

28 Investigating Daily Changes in Food Intake by Ruminants

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Abstract

Trajectories of food intake for 12 sets of animals (weekly average intakes of four individual growing sheep, mean daily intakes of four pens of three growing cattle, and the mean daily intakes of four groups of six pregnant fallow does) were examined. The raw data exhibited expected seasonal trends, including changes in the amount of food eaten with changing live weight (LW) and age. The data were detrended by fitting polynomial equations of time. The residuals between the predicted and actual values were examined to determine the nature of period-to-period variations in food intake. Although the data-sets were obtained in different ways, the detrended data all showed similar food intake behaviours. In all but one case the residuals distributions were skewed negatively. The residuals vs time plots showed that large deviations below the expected values were more likely than deviations above the expected intakes, and that similar types of deviation tended to be clustered. Autoregressive integrated moving average (ARIMA) modelling indicated that autoregressive (AR) and/or moving average (MA) models, usually with a seasonal component, best fitted these data. However, the models had limited ability to predict food intake trajectories in the long term. These results suggest that when models are used to predict day-to-day variations in food intake, they should be primed by measuring actual intakes over at least 7–10 days; that similar intake behaviours are likely to occur together but that intakes that are lower than predicted will occur more often than those that are greater than predicted; and that intakes will additionally fluctuate in an apparently random way.

Introduction

Many relationships are available to predict food intake by ruminants. These are generally deterministic models in which predictor variables are identified and the relationships between these and intake are quantified. Common predictor variables are LW, age or current LW in relation to mature weight, body fat content, stage of lactation, net energy (NE) requirements, feed chemical composition (including cell wall content), ambient temperature, etc. Almost all these models simply attempt to forecast the mean feed intake of groups or of individuals over time, and several have been described and evaluated by Pittroff and Kothmann (2001a,b,c). There have been few

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Changes in Food

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average intakes of four indi-
vidual growing cattle, and the
variations were examined. The raw
data in the amount of food
intake were detrended by fitting poly-
nomial and actual values were
compared with variations in food intake.
The detrended data all showed
normal distributions were
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variations in the long term.
Day-to-day variations in
intake were over at least 7–10 days;
intakes that are lower
than predicted; and
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by ruminants. These
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fied. Common
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attempts to use previous intake records to refine forecasts of feed intake in animals. Oltjen and Owens (1987) compared two methods – (i) a Bayes modification of the Kalman filter, and (ii) an adjustment factor derived from the ratio of actual to predicted intake in the previous period – of refining predictions of feed intake by lot-fed cattle obtained from a mechanistic intake model. Bermejo *et al.* (2003a,b) used an AR approach to forecast short-interval changes in intake in pigs but apparently this approach has not been applied to ruminants.

Average feed intake gives useful information, e.g. for planning feed supplies and storages, or in forecasting average animal performance, but adds very little to our understanding of the magnitudes of expected day-to-day variations and why they occur, or to our capacity to predict meal-eating behaviour. A detailed understanding of short-interval changes in feed intake may allow more accurate updating of dynamic models of animal performance and better estimation of feed intake variability in stochastic models, would reassure animal managers that day-to-day variation in feed intake is normal, would be helpful in forecasting short-term variations in animal performance such as the daily changes in feed intake in lot-fed cattle, and may help to identify breeding objectives as suggested by Bermejo *et al.* (2003a).

Better knowledge of the nature of short-term intake behaviour may help us to understand better the process of feed intake control in ruminants. The purpose of the work described here is to investigate the structure of short-interval changes in feed intake in three different ruminant species, and to investigate the possibility of using feed intake trajectory data to forecast feed intake in ruminants.

Methods

Trajectories of food intake for 12 sets of animals were examined. The datasets were:

1. Sheep: weekly average dry matter intakes (DMIs) of four growing weaned lambs – one Border Leicester and three Suffolk – held in individual indoor pens and fed *ad libitum* a pelleted diet of 50% lucerne meal plus cereal grains and protein meals. Intakes were measured from weaning (average age = 10.6 ± 2.50 weeks, mean \pm SD) for 88–97 weeks. The initial and final LW of these animals were 21.6 ± 2.06 and 124.5 ± 7.01 kg, respectively. DMIs were expressed as $\text{g}/\text{kg}^{0.75}$ daily.
2. Cattle: daily DMIs of four pens of three growing yearling Wagyu cattle, held in outdoor feedlot yards. The initial and final LW of these cattle were 259 ± 17.1 and 287 ± 16.5 kg, respectively. Cattle in two yards were fed a medium-quality lucerne hay unchopped, in amounts sufficient to allow refusals. The other two groups were fed the lucerne hay plus an amount of hydroponically grown barley sprouts equivalent to 5% of average LW/day, equivalent to 25% of the diet DM. The feed was given in troughs

that provided 2 m per animal of linear trough space per pen. Measurements were made over 41 days. DMIs were expressed as kg/day.

3. Deer: daily average metabolizable energy intakes (MEIs) of pregnant *Dama dama* and *D. dama* × *D. mesopotamica* fallow does. The experiment was conducted in 1997 when data from five does in each genotype group were recorded and in 1998 with six does per group. The deer were housed indoors in individual pens. Three deer in each group were given a pelleted lucerne chaff/oat grain ration that had 10.3 MJ ME/kg DM, and the other three were given a pelleted concentrate diet with 14 MJ ME/kg DM. The amount of feed offered to each doe was increased by ~100 g/day, and was sufficient to allow refusals. There was no statistically significant difference between diets in the amount of ME eaten. Measurements were made during the second and third trimesters of pregnancy, over periods of 131–152 days. MEIs were expressed as MJ/day.

