Modelling of Growth and Development for Optimising Beef Cattle Production Systems

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Declaration

I certify that the substance of this thesis has not already been submitted for any degree and is not currently being submitted for any other degree or qualification.

I certify that any help received in preparing this thesis, and all sources used, have been acknowledged in this thesis.

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Signature

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List of Abbreviations

ActEBW	Actual Empty Body Weight
ADIP	Acid Detergent Insoluble Protein
AFRC	Agricultural and Food Research Council
ARC	Agricultural Research Council
B3	Japanese B3
BRD	Bovine Respiratory Disease
BSE	Bovine Spongiform Encephalopathy
BSV	Blood/Skin/Viscera
BT1	Biological-Type 1
BT2	Biological-Type 2
CF	Crude Fibre
ChemDOM	Chemical Degree of Maturity
CHTF	Carcass/Head/Tail/Feet
CNCPS	Cornell Net Carbohydrate and Protein System
CP	Crude Protein
CPC	Crude Protein Content
CRC	Cooperative Research Centre
CSIRO	Commonwealth Scientific and Industrial Research Organisation
DCP	Digestible Crude Protein
DE	Differential Evolution
DigE	Digestible Energy
DM	Dry Matter
DMD	Dry Matter Digestibility
DOM	Degree of Maturity (model)
DP	Dermal Protein
DPLS	Digestible Protein leaving the Stomach
DPLSm	Digestible Protein Leaving the Stomach from microbes
DSS	Decisions Support Systems
EBV	Estimated Breeding Value
EBW	Empty Body Weight
EFP	Endogenous Faecal Protein
EIP	Estimating Individual Parameters

EM	Expectation Maximisation
EP	Evolutionary Programming
EPP	Estimating Population Parameters
ES	Evolutionary Strategies
EU	European Union
EUP	Endogenous Urinary Protein
FBW	Full Body Weight
FFM	Fat Free Matter
FMEI	Fermentable Metabolisable Energy Intake
GA	Genetic Algorithm
GE	Gross Energy
GF	Gut Fill
GH	Growth Hormone
HC	Hot Carcass
HDOM	Hierarchical Degree of Maturity
HS	Heavy Supermarket
IDCP	Ideal Digestible Crude Protein
IMF	Intramuscular Fat Percentage
JSSP	Job Shop Scheduling Problem
LCS	Learning Classifier Systems
LW	Live Weight
MCP	Microbial Crude Protein
ME	Metabolisable Energy
MEE	Maintenance Effective Energy
MEI	Metabolisable Energy Intake
MJ	Mega Joules
MSE	Mean Squared Error
MW	Mature Weight
NE	Net Energy
NRC	National Research Council
P8	P8 Fat Depth
QTL	Quantitative Trait Loci
RDP	Rumen Degradable Protein
RFI	Residual Feed Intake

RK	Random Key Representation
RMD	Remainder
RUP	Rumen Undegradable Protein
SCA	Standing Committee on Agriculture
SB	Separable Bone
SD	Standard Deviation
SF	Separable Fat
SM	Separable Muscle
SSE	Sums of Squares of Error
SST	Total Sums of Squares
TAMU	Texas A&M University
TDN	Total Digestible Nutrients
TGRM	Total Genetic Resource Management
TSP	Travelling Salesman Problem
UDP	Rumen Indigestible Protein
WRSS	Weighted Residual Sums of Squares

List of Parameter Definitions

b	Differential Growth Ratio (Allometric Coefficient)
B^*	General Rate Parameter
B_s	Scaled Rate Parameter
P_m	Mature Protein Content
Q	Mature Lipid to Protein Ratio
SRW	Standard Reference Weight
W_o	Birth Weight

Abstract

The continuous need for improved agricultural production efficiency requires that a greater quantity and quality of information is available for producers to base their decisions upon. This information pertains to current production circumstances (e.g. production levels, price structures and environmental conditions) as well as the outcomes from scientific research. The incorporation of scientific findings into decision support systems (DSS) is increasing the use of available production information and allowing different production scenarios to be explored in order to help improve the quality of decisions made. However, most current DSS do not have the capacity to determine what decisions would be optimal for a given production system. Instead they simply support decisions by predicting possible outcomes that are not immediately obvious and/or obtainable. Scientific outcomes can be incorporated into DSS in the form of simulation models that describe the system under consideration. In the context of beef cattle production, decisions relating to drafting, feeding, marketing, logistics and breeding could be optimised based on the output from a feeding and growth model. The successful application of a DSS of this nature would rely on how indicative the model is of animal growth and development in a variety of production environments and for different animal types.

