EVALUATIONS OF A MATHEMATICAL MODEL IN PREDICTING INTAKE OF

GROWING AND FINISHING CATTLE

A Thesis

by

BRANDI MARIE BOURG

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

December 2007

Major Subject: Animal Science

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Approved by:

Chair of Committee,	Luis Tedeschi
Committee Members,	Gordon Carstens
	F.M. Rouquette, Jr.
Head of Department,	Gary Acuff

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ABSTRACT

Evaluations of a Mathematical Model in Predicting Intake of Growing and Finishing Cattle.

(December 2007)

Brandi Marie Bourg, B.S., Louisiana State University

Chair of Advisory Committee: Dr. Luis Tedeschi

The Cattle Value Discovery System (CVDS) was developed to predict growth and feed requirements of individual cattle fed in groups based on animal, diet, and environment information (Tedeschi et al., 2006). Evaluations of the CVDS using several databases of finishing cattle were conducted to determine the accuracy and precision of the model in predicted dry matter required (DMR) of pen-fed cattle. As well, the sensitivity of the model's predictions to deviations from actual ration metabolizable energy (ME) value was conducted. A meta-analysis of growing and finishing steers evaluated to model's accuracy in predicting DMR of individually fed steers, and the relationships between several model-predicted variables and actual performance and efficiency measures.

Results for the first CVDS model evaluation involving pen-fed Santa Gertrudis cattle fed finishing diets revealed that accurate predictions of DMR are possible. The average mean bias for both steers and heifers was 2.43%. The sensitivity analysis of dietary ME values revealed that the model tends to consistently over- and under-predict DMR when the ME values are under- and over-estimated, respectively. However the ranking of pens was not affected by this mis-estimation of diet ME. In the second evaluations, both methods (mean body weight; MBW, dynamic iterative model; DIM) of CVDS were highly accurate and precise in allocating feed to pens of steers fed diverse types of diets and environmental conditions, with both models having a mean bias under 4%. The DIM model was slightly more accurate than the MBW model in predicting DMR. An evaluation of sources of variation revealed that for both models a large portion of the error was random, indicating that further work is needed to account for this variation. The meta-analysis study revealed that the model was able to account for 64% and 67% of the variation in observed dry matter intake (DMI) for growing and finishing steers, respectively. The two model-predicted efficiency measures, the ratio of DMR to average daily gain (ADG) and predicted intake difference (PID), were strongly to moderately correlated with their observed efficiency counterparts. In growing and finishing steers, DMR: ADG was able to account for 76% and 64% of the variation in observed feed conversion ratio (FCR) in growing and finishing studies, respectively. Strong correlations were also found between residual feed intake (RFI) and PID, suggesting that there may also be some similarity on these two measurements.

NOMENCLATURE

CVDS	Cattle Value Discovery System
CNCPS	Cornell Net Carbohydrate and Protein System
DECI	Decision Evaluator for the Cattle Industry
NRC	National Research Council
BW	Body weight
$BW^{0.75}$	Average metabolic body weight
ADG	Average daily gain
DMI	Dry matter intake
DMR	Dry matter required
RFI	Residual feed intake
PID	Predicted intake difference
FCR	Feed conversion ratio
R: G	DMR: ADG
FFM	Feed for maintenance
FFG	Feed for gain
ME	Metabolizable energy
RE	Retained energy
NEm	Net energy for maintenance
NEg	Net energy for gain
EBF	Empty body fat

EBW	Empty body weight
IBW	Initial body weight
FBW	Final body weight
SBW	Shrunk body weight
AFSBW	Adjusted final shrunk body weight at 28% EBF
FT	12-13th rib fat thickness
REA	*Longissimus dorsi* muscle area, rib-eye area
MRB	Marbling score
PEG	Partial efficiency of growth
KR	Kleiber ratio

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CHAPTER I

INTRODUCTION

The conversion of feed into animal products during the post-weaning growth phase has a large influence on the cost of producing beef (Herd et al., 2003). The beef industry is moving steadily toward a system where cattle and carcasses are managed and marketed on an individual rather than pen basis (Cross and Whitaker, 1992). Individual Cattle Management Systems (ICMS) may aid in improving profitability, minimizing excess fat produced, and improving product consistency by decreasing individual animal variability within a pen. As cattle from multiple owners and biotypes are often fed together within a single pen, successful implementation of ICMS would require more accurate predictions of feed inputs of individual calves based on performance data (Fox et al. 2001). A successful ICMS program has to meet three directives: (1) accurate prediction of rate and cost of gain, (2) accurate prediction of days to finish, and (3) accurate allocation of feed to individual animals based on performance and diet information in order to facilitate marketing of individual animals at their most profitable endpoint.

The Cattle Value Discovery System (CVDS) was developed to predict growth and feed requirements of individual cattle fed in groups based on animal, diet, and environment information (Tedeschi et al., 2006). An enhanced, dynamic version of the CVDS model was developed and evaluated (Tedeschi et al., 2004) to improve the

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accuracy of these predictions. The CVDS utilizes observed BW, average daily gain (ADG), carcass measurements, breed type, environmental conditions, and dietary metabolizable energy (ME) to predict BW at 28% empty body fat (AFBW), feed DM required for maintenance, feed DM required for gain, and their sum of DM required (DMR). From these values the model predicts several feed efficiency indicators, such as DMR: ADG and predicted intake difference (PID), which is calculated as observed DMI minus DMR.

Previous studies have shown model predicted DMR to be highly accurate in allocating feed to individual animals fed in groups with values within 2% of actual pen intakes (Fox et al., 2004a). Williams et al. (2006) found strong genetic correlations (> 0.95) between DMR and observed DMI in finishing steers. Due to the accuracy of CVDS and its relationship to observed traits, it may be a useful tool in identifying efficient animals. Therefore, a thorough evaluation of the CVDS model is needed for growing and finishing animals in different scenarios of production.

CHAPTER II

LITERATURE REVIEW

Mathematical models are very useful tools to apply to livestock production. Often it may be difficult, expensive, or even unethical to apply a certain treatment in an experiment; here a model of the system plays an important role in furthering our understanding the system. They can be used to predict the effects a certain disease may have on a population without having to actually infect any animal. Evaluating environmental effects of large scale animal feeding operations has also benefited from the use of models that predict excreted nutrient run-off and its effect on environmental pollution.

The conversion of feed into animal products during the post-weaning growth phase has a large influence on the cost of producing beef (Tess and Kolstad, 2000; Herd et al., 2003). With increases in feed prices there is a rising interest in improving the efficiency of our beef production systems. In a review beef cattle energetic efficiency, Johnson et al. (2003) noted that fattening steers retain only 16-18% of energy that they consume. However, the cost of measuring individual feed intake is often the prohibiting factor in the collection of individual animal efficiencies which are necessary if genetic improvements are to be made.

The beef industry has been moving steadily toward a system where cattle and their carcasses are managed and marketed on an individual rather than pen basis (Cross and Whitaker, 1992). Fox et al. (2001)described an Individual Cattle Management System (ICMS) and the application of a decision support system to aid these programs. The ICMS may aid in improving profitability, minimizing excess fat produced, and improving product consistency by decreasing individual animal variability within a pen. As cattle from multiple owners and biotypes are often fed together within a single pen, successful implementation of ICMS would require more accurate predictions of feed inputs of individual calves based on performance data (Fox et al. 2001).

Predicting individual animal intake based on performance and diet information provides a useful tool for several scenarios. Not only would this provide a means to more cost-effectively determine individual animal intake for use in determining individual animal efficiency for use in genetic improvement programs, but also provides a tool to allocate feed to individual animals fed in pens of mixed ownership. For a mathematical model to be applied to the prediction of intake in these scenarios, the model must be able to accurately and precisely perform these tasks. Therefore, the objectives of this literature review are to 1) review several current mathematical models whose purpose is to predict intake of growing and finishing beef cattle and 2) to review techniques for evaluating model predictions.

Mathematical Models

As with all agricultural production systems, the production of beef is categorized as a biological system. According to Jones and Luyten (1998), biological systems are highly complex, involving numerous components that interact simultaneously, and often in highly non-linear or chaotic manners. These biological processes are made up of interacting chemical processes, of which in many cases, we have an incomplete understanding. Therefore, often when we study or attempt to understand these systems our work is often impeded by our misunderstanding. This is when modeling or simulations of complex systems are often useful to provide insight into the behavior and management of these systems (Jones and Luyten, 1998).

Jones and Luyten (1998) a system can be defined as “a collection of components and their interrelationships grouped together for the purpose of studying some part of the real world.” These systems are often viewed as a simplified view of reality, and offer us a way to study biological processes without the effects of certain unknown interactions. Rountree (1977) stated that an important property of any system is that it can be defined within a hierarchy of systems. A farm or ranch is a hierarchy of systems and sub-systems. The ranch as a whole is one system, while individual herds within the ranch are another system, and individual animals within a herd are systems within themselves. One can continue to classify systems and sub-systems, but it is important that the system does not become too small and difficult to model. It is also important that our systems are affected by their environment, but that the environment is not affected by the system (Jones and Luyten 1998). This is an important concept because if the system we are trying to study has a significant impact on its environment then it would also require a modeling of the environment and the changes that the system would inflict upon it (Jones and Luyten 1998). This is a vital step during the development phase of a model: determining the model boundary and exogenous variables.

Peart and Curry (1998) define the model of a system as a “set of equations and rules that quantitatively describe the operation of a system through time.” The authors also describe simulation as the solving of these equations used to define the system within set rules over a period of time, or the mimicking of how a system will perform over a set amount of time by calculating values of the variables at a series of time steps.

In a discussion of mathematical models in applied livestock production science, Sorensen (1998) described a model as a simplification of the system from a certain perspective and with a certain purpose. In other words, we design our models to suit the purpose of our particular analysis or theory.

Gill et al. (1989) stated that the representation of biological concepts as equations or sets of equations, and the subsequent solving of these equations simulating the behavior of a system are called mathematical models. In a review of the biochemical basis in the steps taken during the construction of whole animal metabolism, Gill et al. (1989) stated some drawbacks of predictive models, such as those that predict intake, which previously had been derived from statistical analysis of large data sets, making it difficult to apply the model for predictive purposes to dissimilar datasets.

In the chapter on using mathematics as a problem solving tool, Cooke (1998) offers an adaptation of the steps in formulating a mathematical model from Ver Planck and Teare's (1954) suggestions. The author offered five general steps and considerations that should be followed when one is trying to model a process or system. The first step is simply defining the problem, which involves dividing it into a series of specific questions, deciding among alternative approaches, and review previous literature on the topic. The next step in model formulation is planning its treatment. This involves identifying assumptions that must be made, and trying alternative explanations, among other things. Cooke (1998) emphasizes that the rule of Occam's razor should be followed here, with a successful simpler explanation being more desirable than a complex method that yields the same result. Step number three is to execute the plan. This is where the actual model set-up and formulation comes into play. Here it is important to define variables and assign units, number equations, and attempt the use of more than one approach. Good note-keeping is a must at this step. Step four is checking thoroughly, and it may be the most important step when formulating a model. Frequent use of intermediate checks is a must, and often the most effective way to check the development of the model is through the use of a carefully designed experiment. A properly designed experiment may serve to more readily convince one that the model and its underlying assumptions are indeed valid. The final step in model formulation is to learn and generalize from the analysis, and to summarize important findings.

In a review of current mathematical models in ruminant nutrition, Tedeschi et al. (2005) stated that currently most models used for formulating rations consist of a combination of mechanistic and empirical approaches, with empirical models providing a best fit to data obtained at the level of prediction, and mechanistic models incorporating underlying biology of the system. They also stated that these models are typically steady state and static, not incorporating time into predictions. The authors defined a ruminant nutrition model as an integrated set of equations and transfer coefficients that describe nutrient requirements and feed utilization by cattle and sheep for use in formulating diets on farms.

Current Models of Beef Cattle Intake

Intake of individual animals represents a dilemma for some researchers, as it is often difficult and expensive to determine individual animal intake for use in nutrition trials. There are several types of models currently used to predict performance and intake of growing and finishing cattle. The National Research Council (NRC, 2000) incorporates a computer model that can be used to balance rations and predict animal performance. The Cornell Net Carbohydrate and Protein System (CNCPS; Fox et al. 2004b) was first published in 1992 and 1993 in a series of four papers, and has been continually refined and improved over the past ten years. The CNCPS focuses on ration balancing and performance prediction, and uses the same equations as level 2 of the NRC model. Mathematical growth models that can predict DMI when animal performance and nutrient information is known, as well as predict performance when DMI and nutrient content of the feedstuff is known, have also been developed. Both the Cornell/ Cattle Value Discovery System (CVDS; Guiroy et al. 2001; Perry and Fox 1997; and Tedeschi et al. 2004) and the Decision Evaluator for the Cattle Industry (DECI; Williams and Jenkins 2003 a,b) were developed for these type of predictions.