The data were detrended by fitting polynomial equations of time. The equations were fitted by forward inclusion of successively higher-order terms using changes in the significance of the regression equation, the significance of t values for the included regressor variables, and the R^2 value to decide on a satisfactory equation. The residuals between the predicted and actual values were examined to determine the nature of period-to-period variations in food intake.

For each set of residuals the mean and variance were calculated, and tests made for randomness (runs test, and tests for clustering and mixing), normality (kurtosis and skew, and the Andersen–Darling test for normality) using the Minitab (2000) software. Evidence for periodicity was sought from the autocorrelation functions (ACFs; Minitab, 2000), and spectral density plots derived using the Spectra procedure of SAS (2000), which uses a finite Fourier transform, and the Tukey–Hanning window. Multiple regression analysis (the stepwise inclusion method of the Reg procedure of SAS, 2000) of X_t vs $X_{t-1...k}$ was carried out to further investigate the relationships between feed intake on day t (X_t) and on the preceding days, $k = 16$ (cattle) or $k = 20$ days. Variables entered the model at $P < 0.15$.

ARIMA (Box and Jenkins, 1970) modelling (Minitab, 2000) was used to generate prediction models.

Results

Characteristics of the raw data

The raw data exhibited the expected seasonal trends, including changes in the amount of food eaten with changing LW and age. Representative plots of DM and ME intakes vs time are shown in Fig. 28.1. The equations and their statistics are given in Table 28.1.

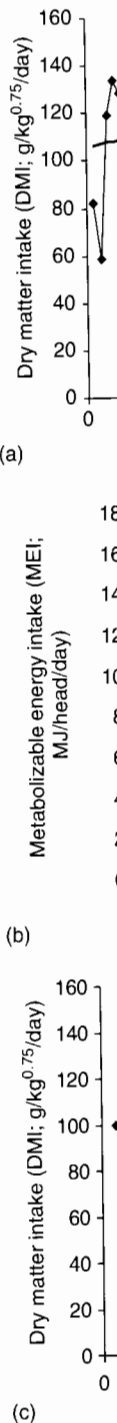


Fig. 28.1. Fo

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The deer were housed
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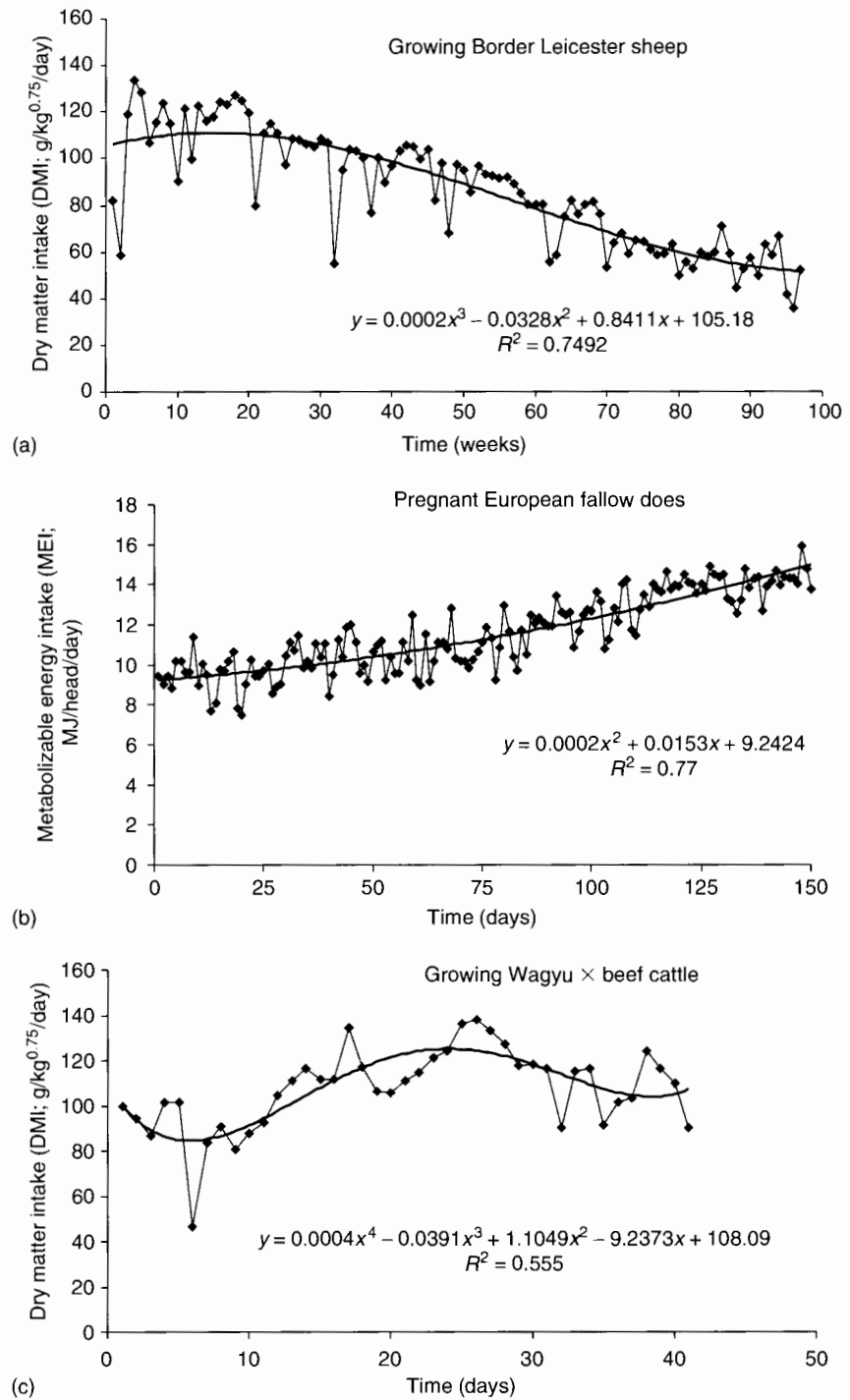


Fig. 28.1. Food intake trajectories, unadjusted for seasonal and other trends.

