Could a Cattle Liveweight Gain Model and a Kalman Filter Help Farmers Short-term Decision Making?

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Abstract: Contract-based payment systems for pastoral beef farmers require timely supply of cattle, within a specified carcass weight range. A farmer must manage seasonal variability in pasture supply to maximise the number of animals achieving the target weight range. Farmers are rewarded for supplying animals in the target weight range, with no penalties for misses. We developed a simple model to predict cattle liveweight gain from estimated pasture quantity (green allowance) and quality (green percentage). The model reflects simple feeding management decisions made by pastoral farmers in New Zealand. Model parameter estimates were updated monthly, using a Kalman filter. This statistical method compares predictions of state variables from the model with actual measurements of the state variables. The liveweight gain model proved useful as an aid to grazing management and supplementation decisions (how much to feed, and when). Constraints on the model structure, lack of knowledge of the process errors (unmodelled biological influences), and errors associated with pasture and animal measurements resulted in instability in the estimates of the model parameters generated by the Kalman filter. The instability of estimated parameters highlights the need to carefully control process and measurement errors when using self-tuning models for decision support. The availability of high quality data to parameterise the model and for self-tuning is critical.

Keywords: Precise supply; Cattle liveweight gain; Model; Kalman filter; Process error; Measurement error

1. INTRODUCTION

There is an increasing move in New Zealand to use contracts to determine payment for beef production from pasture. This requires suppliers of quality pasture-fed beef to meet specifications for carcass weight and time of supply constraints. Managing animals grazing on pasture is complex with interactions occurring between pasture, animals, and the environment. Prediction of animal performance could help farmers by providing early warning of probable shortfalls in targeted cattle growth rates. This would give farmers the opportunity to review grazing management decisions, or use supplements to help achieve targets.

Policy planning models such as Stockpol [Marshall et al., 1991] can be used to set stocking policies resulting in feasible feed plans based on an annual feed (pasture) supply profile. Animal liveweight targets from this longer-term (12 to 24 months) planning process can then be reached by achieving a sequence of shorter-term (1 to 2 monthly) goals.

The purpose of this study was to develop prediction tools for cattle growth to help farmers achieve these short-term goals. A simple model of cattle growth rate was developed, driven by pasture allowance and pasture quality [Nicol and Nicol, 1987]. The model was constrained to use driving variables readily assessed by farmers. A Kalman filter [Meinhold and Singpurwalla, 1983] updated model parameters using current trial data. Practical on-farm application of the tools was emphasised, and a field trial was used to test these tools.

2. DESCRIPTION OF THE CASE STUDY TRIAL

2.1 Trial summary

A cattle growth trial was used to test the utility of the decision support tools developed. A demanding system was set up to provide year round supply of young bull beef from pasture with a target carcass weight range from 245 to 275kg. The trial was located at Whatawhata Research Centre, a summer-dry hill country environment in the Waikato region of New Zealand. Sheep were used to help control pasture, and maintain pasture quality. Bulls were managed in mobs, with all management decisions and reporting of results made monthly at the mob level.

Data from the trial was stored in a custom database, using Microsoft Access97. This paper reports only on the prediction tools tested in the study.

The trial consisted of 2 treatments: (1) no supplementation, and (2) optional supplementation (nitrogen fertiliser, maize grain or pasture silage) to help achieve weight targets. Each treatment was replicated twice, giving 4 farmlets in total. Each year, new calves entered the trial in August (6 per farmlet) and November (12 per farmlet).

2.2 Data Collection

Trial data from June 1999 to December 2000 was used to test the model and Kalman filter. Data collection was a compromise between labour requirements, measurement errors (larger for shorter intervals), and timeliness of the information collected.

Bulls were weighed on electronic scales, as close as practical to the end of the calendar month. A protocol was in place to minimise the effect of gut-fill (variation in stomach contents) on cattle weights.

Pasture cover is the mass of herbage in a paddock. It is typically assessed visually, a subjective method prone to large and unknown errors. Pasture covers (herbage mass assessments) in all paddocks were assessed using calibrated visual estimation [Haydock and Shaw, 1975] around the time the bulls were weighed. Pasture growth rates (ROG) were estimated monthly by subjective adjustment of historical pasture ROG data from Whatawhata.