Predictive Ability of Feeding and Growth Models

Developing mathematical equations to represent the growth of animals is not a new science and has taken many forms during the last century. These range from single equations that fit growth as a function of time to growth simulation models that consider information relating to age, feed intake, feed quality, environmental influences and genetic capacity of animals. Chapter 3 uses a number of criteria to narrow down the models available in the literature and test the capacity of the remaining growth models to predict weight changes, when age and feed intake information is available. The accuracy of model predictions was determined by comparing observed body weights with predicted body weights. This was achieved by keeping breed and sex as well as the nutritional and external environments constant while using model input parameters estimated in external populations. The robustness of the models was determined by testing how accurately models predicted body

weights using data sets that differ in nutritional and external environments but contained the same breed and sex (i.e. Angus steers).

Parameter estimation to test model accuracy revealed that models of a more simplistic nature (polynomial, Gompertz (1825)) and that only consider limited information (e.g. age) provided more accurate fits to live weight data than models that are more complex (Freer (1997), Amer (1998)) and also require larger quantities of information (e.g. feed intake, feed quality). The difference in ability to fit data between the simplistic and complex models is a consequence of the more complex models containing a large number of biological principles which constrains them to follow what is considered to be sensible growth patterns. In contrast, the simplistic models contain few biological principles, if any (polynomial), which allows them the flexibility to alter their shape to match the data. It was also found that the inherently biologically rich structures of the more complex models resulted in a greater number of parameter estimates being anchored against search space boundaries. This occurred as a consequence of the optimisation procedure attempting to achieve the lowest residual sums of squares possible. This is not a desirable outcome and points toward the need to increase the amount of information available to the growth model and the possibility of developing an alternative method for estimating growth model input parameters.

Model robustness was assessed firstly by using datasets to test the transferability of parameter estimates between animal populations when environmental, breed and sex effects were identical. Secondly, other datasets were used for the purpose of testing the transferability of parameter estimates between animal populations when controlling breed and sex effects but allowing nutritional components of the environment to change. In both cases the Freer (1997) and Amer (1998) models were shown to have greater predictive abilities with this being most evident in the results obtained when the nutritional environment changed. This was attributed to both the type of information these models considered, including feed quality (e.g. metabolisable energy and crude protein content) and the inherently biologically rich structure of these models.

Development and Testing of Body Composition Models

The markets serviced by the Australian Beef industry, although different, all have requirements that relate to the physical quantities of carcasses. Thus, to be able to optimise any decisions that relate to these characteristics a model is required that is capable of accurately partitioning the whole body into its physical quantities. There is a lack of such models available in the literature. Chapter 4 attempted to address this by developing a number of models that are based around allometric equations. The predictive ability of these models, when empty body weight was given and growth was occurring *ad libitum*, was tested in comparison to two models taken from the literature.

The allometric coefficients (b) estimated for the models developed in chapter 4 represented sensible patterns of body component development. The estimated allometric constants (a) partitioned the empty body into sensible proportions of flesh, bone, viscera, blood and skin at maturity, e.g. flesh represented the highest proportion while blood represented the smallest, following *ad libitum* growth. The first 'chemical degree of maturity' model developed in this study was found to have a predictive ability that was inferior to the physical body composition models taken from the literature. The remaining four models developed in this study had predictive abilities that were found to be superior to the models taken from the literature. The second 'chemical degree of maturity' model was found to consistently have the lowest predictive ability of these four models. The hierarchical degree of maturity (HDOM) model was found to perform at a consistent level, although not always the best. The predictive abilities of the actual empty body weight (ActEBW) and degree of maturity (DOM) models varied with how data were presented for testing. When data were presented as bone, flesh and non-carcass the DOM model had a superior predictive ability compared to the ActEBW model. In contrast, the ActEBW model had a greater predictive ability when non-carcass was presented as viscera and remainder. Flesh weight was found to be predicted with the greatest accuracy by all models tested (e.g. $R^2 = 0.999$ for the HDOM, DOM and ActEBW models).

Estimating Model Input Parameters for Animal Cohorts

The diversity present in animal growth is a fact that most growth simulation models do not take into consideration. These models are developed to represent what are perceived to be 'average' animals without considering between-animal variation. It has been determined that the responses produced by such models are different to the average responses of an animal population, because of the non-linear relationship between model input parameters and model outputs. This has lead to the realisation that it would be desirable for models to consider between-animal variation particularly when they are used to represent whole production systems and/or for economic optimisation. Chapter 5 explored the speed and accuracy of different methods used for sampling from a simulated population during inverted modelling to estimate growth model population parameters by matching model outputs to observed population parameters (mean and standard deviation of body weight at 250, 450, 650 and 1250 days of age).

