associated with an economic loss in an industry estimated to be worth £1 000 Million per year [1]. Ketosis is traditionally identified at its clinical stage by a vet from symptoms such as a loss of appetite and the sweet smell of propanone (acetone) on the cow's breath [2]. Sub-clinical ketosis is harder to identify and is usually diagnosed by analysis of blood and milk samples in the laboratory; a procedure that is both time-consuming and expensive. Consequently, there is a potential market for a simple non-invasive monitor that can analyse the breath of a dairy cow in order to predict its health, and thus be used to optimise its feeding regime.

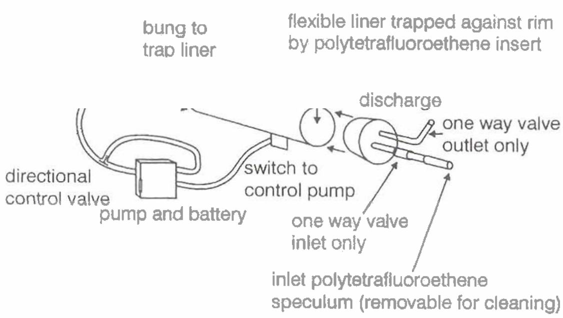

Fig. 1 *Device used for sampling breath of dairy cattle*

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A preliminary investigation has been carried out [3], in which a small portable breath-sampling device was developed by Silsoe Research Institute in conjunction with the Universities of Warwick and Southampton (Fig. 1). The results were encouraging, and they showed that butan-2-one and propanone were present at elevated levels in the breath of ketotic dairy cattle relative to the levels of methane and dimethyl sulphide. In this paper, we report on the results of a more comprehensive study.

2 Materials and methods

Seven cows in early lactation were brought into a tie stall barn and each fed a ration of 80kg fresh cut grass and 8kg of concentrate per day. On the third day the grass was reduced to 30kg and the concentrate to 1kg, and the milking frequency was increased to four times per day for five intervention cows; the other two control cows remained on the original food regime and were milked twice each day. Samples of blood, milk and breath were taken at least two, four and six times per day, respectively. Analyses were recorded with reference to a common start time. Feed reduction began after 52 hours.

A hand-held sampling device (Fig. 1) was used to capture samples of a cow's breath and to discharge approximately 140ml through an electronic nose instrument. The electronic nose was a FOX 2 000 (Alpha MOS SA, France), in which the pipe-work and sensors were modified to fit the application. The six commercial Taguchi-type gas sensors employed are specified in Table 1. The Taguchi sensor was invented in the 1970s and consists of a pair of electrodes monitoring the resistance of a thick stannic oxide film. The sensing element is maintained at a constant temperature of around 380°C through the use of a platinum heating coil driven at 5.0V DC. Many million Taguchi-type gas sensors have been manufactured and their behaviour is well documented [4].

The electrical responses from the odour sensors returned to their base-line values in approximately 15min. The elec-

Table 1: Commercial solid-state sensors employed in electronic nose instrument

Sensor	Description	Manufacturer	Sensor	Description	Manufacturer
1	TGS880 - Food/smoke	Figaro	5	STAQ1A - Air quality	FiS
2	NFIN43 - Ammonia	FiS	6	TGS822 - Alcohols	Figaro
3	NFI1813 - Hydrocarbons	FiS	7	LM35DZ - temperature	National Semiconductor
4	TGS825 - H_2S	Figaro	8	Minicap2-humidity	Panametrics

Heater voltage was set to 5 V DC for all six gas sensors

tronic nose was kept at ambient conditions, and so experienced an external temperature range of 12 to 28°C; however, the temperature of the sensor chamber varied by a few degrees around 40°C. The relative humidity ranged from 50% to 75% during the measurements. The electronic nose was flushed before and after each sample with zero grade air raised to about 50% r.h.