Grazing data consisted of animal information (mob name, mob size, days in paddock) and pasture information (pre and post-grazing cover levels, and area grazed). Pasture data was usually collected within 3 days either side of the actual grazing date. In these cases, pre- and post-grazing cover levels were adjusted using the estimated ROG for the month by adding the growth that occurred.

Pre-grazing herbage samples were also collected for all grazings. These were subsampled and manually dissected to estimate the percentage of green material (%green).

3. CATTLE LIVEWEIGHT GAIN MODEL

Liveweight gain (LWG) is the rate of change in liveweight in a time period, and is used in planning the grazing of the pasture resource. A model of bull LWG was developed based on grazing management decisions influencing the amount of pasture offered to the animals.

The model structure was based on work relating LWG to pasture allowance [Nicol and Nicol, 1987]. The form of the equation used was restricted to being linear in it's parameters, a requirement for use with the Kalman filter [Harvey, 1989].

Model driving variables were restricted to quantities readily assessed in the field. Green pasture allowance was used to represent the amount of pasture offered to cattle. Pasture allowance can be assessed by farmers, but pasture intake is difficult for farmers to estimate [Woodward et al., 2001].

Pasture quality, particularly green herbage, is recognised as an important determinant of animal performance [Lambert et al., 2000]. This motivated the inclusion of a model term capturing it's effect on LWG. Percent green pasture was used as a proxy measure of pasture quality, as this cannot be measured directly.

Green allowance is the amount of green pasture available for consumption by the bulls when grazing a paddock, and is calculated as

$$GreenAllowance = ((PreGrz) \times area \times \%green) / (\#bulls \times \#days \times (avgLWT/100)) \quad (1)$$

where

PreGrz is amount of pasture in the paddock before grazing (kg DM/ha);
area is the area of the paddock being grazed (ha);
%green is the estimated percentage of green herbage in the paddock being grazed
#bulls is number of bulls in the grazing mob;
#days is time spent grazing the paddock (days), and
avgLWT is the average liveweight of bulls in the mob (kg).

The equation used to predict cattle LWG was

$$LWG = a \times \ln(GreenAllowance) + b \times \ln(\%green/\%nongreen) + c \quad (2)$$

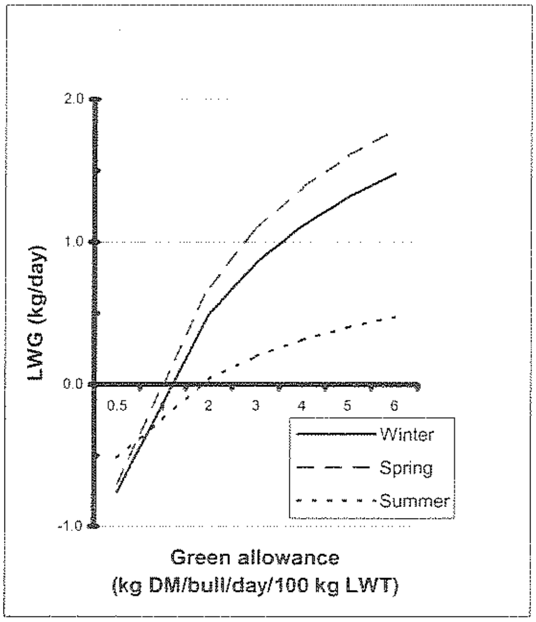

Figure 1. An example of predicted bull live weight gain for a typical range of green allowance levels, based on typical percent green values of 85% (winter), 80% (spring) and 30% (summer).

Equation (2) was programmed into an Excel spreadsheet and provided calculation of LWG for specified pasture conditions.

Liveweight gain is typically low in summer due to low pasture quality (%green). While pasture quality is highest in winter, growth rates of bulls are usually higher in spring than in winter (Figure 1).

Interpretation of model terms

The green allowance term represents the LWG response of a bull to the amount of pasture offered, and a is analogous to the energy content of the pasture. Fitted values of a were highest in winter and spring, dropping sharply in summer (Table 1), consistent with the seasonal energy content of pasture.