CNCPS and NRC

The NRC (2000) developed a computer model which includes two levels of solution available to the user. It incorporates equations to predict nutrient requirements of various classes of beef cattle, as well as empirical equations to predict DMI of various classes of cattle, with adjustments for breed, EBF effect, implant status, temperature, and mud depth. Both levels of the NRC (2000) model use the same set of animal requirement equations. The DMI is predicted per kg of shrunk body weight (SBW). Level 1 uses tabular feed energy values, while level 2 incorporates the CNCPS rumen model to predict protein and carbohydrate fermentation, as well as amino acid supply and requirements. This sub-model predicts microbial growth and passage rates from feed carbohydrate and protein fractions. The NRC (2000) indicated that level 1 should be used by those with limited information on feed composition, and not familiar with how to read and interpret results from level 2 of the model.

The CNCPS model accounts for factors that affect performance, feed efficiency, and nutrient excretion in both beef and dairy cattle in unique production situations (Tedeschi et al. 2006). The CNCPS focuses on accounting for differences in maintenance requirement, mature body size, composition of gain, feeding program, and feeding system (Fox et al. 2004b). In the proceedings of the 1996 Cornell Nutrition Conference, Pitt et al. (1996a) briefly described CNCPS as an integrated set of equations and transfer coefficients that describe physiological processes in cattle. The CNCPS model incorporates information on feed, cattle, and environment to predict the nutrient supply from digestion and absorption, as well as nutrient requirements for metabolism and production, and nutrient excretion.

According to Fox et al. (2004a), the CNCPS sub-models are classified according to physiological functions. These sub-models include maintenance, growth, pregnancy, lactation, reserves, feed intake and composition, rumen fermentation, intestinal digestion, metabolism, and nutrient excretion. A brief description of the mathematical equations of each sub-model as described by Fox et al. (2004a) follows. The maintenance sub-model computes maintenance requirements by accounting for breed, physiological state, activity, urea excretion, heat or cold stress, and environmental acclimatization effects; with adjustment for previous plane of nutrition using body condition score (BCS). Growth requirements include adjustments for the rate of gain and chemical composition of gain, and mature weight, with adjustments for effects of body weight. Pregnancy requirements and weight gain from uterine growth are computed from expected calf birth weight and day of gestation. The body reserves sub-model uses BCS to compute energy reserves, with change in BCS used to determine energy and protein gain or loss.

Requirements for lactation are determined from actual milk production and milk components when available, or prediction based on weaning weights.

The rumen sub-model provides estimations of microbial protein, and materials that are fermented or escape ruminal degradation, such as carbohydrates and proteins. Additionally, an amino acid sub-model is available to predict the adequacy of absorbed essential amino acids in cattle diets (O'Connor et al., 1993). The CNCPS model also separates feedstuffs into several fractions, assuming that feedstuffs are made up not only of protein, carbohydrate, fat, ash, and water, but also further subdivides protein and carbohydrate by their digestibility characteristics in the rumen or post-ruminally.

Fox et al. (2004b) described the equations currently incorporated into the CNCPS model, and provided a summary of evaluations and sensitivity analyses. In an evaluation of growing cattle individually fed high grain rations, the CNCPS accounted for a large portion (89%) of the variation in ADG. A separate sensitivity analysis was also conducted with lactating dairy data to determine the effects of changes in feed composition to responses of the rumen sub-model. It was found that all pools and responses were affected by a change in DMI, with increased DMI, diet ME was reduced due to an increased rate of passage, which indicates the importance of accurate estimates of DMI. It was found that under some conditions the rumen sub-model is sensitive to all pools of carbohydrate and protein. The results of Fox et al. (2004b) indicated that the CNCPS can provide accurate predictions of nutrient requirements, feed utilization, and nutrient excretion under various production conditions.

DECI and CVDS

The DECI model is a combination of several models that were published previously. It is a biological model with the ability to predict animal performance when DMI and nutrient content of the ration are known, as well as having the ability to predict DMI when animal performance and nutrient content of the ration are known (Williams et al, 2006).

The DECI model development initiated with the description of a computer model that was developed to predict empty body weight (EBW) in cattle as a function of animal and diet characteristics by Williams et al. (1992a). With inputs of forage NDF, physical form of forage, fraction of concentrates in the ration, and final BW of the animal, it was found that this new model more accurately predicted EBW than previous systems, with an R^2 of 0.99.

Keele et al.(1992) and Williams et al.(1992b), described the theory, the development, and an evaluation of a computer model designed to predict composition of gain in EBW of cattle fed at different levels of nutrition. According to Keele et al. (1992), the model was based on the following four assumptions: 1) as animals mature, there is a greater proportion of fat in gain than in body weight, 2) the effects of plane of nutrition on body composition that are not associated with EBW can be predicted from rate of EBW gain, 3) the effects of changes in nutrition are not immediate nor permanent, 4) when EBW gain is zero, cattle approach an empty body composition equilibrium. In this model, rate of EBW gain is used to predict the amount of fat free matter in the EBW gain. The amount of fat in EBW gain is obtained by difference. The evaluation of this model indicated that it could accurately predict some of the effects that nutrition has on fat deposition that are not associated with EBW gain.

Williams and Bennett (1995) developed a bioeconomic model to predict slaughter end points of cattle of varying breed types with either maximization of profit/day or profit/rotation. The authors found that when the goal was maximum profit/day compared to maximum profit/rotation, as profitability increased rotation length was decreased and steers were also marketed at lighter carcass weights. Results of the evaluation of this model suggested that it has potential to offer more profitable options in the marketing of fed cattle.

In 1998, Williams and Jenkins integrated models developed by Keele et al.(1992) and Williams and Jenkins (1997) which both partitioned EBW gain into fat and fat free matter, with the model of Keele et al.(1992) being for growing cattle and Williams and Jenkins (1997) for mature cattle. The authors assumed that as cattle grow, a transition would occur from the equations for growing cattle to those for finishing cattle. Their evaluation of the integrated model suggested that it could accurately predict changes in body composition of cattle across ages and systems of nutritional management.

A dynamic model developed to estimate ME utilization for maintenance and to estimate additional responses in heat production that result from level of feeding and previous plane of nutrition was developed by Williams and Jenkins (2003a, b), in which they described the model prediction of EBW gain from ME available for gain. Based on previous experiments, which indicated a simple proportional relationship between maintenance requirements and body weight for different breeds of mature cattle, as well as calves and growing steers and BW stasis, this model uses this proportionality to predict ME utilized for maintenance. Heat production to support metabolism is then calculated as a multiple of maintenance intake. The evaluation of the maintenance portion of the model, when compared to other experimental data where ME for maintenance was known, was shown to be similar in prediction. The portion of the model that predicts ME utilized for gain and also ADG by using recovered energy as the input has several components. One predicts net efficiency of ME utilized for gain using constant partial net efficiencies for protein and fat gain of 0.20 and 0.75 respectively. The other component uses recovered energy to predict daily gain using a system of differential equations that are numerically integrated on a daily basis. Retained energy as a function of change in EBW was predicted according to the model of Williams and Jenkins (1998). Retained energy is first predicted from ME for gain, and change in EBW is then predicted from retained energy. An evaluation of the model by Williams and Jenkins (2003c) indicated that the integrated model provided accurate predictions of body weight gain using ME intake as an input.

The CVDS model was developed as a deterministic and mechanistic growth model to dynamically predict growth rate, accumulated weight, days required to reach a target body composition, carcass weight, and composition of individual beef cattle for use in ICMS (Tedeschi et al. 2004). These ICMS are necessitated and have been developed to help the beef industry in marketing individual animals at their own optimum endpoint rather than a group average. They may help to improve profitability, minimize excess fat, which may come about in attempting to feed to a pen optimum average, and increase consistency of product. These ICMS bring about a need to co-mingle cattle from different owners in the same pen, which in turn brings up the need for a system to accurately allocate feed to individual animals in pens of mixed ownership.

The CVDS provides a method for predicting energy requirements, performance and feed required for individual animals fed in groups (Tedeschi et al., 2003). It accounts for the following variables in its predictions: NE values of the fed ration, DMI on a daily basis, environmental effects on maintenance and gain requirements, effect of stage of growth on ADG and NEg, as well as body weight, carcass weight, and body composition. The model utilizes the above factors to predict a body weight at 28% empty body fat (EBF), which corresponds to USDA low choice grade, and then it is used to predict animal nutrient requirements and gain needed to finish based on this grade (Tedeschi et al., 2003). Feed is then allotted to individual animals for maintenance (FFM) and gain (FFG), as well as an overall daily dry matter required (DMR) for each animal.

Fox and Black (1984) described a system for predicting body composition and performance of growing cattle, with adjustments for factors known to have an effect on composition and requirements. DMI prediction equations are also described by the authors. When the model was evaluated with data from three trials of Holstein steers, it was found that actual DMI averaged 99% of predicted and actual gains averaged 87% of those predicted from actual DMI. An evaluation with feedlot data from central Florida indicated that the model under-predicted intake for steers by 11% and by 13% for heifers. However, when actual intake was used to predict ADG and feed efficiency the results were within 1% for steers and 3% for heifers. From these results, the authors concluded that the value of this model lay in its ability to predict performance accurately in unique production and management conditions.

Perry and Fox (1997) described a model with equations to predict proportional carcass fat and yield grade in live cattle, while also predicting final EBF from carcass fat which was then used to predict energy and feed required for individual animals fed within a pen. An evaluation of this system indicated a 3% over-prediction bias, with 98.79% of predicted values consumed. However, only 48% of the variation in actual DMI was accounted for by the model which indicated that further work needed to be done to account for this variation. The authors concluded that equations to predict carcass weight and composition, along with the proposed system for allocating feed to individual animals fed in a group could be used to market cattle at an optimum time.

Guiroy et al. (2001) revised the equations of Perry and Fox (1997) in predicting EBF, and evaluated the CVDS with these new equations for the purpose of predicting individual feed requirements of cattle fed in groups. Data from 401 steers were used to develop the equations that the model uses to predict EBF from carcass measurements, and the equation developed accounted for 61% of the variation in EBF in his original dataset. Analysis with an independent dataset showed that the equation developed accounted for 51% of the variation in EBF. The CVDS model for prediction of DMR was evaluated with his adjustments for EBF with a database of individually fed cattle, and it was found that DMR accounted for 74% of the variation in observed DMI. When the CVDS with the new EBF equations was applied to the prediction of DMR in actual feedlot data, a bias of -0.91% for steers and 0.89% for heifers was noted. The author’s evaluation indicated that the CVDS can be used to accurately allocate feed to individual animals fed in a group.

Tedeschi et al. (2004) described the development and evaluation of a dynamic iterative version of the CVDS model. The authors described in detail the calculation of harvest body weight and composition, prediction of DMI, prediction of energy requirements for maintenance, and prediction of EBF. It was assumed that the most important variable determining composition of gain is the retained energy per unit of gain, and the importance of inputs of initial body composition to allow the model to predict the accumulation of fat over time is emphasized. Tedeschi et al. (2004) discusses that the CVDS model uses the equations described by the NRC (2000) for prediction of DMI with adjustments for the relationship between equivalent SBW and EBF.

Evaluations of three methods of the CVDS were conducted by Tedeschi et al. (2004): 1) prediction of ADG based on animal, diet, and environment information; 2) the dynamic iterative version of the model to predict body composition, DMR, and feed efficiency when animal performance was known; and 3) the mean body weight method, which uses mean values for SBW, diet ME, and a constant ADG to predict DMR, body composition, and feed efficiency. The first method indicated that the model accounted for 89% of the variation in actual ADG, with a bias ranging from an over-prediction of -6% to an under-prediction of 7.5%. The second method indicated a high precision for prediction of DMR with an r^2 ranging from 0.71 to 0.74 depending upon whether NEg was adjusted for portion of retained energy. This method had a bias ranging from -5.7% (over-prediction) to 4.2% (under-prediction). The third method of the CVDS had similar r^2 values to the second (0.75 to 0.78), but indicated a greater bias ranging from -4.7% to 23.5%. It was concluded that the new dynamic iterative method of the CVDS could predict animal performance and composition with acceptable accuracy.

Similar studies evaluating phenotypic correlation between DMR and observed DMI found correlations of 0.75 (Tedeschi et al., 2006) and 0.80 (Bourg et al., 2006b). Additionally, an analysis of Santa Gertrudis steers and heifers (N = 457) by Bourg et al. (2006a) found an overall mean bias between actual feed fed and model predicted DMR of 2.43%, which suggests that the model was accurate in predicting the DMR for these pens of cattle.