Table 28.1. Statistics for the residuals from the detrended data.

Data-set ^a	SD	Tests for normality			Tests for randomness		
		Distribution ($P =$) ^b	Skew	Kurtosis	Clustering ^c ($P =$)	Mixtures ^c ($P =$)	Runs ($P =$)
Pregnant deer (ME intake MJ/day)							
97-98E	0.923	0.086	-0.208	-0.530	0.025	0.975	0.013
97-98H	0.786	0.007	-0.514	0.645	0.000	1.000	0.000
98-99E	0.716	0.462	0.295	0.020	0.284	0.716	0.382
98-99H	0.644	0.740	-0.143	-0.395	0.022	0.978	0.286
Growing sheep (DM intake g/kg ^{0.75} /day)							
BL100	12.294	0.000	-1.591	4.142	0.002	0.999	0.478
SF4	13.769	0.000	-1.126	5.245	0.099	0.901	0.401
SF6	12.704	0.000	-1.381	8.079	0.092	0.908	0.264
SF62	14.008	0.000	-1.199	4.511	0.002	0.999	0.082
Growing cattle (DM intake g/kg ^{0.75} /day)							
L-C1	14.675	0.434	-0.037	1.144	0.041	0.949	0.082
L-C2	11.858	0.187	-0.815	1.525	0.078	0.922	0.162
L-5S7	15.349	0.513	-0.276	0.257	0.319	0.681	0.281
L-5S8	13.320	0.372	-0.434	-0.209	0.439	0.561	0.447

^aFor all data-sets, mean \rightarrow 0.0000.

^bSignificance of the Anderson-Darling normality test.

^cOne-tailed tests.

The tests for randomness gave ambiguous results. According to the runs test, except for two cases (Table 28.1), the residuals were apparently randomly distributed about the mean. However, tests for clustering were significant in 6 of the 12 cases. In many cases the residuals were not distributed normally, and 11 of the 12 sets were negatively skewed, indicating that values less than the mean were more common than those greater than the mean (see also Fig. 28.1).

Evidence of periodicity

Multiple regression analysis (Table 28.2) was used to investigate possible relationships between residuals obtained at varying times along the intake trajectory. One or more significant relationships ($P \leq 0.05$) were discovered for each data-set. While all of the multiple regression equations were significant ($P < 0.05$), they generally explained very little of the variance in the dependent variable. The notable exceptions were L-C1 and 97-98H where the equations explained about 60% of the variance in the dependent variable. The characteristics of these equations are summarized in Table 28.3.

The spectral density plots generally did not have the classic pattern of a fundamental followed by a series of harmonics. Instead, in many cases, there

Table 28.2. Multiple regressions

Data-set	R^2	P
Pregnant deer		
97-98E	0.196	0.00
97-98H	0.620	0.00
98-99E	0.217	0.00
98-99H	0.212	0.00
Growing sheep		
BL100	0.205	0.00
SF4	0.113	0.00
SF6	0.289	0.00
SF62	0.300	0.00
Growing cattle		
L-C1	0.587	0.00
L-C2	0.394	0.00
L-5S7	0.630	0.00
L-5S8	0.352	0.00

was a series of peaks in the spectral density plot. The location of the peaks is given in Table 28.3. Two peaks were observed in 17 (more common)

ARIMA modelling

ARIMA models were fitted to the residuals with the highest variance (RMS); (iii) pure AR and/or MA models were fitted to the data (Table 28.4). The models were compared to the residuals. In particular, the models were compared to accurately predict the period-to-period

Tests for randomness	Mixtures ^c (<i>P</i> =)	Runs (<i>P</i> =)
	0.975	0.013
	1.000	0.000
	0.716	0.382
	0.978	0.286
	0.999	0.478
	0.901	0.401
	0.908	0.264
	0.999	0.082
	0.949	0.082
	0.922	0.162
	0.681	0.281
	0.561	0.447

According to the runs were apparently ran- or clustering were sig- s were not distributed d, indicating that val- greater than the mean

to investigate possible times along the intake (0.05) were discovered equations were signif- of the variance in the 1 and 97-98H where e dependent variable. in Table 28.3. he classic pattern of a , in many cases, there

Table 28.2. Multiple regression analysis of residuals.

