MODELLING DECLINE OF pH AND TEMPERATURE DURING RIGOR ONSET

van de Ven R.J.[1], Pearce K.L.[2] and Hopkins D.L.[3]

[1]NSW Department of Primary Industries, Orange Agricultural Institute, Forest Road, Orange NSW 2800, Australia

[2]Murdoch University, Division of Veterinary and Biomedical Science, South Street, Murdoch, WA 6150, Australia

[3]NSW Department of Primary Industries, Centre for Red Meat and Sheep Development, PO Box 129, Cowra NSW 2794, Australia

Abstract— **The aim of this study was to compare two modelling approaches for estimating the proportion (P_c) of carcases in a chiller that comply with a Meat Standards Australia pH - Temperature window requirement. For sheep meat this requirement is for the pH to drop below 6 when the temperature is between 18 and 35°C. Currently P_c is estimated by fitting separate pH versus Temperature models to each carcase and then determining the proportion of fitted lines that meet the window requirement. The alternative modelling approach proposed is to fit models to the carcases collectively using a random effects modelling approach. Here the parameters for each carcase's model are assumed to be a sample from a multivariate distribution. Using this modelling approach, P_c can again be estimated as the proportion of fitted lines meeting the window requirement, or alternatively, from the estimated distribution of carcase parameters. To compare these estimates of P_c a limited simulation study was undertaken. This limited study demonstrates the improvement in the estimation of P_c using the random effects modelling approach. A major improvement with the proposed modelling approach, in particular estimation based on the estimated distribution of carcase parameters, is the removal of much of the bias associated with estimation of P_c using the current method. The conclusion of the simulation study is that random effects modelling is preferable to the current modelling approach for estimating P_c.**

Keywords— Lamb, pH decline, models

I. INTRODUCTION

The Sheep Meat Eating Quality (SMEQ) program, incorporated into MSA Sheepmeat, identified that for optimal eating quality the meat destined for the domestic or overseas (air freight) markets should reach pH 6 when the carcase temperature is between 18-25°C [1] and the range was subsequently increased to 18-35°C. A high percentage of Australian processors have installed Australian designed medium voltage electrical stimulation units to comply with this pH-temperature window guideline to optimise their eating quality [2]. As part of MSA requirements, sheep meat consignments of lamb carcases must be measured for pH decline during the onset of rigor in order to establish that the carcases fall within the pH-temperature guidelines. Currently however this data is not subjected to statistical modelling to verify the percentage of carcases that meet the guidelines, whereas linear regression methods have been used [3] as have non-linear models [4]. Indeed [3] outlined an approach that included the use of random regression to improve the reliability of the estimate of the proportion of carcases complying with the pH-temperature guidelines. This paper details the modelling approach required to achieve this improvement in estimate reliability.

II. MATERIALS AND METHODS

When carcases are placed in a chiller post slaughter the pH and temperature of the muscles decline with time to ultimate values for pH and temperature. An exponential decay model has been proposed as a model for the decline for each trait [4]. That is, $pH = A_{pH} + B_{pH} \exp(K_{pH}\, t)$ and $T = A_T + B_T \exp(K_T\, t)$ where t and T denote time and temperature respectively. The constants in the model, A, B and K, depend on the trait and hence the corresponding subscripts. In each case, under the rate of decline assumptions above, we have $B > 0$ and $K < 0$. Assuming the validity of the exponential decay models, it can then be shown that

$pH = a + b (c + d T)^k$ where $a = A_{pH}$, $b = B_{pH}$, $c = -A_T / B_T$, $d = 1 / B_T$ and $k = K_{pH}/K_T > 0$. Further, it is easily shown that, since $A_T \leq T \leq (A_T + B_T)$, pH is decreasing with decreasing T. Depending on k (= K_{pH}/K_T) this model for pH on T can be approximately linear ($k \approx 1$), concave downwards ($k < 1$) or concave upwards ($k > 1$). Bruce [5] showed that an exponential model can generally adequately approximate this model, though when k is approximately 1, a linear model may suffice.