Williams et al. (2006) evaluated both the DECI and CVDS for their accuracy in predicting individual DMI and the feasibility of their prediction for use in genetic evaluations. A comparison of observed DMI to DMR predicted by the DECI and CVDS models indicated that the DECI prediction was very similar to the mean observed DMI, while the prediction of the CVDS was 3.5% lower. The authors suggested that these differences in prediction may be due to an under-prediction of maintenance requirements by the CVDS as compared to the DECI. In comparing actual individual DMI to predicted individual DMI, the CVDS accounted for 44.3% of the variation in observed DMI, and the DECI accounted for 53.4%. Both models indicated a bias in prediction, with the CVDS under-predicting with an average bias of 3.4% and the DECI over-predicting with an average bias of 0.4%. In their evaluation of phenotypic and genetic correlations of observed DMI with DMR, it was noted that genetic relationships (0.79 for both models) were much stronger than phenotypic (0.95 and 0.96 for CVDS and DECI; respectively). It was concluded that a genetic relationship between observed and predicted feed intake does exist, but that both models need further evaluation in populations with genetic variance in feed efficiency, to determine further if predicted DMR could be substituted for actual DMI in genetic evaluations of feed efficiency.

These models would drastically decrease the costs that are now associated with collecting individual intake data, to identify those cattle that are able to convert feed into to product more efficiently. Tedeschi et al. (2006) recently evaluated the effectiveness of the CVDS in predicting efficiency in cattle when individual intake is not known. It was concluded that the CVDS model could be used to identify difference in feed: gain or gain: feed ratio of individual cattle fed in groups through its prediction of individual DMR. This prediction can also be useful in determining genetic evaluations of DMR (William and Jenkins, 2006; Kirschten et al., 2006).

Model Evaluation

Tedeschi (2006) reviewed several techniques for assessing the adequacy of mathematical models, and stated that testing for the adequacy of a mathematical model is typically done to prove the rightness of a model. These tests of rightness are then typically presented as evidence to promote acceptance and use of a model, and that these tests should be designed to evaluate and identify model weaknesses that should be addressed. Tedeschi (2006) proposed that the terms evaluation and testing indicate the measurement of model adequacy based on criteria of acceptable model performance that have been pre-determined. The author also cautioned of errors in model evaluation such as a type I error or rejecting an appropriate model, which is likely if incorrect or biased observations are chosen in evaluating the model, or a type II error, accepting an inappropriate model, which is likely if during the development of the model biased or incorrect observations were used.

Meta-analysis to remove effects of study when data are obtained from literature to develop or evaluate models is offered by Tedeschi (2006) as a useful technique to further decrease the risks associated with sampling error. St. Pierre (2001) discussed the application of compiling data from multiple published studies in attempt to obtain relationships among key variables. This statistical process has been labeled meta-analysis. The use of meta-analysis is a powerful technique for interpretation of results from multiple studies.

The concepts of accuracy and precision of a model are discussed by Tedeschi (2006) as well. Accuracy is defined as the closeness of model predicted values to actual values, while precision is defined as the model's ability to predict similar values consistently, whether or not they are close to actual values. Precision and accuracy are independent of each other, and a case of one being high does not guarantee that the other will be. Numerous statistical techniques are available to determine model accuracy and precision, several of which will be discussed below.

Model precision (r^2) can be assesed by regression of observed values (y-variate) on model-predicted values (x-variate). As discussed by Tedeschi (2006), observed values are plotted on the y-axis due to inherent natural variability, while model predicted variables do not contain this random variation. Data points below the Y=X line indicate an over-prediction by the model.

Model accuracy can be determined from several techniques. Ideally, the linear regression between model-predicted and observed values passes through the origin and has a slope of unity (Dent and Blackie, 1979). When performing a linear regression of model-predicted and observed values several assumptions must first be made (Tedeschi, 2006). The first assumption the X-axis values (model-predicted) are known to be without errors. The second assumption is that observed values (Y-axis) are random, independent, and homocedastic. The final assumption is that the residuals of the regression are independent and normally distributed. Performing separate tests of the null hypotheses that slope = 1 and intercept = 0 may not provide an accurate result if there is a large amount of scatter in the data points, as it would be harder to reject the null hypotheses either because the slope is really not different from unity or because there is too much scatter around the regression line (Tedeschi, 2006). Therefore, the more relevant test of the null hypothesis that slope and intercept coefficients were simultaneously different from 0 and 1 based on equations by Dent and Blackie (1979) is used to determine if the model's predictions represent the ideal. Tedeschi (2006) cautions that although linear regression may provide reliable estimates to model accuracy and precision, its results should be interpreted after first being certain that several assumptions are met.

Lin (1989) developed a reproducibility index also known as the concordance correlation coefficient (CCC), which simultaneously accounts for accuracy and precision. The concordance between two pairs of samples can be characterized by the expected value of their squared difference, which incorporates Pearson correlation coefficient. This value can be transformed to a scale between -1 and 1 as Lin (1989) described. The C_b statistic is the component of the CCC that measures accuracy. It is a bias correction factor that indicates how far the regression line deviates from the Y=X line, and ranges from 0 to 1, with a value of 1 indicating that no deviation from this line occurred. The Pearson correlation coefficient is the component of the CCC that measures precision by measuring how far each observation deviates from the Y=X line.

Mean bias is perhaps the oldest and most widely used method to assess model accuracy (Tedeschi, 2006). It provides an indication of how close the predictions are to the observed values. Mean bias is calculated based on the mean difference between observed and model-predicted values as a percent of predicted values.

Mean square error of prediction (MSEP, also known as mean square prediction error, MSPE) is used to measure predictive accuracy of a model (Tedeschi, 2006). For the MSEP to provide a reliable estimate of accuracy, the paired data points must be mutually independent, and the model must be independent of the experiment from which the data points were obtained. However, the reliability of MSEP decreases as sample size decreases. A comparison of two models can be obtained, such that the model with the smaller MSEP is more accurate. The sources of variation of MSEP can be decomposed into errors in central tendency (mean bias), errors due to regression, or random errors that cannot be accounted for by linear regression. These terms are represented as the mean bias, variance, and covariance (Tedeschi, 2006).

Non-parametric tests can be a good test of model adequacy as they are resistant to abnormalities in the data, such as outliers. A balance analysis using non-parametric techniques can be used to evaluate the balance of data points that were over or under-predicted by a model from the model-predicted and observed means (Tedeschi, 2006). Tedeschi (2006) described two χ^2 tests that are used to test the distribution of data in a contingency table that sorts data points into four quadrants, or those over- or under-predicted above or below the observed- or model-predicted means. The first χ^2 hypothesis tests if 25% of the data points are located in each of four quadrants (below the observed mean and over-predicted, below the observed mean and under-predicted, above the observed mean and over-predicted, and above the observed mean and under-predicted). The test reveals whether data points are distributed evenly in each quadrant, indicating whether the model tends to over- or under-predict above or below the mean. The second χ^2 hypothesis tests for associations between model behavior and locations about the mean, or whether each of the cells in the balance allocation is independent of each other (Tedeschi, 2006). The odds ratio statistics tests whether the predictions above or below the mean and over- or under-prediction are independent, with a value of 1 indicating that the data are independent. The odds ration can be any non-negative number (Agresti, 1996). The natural logarithm of the odds ratio statistic is more resistant to skewness of data due to small sample size, and follows a normal distribution. It provides a more reliable test of independence, with a value equal to 0 indicating independence (Agresti, 1996).

Conclusion

Nutrition models discussed (e.g. NRC, CNCPS, CVDS and DECI serve an increasingly important purpose in our knowledge of our beef cattle nutrition systems. Although each were designed with slightly different objectives in mind, with the CNCPS and NRC more focused on diet formulation and nutrient utilization, and the DECI and CVDS more focused toward prediction of individual animal performance or individual animal intake. However, both models types of models have the potential to improve the efficiency of beef production systems. The CNCPS or the NRC can be utilized to maximize nutrient utilization through more accurate formulation of diets to better meet nutrient requirements, which in turn will reduce nutrient run-off and waste, and therefore environmental pollution. The CVDS and DECI models, on the other hand, offer a different alternative, to identify differences in feed efficiency among individual animals fed in groups, or to project individual cattle to their most profitable endpoint, and thereby reducing variation in animal performance and carcass quality. The future applications of both types of models are numerous to improve the overall efficiency of beef production systems. However, these models must continue to be refined and tested so as to offer more accurate and precise predictions. Model sensitivity analysis is needed to determine which biological components have the greatest impact on results. This would illustrate which of these components is most in need of accurate measurement or further model refinement. As well, use of these models must be streamlined and simplified, with ease of input being a large priority, to further aid in their adoption by industry personnel.

Mathematical models are important tools that will help to further understanding of our beef production systems. There are numerous applications of mathematical models for the beef industry. Whether it be modeling forage intake of a beef cow-calf unit in western Montana to determine supplementation needs, or modeling the effects of various management decisions on profitability of an operation, or modeling intake of feedlot cattle in an effort to improve production efficiency, these models will continue to aid in our development of research programs that will assist us in furthering our understanding of how our biological systems work, in particular those involved with beef production. Our biological systems are and will continue to be complex processes of which we have an incomplete understanding, and these and future mathematical models will help to further our understanding.

CHAPTER III

ANALYSIS OF THE SENSITIVITY OF THE CVDS MODEL TO VARIATION FROM ACTUAL RATION ENERGY VALUES

Objectives

1) To evaluate the CVDS model's effectiveness in predicting total DM required (DMR) of Santa Gertrudis steers and heifers

2) To conduct a sensitivity analysis of the accuracy of dietary ME value on the model's predictions of DMR.

Materials and Methods

The cattle in the evaluation database consisted of five pens of Santa Gertrudis steers and heifers (n= 457) fed at the King Ranch feedyard (Kingsville, TX). Table 3.1 summarizes the calves used in the evaluation. Pens 1 and 4 contained only heifers, while pens 3 and 5 contained only steers, and pen 2 contained both steers and heifers. Average initial BW ranged from 202 to 297 kg. Cattle were slaughtered over four dates from June 15 to August 18.

The cattle were fed three step-up rations and one finishing ration that ranged from 2.3 to 2.82 Mcal ME/kg DM. The finishing ration consisted of 67% milo, 9% pressed brewer's grain, 7% premix, 6% molasses, 5.5% whole cottonseed, 2.5% cotton burrs, 2% fat, and 1% cottonseed meal. Dietary ME was calculated using actual feed

Table 3.1. Summary of pens used in the model evaluation [1]

Pen	Sex[2]	n	DOF	IBW	FBW	REA	FT
1	H	84	180-208	265.3	496.4	74.8	1.68
2	S & H	109	223-243	202.1	459.3	71.6	1.45
3	S	85	180-223	296.5	561.6	77.4	1.40
4	H	110	208	233.9	476.3	71.6	1.83
5	S	69	208-223	258.1	530.3	78.1	1.42
Mean			208	251.2	504.8	74.7	1.55

[1]DOF = days on feed; IBW= initial body weight, kg; FBW= final body weight, kg; REA = rib-eye area, cm^2; FT = 12-13th rib fat thickness, cm.
[2]S = steer; H = heifer.

analysis of individual feed ingredients in the Cornell Net Carbohydrate and Protein System (CNCPS; Fox et al., 2004b) model.

For each pen, model inputs included dietary ME, days on each ration, and number of animals fed each ration. Individual animal performance and carcass data used for model prediction included: sex, breed type (beef or dairy), hide thickness, initial date of feeding period, approximate age, BCS, initial and final BW, yield grade, hot carcass weight, 12th rib fat thickness (FT), marbling (MRB) class and percentile, and rib-eye area (REA). Additionally for each individual animal in the dataset, BW and carcass composition (HCW, LMA, FT, and MRB) were used to predict a BW at 28% empty body fat (EBF). Empty BW (EBW) was computed from HCW, and adjusted final shrunk BW at 28% fat (AFSBW) was then computed using carcass information as described by Guiroy et al. (2001), which was estimated using the relationship between EBF and

EBW. The CVDS model with the adjustment of ME to NE efficiency for composition of gain was used to predict individual DMR and to estimate total DMR of the pen.

The CVDS model's effectiveness in predicting DMR of group-fed cattle was evaluated using mean bias, which was calculated as mean difference between observed feed intake and model-predicted values as a percent of predicted values. Aditionally, a sensitivity analysis was conducted to test the effects of over and under-estimation of diet ME values on the CVDS prediction of DMR. Metabolizable energy values were evaluated at 5 or 10 percent below or above actual ME values.

Results and Discussion

The 90% confidence interval for predicted EBF at the harvest body weight ranged from 25-36% fat, and was similar for both steers and heifers. In an evaluation of the relationship between quality grade and EBF, Guiroy et al. (2001) noted that at a target quality grade of low choice the mean EBF percent was 28.61%, which is in agreement with the value of 27.8% fat at low choice reported by the NRC (2000).