The reduction in the feed for the intervention cows produced the predicted result of elevated acetone in the breath, elevated ketone bodies in the milk, elevated β-hydroxybutryate levels in the blood, depressed glucose and eventually reduced milk yield, and some clinical signs of ketosis (these data will be reported elsewhere). The most common clinical sign of ketosis, inappetance, was not apparent until the cows were in a weak state. A comparison was made between the breath sample and the nearest temporal blood sample. The blood analysis allowed the cows to be classed as healthy, sub-clinically ketotic and ketotic on the basis of the β-hydroxybutryate levels.

3 Analysis of response of odour sensor to breath samples

3.1 Parametric model of dynamic sensor response

Fig. 2 shows a typical plot of the time response of an array of semiconducting oxide gas sensors to a sample of cow breath delivered using the sampling device illustrated in Fig. 1. Conventional analysis of electronic nose data involves the determination of the base-line signal in air, V^{air}, and the maximum signal in the odour, V^{odour}, followed by the definition of a suitable static pre-processing algorithm, such as the fractional change [5].

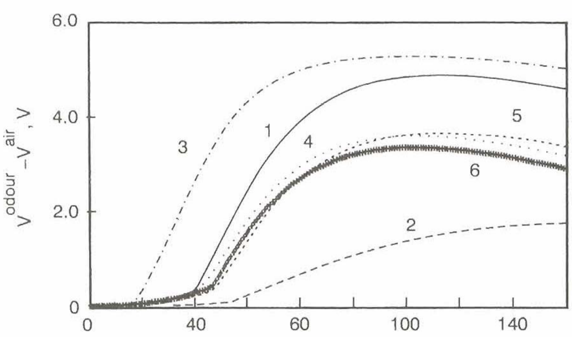

Fig. 2 *Typical dynamic response of array of six odour sensors to pulse of odour delivered by sampling device, i.e. the breath of a cow*
Signal voltage V is proportional to sensor resistance
The number by each curve refers to sensors listed in Table 1

Previous work suggests that the dynamic response of a semiconducting oxide sensor may be described by a multi-exponential model of the system [6], and also that the dynamic response contains useful information [7]. Consequently, we propose a basic dynamic model of the sensor system, in which we assume that the input signal (i.e. odour pulse) is an ideal step function at time t equal to zero and that the transfer function is a second-order polynomial equation.

We also found that it was necessary to include a variable time delay d_i between the introduction of the odour pulse at $t = 0$ and the response of the sensor i. This time delay represents the variation in the time taken for the sampling device to be manually discharged, the mixing time of the odour pulse in the chamber containing the array of sensors, and the open-loop control of the carrier gas pumping speed. Thus, the equation used to model the time-dependent response $y_i(t)$ of an odour sensor i to an odour is

$$y_i(t) = K_i\left[1 - \frac{a_i \exp[-(t-d_i)/a_i] - b_i \exp[-(t-d_i)/b_i]}{(a_i - b_i)}\right] \tag{1}$$

where $a_i > b_i$; K_i is the static response term and is strongly correlated with the odour intensity; d_i is a time delay and is related to the physical dynamics of the sampling system; and the coefficients a_i and b_i are characteristic time constants of the system dynamics for sensor i.

The time constants a_i and b_i contain both physical and chemical information. The dominant feature is assumed to be dependent on the nature of the odour, sensing material and flow system. For example, there have been reports of the effect of odour intensity on the response time of a tin-oxide gas sensor [8] as well as the chemical species under analysis [9]. The time constant b_i represents the initial rapid increase in the sensor output when the odour pulse enters the sensor chamber. The larger time constant a_i represents the more gradual decrease in the sensor output for longer times when the breath sample has finished entering the chamber and it starts to slowly flush out of it. It has been shown that it is the first part of the dynamic signal of MOS sensors that is most useful for discriminating odours because it relates to the chemical rate reaction which is species dependent [10].