The second term that represents pasture quality, defines a family of curves for LWG as a function of green herbage content. The structure of this term (%green/%non-green) was based on the observation that similar green allowances result in different levels of animal performance. It reflects the balance between green and non-green pasture components on cattle growth. The upper limit to animal performance, for a given green allowance, is determined by b, and occurs when pasture quality is highest. Measured LWGs were highest in spring, when observed %green values peaked (at 95%). Seasonal pasture quality patterns are mirrored in the fitted values of b (Table 1), being highest in winter, and lowest in summer. We expect b to be positive, as LWG increases with increasing pasture quality.

The constant term (c) represents animal-only affects, such as sex, breed, or maintenance requirements of the cattle.

The shape of the curve is determined by a and b, while c simply moves the curve up and down.

4. MODEL CALIBRATION

The model was initially calibrated using data sets from 3 previous cattle trials at Whatawhata Research Centre. These trials examined the growth rate responses of Friesian bulls and Angus steers (unpublished), the responses of 18-month-old mixed breed steers to grain supplementation [Boom and Sheath, 1999], and bull and steer responses to pasture intake levels (unpublished). Measurement techniques were the same as used in the case study trial. Only data from cattle fed exclusively on pasture was used to calibrate the model. LWG and pasture data was averaged for each month. The model was calibrated by season because most trials were run on a seasonal basis, and previous analysis had indicated distinct seasonal patterns in LWG response. No allowance was made for animal genotype.

Formal statistical fitting was followed by subjective assignment of the final parameter values based on animal sex (bull or steer), the statistical quality of the fit, and assessed trends of parameter values for similar animals in a given season (e.g., fits with negative b values were rejected). The initial parameter values selected for the model are listed in Table 1.

Table 1. Parameter values selected after fitting to historical data sets, for liveweight gain model of bulls grazing pasture at Whatawhata.

Parameter	Winter	Spring	Summer
a	0.9	1.0	0.4
b	0.5	0.3	0.2
c	-1.0	-0.42	-0.2

5. KALMAN FILTER

We wanted to improve the model predictions by using the results from the case study trial. The Kalman filter method, widely used in the engineering sciences, was identified as a suitable technique. The Kalman filter is a recursive procedure that updates model parameters as new observations become available [Harvey, 1989]. Meinhold and Singpurwalla [1983] provide a basic introduction to the Kalman filter, while Harvey [1989] provides a more in-depth treatment.

The system state variables are observed (measured) properties of a system, e.g. pasture cover and LWG (indirectly calculated from changes in liveweight). The control variables represent the inputs to the system (e.g. green allowance), and are set to influence the system state (e.g. LWG).

The biological system was managed to ensure that the values of state variables were close to targets. The Kalman filter was then used to update the model parameter estimates by comparing the observed and predicted values of LWG.

Operation of a Kalman filter requires estimation of hyperparameters, such as error covariance matrices [Harvey, 1989]. Hyperparameter estimates could not be calculated using the calibration data, so error covariance matrices were initialised to the identity matrix [Harvey, 1989].

6. RESULTS USING CATTLE GROWTH MODEL AND KALMAN FILTER WITH CURRENT CASE STUDY DATA

The model was run 'live' using data from the current case study trial. Bull LWGs were predicted up to 2 months ahead using the parameters provided in Table 1, planned pasture allowance levels, and historical records of pasture %green at Whatawhata. New data became available at the end of each month. Actual pasture data for each mob was averaged to give monthly values of green allowance and %green. These values were used in the model to calculate LWG for the month and compared with measured LWG.

LWG is highly variable, as expected from a rate variable. The coefficient of variation of LWG data from the trial ranged from 0.15 to 0.86, indicating difficulty predicting LWG with precision over short time periods.