Using the above results, we consider estimation of the proportion of carcases placed in a chiller that achieve the target pH (denoted by pH* and equal to 6) during the chilling process when the temperature (T) is within a given range (L, U), equal (18, 35ºC). Meeting this condition will be denoted as *Hitting the Window*. Given the monotonicity of pH as a function of T, this corresponds to $pH \leq pH^*$ when $T = L$ and $pH \geq pH^*$ when $T = U$. For a given functional relationship between pH and T, be it either linear or exponential, with the model defined by a parameter vector ($\boldsymbol{\theta}$ say), a carcase *Hits the Window* if and only if $\boldsymbol{\theta}$ is in some restricted (acceptance) region of the total parameter space for all possible $\boldsymbol{\theta}$. For example, if the relationship between pH and T is linear, that is $pH = \alpha + \beta T$, in which case $\boldsymbol{\theta} = (\alpha, \beta)'$, the carcase *Hits the Window* if and only if $(\alpha, \beta)'$ is in the acceptance region $\alpha \leq pH^*$ and $(pH^* - \alpha)/U \leq \beta \leq (pH^* - \alpha)/L$. For the exponential models, for which $\boldsymbol{\theta}$ is a three component vector $(\alpha_i, \beta_i, \gamma_i)$, the acceptance region corresponds to a sub-region (not easily defined) of three dimensional space.

When aiming to determine the proportion of carcases in a chiller that *Hit the Window*, common practice is to monitor a limited number of carcases (randomly selected) over time, recording both pH and temperature at discrete times on each carcase. The appropriate model for pH versus temperature (linear or exponential) is then fitted to the data. In the linear case, the model for data from the i^{th} carcase is $pH = \alpha_i + \beta_i T$ + error whilst for the exponential case $pH = \alpha_i + \beta_i \exp(\gamma_i T)$ + error. The parameter vector for the i^{th} carcase is denoted by $\boldsymbol{\theta}_i$ and the objective is to estimate what proportion of population $\boldsymbol{\theta}$ values fall within the acceptance region of the parameter space.

Having obtained the data, there are a number of approaches to estimating the proportion P_c of carcasses in the chiller that *Hit the Window*. One approach is to fit the model to each carcase, ignoring any distributional assumption for $\boldsymbol{\theta}_i$, and then estimate P_c as the proportion of the estimated $\boldsymbol{\theta}_i$ in the acceptance region. This approach can lead to very biased estimates. A better approach is to incorporate in the model the clustering characteristics of the $\boldsymbol{\theta}_i$ for carcases in a chiller. Clustering is to be expected given a number of common features associated with carcases in a chiller. For example, all of the carcases are subjected to a set of common characteristics of the chiller at that time. In addition, there may be common animal characteristics associated with these carcases, such as similar breed, age, source and/or stress factors. To accommodate this additional feature in the model corresponds to placing some distribution assumption on the $\boldsymbol{\theta}$ values. An approach to doing this is to assume the $\boldsymbol{\theta}_i$ are independent samples from a multivariate normal distribution with mean $\boldsymbol{\theta}_0$ and variance-covariance matrix $\boldsymbol{\Gamma}$. That is, $\boldsymbol{\theta}_i \sim N(\boldsymbol{\theta}_0, \boldsymbol{\Gamma})$. Both $\boldsymbol{\theta}_0$ and $\boldsymbol{\Gamma}$ are assumed unknown and need to be estimated from the data. Fitting such models corresponds to fitting a random effects model, as opposed to a fixed effects model where no distributional assumptions are made on the $\boldsymbol{\theta}_i$ values.

Having fitted a random effects model to the data there are at least two approaches to estimating P_c. One is to estimate the proportion of estimated $\boldsymbol{\theta}_i$ that fall in the acceptance region. An alternative is to determine what proportion of samples a from multivariate normal distribution $N(\boldsymbol{\theta}_0, \boldsymbol{\Gamma})$, with parameters replaced by estimates, fall within the acceptance region. Hence three possible estimates for P_c have been proposed, these being;

Estimate 1. Proportion of estimated $\boldsymbol{\theta}_i$ (fixed effects model) in acceptance region

Estimate 2. Proportion of estimated $\boldsymbol{\theta}_i$ (random effects model) in acceptance region

Estimate 3. Prob($\boldsymbol{\theta}$ in acceptance region) given $\boldsymbol{\theta} \sim$ N(estimated $\boldsymbol{\theta}_0$, estimated $\boldsymbol{\Gamma}$).