Stochastic sampling from parameter distributions produces sampling errors that reduce accuracy unless very large numbers of samples are taken. Deterministic sampling is a fully repeatable method that offers the opportunity to overcome these sampling errors. The difference in accuracy between deterministic and stochastic sampling was found to approach statistical significance ($p=0.077$) when estimating growth model input parameters. Greater uncertainty was associated with the parameter estimates made using stochastic random sampling. The predictive ability of the parameter estimates made by both methods was tested in comparison to those estimated in chapter 3, which Estimated Individual animal Parameters (EIP) and subsequently calculated parameter averages and standard deviations. The parameters estimated by EIP were found to have the greatest predictive ability, probably because they used all age and feed intake data available. This predictive ability was reduced when tested with a second less information-rich dataset. The parameters estimated by both sampling methods were found to be more accurate for this dataset. When even smaller quantities of data were available the parameters estimated using deterministic sampling had greater predictive abilities than those estimated with either random sampling or EIP.

Selective Drafting of Cohorts

The efficiency of animal production is a function of how the available resources are used to achieve the desired outcomes of a production system. Drafting animals into cohorts is a practice commonly used to help manipulate animal growth to meet the physical constraints of production systems. Drafting also offers the opportunity to take advantage of the diversity that is inherently present in animal growth by matching animals to the needs of different target markets as well as the opportunity to use different management options for these markets. The growth and composition models tested in chapters 3 and 4 along with the input parameters estimated in chapter 5 were combined within a simulated production system to predict growth outcomes in chapter 6. These predictions formed the basis of a method that uses the random keys representation (RK) to draft animals into market cohorts that are custom managed to the market's needs and appropriate for the animals' growth potentials.

Four production scenarios similar to those that have been seen in the Australian production environment were used to test how drafting with Differential Evolution (DE) using RK reacts to different prevailing production conditions. DE drafted animals toward the Heavy Supermarket (HS), European Union (EU) or Japanese B3 (B3) markets under optimal conditions in scenario 1. In scenario 2, when the value of the B3 market was reduced, DE reallocated animals into either the HS or EU markets. In response to this reallocation new optimal slaughter ages were determined to compensate for animals with higher mature protein (P_m) and general growth rate (B^*) parameters being included in the EU market. The lower slaughter age of 590 days also prevented some animals allocated to the EU market in scenario 1 from achieving the desired carcass characteristics in scenario 2 resulting in them being reallocated to the HS market.

The allocation of animals to market cohorts by DE was explored in scenario 3 when drought conditions reduced pasture availability. A distinct outcome in this scenario was the depressed growth trajectories of all market cohorts. The animals allocated to the B3 market were identical to those allocated in scenario 1, indicating that even though the growth of these animals was suppressed due to the drought conditions they were able to achieve the carcass characteristics required by the B3 market when feedlotted. In contrast to scenario 1, more animals were allocated to the HS and less to the EU markets. Animals that were reallocated were either unable to attain the carcass characteristics required by the EU market or the carcass they produced was less valuable than the carcass they produced for the HS market. Scenario 4 explored what impact increased costs of production in the B3 market would have on animal allocation. The profitability of some animals was still at its maximum when allocated to the B3 market even though the costs of production were elevated. However, the majority of animals from the B3 market in scenario 1 were reallocated to the EU market, which caused a reallocation of animals to the HS market, similar to what occurred in scenario 2. This reallocation occurred in conjunction with the optimal slaughter age for the EU market being reduced from 740 to 590 days. In scenarios 3 and 4, interactions between individual growth model input parameters along with interactions between the parameters and optimal slaughter ages had important impacts on the allocation of animals to market endpoints.

The behaviour of the drafting system was found to be sensible in each of the production scenarios presented. However, there are possible refinements that could be made to the predictive models and the optimisation procedure that would increase the number of production scenarios it could be applied to (e.g. include heifers, cows and bulls in the drafting process) and the confidence that can be placed in the results obtained. The most obvious of these changes would involve further development of linear regressions used to predict P8 fat depth and IMF percentage to include factors such as nutrition, breed and sex.

The methods developed and results obtained in this last chapter point to the feasibility of using growth models, animal data and decision support systems with optimisation engines to help drive a wide range of management decisions to best exploit animal performance and market opportunities.