The total feed DM fed to pen 1 was 117,141 kg for the entire feeding period, and the model's prediction of DMR was 124,559 kg. This indicated a model over-prediction, with a mean bias of 6.22%. For pen 2, total feed fed was 168,471 kg, and DMR predicted was 168,265 kg. This indicated a slight under-prediction, with a mean bias of -0.12%. Pen 3 received 138,171 kg of feed over the period, and predicted DMR was 156,861 kg, with a mean bias of -1.26% indicating a slight model under-prediction. Total feed fed to pen 4 was 156,861 kg, and the CVDS predicted a DMR of 162,213 kg, with a mean bias of 3.41%. Pen 5 received 105,517 kg of feed, and the CVDS predicted a DMR of 109,378 kg, which indicated an over-prediction of 3.66%. These predictions indicated that for this evaluation, the CVDS model was more accurate for some pens than for others. The model had a mean bias of 4.64% and 1.46% for heifers and steers respectively, and with an overall value of 2.43% the model was highly accurate across pens. Guiroy et al. (2001) indicated that an under-prediction bias of up to 2% may be expected in DMR due to feed delivered to the pen that was lost or not consumed by the cattle. When Perry and Fox (1997) compared DMR to DMI of individually fed steers, a bias of 3% was noted, which was very similar to the overall bias in this analysis.

In Guiroy et al. (2001), a dataset of 12,105 feedlot cattle was used to evaluate the model in real world situations, and a mean bias of -0.91% and 0.89% for steers and heifers respectively was observed. The values noted in this evaluation were slightly higher than those reported by Guiroy et al (2001), which may be due to the size of the database in each evaluation. In this evaluation, only 457 steers and heifers were used, while Guiroy (2001) utilized a feedlot dataset of 12,105 steers and heifers.

The results of the ME sensitivity analysis are reported in Figure 3.1. The sensitivity analysis revealed that the model tended to under-predict DMR when ME values were over-estimated, and tended to over-predict when ME values were under-estimated, as was expected. If ME values are over-estimated, the model calculates DMR based on a greater amount of available energy from the feedstuff that would have been utilized in the resultant composition. Therefore the CVDS predicted that the animal

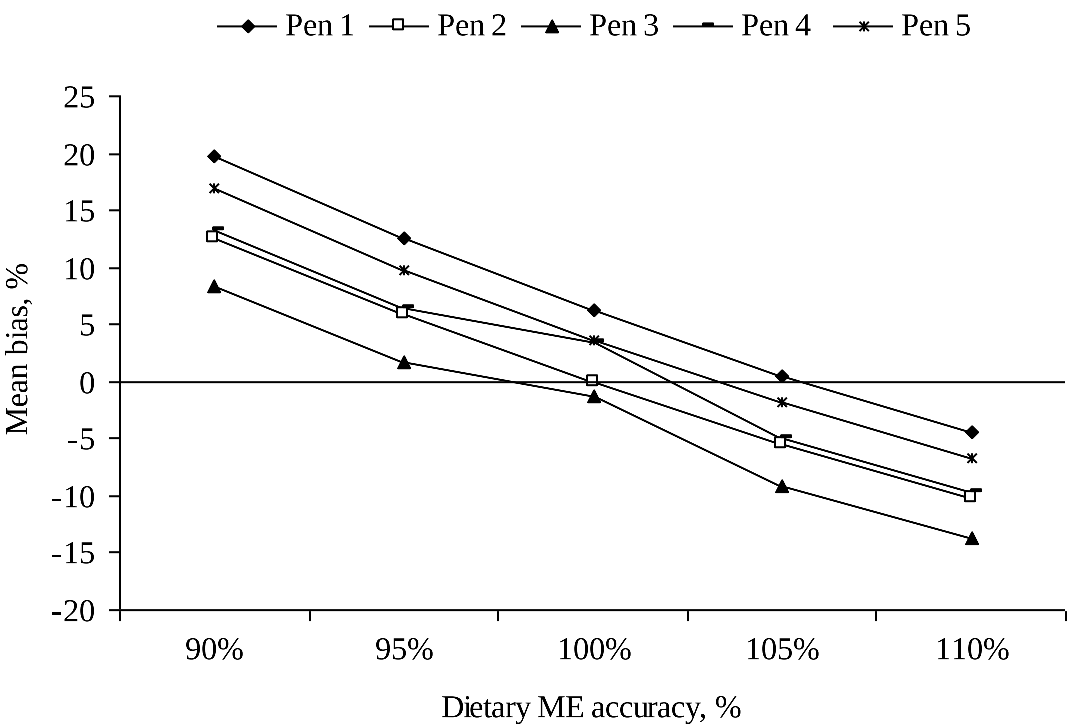

Figure 3.1. Relationship between accuracy of ration ME values and mean bias of the CVDS prediction of DMR

would have consumed a lower amount of feed than was actual, with the opposite being true when ME was under-estimated. However, there appears to be no interaction between the mean bias of model predicted intake for the total pen and accuracy of ME used in the predictions, as the ranking of pens when ME was adjusted above or below the actual value did not change. This indicates that even if estimates of dietary ME values were incorrect the CVDS model would still rank feed required for pens and individual cattle in the same order. This is an important aspect of the CVDS model when it is used in genetic evaluations. Kirschten et al. (2006) evaluated the model for genetic purpose using the individually fed steer contemporaries of the cattle used in this evaluation. Strong genetic relationships were observed between DMI, DMR calculated from ultrasound traits, and DMR calculated from carcass traits. Kirschten et al. (2006) also noted minimal re-ranking of sires which is extremely desirable in genetic predictions.

Implications

This evaluation of the CVDS model revealed that accurate prediction of individual DMR of pen-fed cattle was possible. This suggests that the CVDS model may be a useful tool to successfully implement ICMS, although further research is needed to improve inconsistencies in mean bias of DMR prediction. The sensitivity analysis of dietary ME values revealed that the model tends to consistently over- and under-predict DMR when the ME values were under- and over-estimated respectively. However the ranking of pens was not affected by this mis-estimation of diet ME, which suggests that the CVDS prediction of DMR may also have utility in the prediction of feed inputs for genetic evaluation.

CHAPTER IV

EVALUTION OF A MATHEMATICAL MODEL TO ESTIMATE TOTAL FEED REQUIRED FOR PEN-FED ANIMALS BASED ON PERFORMANCE AND DIET INFORMATION

Objective

1) to evaluate the adequacy of the CVDS in predicting total dry matter required (DMR) of pen-fed steers from eight independent studies, using two methods to compute growth and carcass composition.

Materials and Methods

Study Description

A database consisting of 1,314 steers in 8 separate finishing studies conducted at West Texas A&M University was compiled to evaluate the CVDS. Table 4.1 summarizes the studies used in this database. Steers of varying breed types were fed in 173 pens, with an average of 8 steers per pen, and were on test for 70 to 206 d dependent upon the study objectives. Cattle were fed a high percent grain ration with ME from 2.78 to 3.13 Mcal/kg DM.

Study 1 evaluated the effects of DMI restriction on performance and carcass characteristics of steers. Only steers included in the ad libitum treatment were included in the database. Seven pens, totaling 66 steers, were included in the evaluation database from this study. Steers were fed diets described by Drager et al. (2004a) and included a 65% concentrate diet prior to the beginning of the study to minimize fill differences.

Table 4.1. Summary of trials used in the evaluation database [1]

Study	Reference	Sex	N		DOF	ME	ADG	IBW	FBW
			Pen	Steer	d	Mcal/kg	kg/d	kg	kg
1	Drager et al. 2004a	S	7	66	151	2.80	1.61	414.3	558.7
2	Silva et al. 2006	S	30	266	139	2.80	1.69	325.1	560.7
3	Biggs et al. 2004	S	45	316	112	3.06	1.59	375.4	540.4
4	Drager et al. 2004b	S	6	39	70	2.97	1.86	486.0	616.0
5	M.S. Brown, unpublished observations	S	35	210	114	3.13	2.18	367.6	618.9
6	Silva et al. 2006	S	36	320	198	2.95	1.76	284.6	589.8
7	Bumpus 2006	S	6	58	119	3.09	1.41	362.6	530.3
8	Vann et al. 2006	S	8	39	179	2.93	1.41	305.2	553.5
Mean			22	164	135	2.97	1.69	365.1	571.0

[1] DOF = days on feed, IBW = initial BW, and FBW = final BW.

Steers were adapted to a 90% concentrate diet (ME = 2.8 Mcal/ kg DM) with 6 d each adaptation to a 65, 75, and 82.5% concentrate diet. The 90% concentrate finishing diet (CP = 13.51%) contained 75.49% whole corn, 5% cottonseed hulls, 5% ground alfalfa hay, 4.01% cottonseed meal, 4% cane molasses, 3% white grease, and 3.5% supplement. Steers were on test for 151 d with an ADG of 1.61 kg/d.

Study 2 evaluated the effects of zinc source and level on both performance and carcass characteristics of finishing steers, as described by Silva et al. (2006). Steers were fed a 55% concentrate diet for 8 d before initial BW were obtained. Upon commencement of the trial, 266 steers were adapted to a 92% (ME = 2.8 Mcal/kg DM) concentrate diet by feeding a 70% concentrate diet for 6 d and an 81% concentrate diet for 7 d. The 92% concentrate diet (CP = 12.5%) contained 79.25% whole corn, 8% alfalfa hay, 5% cane molasses, 3% supplement, 2.5% choice white grease, and 2.25% cottonseed meal. Steers were blocked by BW and assigned to treatments. The heaviest block was on feed for 126 d, the lightest two blocks for 166 d, and the intermediate blocks for 151 d, with an ADG for all blocks of 1.69 kg/d.

Study 3 utilized in the evaluation database was described by Biggs et al. (2004), and evaluated effects of dietary crude protein and degradable protein concentration on performance, carcass characteristics and estimated nutrient excretion of 316 beef steers. Steers were fed one of three CP concentrations (11.5, 13. or 14.5% of DM) provided by one of three proportions of supplemental degraded intake protein (50, 75 or 100% of CP) in 45 separate pens for 112 d. Steers were adapted to 90% concentrate diets, with an average ME of 3.06 Mcal/kg DM, and steers gained an average of 1.59 kg/d across all treatments.

Study 4 utilized 39 steers in 6 pens to evaluate the effect of Sucram C-150® on feedlot performance and carcass characteristics of finishing steers, as described by Drager et al. (2004b). Steers were fed a 90% (ME = 2.97 Mcal/kg DM) concentrate diet for 70 d that was supplemented to contain 0 or 180 g of Sucram/ton of diet DM. The 90% concentrate diet contained 13.57% CP and consisted of 74% steam-flaked corn, 10% alfalfa hay, 5% cane molasses, 4% supplement, and 3% tallow. Across both treatments steers gained an average of 1.86 kg/d.

Study 5 contained unpublished observations of 210 steers on feed at West Texas A & M University (M.S. Brown, unpublished observations). Thirty five pens of steers were on feed for 114 days. Steers were fed a 55% concentrate diet until the study began, and were then adapted to a 90% (ME = 3.13 Mcal/kg DM) concentrate diet by offering 70 and 80% concentrate diets for 7 d each. The finishing ration (CP = 13%) contained 78.5% steam-flaked corn, 10% alfalfa hay, 4% cane molasses, 3% yellow grease, 3% supplement, and 1.5% cottonseed meal. Across treatments, steers gained an average of 2.18 kg/d.

Study 6 was also described by Silva et al. (2006), and as was the case with study 2, Study 6 evaluated the effects of different sources and levels of zinc on performance and carcass characteristics of 320 feedlot steers fed in 36 pens. Steers were adapted to the finishing diet by offering 55 (14 d), 70 (7 d) and 80% (7 d) concentrate diets. The 90% concentrate finishing diet contained 13.2% CP and 2.95 Mcal/kg DM of ME, and consisted of 78% steam-flaked corn, 10% alfalfa hay, 4% cane molasses, 3% yellow grease, 3% supplement, and 2% cottonseed meal. Across treatments, steers gained an average of 1.76 kg/d for 198 days on feed (DOF).

Study 7 of the evaluation database was the finishing phase of a grazing trial in which steers were fed one of 3 treatments with 2 replication of each, as described by Bumpus (2006). During the finishing phase, 58 steers were fed in 6 pens for 119 days. The common finishing diet contained approximately 13% CP and 3.09 Mcal/kg DM of

ME and consisted of 73% steam-flaked corn, 12.5% ground alfalfa, 4% cottonseed meal, 4% steep:molasses (70:30), 3.5% supplement, and 3% vegetable oil. Across treatments, steers had an ADG of 1.41 kg/d. Steep, or corn steep liquor is a liquid co-product of the wet milling of corn to produce ethanol, and for this as well as study 8, steep was mixed with molasses on a 70:30 basis.