The results of a limited set of simulation studies for these alternative estimates are reported in the following section. Attention is restricted to the linear model.

III. RESULTS AND DISCUSSION

To illustrate the potential bias of Estimates 1 and 2 above for the linear model case, simulations were based on twelve real life data sets. Each data set comprised three pH and temperature recordings over time for each of twenty carcasses sampled from a population of carcases in a chiller. The actual data for one of the data sets, DataSet 1, are plotted in Figure 1, with dashed lines connecting the data for each carcase. Also included on this plot is the target window (solid horizontal line). A carcase *Hits the Window* if pH > 6 when temperature > 35°C and pH < 6 when temperature < 18°C.

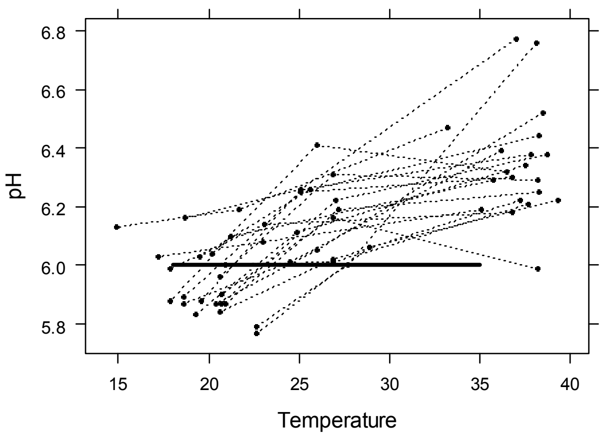

Figure 1. Example data set of pH vs Temperature.

For each of the twelve data set a linear mixed model $pH_{ij} = \alpha_0 + \beta_0 T_{ij} + \alpha_i + \beta_i T_{ij} + e_{ij}$ was fitted. Here i and j correspond to the carcase and reading respectively, so that pH_{ij} and T_{ij} are pH and temperature for the j^{th} reading on the i^{th} carcase. The $(\alpha_i, \beta_i)'$ in the model were modelled as independent $N(\mathbf{0}, \mathbf{\Gamma})$ random variables and the e_{ij} as $N(0, \sigma^2)$. For each data set the parameters α_0, β_0, $\mathbf{\Gamma}$ and σ^2 are estimated using the *lmer* function in the *lme4* package [6] under R [7].

Next, for each of the twelve data sets, using the corresponding estimates of α_0, β_0, $\mathbf{\Gamma}$ and σ^2, 2000 independent data sets were subsequently simulated. Each simulated data set comprised 20 "carcases" with the $(\alpha_i, \beta_i)'$ simulated from a $N(\mathbf{0}, \mathbf{\Gamma})$; the T_{ij} (j = 1, 2, 3, 4) simulated from symmetric triangle distributions on (15ºC, 20.25ºC), (20.25ºC, 25.5ºC), (25.5ºC, 30.75ºC) and (30.75ºC, 36ºC) respectively, and independently for each carcase; and the pH_{ij} then simulated from $N(\alpha_0 + \beta_0 T_{ij} + \alpha_i + \beta_i T_{ij}, \sigma^2)$. A linear fixed effects model (i.e. treating α_i and β_i in the above model as fixed effects) was fitted to the simulated data using the *lm* function in R, whilst the linear mixed model is fitted using the *lmer* function. Estimates 1, 2 and 3 were obtained for each simulation using the results from the fitted models.

A summary of the simulation results for each estimate for each data set are presented in Table 1. Herein are given, for each dataset, the actual mean number of lines *Hitting the Window* (P_c) and the means (standard deviations) for each estimate.

Table 1. Actual proportion of carcases in the window (**P_c**), and the mean estimated probabilities (std.dev.) for the three estimates. Estimate 1 and 2 are the proportion of fitted lines (fixed and random effects models respectively) passing through the window, Estimate 3 is based on the estimates of the parameters of the random effects model.