Note that our chosen parametric algorithm is a difference one (i.e. $V^{odour} - V^{air}$), in that the response is recorded relative to the base-line or zero gas signal. The adoption of a difference model is advantageous when the base-line signal is known to vary in magnitude because of changes in ambient conditions, such as the temperature and humidity. The static response parameter K_i and time constants a_i and b_i still have some correlation with ambient conditions, but customarily to a reduced level.

3.2 Estimation of dynamic model parameters

Our basic sensor model (eqn. 1) has four unknown parameters that need to be estimated from each sensor's data. Fig. 3 shows a typical least-squares fit of the four-parameter model to one sensor's data for $t > d_i$; in this case, K_i takes a value of 6.95V, a_i of 15.9s, b_i of 1.0s and d_i of 13.4s. It can be seen that the overall fit is reasonable; the quality of the fit is poorer near the start of the odour pulse because the mixing time is ignored, and for longer times when the odour intensity begins to diminish.

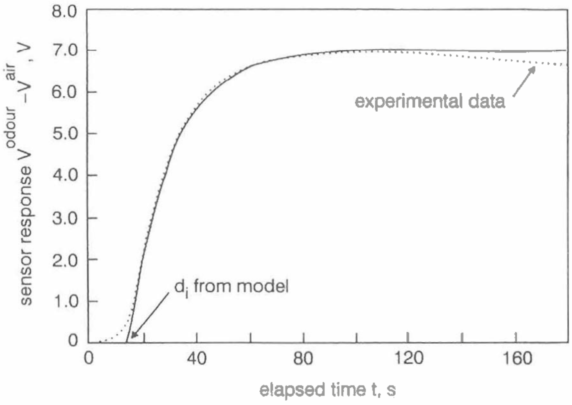

Fig. 3 *Graph showing effect of fitting four-parameter second-order model to actual sensor response*
Four terms are time-delay d_i, static response K_i, short-term and long-term time constants a_i and b_i

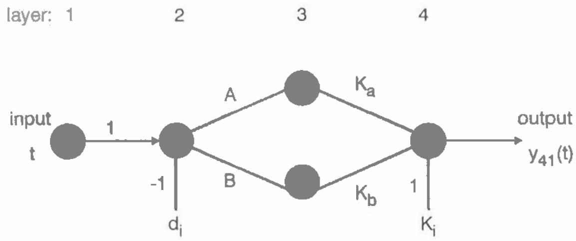

Fig. 4 *Neural network used to estimate values of four sensor parameters in our second-order model*
Layer 1 is the input and layer 4 is the output

However, a semi-manual curve-fitting procedure of this nature is rather impractical for the large number of data files generated in our experiments (over 200), and a least-squares technique is the most well behaved of techniques; so an artificial neural network was constructed to estimate the parameters in a fully automated, gradient-descent procedure (Fig. 4). The four-layer neural network generates an output given by

$$y_{41}(t) = K_i + K_{a_i} \exp A(t - d_i) + K_{b_i} \exp B(t - d_i) \qquad (2)$$

where the new neural parameters of A, B, K_a, and K_b are related to the earlier model parameters by

$$K_{a_i} = -\frac{K_i a_i}{(a_i - b_i)}; \quad A = -1/a_i$$
$$K_{b_i} = -\frac{K_i b_i}{(a_i - b_i)} \quad \text{and} \quad B = -1/b_i \qquad (3)$$

K_a and K_b are two constants introduced here that represent the static sensor response, and they are set to the values given by eqn. 1. The neural network is trained on the time-dependent sensor data, using the common back-propagation technique, so that the four parameters (a_i, b_i, K_i and d_i) may be estimated for each of the six odour sensors.

The static response parameter K_i was calculated for each of the six sensors, and the values have been plotted in Fig. 5 to show the sensor interdependencies. From these graphs and further error analysis not described here, it was evident that sensors 4 and 6 are highly correlated not only with each other, but also with sensor 5, and so contribute negligible additional variance to the data. Consequently, the responses of sensors 4 and 6 were omitted at this stage, to leave an array of only four sensors to characterise the breath samples of the dairy cows.