It was hoped that the Kalman filter would be able to adjust the model parameters to reflect the anticipated seasonal changes (Table 1). Results of updating the model parameters using the Kalman filter are presented for bulls born in Spring 1998 (Table 2). Parameter values initially varied acceptably (Jun99 to Sep99), before becoming unstable (Sep99 to Apr00), with unacceptably large fluctuations occurring. Negative values of a (Oct99) and b (Jan00) are inconsistent with the expected positive values for these parameters. Parameters for other mobs showed similar behaviour.

Table 2. Model parameter values updated using the Kalman filter and data from Whatawhata case study trial (bulls born in spring 1998, results from 4 farmlets pooled).

Month	a	b	c
Initial value	0.9	0.5	-1.0
Jun99	0.75	0.42	-1.04
Jul99	0.76	0.39	-1.06
Aug99	1.07	0.25	-1.28
Sep99	0.85	0.38	-1.09
Oct99	-0.30	0.91	-0.53
Nov99	0.88	0.27	-1.17
Dec99	-0.18	1.12	-0.35
Jan00	2.80	-1.77	-3.17
Feb00	1.13	0.02	-1.29
Mar00	3.12	-2.21	-4.58
Apr00	7.11	-6.87	-12.20

7. MODEL RECALIBRATION

When sufficient data from the case study trial had become available (June 1999 to April 2000), equation 1 was recalibrated using regression analysis (Table 3), and then updated monthly until December 2000 (Table 4). The data was split into 2 age groups as young bulls (<=10months) were fed preferentially. Data used in the initial calibration was not used for recalibration.

Table 3. Parameter values recalibrated based on animal age using the case study trial data (Jun99 to Apr00), for the model used to predict LWG of bulls grazing pasture at Whatawhata.

Parameters	Young bulls <=10 months	Old bulls >10 months
a	0.17	0.53
b	0.23	0.34
c	0.04	-0.56

The impact of the initial calibrated parameter values on subsequent model performance, without the Kalman filter, was investigated by comparing the actual and predicted LWGs in the current trial from May 2000 to December 2000 for bulls born in 1999 (Table 5). Bull LWGs were consistently over-predicted for these animals when the original calibrated parameters (Table 1) were used.

Table 4. Parameter values, recalibrated using the case study data (Jun99 to Dec00), for the model used to predict LWG of bulls born in 1999, grazing pasture at Whatawhata.

Parameters	Young bulls <=10 months	Old bulls >10 months
a	0.19	0.22
b	0.23	0.37
c	0.01	-0.05

Table 5. Actual - Predicted LWG (kg/day) for bulls born in 1999. Model parameters used were from the original calibration (Table 1) and the revised calibration (Table 4).

	Bulls born autumn 99 Parameters		Bulls born spring 99 Parameters	
Month	Original	Revised	Original	Revised
May00	-0.3	-0.1	-0.2	0.0
Jun00	-0.6	-0.2	-0.7	0.0
Jul00	-0.3	0.1	-0.7	-0.3
Aug00	-0.6	0.0	-0.2	0.3
Sep00	-0.5	0.3	-0.7	0.0
Oct00	-0.7	0.1	-0.6	0.1
Nov00	-1.5	-0.3	-0.6	0.3
Dec00	-1.3	-0.2	-0.5	0.4

8. DISCUSSION

The idea of a self-tuning model to help with decision support for farmers is alluring. Several factors made this unachievable when the model was run with a Kalman filter and real-time trial data.

The LWG model proved a useful tool for planning allocation of pasture resources to cattle, and was used to calculate target green pasture allowances, from target LWG. With the recalibrated parameters (Table 3), the model explained up to R^2=85% of the variation in LWG for some bull mobs.

The performance of the tools tested was affected by the complexity of the system modelled, process errors (simplifications made in the model), measurement errors (bull liveweight and pasture variables), and the initial parameterisation of the model and Kalman filter.

Goodall and Sprevak [1985] successfully predicted annual milk yield of dairy cows, using data from the previous year to parameterise their model and estimate error covariance matrices. Their model updating was based on milk yield values, which are easily measured objectively. The LWG of a range of age classes of bulls in a hill country farming system is subject to much greater variation than milk production in mature dairy cows. Model calibration using data from a trial similar to the case study would have improved model performance (Table 5), but more importantly would also have allowed estimation of the hyperparameters associated with the Kalman filter, e.g., the initial values of the error covariance matrices. Poor initial parameterisation contributed to the failure of the Kalman filter to effectively update the model parameters (Table 2). Unknown process errors introduced by the constrained structure of the LWG model, unknown measurement errors, and large variation in LWG responses, made recovery of correct parameters by the Kalman filter unlikely.