DataSet	P_c	Estimate 1	Estimate 2	Estimate 3
1	0.722	0.635	0.784	0.732
		(0.104)	(0.170)	(0.144)
2	0.991	0.922	0.985	0.973
		(0.061)	(0.030)	(0.028)
3	0.689	0.645	0.708	0.688
		(0.106)	(0.136)	(0.112)
4	0.994	0.874	0.991	0.969
		(0.073)	(0.030)	(0.046)
5	0.925	0.905	0.936	0.922
		(0.065)	(0.061)	(0.050)
6	0.994	0.875	0.990	0.968
		(0.074)	(0.031)	(0.045)
7	0.803	0.771	0.809	0.797
		(0.094)	(0.100)	(0.085)
8	0.018	0.046	0.017	0.027
		(0.047)	(0.032)	(0.028)
9	0.317	0.343	0.303	0.318
		(0.106)	(0.126)	(0.103)
10	0.825	0.763	0.838	0.814
		(0.094)	(0.097)	(0.082)
11	0.364	0.381	0.358	0.362
		(0.111)	(0.127)	(0.104)
12	0.885	0.845	0.901	0.881
		(0.082)	(0.081)	(0.069)

This limited simulation study suggests Estimate 3 is a reasonable estimate for P_c in each case whereas Estimates 1 and 2 have significant bias for some of the data sets. Similar results have been found in other simulations undertaken. Not included in this paper are results for the case where the exponential model is the more appropriate model for pH as a function of temperature. For many of the data sets observed in practice there is curvature in this relationship and, as outlined earlier, this curvature is generally either concave upwards or concave downwards for all carcases sampled within a chiller. This similarity in trend across carcases within a chiller points again to the benefit of using a random effects model. Random effects non-linear exponential models can be fitted in R [7] using the *nlmer* function in the *lme4* package [6]. Simulations undertaken to date comparing the three estimates above for the exponential model demonstrate similar results to that for the linear model comparison.

IV. CONCLUSION

When modelling pH and temperature, either jointly or separately against time, for carcases sampled from a population of carcases subjected to similar extraneous factors (such as the same chiller), it is appropriate to include in the model a clustering characteristic for the parameters of the carcases. This is most readily accommodated using a random effects model and imposing a distributional assumption on the population of carcase parameters. The most easily implemented distributional assumption, and generally a reasonable first approximation, is to assume that the parameters are a sample from a (multivariate) normal distribution.

ACKNOWLEDGEMENT

The authors acknowledge the provision of data sets by MSA.

REFERENCES

1. Thompson, J.M., Hopkins, D.L., D'Souza, D.N., Walker, P.J., Baud, S.R. & Pethick, D.W. (2005) The impact of processing on sensory and objective measurements of sheep meat eating quality. *Australian Journal of Experimental Agriculture* 45: 561-573.
2. Hopkins, D.L., Toohe,y E.S., Pearce, K.L., Richards, I., & Keane, P. (2008). Some important changes in the Australian sheep meat processing industry. *Animal Production Science* 48: 752-756.
3. Pearce, K.L., van de Ven, R., Mudford, C., Warner, R.D., Hocking-Edwards, J., Jacob, R., Pethick, D.W. & Hopkins, D.L. (2010). Case studies demonstrating the benefits of optimising medium voltage electrical stimulation of lamb carcases. *Animal Production Science* 50: 1107-1114.
4. Bruce, H. L., Scott, J. R. & Thompson, J. M. (2001). Application of an exponential model to early postmortem bovine muscle pH decline. *Meat Science*, 58: 39–44.
5. Bruce, H.L. (2004). A note on the suitability of an exponential equation to characterize pH decline corrected for muscle temperature in bovine muscle early post mortem. *Meat Science* 66: 507-512.
6. Bates, D. & Maechler, M. (2009). lme4: Linear mixed-effects models using S4 classes. R package version 0.999375-32. http://CRAN.R-project.org/package=lme4
7. R Development Core Team (2009). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org.