Data-set	Equation		
	<i>R</i> ²	<i>P</i> =	<i>X</i> _{<i>t</i>} =
Pregnant deer			
97-98E	0.196	0.0001	$0.03 + 0.14(X1) + 0.16(X6) + 0.15(X7) - 0.0003(X15) - 0.18(X18)$
97-98H	0.620	0.0001	$-0.01 + 0.99(X1) - 0.76(X2) + 0.58(X3) - 0.39(X4) + 0.34(X5) - 0.15(X10) - 0.09(X12)$
98-99E	0.217	0.0001	$-0.01 + 0.18(X2) + 0.19(X3) + 0.12(X10) - 0.18(X16) - 0.27(X18) + 0.18(X20)$
98-99H	0.212	0.0001	$0.01 + 0.32(X2) + 0.23(X3) - 0.15(X19)$
Growing sheep			
BL100	0.205	0.009	$-0.034 - 0.22(X6) + 0.29(X7) + 0.26(X11) - 0.21(X12) - 0.25(X18)$
SF4	0.113	0.044	$-0.53 + 0.17(X7) - 0.16(X13) - 0.14(X16)$
SF6	0.289	0.0002	$-0.61 - 0.15(X2) - 0.25(X4) - 0.19(X5) - 0.12(X17) + 0.25(X18)$
SF62	0.300	0.0001	$0.32 + 0.19(X1) + 0.17(X8) - 0.26(X14) - 0.11(X18)$
Growing cattle			
L-C1	0.587	0.003	$-1.86 - 0.32(X2) - 0.70(X4) - 0.94(X8) + 0.33(X9) + 0.21(X15)$
L-C2	0.394	0.004	$-0.79 + 0.31(X12) + 0.43(X13)$
L-5S7	0.630	0.004	$-6.79 - 0.38(X2) - 0.25(X3) + 0.32(X10) + 0.66(X13) + 0.80(X16)$
L-5S8	0.352	0.007	$-0.61 + 0.39(X9) - 0.42(X11)$

was a series of peaks of approximately similar size (Table 28.3; examples of spectral density plots are given in Fig. 28.2).

The locations (i.e. lags) of significant autocorrelations are indicated in Table 28.3. Two of the cattle data-sets exhibited no significant autocorrelation. In the other data, significant ACFs were located at lags of between 1 and 17 (more commonly 1 and 7) time periods.

ARIMA modelling

ARIMA models were chosen on the basis of: (i) the best fitting model (i.e. with the highest level of significance); (ii) the smallest residual mean square (RMS); (iii) parsimony; and (iv) the absence of correlated residuals. AR and/or MA models, usually with a seasonal component, best fitted these data (Table 28.4).

The models had limited ability to predict long-term feed intake trajectories. In particular, AR and MA models converged rapidly and while they accurately predicted the mean feed intake, they were of no use in modelling period-to-period variations (Fig. 28.3a). Seasonal models (Fig. 28.3b) gave

Table 28.3. Comparison of evidence for periodicity from three different approaches.

Data-set	Spectral analysis ^a	Multiple regression ^b	Autocorrelation analysis	
			ACF ^c	lag ^d
Growing cattle				
L-C1	2.5, 3.25, 6.75	2, 4, 8 , 9, 15	-0.34	4
L-C2	2.5, 3.25, 4.25 , 5.5, 7	12, 13	-	-
L-5S7	2.25, 3.5, 5, 7	2, 3, 10, 13, 16	-0.38	8
L-5S8	2.5, 3.25, 4.5, 8.5	9, 11	-	-
Pregnant deer				
97-98E	2.25, 3, 3.5, 7	1, 6, 7, 15, 18	0.24	1, 6, 7
97-98H	4.75, 7, 8.5, 10.25	1, 2, 3, 4, 5, 10, 12	0.66	1, 2, 16
98-99E	2, 2.5, 3, 3.25, 4, 5.25, 11	2, 3, 10, 16, 18, 20	0.21	2, 3
98-99H	2.25, 2.5, 3.5, 4, 7, 10, 15.5	2, 3, 19	0.35	2, 3
Growing sheep				
BL100	2.25, 2.75, 3.75, 8.25, 12.5	6, 7, 11, 12, 18	-0.24	17
SF4	2.25, 3.25, 3.75, 4.75, 6.5, 11	7, 13, 16	0.24	1
SF6	2.25, 3.25, 3.5, 3.75, 4.75, 9.5, 12	2, 4, 5, 17, 18	0.24	1, 5, 6
SF62	4, 4.75, 7, 9.75	1, 8, 14, 18	0.24	1, 5, 6

^aLocations of peaks in the spectral density vs period plots; values in bold indicate the main peaks.

^bVariables (X_i) included in the final regression equations; values in bold indicate variables with significant ($P < 0.05$) regression coefficients.

^cThe value of first significant (i.e. Student's $t > 2$) autocorrelation function (ACF).

^dLocations (i.e. lags) of statistically significant ACF; values in bold indicate the lag of the largest ACF.

better simulations of day-to-day variations, but again their tendency to converge meant that the accuracy of predictions declined after some 7–10 time units. When the model was reinitialized every seven time periods (Fig. 28.4), the simulation accuracy improved, giving deviations between actual and simulated intakes of 3.1 ± 2.36 g DM/kg^{0.75} daily (mean \pm SE). However, this obscures the fact that the maximum and minimum deviations were 410.9% and 5.7% of the corresponding actual intake.