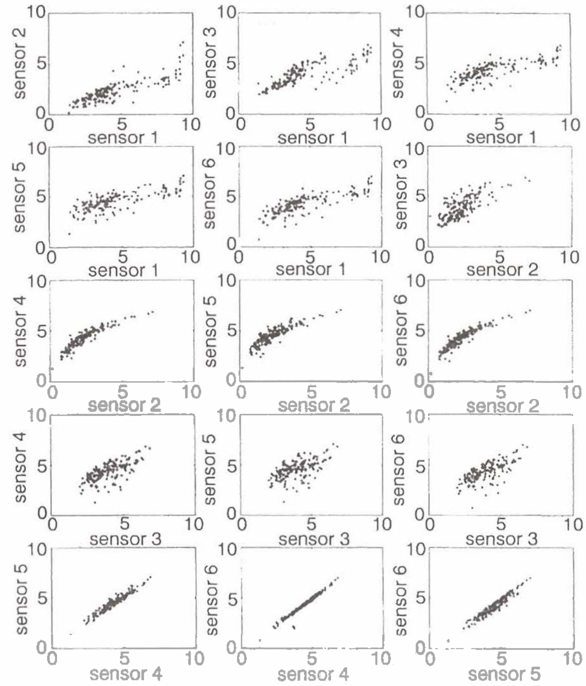

Fig. 5 *Plots showing interdependencies of six sensors in array*
They indicate that sensors 4, 5 and 6 have significant co-linearity, and so only four of the six sensors are sufficient to model most of the variance present in the data (Refer to Table 1 for details of sensors)

4 Prediction of cow health from estimated sensor parameters

There have been several reports on the successful use of a multilayer perceptron (MLP) to predict odour class from electronic nose data [10–12]. Consequently, we decided to construct a basic MLP network, with the input nodes being the values of the sensor parameters, a single hidden layer, and the target outputs representing the class (e.g. health) of the cow. The method of gradient descent was used to train a network using half of the data set; the other half was used to test the network (i.e. two-fold validation). N-fold cross-validation error estimation is usually deemed accurate and less computationally intensive than the leaving-one-out method [13]; however, a higher fold may give some marginal improvement to the classification rate.

The optimal values of the learning rates, and the number of hidden neurones were determined experimentally for both a single-output neurone layer and three-output neurone layer. The single-output network used one output neurone to categorise the state of health of the cow into one of three classes: healthy, sub-clinically ketotic or ketotic, based on the three target classes defined by the body fluid data within the range of [–1, +1]. On the other hand, the three-output network allocated one neurone in the output layer per class for the state of health of the cow.

Table 2: Sensor and neural network parameters used to analyse breath samples and classify state of health of cows

Sensor parameter(s)	Network outputs	Learning rate	Size of hidden layer
K_i	1	1×10^{-2}	5
	3	4×10^{-4}	6
b_i	1	4×10^{-3}	6
	3	1×10^{-4}	6
K_i and b_i	1	3×10^{-4}	4
	3	1×10^{-3}	4
K_i, b_i and d_i	1	1×10^{-4}	8
	3	3×10^{-4}	6

Table 2 shows the sensor model parameters selected as inputs to the one-output and three-output networks, with their experimentally derived values for the optimal learning rate and number of units in the hidden layer.

5 Results

Table 3 shows a three-class confusion matrix for the prediction of the state of health of the cows based on one-output and three-output neural networks, using only an estimate of the static response parameters K_i for an array of four sensors. The network was only trained for 1 000 epochs; a number experimentally determined to be a suitable point to optimise generalisation performance on this data set. For both networks, the static response parameter K_i could be employed to predict correctly 84% of the clinically ketotic cows. However, none of the sub-clinically ketotic cows was correctly identified. In the case of the one-output network, all three were identified as ketotic. Thus, the state of health of 23 out of 34 states (i.e. 68%) was correctly predicted by the one-output network in a three-class test, or 76% when only discriminating between either healthy or sick (i.e. sub-clinical or clinical) cow states in a simplified two-class test.