Study 8 examined the effects of breed type and temperament classification on feedlot performance, utilizing 39 Brahman and Angus steers that were classified as calm or excited, and was described by Vann et al. (2006). Steers were fed in 8 separate pens based on breed and temperament for an average of 179 d. The finishing ration contained 13.1% CP and 2.93 Mcal/kg DM of ME and consisted of 72.5% steam-flaked corn, 12.5% alfalfa hay, 4.5% cottonseed meal, 4.0% steep: molasses (70:30), 3.5% supplement, and 3% yellow grease. Across breed and temperament group steers had ADG of 1.41 kg/d over the length of the feeding period.

The Cattle Value Discovery System

For each pen within study, model inputs included diet information (ME, Mcal/kg), DOF, and ionophore status, as dietary NEm was increased by 12% if ionophores were included in the ration (Tedeschi et al., 2003). Individual animal performance and carcass data used as model inputs included: sex, implant status, breed type (beef or dairy), and hide thickness, initial date of feeding period, approximate age, BCS, initial and final BW, yield grade, hot carcass weight, 12th rib fat thickness (FT), marbling (MRB) class and percentile, *Longissimus dorsi* muscle area (LMA). Additionally for each individual animal in the dataset, BW and carcass composition

(HCW, LMA, FT, and MRB) were used to predict a BW at 28% empty body fat (EBF). Empty BW was computed from HCW, and AFSBW was then computed using carcass information as described by Guiroy et al. (2001), which was estimated using the relationship between EBF and empty BW. For each pen within study, CVDS model predicted total DMR using both the mean BW method and the dynamic iterative growth (DIM) model, resulting in two DMR predictions for each pen. The mean BW method of the CVDS assumes a linear relationship between ADG and BW. With this method, all of the calculations were performed using the average BW of each period. For the DIM model, ration energy values, BW, and expected weight at 28% fat were used to predict accumulated BW, composition, and feed required for each pen of cattle.

Model Evaluation

Analysis was conducted using two methods. An un-weighted analysis was conducted using DMR predictions from each method (mean BW, DIM) for each pen of steers in the database. A second analysis was conducted with DMR predictions weighted by the number of steers per day within pen. These two analyses were evaluated in the same manner for each method.

A computer program (http://nutritionmodels.tamu.edu/mes.htm), as described by Tedeschi (2006), combining the following statistical procedures was used to assess the accuracy and precision of each method in predicting the total DMR of each pen of steers compared to the amount the was delivered to the pen. Model precision (r^2) was determined by regression of observed values (y-variate) on model-predicted values (x-variate). As discussed by Tedeschi (2006), observed values were plotted on the y-axis due to inherent natural variability, while model predicted variables do not contain this random variation.

Model accuracy was determined from several techniques. Ideally, the linear regression between observed and model-predicted values passes through the origin and has a slope of unity (Dent and Blackie, 1979). Performing separate tests of the null hypotheses that slope = 1 and intercept = 0 may not provide an accurate result if there is a large amount of scatter in the data points, as it would be harder to reject the null hypotheses either because the slope was really not different from unity or because there was too much scatter around the regression line (Tedeschi, 2006). Therefore, the more relevant test of the null hypothesis that slope and intercept coefficients were simultaneously different from 0 and 1 based on equations by Dent and Blackie (1979) was used in this evaluation to determine if the model's predictions represented the ideal.

Another measure of accuracy was the bias correction factor (C_b), which was proposed by Lin (1989) when developing a reproducibility index also known as the concordance correlation coefficient (CCC), which simultaneously accounts for accuracy and precision. The C_b statistic is the component of the CCC that measures accuracy. It indicates how far the regression line deviates from the Y=X line, and ranges from 0 to 1, with a value of 1 indicating that no deviation from this line occurred.

Mean bias is perhaps the oldest and most widely used method to assess model accuracy (Tedeschi 2006). It provides an indication of how close the predictions are to the observed values. For this analysis, mean bias was calculated based on the mean difference between observed and model-predicted values as a percent of predicted values.

Mean square error of prediction (MSEP, also known as mean square prediction error, MSPE) was used to measure predictive accuracy of a model (Tedeschi, 2006). The MSEP statistic evaluates the precision of the fitted linear regression using the difference between observed values and model-predicted values (Tedeschi, 2006). For this analysis, the sources of variation of MSEP were decomposed into errors in central tendency (mean bias), errors due to regression, or random errors (Tedeschi, 2006).

A balance analysis using non-parametric techniques was used to evaluate the balance of data points that were over or under-predicted by CVDS from the model-predicted and observed mean (Tedeschi, 2006). The first χ^2 hypothesis tests if 25% of the data points were located in each of four quadrants (below the observed mean and over-predicted, below the observed mean and under-predicted, above the observed mean and over-predicted, and above the observed mean and under-predicted). The test reveals whether data points are distributed evenly in each quadrant, indicating whether the model tends to over- or under-predict above or below the mean. The second χ^2 hypothesis tests for associations between model behavior and locations about the mean, or whether each of the cells in the balance allocation was independent of each other (Tedeschi, 2006). The odds ratio statistics tests whether the predictions above or below the mean and over- or under-prediction were independent, with a value of 1 indicating that the data are independent. The natural logarithm of the odds ratio statistic is more resistant to skewness of data due to small sample size, and follows a normal distribution

(Agresti, 1996). It was used in this analysis to provide a more reliable test of independence, with a value of 0 indicating independence among the cells.

Pens were assigned to two groups: either DIM or MBW model depending on which method provided a mean bias closer to zero. Least-squares procedures of SAS (SAS Inst. Inc., Cary, NC) were used to examine differences between means of these two groups of pens for performance and carcass traits with differences in preferred method of model prediction.

Results and Discussion

Un-weighted Analysis

Mean observed DMI for pens was 10,258 kg and the mean pen DMR predicted using the mean BW method of CVDS was 10,630, while the mean pen DMR predicted using the DIM model of CVDS was 10,267 kg. Guiroy et al. (2001) indicated that an under-prediction bias of up to 2% may be expected in DMR due to feed delivered to the pen that was lost or not consumed by the cattle. This was not the case with the mean BW method of the CVDS model, with a mean bias of 3.5% ($P < 0.01$). A mean bias of 0.08% ($P = 0.83$), which was not different from zero, was calculated for the DIM model. These low bias values indicated that both methods were highly accurate in predicting the DMR of these steers, with the DIM model being slightly more accurate. In a previous analysis of a version of the CVDS predictions, Perry and Fox (1997) noted an over-prediction bias of 3%, which was similar to the mean BW method prediction. However the equations used to predict 28% EBF in the Perry and Fox (1997) evaluation only utilized

EBW and yield grade, while this evaluation used the equations to predict EBF developed by Guiroy et al. (2001) which include 12th rib fat thickness, HCW, QG, and LMA.

In Guiroy et al. (2001), a dataset of 12,105 feedlot cattle was used to evaluate the model in real world situations, and a mean bias of -0.91% and 0.89% for steers and heifers respectively was observed. The lower bias noted in the Guiroy et al. (2001) analysis as compared to the mean BW method was likely due to the fact that DMR was predicted for larger pens of cattle, while in this analysis there were only an average of 8 steers per pen. Guiroy et al. (2001) found that prediction error was greatly reduced in predicting groups of animals rather than individuals, and that as group size increased, error decreased more rapidly. The mean bias of the DIM model was very similar to that calculated in the evaluation of feedlot data by Guiroy et al. (2001), and was considerably lower than the bias reported by Perry and Fox (1997) of 3%. When Tedeschi et al. (2004) evaluated the DIM model with individually fed cattle, a bias of -5.7% was reported. These inconsistencies in mean bias across the three evaluations may be due to the fact that for both Tedeschi et al. (2004) and Perry and Fox (1997) predictions were compared to individual animal intake, while in this evaluation and the feedlot portion of the analysis by Guiroy et al. (2001) model predictions were compared on a per pen basis. The regression analysis revealed a high precision (r^2 = 0.97) of model prediction for both methods, and no outliers were identified in the dataset. Figure 4.1 illustrates the relationship between observed DMI and DMR predicted by pen when the mean BW method was used. Figure 4.2 illustrates the relationship between observed DMI and DMR predicted by pen when the DIM model was used. Both the evaluations of Tedeschi et al. (2004) and Guiroy et al. (2001) indicated a lower model precision (r^2 of 0.75 and 0.74, respectively) when using the mean BW method. However, a similar r^2 value was reported in Tedeschi et al. (2004), using the DIM model, with an r^2 of 0.91. These high values indicate that the CVDS using the DIM model was consistently precise in predicting DMR. The lower precision noted for the mean BW method may be due to the fact that the mean BW method only uses an average BW across the period, while the DIM method's use of trends in ADG and composition across the period may be a more reliable method of predicting DMR for certain pens.

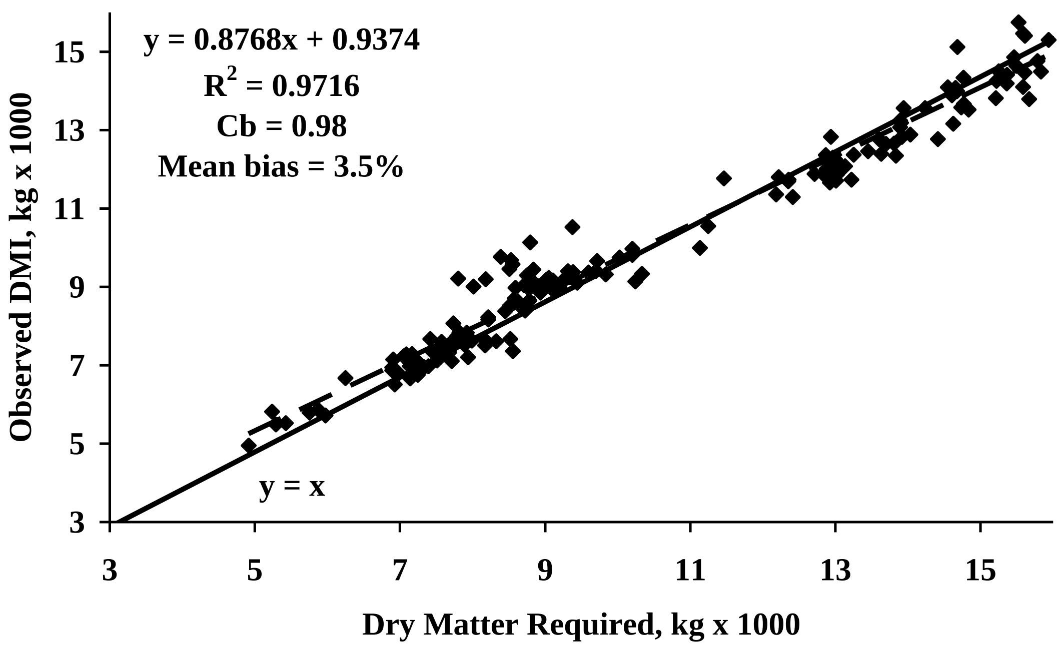

Figure 4.1. Relationship between observed DMI and DMR predicted using the mean BW method of the CVDS for each pen, with each value represented as kg per pen × 1000.

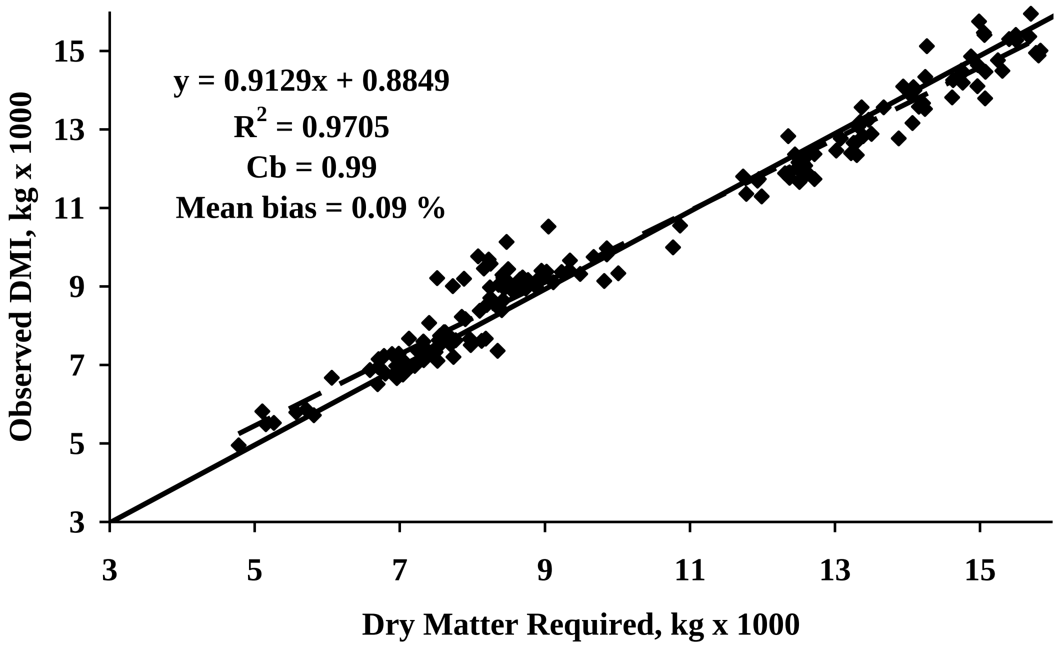

Figure 4.2. Relationship between observed DMI and DMR predicted using the DIM model of the CVDS for each pen, with each value represented as total kg for each pen x 1000.