Discussion

The three data-sets allowed three types of feed intake data to be tested. ARIMA models obtained from relatively short data runs (41 days), compared with those from longer runs (131–152 days), suggest that relatively short runs can give acceptable models. Bermejo *et al.* (2003b) similarly obtained useful data from only 25-day observations. It is perhaps surprising

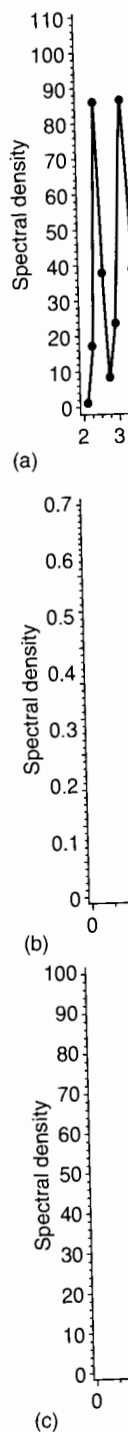


Fig. 28.2. Sp...
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Autocorrelation analysis	
ACF ^c	lag ^d
-0.34	4
-	-
-0.38	8
-	-
0.24	1, 6, 7
0.66	1, 2, 16
0.21	2, 3
0.35	2, 3
-0.24	17
0.24	1
0.24	1, 5, 6
0.24	1, 5, 6

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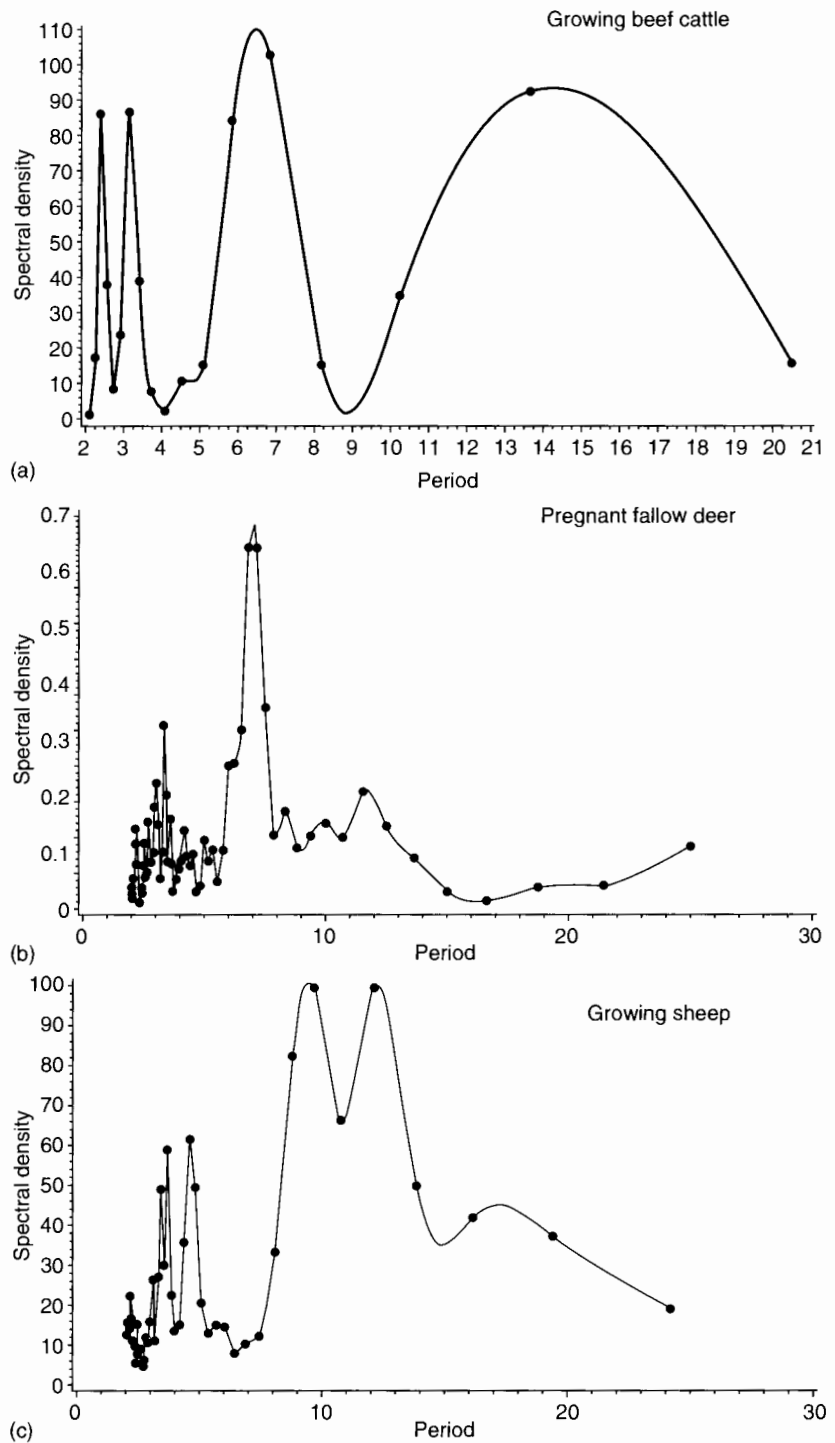


Fig. 28.2. Spectral density vs period plots of daily variations in feed intakes over time.

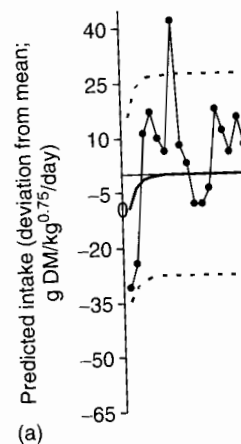
Table 28.4. Best ARIMA models for the estimation of food intake by growing sheep and cattle, and pregnant deer.