Table 3: Confusion matrix for prediction of state of health of cows using only sensitivity parameter K_i as input to one-output MLP

	Actual condition		
Diagnosis	Healthy	Sub-clinical	Clinical
Healthy	**7 (4)**	0 (1)	3 (3)
Sub-clinical	0 (0)	**0 (0)**	0 (0)
Clinical	5 (8)	3 (2)	**16 (16)**
Class size = 34	12	3	19

Results for the three-output MLP are shown in brackets

Table 4: Confusion matrix for prediction of state of health of cows using only characteristic time constant parameter b_i as input to one-output MLP

	Actual condition		
Diagnosis	Healthy	Sub-clinical	Clinical
Healthy	**4 (4)**	2 (2)	3 (3)
Sub-clinical	0 (0)	**0 (0)**	0 (0)
Clinical	8 (8)	1 (1)	**16 (16)**
Class size = 34	12	3	19

Results for the three-output MLP are shown in brackets

The MLP networks were then trained on the shorter time constant parameters b_i, which is an estimate of the initial transient response of the sensors to the odour pulse. The results are shown in Table 4. It is evident that the performance of both the one-output and three-output networks are identical and only slightly worse than that for the static response parameter K_i. The overall three-class success rate is (4 + 0 + 16)/34 or 59%, whereas the two-class rate is down from 76% to only 62%. However, these results suggest that there is significant classification information within the dynamic sensor signals, as reported elsewhere [9].

MLP networks were then trained using both the static response parameter K_i and the characteristic time constant b_i as inputs. The classification results are summarised in Table 5. The results are slightly better than only using the time constant b_i; with an overall classification of (6 + 0 + 16)/34 or 65% correctly predicted by the one-output network in a three-class test, and 68% for the two-class test. Therefore, it is evident that the addition of the dynamic parameter did not improve the discrimination, but rather slightly reduced the sucess rate from 76% to 68%. This result may be due to the difference in the size of the two networks, with the two parameter network having more weights to learn. The introduction of the time delay d_i produced, as expected, no discernible improvement in the discrimination power of the sensor array.

Table 5: Confusion matrix for prediction of state of health of cows using both static sensitivity parameter K_i and dynamic parameter b_i as input to one-output MLP

	Actual condition		
Diagnosis	Healthy	Sub-clinical	Clinical
Healthy	**6 (5)**	2 (2)	3 (3)
Sub-clinical	0 (0)	**0 (0)**	0 (0)
Clinical	6 (7)	1 (1)	**16 (16)**
Class size = 34	12	3	19

Results for the three-output MLP are shown in brackets

6 Conclusions

We have shown that it is possible to predict the health of a cow from its exhaled breath using an electronic nose and a neural networking technique. Our pattern recognition approach differs from others, in that we have designed a second-order linear model with a time lag to predict the generalised dynamic response of a semiconducting oxide sensor to odour pulses. Our four-parameter model has been fitted to all of the signals obtained from the response of an array of commercial gas sensors to samples taken from the exhaled breath of cows in the first study of its kind. Using either the set of estimated static response terms $\{K_i\}$ or time constants $\{b_i\}$, it is possible to predict the state of health of a cow from its breath with an accuracy of up to 76%. These results are encouraging because they were obtained employing a 'difference response' of an array of only four MOS sensors, in which the background air was monitored in the field over a two-week period and was thus subject to considerable environmental variations, in terms of ambient temperature and humidity. Even so, the prediction accuracy would be improved by a few percent with either better temperature control of the sensor chamber (current systems now employ closed-loop control to ±0.1°C [14]) or parametric compensation via an input to the neural network.