Slope and intercepts differed from one and zero simultaneously using the test by Dent and Blackie (1979), indicating that for the regression of observed on predicted values the slope and intercept simultaneously differed from unity and zero, for both methods. This indicates that the regression differed from the ideal, which would pass through the origin, with an intercept of zero, and have a slope of unity. However, the Cb of 0.98 for the mean BW method and 0.99 for the DIM model indicated the regression line was very close to the Y = X line of the regression, indicating that the model was highly accurate.

Table 4.2 provides the values for the balance analysis for both mean BW and DIM methods, indicating the proportion of data points about the observed mean. A tendency for the model to over-predict DMR for pens with greater than average DMI was revealed for the mean BW method, with 39% of the data points falling above the mean DMI and being over-predicted by the model. The majority of pens were slightly over-predicted (74.57%) by the mean BW method of the CVDS. The first and second χ^2 tests revealed that the cells were not homogeneously distributed at 25%, and not independent, with χ^2 of 57.31 ($P < 0.01$) and 25.70 ($P < 0.01$), respectively. Similarly, the odds ratio statistic of 0.10 indicated that the cells were not independent and this conclusion was supported with the natural logarithm transformation of the odds ratio statistic of -2.31.

Table 4.2. Data points over- and under-predicted above and below the observed mean for the mean BW and dynamic iterative growth model (DIM) methods of CVDS for the un-weighted analysis on a per pen basis

	Mean BW method		DIM method	
Model prediction	Observed mean		Observed mean	
	Below	Above	Below	Above
Over-predicted	35.26%	39.31%	19.08%	34.68%
Under-predicted	23.12%	2.31%	39.31%	6.94%

The balance analysis of the DIM method revealed a tendency to over-predict values above the observed mean (34.68%), and to under-predict values below the observed mean (39.31%). The DIM method also tended to over-predict a greater portion of the data points (53.76% vs. 46.24%) compared to under-prediction. The first and second χ^2 tests revealed that the cells were not homogeneously distribute at 25%, and not independent, with χ^2 of 45.66 ($P < 0.01$) and 43.40 ($P < 0.01$) respectively. The odds ratio statistic of 0.10 also revealed that the cells in the DIM method were not independent. This was also confirmed with the natural logarithm transformation of the odds ratio (-2.44). The balance analysis suggests that the CVDS using the either the mean BW method or the DIM method may be somewhat biased as to over- or under-predicting pens of cattle based on their location about the observed mean DMI.

The over-prediction by both methods above the mean may be due to errors in estimation of diet ME. If ME of the diet was underestimated an over-prediction of DMR was likely as CVDS would estimate that the cattle would require more of the diet to meet the energy needs required to meet the steer's level of performance. The same trend was also noted with the DIM method's under-prediction for pens with below average DMI, which would be caused by an underestimation of diet ME. This error was noted in a sensitivity analysis of dietary ME by Bourg et al. (2006a), where ME was over- or under-predicted by 5 or 10%, and a corresponding decrease and increase in model predicted DMR was seen in subsequent evaluations.

The evaluation of sources of variation by decomposing MSEP showed that the largest portion of variation in the mean BW method analysis was in the random, uncontrollable error (44%). However, a large amount of variation was also noted for the other sources, with errors due to mean bias accounting for 26%, and errors due to regression accounting for 30% of the variation in MSEP. This indicates that although a large portion of the variation in DMR predicted by the mean BW method was due to random error, a substantial portion is attributed to regression error and mean bias suggesting that there may be inherent variation in the prediction of DMR of these pen fed steers using the mean BW method of CVDS.

The evaluation of sources of variation by decomposing MSEP for the DIM model showed that the largest portion of variation in the analysis was in the random, uncontrollable error (77%). As expected due to the very low mean bias in this model prediction, very little variation was attributed to error due to mean bias (0.025%). Twenty three percent of the variation was due to regression error. The large portion of variation attributed to uncontrollable error suggests that there are factors in the prediction of DMR that the DIM model is not accounting for that may be unknown.

Weighted Analysis

When the predictions of DMR were weighted per steer per d for each pen, the observed DMI was 10.26 kg/steer/d. The mean BW method predicted an average DMR per steer per d of 10.57, which was very similar to actual DMI as indicated by the mean bias of 2.87%. This mean bias was actually lower than when values were reported on a per pen basis. The DIM model of CVDS when adjusted to a per steer per d basis predicted a DMR of 10.21 kg. This indicated a slight under-prediction, with a mean bias of - 0.51%. This was slightly higher than was predicted on a per pen basis. The results of the mean BW prediction were very similar to values reported by Guiroy et al. (2001) in predicting individual animals, who reported a mean bias of 2.28% when the same EBF equations were used.

The regression analysis revealed that r^2 values decreased for both methods when DMR was weighted on a per steer per d basis. For the mean BW method, the r^2 of the regression decreased from 0.97 to 0.82 as represented in Figure 4.3, and for the DIM method, r^2 values decreased from 0.97 to 0.82 as well, as is represented in Figure 4.4. The decrease in r^2 may be due to the decrease in precision noted by Guiroy et al. (2001) when predicting individuals compared to groups of animals. When Guiroy et al. (2001) randomly divided 365 individually fed steers into groups of 5, 10, 20, 40, or 80 steers; a decrease in CV was noted as group size increased. This decrease in error when predicting individuals versus groups of cattle in a pen is important when this application is applied on a real world basis as was noted by Guiroy et al. (2001).

As was the case in the un-weighted analysis, slope and intercepts differed from one and zero simultaneously using the test by Dent and Blackie (1979) for both methods. However, the C_b for the mean BW method when weighted decreased slightly to 0.97 compared to the un-weighted analysis with a value of 0.98, although the value of 0.97 is still very close to the ideal of 1.

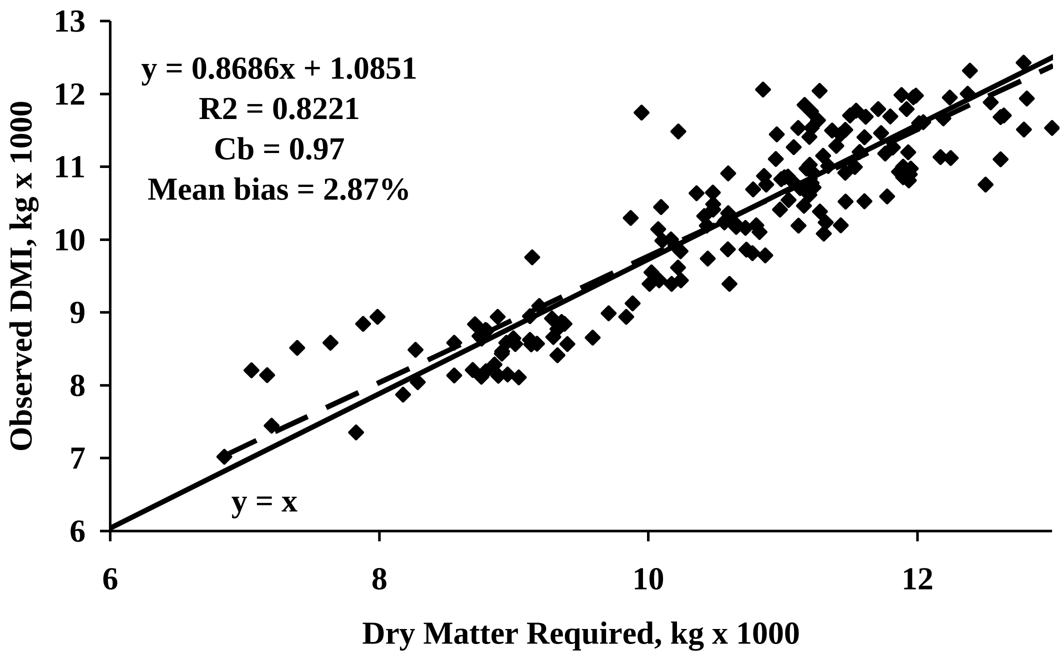

Figure 4.3. Relationship between observed DMI and DMR predicted using the mean BW method weighted by number of steers/pen, shown as kg/steer/d.

For the DIM model, the C_b value for the weighted analysis was 0.99 which did not differ from the un-weighted analysis. Both C_b values indicate that when the predictions were weighted on a kg per steer per d basis, the regression of observed on predicted values was still very similar to the Y = X line. The regression analysis of weighted values revealed that both the mean BW method and the DIM model were still highly precise in their predictions when weighted on a per steer per d basis.

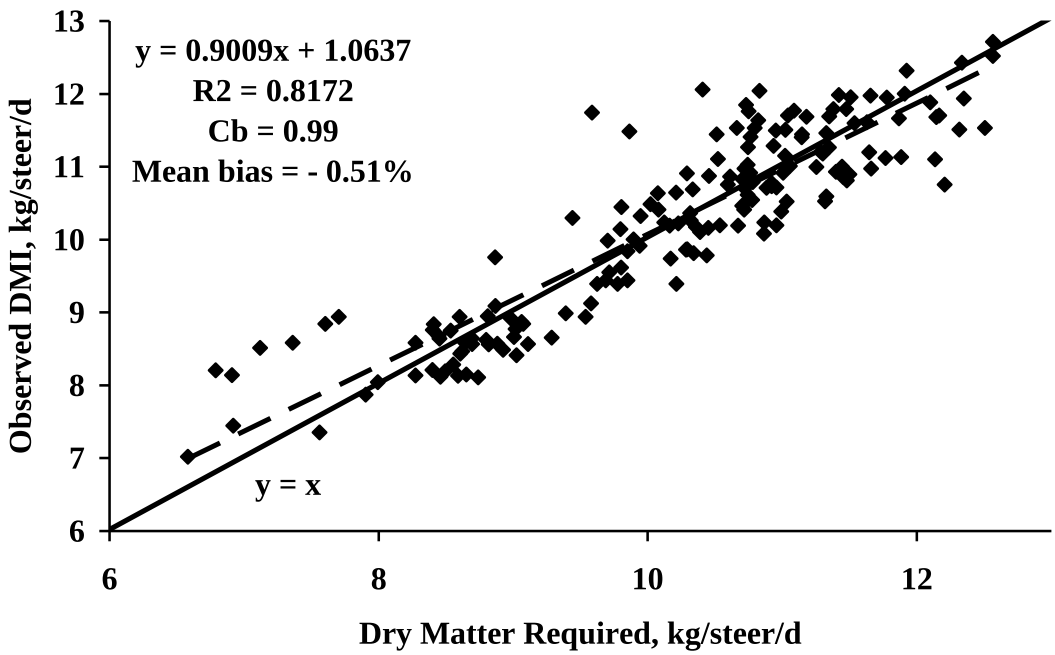

Figure 4.4. Relationship between observed DMI and DMR predicted using the DIM model weighted by number of steers/pen, shown as kg/steer/d.

Table 4.3 provides the values for the balance analysis for both mean BW and DIM methods, indicating the proportion of data points about the observed mean, when values were weighted on a per steer per d basis. For the mean BW method, the model tended to over-predict more values than under-predict; 74.56% compared to 25.44% respectively. A similar percentage of values were over-predicted below and above the mean (36.99% and 37.57%; respectively) for the mean BW method. However, more values above the mean observed DMI were under-predicted than those below the mean.

Table 4.3. Data points over- and under-predicted above and below the observed mean for the mean BW and dynamic iterative growth model (DIM) methods of CVDS for the weighted analysis on a per steer per d basis

	Mean BW method		DIM method	
Model prediction	Observed mean		Observed mean	
	Below	Above	Below	Above
Over-predicted	36.99%	37.57%	31.21%	22.54%
Under-predicted	8.09%	17.34%	13.87%	32.37%

The tendency to over-predict was similar to what was noted on the un-weighted basis. The first χ^2 test revealed that the cells were not distributed evenly at 25%, with χ^2 of 50.24 ($P < 0.01$). The second χ^2 test reveled that, with χ^2 of 4.19 ($P = 0.04$), that the cells were not independent. The odds ratio statistic of 2.07 indicated that the cells were not independent, as well. The conclusion was supported with the natural logarithm transformation of the odds ratio statistic of 0.72. The results for the balance allocation for the weighted analysis of mean BW predictions were similar to those found in the un-weighted analysis, although under-predicted values differed when weighted on a per steer per d basis. For the un-weighted analysis, the model under-predicted more values below the observed mean DMI, but for the weighted analysis the model under-predicted more values above the observed mean. This may be due to the fact that when the values were weighted on a per steer per d basis, some of the variation in DOF that was seen in the un-weighted analysis was removed, as there was a wide range in DOF for this evaluation (70- 198 d).