Data-set	Model type	Residual mean square (RMS)	Model			Autocorrelation of residuals to lag 24 ^a
			t	P =	R ²	
Pregnant deer						
97-98E	SAR(7)	0.8000	3.10	0.002	0.105	<i>P</i> > 0.05
97-98H	AR(1)		4.13	0.000		
		0.2247			0.641	<i>P</i> > 0.05
	MA(1)		-35.31	0.000		
98-99E	SMA(2)	0.4901	-2.57	0.011	0.056	<i>P</i> = 0.055
98-99H	SAR(2)	0.3642	4.27	0.000	0.136	<i>P</i> > 0.05
Growing sheep						
BL100	SAR(11)	133.9	3.68	0.000	0.216	<i>P</i> > 0.05
SF4	AR(1)	178.0	2.38	0.020	0.072	<i>P</i> > 0.05
SF6	SAR(6)	139.9	-3.95	0.000	0.187	<i>P</i> > 0.05
SF62	AR(1)	166.6	4.16	0.000	0.160	<i>P</i> > 0.05
Growing cattle						
L-C1	SAR(4)	168.05	-3.60	0.001	0.298	<i>P</i> > 0.05
L-C2	SAR(7)	96.44	-5.35	0.000	0.434	<i>P</i> > 0.05
L-5S7	SAR(8)	165.98	-4.63	0.000	0.436	<i>P</i> = 0.012
L-5S8	SAR(9)	154.87	2.52	0.016	0.324	<i>P</i> > 0.05

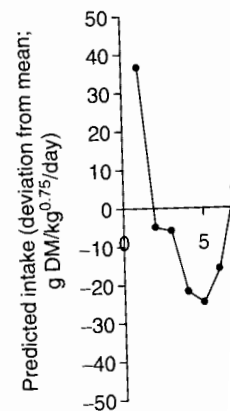
^aUsing the Box-Ljung χ^2 test.

that feed intake averaged over several animals (three cattle and five or six deer) gave very similar patterns of day-to-day variation in feed intake to those recorded for individual sheep. If endogenous factors (e.g. digestive tract fill, energy status) that regulate feed intake in animals do not become entrained when animals are kept in groups, they are likely to appear to act 'randomly' when the feed consumptions of individuals in a group of animals are compared. The similarity of feed intake patterns between the individuals and the groups of animals examined in this study suggests that exogenous factors may have important influences on feed intake. These factors could include changes in feed type, the effects of weather, social cues, etc. The management of housed animals may induce a weekly cycle; taking the weekly average of feed intakes, e.g. as in the sheep data, will remove this effect. However, comparison of the sheep data with those from deer and cattle does not offer any evidence that weekly cycles in feed intake occurred with the deer or cattle.

The probes of data structure reported in Table 28.1 suggest that between-time period variations in feed intake are: (i) often, but not always, normally distributed; (ii) generally negatively skewed; and (iii) often clustered so that there are runs of observations on the same side of the mean. Feed intake will



(a)



(b)

Fig. 28.3. Examples variation in food intake and lower 95% conf

be bounded by ze easily quantified, neural responses t digestive tract for upper bound fror are common. This the factors that cc ARIMA mod seasonal compor Bermejo *et al.* (2 workers found t ronmental fluctu

by growing sheep and

R^2	Autocorrelation of residuals to lag 24 ^a
0.105	$P > 0.05$
0.641	$P > 0.05$
0.056	$P = 0.055$
0.136	$P > 0.05$
0.216	$P > 0.05$
0.072	$P > 0.05$
0.187	$P > 0.05$
0.160	$P > 0.05$
0.298	$P > 0.05$
0.434	$P > 0.05$
0.436	$P = 0.012$
0.324	$P > 0.05$

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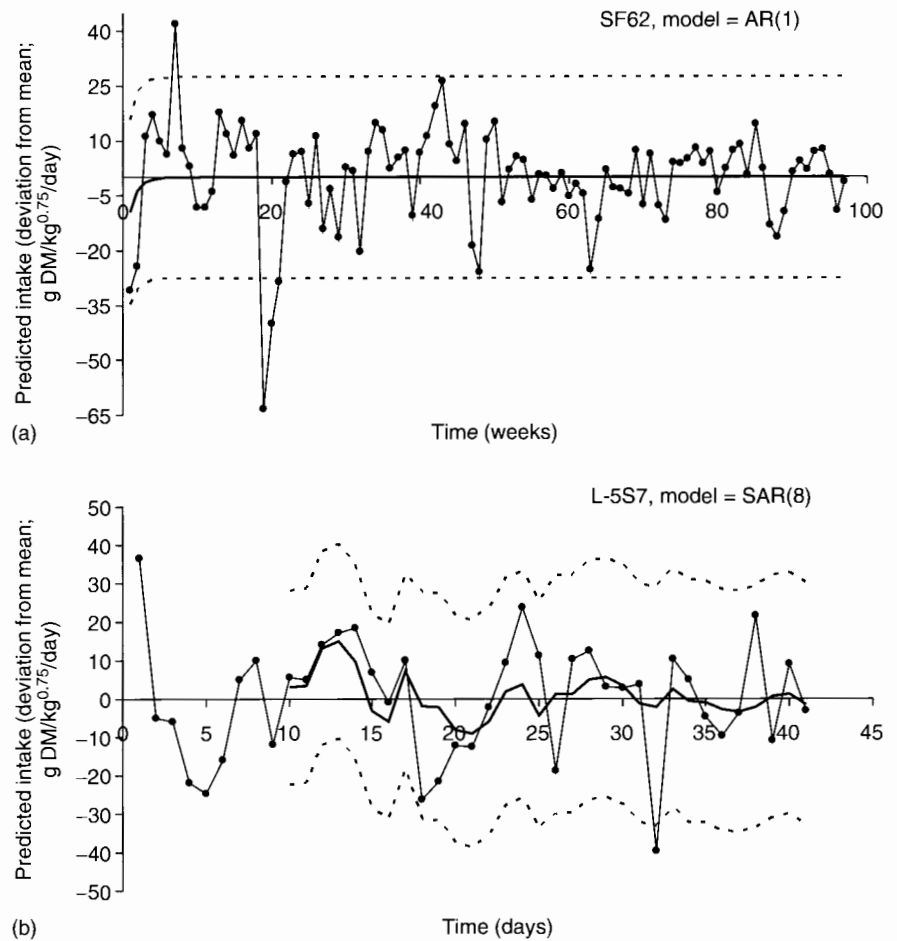