In practice, we believe that the most significant source of error is from the way in which the samples are manually gathered, rather than the repeatability of the electronic nose instrument *per se* (the repeatability of this type of electronic nose has been investigated elsewhere [14] and is less than the sampling error estimated here). This must lead to considerable variation in the levels of odour and water vapour present in the sample, estimated to be ±20%, which could be reduced through a fully automated sampling system. Moreover, the classification of the true state of health of the cow was based on the body fluid results, which are also subject to error.

Currently, no simple non-invasive monitor of a cow's breath exists. We now believe, on the basis of this work, that such a monitor shows considerable promise and would help farmers not only to monitor the health of their cows, but also to optimise the yield of their milk.

7 Acknowledgments

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8 References

1 NIX, J.: 'Farm management pocketbook' (Wye College Press, University of London, 1995, 26th edn.)

2 BRUSS, M.L.: 'Ketogenesis and ketosis' *in* 'Clinical biochemistry of domestic animals' (Academic Press Inc., USA, 1989, 4th edn.), pp.86–105

3 ELLIOTT-MARTIN, R.J., MOTTRAM, T.T., GARDNER, J.W., HOBBS, P.J., and BARTLETT, P.N.: 'Preliminary investigation of breath sampling as a monitor of health in dairy cattle', *J. Agric. Eng. Res.*, 1997, **67**, pp. 267–275

4 IKOHURA, K., and WATSON, J.: 'Stannic oxide gas sensor' (CRC Press Inc., Florida, 1994)

5 GARDNER, J.W.: 'Detection of vapours and odours from a multisensor array using pattern recognition. Part 1: Principal component & cluster analysis', *Sens. Actuators B, Chem.*, 1991, **4**, pp. 109–116

6 ENDRES, H., GOTTLER, W., JANDER, H.D., DROST, S., SBERVEGLIERI, G., FAGLIA, G., and PEREGO, C.: 'A systematic investigation on the use of time-dependent sensor signals in signal processing techniques', *Sens. Actuators B, Chem.*, 1995, **24-25**, pp. 785–789

7 VILANOVA, X., LLOBET, E., ALCUBILLA, R., SUEIRAS, J.E., and CORREIG, X.: 'Analysis of conductance transient in thick-film tin oxide gas sensors', *Sens. Actuators B, Chem.*, 1996, **31**, pp. 175–180

8 GARDNER, J.W.: 'A diffusion-reaction model of electrical conduction in tin oxide gas sensors', *Semicond. Sci. Technol.*, 1989, **4**, pp. 345–350

9 LLOBET, E., BREZMES, J., VILANOVA, X., FONDEVILA, L., and CORREIG, X.: 'Quantitative vapor analysis using the transient response of non-selective thick-film tin oxide gas sensors'. Proceedings of Transducers '97, Chicago, USA, June 1997

10 GARDNER, J.W., HINES, E.L., and WILKINSON, M.: 'The application of artificial neural networks in an electronic nose', *Meas. Sci. Technol.*, 1990, **1**, pp. 446–451

11 HINES, E.L., GIANNA, C.C., and GARDNER, J.W.: 'Neural network based electronic nose using constructive algorithms' *in* LISBOA, P.J., and TAYLOR, M.J. (Eds.): 'Neural networks: techniques & applications' (Ellis Horwood, 1993)

12 SUNDGREN, H., WINQUIST, F., LUKKARI, I., and LUNDSTRÖM, I.: 'Artificial neural networks and gas sensor arrays: quantification of individual components in gas mixtures', *Meas. Sci. Technol.*, 1992, **2**, pp. 464–469

13 WEISS, S.M., and KULIKOWSKI, C.A.: 'Computer systems that learn' (Morgan Kauffman Publishers Inc., San Francisco, 1991)

14 CRAVEN, M.A., and GARDNER, J.W.: 'Rapid static head-space sampler for automated odour analysis', *Trans. Inst. Meas. Control*, 1998, **20**