The balance analysis of the weighted values of the DIM method revealed a tendency to over-predict values below the observed mean (31.21%), and to under-predict values above the observed mean (32.37%). This was the opposite of the tendencies for the un-weighted values, and may once again be due to the fact that some of the variation attributed to the wide range in DOF in the dataset was removed. The DIM method also tended to over-predict a greater portion of the data points (53.76% vs. 46.24%) compared to under-prediction, as was the case with the un-weighted analysis. The first and second χ^2 tests revealed that the cells were not homogeneously distributed, and not independent, with χ^2 of 15.42 ($P < 0.01$) and 13.68 ($P < 0.01$) respectively. The odds ratio statistic of 3.18 also revealed that the cells in the DIM method were not independent, as this value was not equal to 1. This was also confirmed with the natural logarithm transformation of the odds ratio (1.16).

The evaluation of sources of variation by decomposing MSEP showed that the largest portion of variation in the mean BW method analysis for weighted values was in the random, uncontrollable error (71.39%), which was much larger than the 44.63% noted in the un-weighted analysis. The other sources of errors included mean bias accounting for 21.06%, and errors due to regression accounting for only 7.55% of the variation in MSEP. The variation due to regression was decreased significantly from 29.68% to only 7.55% which indicates that a portion of the variation in the regression may have been due to variation in number of steers per pen or number of DOF. This may be important for future analyses.

The decomposition of MSEP for the weighted analysis of DIM model predictions indicated that a substantial portion of variation was still attributable to random error at 94.12%, and a very small amount of error was due to mean bias as was expected to the very low mean bias, although the 0.79% in the weighted analysis was slightly higher than the 0.03% in the un-weighted analysis. However, as was noted in the mean BW weighted analysis, the error due to regression was significantly reduced from 23.01% in the un-weighted analysis to 5.09% in the weighted analysis.

Method Comparison

Least-square means for performance and carcass traits of each method are presented in Table 4.4, with preferred method determined by that which provided a mean bias closer to zero. The DIM model was more accurate for 110 pens of 173 total pens, compared to 63 pens for the mean BW method. For the carcass traits presented, HCW and 12th rib fat thickness did not differ between the two methods ($P > 0.10$). LMA tended to differ between the two treatments ($P = 0.09$), with mean BW pens having slightly larger LMA. Yield grade and marbling score differed ($P < 0.05$) between the two methods, such that mean BW method pens had lower yield grade and higher marbling score. On average, there were fewer steers per pen ($P < 0.05$) in those where mean BW method provided a lower mean bias compared to the DIM pens (7.14 and 7.85, respectively). Pens where mean BW provided a lower mean bias also had ($P < 0.05$) compared to the DIM method, 16.5 fewer DOF (122.6, 139.1; respectively), and a more energy dense ration (3.04 Mcal ME/kg DM, 2.95 Mcal ME/kg DM; respectively).

Table 4.4. Comparison of two methods to predict dry matter required

Trait[1]	Methods [2] MBW	DIM	SE
Number	63	110	------
Steers per pen	7.14[a]	7.85[b]	0.17
DOF, d	122.6[a]	139.1[b]	3.7
ME, Mcal/kg	3.04[a]	2.95[b]	0.01
ADG, kg/d	1.62[a]	1.83[b]	0.03
DMI, kg/d	9,051[a]	10,949[b]	349.2
HCW, kg	365.6[a]	370.1[a]	2.6
FT, cm	1.15[a]	1.20[a]	0.03
LMA, cm^2	90.09[c]	88.64[d]	0.69
YG	2.60[a]	2.77[b]	0.04
MRB score	421[a]	409[b]	4.8

[a,b] – means with different superscript in the same row differ $P < 0.05$
[c,d] – means with different superscripts in the same row tended to differ $P < 0.10$
[1] DOF, HCW, FT, LMA, YG, MRB score = days on feed, hot carcass weight, 12th rib fat thickness, *Longissimus dorsi* muscle area, USDA Yield Grade, marbling score
[2] MBW = mean body weight method and DIM = dynamic iterative growth model method.

These steers also consumed 17% less total feed, 9,051 kg compared to 10,949 kg for the DIM method. These steers also gained 0.21 kg per d less than those steers where the DIM offered a more desirable mean bias. These differences may be partially explained by the method that each uses to calculate DMR. The mean BW method uses the linear relationship between BW and ADG to determine the average BW of the period, while the DIM model relies more on differences in composition and dynamically predicts accumulated BW. Those pens where mean BW offered a more desirable mean bias differed from expected composition with no difference in 12th rib fat thickness, a greater amount of marbling, lower numerical yields, and a tendency to have larger LMA. The variation in DMI may have been better explained by variation in BW rather than differences in composition.

Summary

Both methods (mean body weight and DIM) of CVDS were highly accurate and precise in allocating feed to pens of steers fed diverse type of diets and environmental conditions. The DIM model was slightly more accurate. Both methods tended to over-predict DMR slightly when pens consumed more than the average of the database. The decomposition of the MSEP revealed that a greater proportion of error was random when the dynamic model was used rather than mean BW, suggesting that more information might be needed to account for more of the variation in dry matter intake. A larger proportion of error was attributed to mean and systematic biases when the mean BW method was used, suggesting that further improvements in the equations are needed. Further work is needed to decrease mean and systematic bias when using the mean BW method, and to account for more random variation in the dynamic model.

Implications

These results suggest that CVDS using either the mean BW method or the DIM model can accurately and precisely allocate feed to cattle fed in pens. For this reason, CVDS may be a useful tool in ICMS programs.

CHAPTER V

META-ANALYSIS OF THE CVDS PREDICTIONS OF INTAKE AND EFFICIENCY IN GROWING AND FINISHING CATTLE

Objectives

1) To evaluate the effectiveness of the CVDS in predicting DMR from individually fed animal's observed ADG.
2) To examine phenotypic correlations between predicted and observed DMI and feed efficiency traits from eight studies using meta-analysis.

Materials and Method

Table 5.1 lists definition of terms used in this evaluation. Each abbreviation is defined, and a definition and formula for each trait is listed.

Database Description

Two databases were compiled based on growing or finishing diets. The descriptive statistics for 403 steers used in the growing database are presented in table 5.2. All studies in the growing database were conducted in Texas across several years, and were designed to characterize feed efficiency traits. The four studies consisted of individually fed steers, with individual animal intake measured using a Calan Gates system or Growsafe® technology. Diet ME ranged from 2.06 to 2.26 Mcal/kg of DM dependent upon study. Steers had similar average IBW, although Santa Gertrudis steers in study 1 and 2 were slightly heavier at the

Table 5.1. Definition of traits

Trait Name	Abbreviation	Definition	Formula
Initial body weight	IBW	Body weight at start of test	
Metabolic body weight	$BW^{0.75}$	Mid-test body weight raised to the 0.75	
Average daily gain	ADG	Body weight gain per day	
Metabolizable energy	ME	Mcal/kg DM	
Dry matter intake	DMI	Feed intake per day	
Fat thickness	FT	12-13th rib fat thickness	
Rib-eye area	REA	*Longissimus dorsi* muscle area	
Residual feed intake I	RFIx	Difference between actual feed intake and expected FI from the regression of DMI on gain and BW	Calculated from the linear regression of DMI on ADG and $BW^{0.75}$ using mixed models across all studies
Residual feed intake II	RFIinra	Difference between actual feed intake and expected FI from French feeding standards formula	DMI- expected feed intake from French feeding standards formula
Feed conversion ratio	FCR	Feed intake per unit of gain	DMI ÷ ADG
Partial efficiency of growth	PEG	Efficiency of weight gain net of maintenance feed requirements	ADG ÷ (DMI-intake for maintenance)
Kleiber ratio	KR	Body weight gain per unit of metabolic body weight	ADG ÷ $BW^{0.75}$
Dry matter required	DMR	Computed from CVDS model	The sum of FFM and FFG
Feed for maintenance	FFM	Computed from CVDS model	
Feed for gain	FFG	Computed from CVDS model	
DMR:ADG	R:G	The ratio of DMR to ADG	
Predicted intake difference	PID	Difference between actual feed intake and that predicted by the CVDS model	DMI - DMR

Table 5.2. Descriptive statistics (mean ± SD) of cattle in the growing database[1,2]

Study	Reference	Sex	Breed	N	ME	IBW	ADG	DMI	uFT[3]	uREA[4]
1	Brown et al. 2005	S	SG	116	2.14	299.3 ± 33.7	1.25 ± 0.21	10.07 ± 1.30	0.32 ± 0.16	60.55 ± 6.57
2	Gomez et al. 2007	S	SG	118	2.26	308.8 ± 27.9	0.84 ± 0.16	9.44 ± 0.99	0.45 ± 0.13	60.53 ±6.45
3	Carstens et al. 2002	S	BR	112	2.06	255.5 ± 28.7	0.97 ± 0.20	9.75 ± 1.54	0.39 ± 0.07	53.24 ± 5.89
4	Carstens et al. 2002	S	BR	57	2.06	249.2 ± 26.2	1.09 ± 0.22	10.40 ± 1.35	0.44 ± 0.06	53.49 ± 4.99
Mean					2.13	282.8 ± 39.0	1.03 ± 0.25	9.84 ± 1.34	0.40 ± 0.13	57.52 ± 7.09

[1] S= steer, SG= Santa Gertrudis, BR= Braunvieh,
[2]ME, Mcal/kg, IBW, kg, ADG, kg, DMI, kg
[3] Final ultrasound 12-13th rib fat thickness, cm
[4]Final ultrasound *Longissimus dorsi* muscle area, cm^2

Table 5.3. Descriptive statistics (mean ± SD) of cattle in finishing database[1,2]

Study	Reference	Sex	Breed[1]	N	ME	IBW	ADG	DMI	cFT[3]	cREA[4]
1	Guiroy 2001	S	AN	37	2.97	302.5 ± 18.7	2.03 ± 0.22	10.91 ± 0.86	1.50 ± 0.43	77.98 ± 5.28
2	Brown et al. 2005	S	SG	106	2.99	430.9 ± 43.3	1.09 ± 0.22	9.28 ± 1.57	1.26 ± 0.50	72.59 ± 15.59
3	Lancaster et al. 2005	S	AR	117	2.73	353.7 ± 41.3	1.32 ± 0.24	10.35 ± 1.36	1.43 ± 0.35	72.20 ± 5.48
4	Perry and Fox 1997	S	MX	49	2.85	237.7 ± 36.1	1.35 ± 0.21	8.08 ± 0.93	0.87 ± 0.50	85.12 ± 10.02
Mean					2.89	355.7 ± 77.6	1.33 ± 0.36	9.69 ± 1.61	1.29 ± 0.48	75.08 ± 11.63

[1] S= Steer, AN=Angus, SG=Santa Gertrudis, AR= Red Angus, MX= Crossbred
[2]ME, Mcal/kg, IBW, kg, ADG, kg, DMI, kg
[3]Carcass 12-13th rib fat thickness, cm
[4]Carcass *Longissimus dorsi* muscle area, cm^2

start of the trial than Braunvieh steers in studies 3 and 4, with an overall SD of 38.97 across all studies in the database. Steers in study 2 gained the least per day (0.84 kg/d), as compared to study 1 which had the greatest weight gains (1.25 kg/d). Steers in study 2 also had the lowest DMI of the four studies. Steers across studies had similar final ultrasound FT; however Santa Gertrudis steers had slightly larger final ultrasound REA. Within studies, cattle were individually fed and managed in a similar manner.

Summary statistics for the four studies used to compile the finishing database are presented in table 5.3. The database consisted of 309 individually fed steers. A total of eleven steers were removed from the database, nine from study 2 and two from study 3, due to periods during the trial in which BW was lost from one weigh period to the next. Study 1 and 4 were conducted in New York by Cornell University. Study 2 and 3 were conducted in Texas. Red Angus steers in study 3 had slightly lower metabolizable energy than other studies. Santa Gertrudis steers in study 2 had the heaviest initial BW, while crossbred steers in study 4 had the lowest initial BW. The finishing database contained more variation in initial BW as compared to the growing database, with a SD of 77.64 kg. Angus steers in study 1 recorded the highest gains, at slightly less than 1 kg per day more than Santa Gertrudis steers in study 2, who recorded the lowest gains over the feeding period. Crossbred steers in study 4 not only had the lowest DMI, but also had the leanest carcasses by 0.39 cm, with the largest rib-eyes by 12.92 cm^2. As the steers in study 4 were selected to represent five breed types, and fed to three different carcass weight endpoints, their carcass composition differs slightly from the other studies in the database. Thus, data in study 4 may present a problem in the combined analysis. The Santa Gertrudis steers also may present a problem in the analysis as they had the lowest ADG by 0.23 kg as compared to the Red Angus steers whose ADG was the next lowest, and gained 0.24 kg less than the average of the database, after those steers with questionable BW were removed. As was the case with the growing database, within study, cattle were fed and managed in a similar manner.