Fig. 28.3. Examples of the ability of ARIMA models to predict period-to-period variation in food intake (●—● original values; — forecast values; ---- upper and lower 95% confidence intervals for the forecasts).

be bounded by zero intake at the minimum and an upper value that is less easily quantified, but that will be a function of the animal's hormonal and neural responses to its energy status/demand, and possibly the capacity of its digestive tract for undigested feed. In practice, feed intakes will approach the upper bound from time to time, but quite large reductions below the mean are common. This suggests that it would be fruitful to identify and quantify the factors that commonly reduce feed intake below expected levels.

ARIMA modelling indicated that AR and/or MA models, usually with a seasonal component, best fitted these data. Similar results were reported by Bermejo *et al.* (2003a,b) for variations in daily feed intake by pigs. These workers found that ARMA(1,1) models adequately described the non-environmental fluctuations in daily feed intake. Taking the simplest general case,

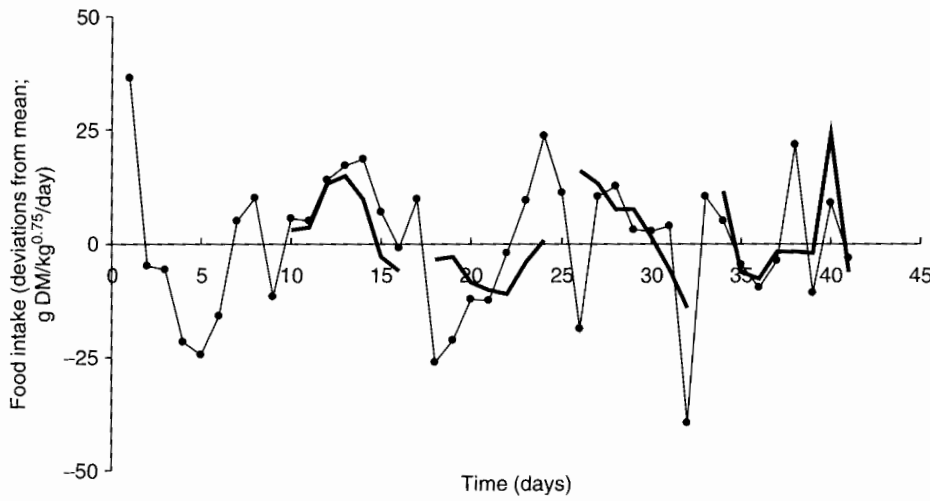


Fig. 28.4. Trajectory of food intake (for data-set L-5S7) simulated by an SAR(8) model, reinitialized every 7 days (●—● actual values; — predicted values).

an AR(1) model (Chatfield, 1996) of feed intake would be described by a relationship between today's intake (X_t), the overall mean intake (μ), a proportion (a) of yesterday's intake (X_{t-1}) and an error term (e_t):

$$X_t = \mu + a(X_{t-1} - \mu) + e_t \tag{28.1}$$

It is possible to expand the error term in equation (28.1) after the manner suggested by Turchin and Ellner (2000) to explicitly identify: (i) a component attributable to whatever relationship exists between intake today (X_t) and intakes in the few days before ($X_{t-1..k}$); (ii) the effects of other endogenous but unmeasured factors that may not be closely related to the effects of previous days' intakes but that also operate to regulate today's intake (U_t); and (iii) unidentified and unmeasured effects (e_t), so that

$$X_t = \mu + [a_1(X_{t-1} - \mu) + \dots + a_k(X_{t-k} - \mu)] + U_t + e_t \tag{28.2}$$

Significant relationships were obtained for most data-sets between previous days' intakes and present intake. Biological explanations for this may involve digestive tract-level factors that affect rumen fill (Faverdin *et al.*, 1995), such as rumen microbial metabolism, capacity of the reticulo-rumen, digestion kinetics and digesta flow kinetics; or behavioural responses to eating indigestible feeds such as more frequent meal-eating and rumination (Baumont *et al.*, 1990). All of these will influence the amount of free space in the digestive tract, and thus the amount of new feed that can be eaten. It might be expected that slower-digesting feeds, such as the lucerne hay fed to

the growing cattle, v the concentrate-rich ever, there is no cor better than the deer

The highly sign sarily mean that p intake. There may b endocrine system. I tion in the third ven by goats (Mogi *et al* effect of feed intake also be modelled as lags. This might ex tends to cluster on t

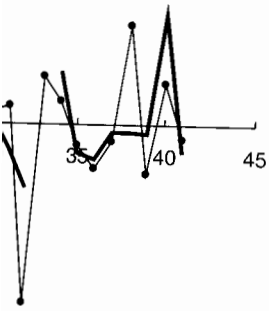
Statistical signi equate with good p component in the m gence to the mean, time intervals. This (Cryer, 1986, p. 164 to be necessary to g intake.