Measuring control or state variables results in measurement errors. Cattle liveweights are subject to gut-fill effects, and accurate assessment of pasture cover and pasture quality is difficult as a result of sampling and calibration issues. Pasture quantity is commonly assessed visually [Haydock and Shaw, 1975], and while these assessments are calibrated to objective measurements, this calibration process is also essentially subjective, and time-consuming.

Plant [2001] discusses 'soft' (e.g. visual pasture assessment) and 'hard' (e.g. electronic instruments) data collection technologies, as well as the use of 'hard' management technologies (e.g. statistical methods). Recent developments in on-farm [Kunnemeyer et al., 2001] and remote [Donald and Edrisinghe, 2001] pasture assessment techniques have the potential to give farmers easy access to greatly improved quantity and quality of pasture data.

9. CONCLUSIONS

Mathematical tools are available that could improve the prediction of cattle performance grazing pasture, and help farmers plan feeding to meet contract weight targets.

The LWG model developed proved useful as a grazing management tool, but appropriate quality pasture and animal data are required to calibrate and run the model for specific farm application. Recent advances in technology provide the potential for greatly improved access by farmers to the required pasture data.

The combination of LWG model and Kalman filter tested in this study was not able to cope with the poor initial parameterisation and errors in the system modelled. After the model was recalibrated, statistical regression fitting was sufficient to provide specific farm predictions of LWG in our case study trial.

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11. REFERENCES

Boom, C.J. and G.W. Sheath, Tactical supplementation of beef finishing cattle, *Proceedings of the New Zealand Society of Animal Production*, 59, 162-165, 1999.

Donald G. and A. Edrisinghe, Remote view of pasture assists feed budgeting, *Farming Ahead*, 112, 51-53, 2001.

Goodall, E.A. and D. Sprevak, A Bayesian Estimation of the Lactation Curve of a Dairy Cow, *Animal Production*, 40, 189-193, 1985.

Harvey, A.C., *Forecasting, Structural Time Series Models, and the Kalman Filter,* Cambridge: Cambridge University Press, 1989.

Haydock, K.P. and N.H. Shaw, The comparative yield method for estimating dry matter yield of pasture, *Australian Journal of Experimental Agriculture and Animal Husbandry*, 15, 663-670, 1975.

Kunnemeyer, R., P.N. Schaare and M.M. Hanna, A simple reflectometer for on-farm pasture assessment, *Computers and Electronics in Agriculture*, 31, 125-136, 2001.

Lambert, M.G., M.S. Paine, G.W. Sheath, R.W. Webby, A.J. Litherland, T.J. Fraser and D.R. Stevens, How do sheep and beef farmers manage quality? *Proceedings of the New Zealand Grassland Association*, 62, 117-121, 2000.

Marshall P.R., D.G. McCall and K.L. Johns, Stockpol: A decision support model for livestock farms, *Proceedings of the New Zealand Grassland Association*, 53, 137-140, 1991.

Meinhold, R.J. and N.D. Singpurwalla, Understanding the Kalman Filter, *The American Statistician*, 37/2, 123-127, 1983.

Nicol, A.M. and G.B. Nicol, Pastures for Beef Cattle, In: Livestock Feeding on Pasture, Occasional Publication No. 10 by the *New Zealand Society of Animal Production,* A.M. Nicol (Ed.), 1987.

Plant, R.E., Site-specific management: the application of information technology to crop production, *Computers and Electronics in Agriculture*, 30, 9-29, 2001.

Woodward, S.J.R., M.G. Lambert, A.J. Litherland and C.J. Boom, Can a mathematical model accurately predict intake of grazing animals? Testing the Q-Graze model, *Proceedings of the New Zealand Society of Animal Production*, 61, 4-7, 2001.