The U_t term in e perturb the expecte recorded in these c uniform nature of t from exogenous so adequately forecast Shocks may includ feed, introduction o or method of feed regular exogenous model the effects c of the shock can be X_{t-k} , and the natur defined as:

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The time periods short ($r \approx 7$) to be in this analysis a unexpected chan

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$$I_t + e_t \quad (28.2)$$

...a-sets between previous ...anations for this may ...en fill (Faverdin *et al.*, ... of the reticulo-rumen, ... ioural responses to eat- ...eating and rumination ... amount of free space in ...d that can be eaten. It ...s the lucerne hay fed to

the growing cattle, would give closer relationships between X_t and X_{t-k} , than the concentrate-rich, pelleted diets used in the deer and sheep studies. However, there is no convincing evidence that AR models fitted the cattle data better than the deer or sheep data.

The highly significant AR terms in many of these models do not necessarily mean that previous days' intakes per se directly influence present intake. There may be rapid, but indirect, AR effects mediated via the neuro-endocrine system. For example, fluctuations in neuropeptide Y concentration in the third ventricle preceded exactly by 24 min episodes of meal-eating by goats (Mogi *et al.*, 2003). Less direct effects, e.g. where leptin acts via the effect of feed intake on the size of adipose tissue (e.g. Vega *et al.*, 2004), will also be modelled as AR effects, although in these cases there may be long lags. This might explain why a succession of daily feed intake variations tends to cluster on the same side of the mean.

Statistical significance of the model components did not necessarily equate with good predictive ability, as is easily seen in Fig. 28.3a. A seasonal component in the model appeared to be necessary to prevent rapid convergence to the mean, and even the seasonal models converged after several time intervals. This convergence is a characteristic of stationary AR models (Cryer, 1986, p. 164). Reinitialization every few time intervals thus appears to be necessary to get a reasonably good simulation of actual day-to-day feed intake.

The U_t term in equation (28.2) may represent shocks or innovations that perturb the expected feed intake trajectory. The sharp changes in trajectory recorded in these data-sets suggest that such shocks occurred. Given the uniform nature of the feeds used in these experiments, they were probably from exogenous sources. It is noticeable that the ARIMA models did not adequately forecast these peaks and troughs of feed intake (Fig. 28.4). Shocks may include social interactions such as bullying or competition for feed, introduction of a new feed type, rapid changes in ambient conditions or method of feeding management. Seasonal ARIMA models can model regular exogenous shocks, but not erratic ones. Threshold models can model the effects of exogenous shocks (Chatfield, 1996), and the timing (r) of the shock can be set to suit the data. The relationships (a) between X_t and X_{t-k} and the nature of U_t , change as a result of the shock. Such a model is defined as:

$$X_t = \begin{cases} \mu + a_1(X_{t-1} - \mu) + \dots + a_k(X_{t-k} - \mu) + U_t + e_t & \text{where } t < r \\ \mu + a_1^*(X_{t-1} - \mu) + \dots + a_k^*(X_{t-k} - \mu) + U_t^* + e_t & \text{where } t \geq r \end{cases} \quad (28.3)$$

The time periods between the apparent shocks in these data-sets are too short ($r \approx 7$) to be able to fit appropriate threshold models, and the data used in this analysis are not sufficiently rich to identify exogenous reasons for unexpected changes in the direction of the feed intake trajectories.

Although reasonable short forecasts of actual intakes were achieved with some models, the residuals between forecast and actual observations, and the

low estimated model R^2 , suggest that a substantial part of the variation in day-to-day changes in feed intake remains unexplained. The structure of this variation needs to be identified before we can expect to predict daily intake in ruminants with any accuracy. The ARIMA analyses indicated that the residuals were uncorrelated, and in all but the sheep data they were normally distributed. The e_t term in equation (28.2) thus appears to be random. This apparent randomness could be a result of the interaction of an unknown number of deterministic factors, as it seems counter-intuitive that animal metabolism should act in a random fashion.

The nature of the error in these models is crucial, as certain error structures would imply that it is impossible to model short-term food intake. Food intake is subject to deterministic control, but if it is non-linear, the process could be chaotic. This of course means that daily food intake could only be modelled broadly, within certain bounds, as the trajectory would be sensitively dependent on initial conditions. It would almost certainly be impossible to adequately describe these. There are many examples of chaotic systems in biology, e.g. ecological systems, kidney function, disease outbreaks and mammalian enzyme systems (Degn *et al.*, 1987; Perry *et al.*, 2000), but the possibility of a chaotic component to food intake in ruminants does not appear to have been tested.

Conclusions

These results suggest that when models are used to predict short-term variations in food intake, they should be primed by measuring actual intakes over at least 7–10 days so that periodicity can be adequately quantified; that similar intake behaviours are likely to occur together but that intakes that are lower than predicted will occur more often than those that are greater than predicted; and that intakes will additionally fluctuate in an apparently random way.

ARIMA modelling may offer a way of forecasting feed intake in ruminants. The main constraint to its use is a tendency for the model estimates to converge and ultimately to simply give an estimate of the mean intake. In practice, this constraint may be overcome by using ARIMA models for only short-term feed intake forecasts, and to reinitialize the model at short (e.g. 7-day) intervals.

Better understanding of the structure of unexplained error is needed before we can devise completely adequate models of day-to-day intake by ruminants.

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