Feed efficiency traits calculated within study included FCR, which was calculated as the ratio of DMI to ADG, PEG, which as described by (Geay and Micol, 1988) offers an efficiency of weight gain in excess of estimated maintenance requirements, and KR, which gives body weight gain per unit of metabolic weight.

The Cattle Value Discovery System

Dry matter required for individual animals was calculated using the CVDS model. Individual animal performance and carcass information that were input into the model included: sex, implant status, breed type (beef or dairy), hide thickness, initial date of feeding period, approximate age, BCS, initial and final BW, yield grade, hot carcass weight, 12^{th} rib fat thickness, marbling (MRB) class and percentile, and *Longissimus dorsi* muscle area. For growing steers, equivalent HCW was calculated from empty final body weight as HCW = (EBW- 30.26) ⁄ 1.326 as described by Perry and Fox (1997). For finishing steers, actual carcass data was available for MRB, LMA, and FT, while for growing steers, ultrasound measurements, taken at the end of each trial, of percentage intra-muscular fat (%IMF), LMA, and FT were utilized in CVDS predictions. Additionally for each individual animal in the dataset, BW and carcass composition (HCW, LMA, FT, and MRB) were used to predict a BW at 28% empty body fat (EBF).

The dynamic iterative growth model of CVDS as described by (Tedeschi et al., 2004) was used to calculate individual animal FFM, FFG, and their sum, or DMR. Several feed efficiency traits were then calculated using this prediction of intake. These include the ratio of DMR to ADG and the predicted intake difference, which was the difference between actual DMI and DMR.

Statistical Analysis

St. Pierre (2001) discussed the application of compiling data from multiple published studies in attempt to obtain relationships among key variables. This statistical process has been labeled meta-analysis. Tedeschi (2006) offered the use of meta-analysis as a useful technique to remove effects of study when data are obtained from literature to develop or evaluate models to further decrease the risks associated with sampling error. For this analysis, the results of the previously described studies were adjusted for the effect of study using the following statistical techniques.

The MIXED procedure of SAS (SAS Institute Inc, Cary, NC) was used to compute the mixed RFI (RFIx) for growing and finishing databases assuming studies within databases as random effects and variance components for the variance-(co)variance matrix using Equation [1].

$$RFIx_{ij} = DMI_{ij} - \overline{DMI}_{ij} \quad \text{and} \quad \overline{DMI}_{ij} = a_i + b_i \times ADG_{ij} + c_i \times BW^{0.75} \qquad [1]$$

Where a, b, and c are N ((β_0, β_1, β_2), Ψ), and e_{ij} is random, uncontrolled errors N (0, σ^2).

A simpler random coefficient model (RCM) was used to adjust the Y-variate to the effects of studies. The fixed effects plus the residual error from the RCM were combined and Pearson correlation coefficients were obtained. In these two RCM, both intercept and slopes were adjusted for studies. Similarly, a third RCM was used to compare RFIx and other variables, but no adjustment on the intercept for studies was allowed.

Results and Discussion

Model-Predicted Traits

The Pearson correlation coefficients between model-predicted intake and efficiency traits for both growing and finishing steers are presented in table 5.4. As expected, due to the relationships among the calculation of these traits, all correlations were significantly different from zero. For growing steers, as expected, there were strong correlations between DMR and FFM and FFG (0.70 and 0.99, respectively) for these 403 individually fed steers, indicating that a larger proportion of DMR was explained by feed partitioned for gain than that explained by maintenance. The FFM was moderately correlated ($r = 0.60$) with FFG.

There were moderate to strong negative correlations between DMR and the two model calculated efficiency traits, R: G and PID (-0.50 and -0.69, respectively). When DMR increased, the R: G decreased, such that more efficient animals had higher DMR. The negative relationship between DMR and PID also indicated a more efficient animal when DMR was increased.

Table 5.4. Pearson correlation coefficients of model-predicted traits of growing (above diagonal) and finishing (below diagonal) cattle

	DMR	FFM	FFG	R:G	PID
DMR	---	0.70	0.99	-0.50	-0.69
FFM	0.79	---	0.60	0.25	-0.25
FFG	0.99	0.61	---	-0.62	-0.72
R:G	0.09[b]	0.50	-0.19	---	0.46
PID	-0.52	-0.25	-0.57	-0.21	---

[a] Correlation was not different from zero at P > 0.05
[b] Correlation tended to differ from zero at P < 0.10

Arthur et al. (2001b), in their estimation of phenotypic and genetic correlations between growth and feed efficiency in growing Charolais bulls, noted a moderate positive correlation between actual feed intake and RFIinra, which calculated expected feed intake from French feeding standards rather than linear regression. The RFIinra estimates were similar to PID analyzed in this database. However, the relationship between PID and DMR is still expected to be similar in direction to that reported between DMI and RFIinra. This contrast may be due to the use of actual DMI as compared to DMR or the differences in the calculation of expected feed intake in the feed efficiency measures.

The FFM was weakly correlated with both R: G and PID, although positively with R: G (r = 0.25), and a negatively with PID (r = -0.25). This was such that as an animal's FFM increased, the R: G increased, which indicated a less efficient animal. However, a contrasting relationship was noted with PID and FFM. As an animal's feed requirement for maintenance increased it became more efficient, with a smaller PID value. This differs from the results of Castro Bulle et al. (2007), who found the tendency for a moderate positive correlation between RFI and ME for maintenance, and although not statistically significant, they found that low RFI steers had lower numerical ME for maintenance.

The FFG had moderate to strong negative correlations with both efficiency measures. As an animal's feed available for gain increased, the R: G decreased, indicating a more efficient animal. A similar relationship was noted between FFG and PID. As FFG increased, PID decreased, indicating that the animal was more efficient. This may be highly related to the animal's maintenance requirements. As an animal's maintenance requirement was decreased, more feed was available for gain, which may be indicative of the relationship found in this dataset.

In the finishing database, all traits except DMR and R: G were significantly correlated with $P < 0.05$. As in the growing database, DMR had a strong positive correlation with both FFM and FFG (0.79 and 0.99; respectively), with a slightly stronger correlation with FFG. This also indicates that there may be a slightly stronger relationship between FFG and DMR than FFM.

A moderate negative correlation was found between DMR and PID for the finishing database. This correlation was slightly stronger than that found by Tedeschi et al. (2006). Unlike the growing database, there was the tendency ($P = 0.08$) for a weak positive correlation between DMR and R: G. Figure 5.1. illustrates this relationship between DMR and R: G. An examination of intercepts for the regression line of individual studies revealed that study 1 had a slope of -0.79, study 2 had a slope of 1.51, study 3 had a slope of 1.38, and study 4 had a slope of -2.0974. This suggested that the relationship being represented in this partial correlation may be difficult to interpret due to the large amount of between study variation present in this dataset. This differs from the relationship reported by Tedeschi et al. (2006), who found a moderate negative relationship between DMR and R: G with r = -0.40. These differences may be due to inherent problems in the studies combined to form the finishing database. Santa Gertrudis steers used in this data set had low ADG even after those steers with losses in BW were removed from the dataset. This may be masking the true relationship between DMR and R: G.

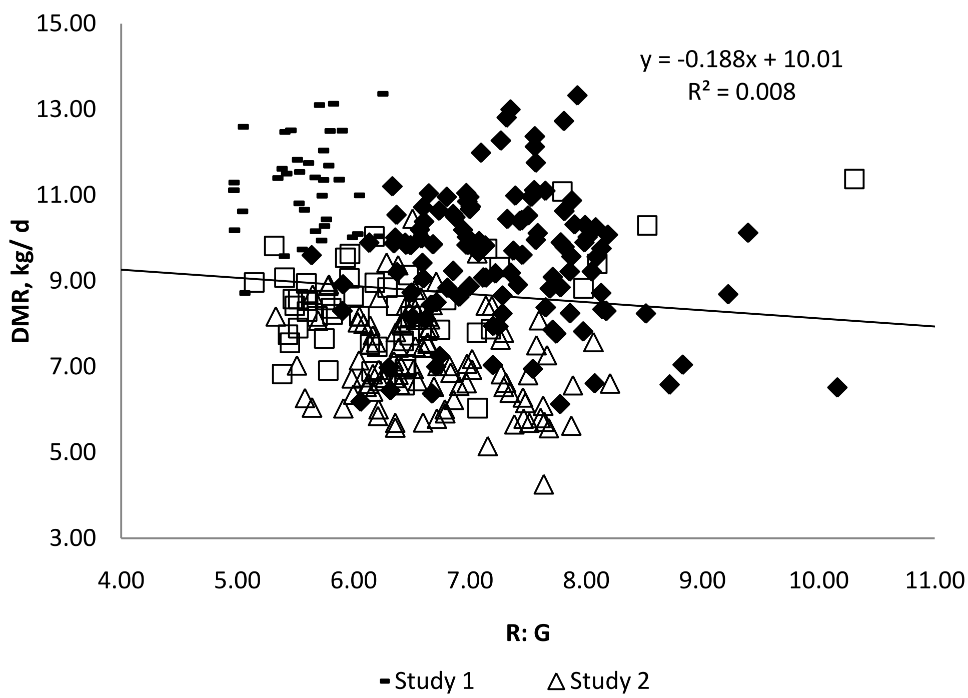

Figure 5.1. Relationship between DMR and R: G for finishing steers.

The FFM and FFG were moderately correlated with a similar Pearson correlation coefficient to the growing database. The FFM was positively correlated with R: G and negatively correlated with PID, indicating a contradictory trend in regards to efficiency. This relationship was similar to that found with growing steers, but was also contradictory to the results of Castro Bulle et al. (2007), as was discussed with the growing database. Johnson et al. (2003) noted that fattening steers retained only 16-18% of energy that they consumed, with the largest loss associated with maintenance function, and that the maintenance component comprises approximately 50% of ME requirements. This indicates that in regards to efficiency of ME utilization, the function of maintenance represents the most inefficient portion, which may be causative of the contradictory relationships between FFM and the two model-predicted efficiency measures.

Weaker correlations were noted between FFG and R: G and PID in the finishing as compared to the growing database. A weak negative correlation was found between FFG and R: G and may be partially due to problems associated with ADG in the Santa Gertrudis study. The negative relationship between PID and FFG was similar to that found in the growing database, but was slightly weaker.

With the growing steers, a moderate positive correlation was found between R: G and PID, which was slightly stronger than that found by Tedeschi et al. (2006), who reported an r = 0.34. This was not the case with the finishing steers, where a weak negative correlation was found between the two model-predicted efficiency traits. The dataset used by Tedeschi et al. (2006) contained two of the same studies as the finishing database in this analysis. However, several of the correlations in this analysis were contradictory to those noted by Tedeschi et al. (2006). This was likely due to the other two studies included in this analysis.

Model-Predicted Traits and Performance

Pearson correlation coefficients for model-predicted traits and performance and carcass traits for steers in the growing and finishing databases are presented in tables 5.5 and 5.6, respectively. The CVDS explained 64% of the variation in observed DMI in the growing database, and 67% of the variation in the finishing database. This was slightly higher than was reported by Tedeschi et al. (2006) and Williams et al. (2006), who found that the CVDS accounted for 56% and 53% of this variation respectively.

In the growing database, strong correlations were found between DMR and both ADG and $BW^{0.75}$. This relationship was expected as DMR was calculated from the sum of FFM and FFG, which were based on the animal's BW, gain, and composition of gain. However, weak positive correlations were noted between DMR and the two measures of body composition in the growing database, ultrasound 12-13th rib fat thickness and *longissimus dorsi* muscle area taken at the end of each trial. The strong relationship between DMR and measures of BW and gain as compared to relatively weak relationship with DMR and measures of body composition suggests that ADG and BW have a greater impact on the estimation of DMR than composition of gain. Further research is needed to assess the sensitivity of DMR to errors in the measurements of BW, gain, and composition of gain, and to determine which of these errors has the most serious effect on DMR. A similar relationship between the two measures of body composition and FFM and FFG were also noted. However, the relationship between FFM and uREA was slightly stronger.

Table 5.5. Pearson correlation coefficients of model-predicted traits and selected performance and carcass traits for growing calves

	DMR	FFM	FFG	R:G	PID
DMI	0.80	0.65	0.75	-0.19	0.30
ADG	0.96	0.47	0.99	-0.84	-0.69
$BW^{0.75}$	0.73	1.0	0.58	0.26	-0.22
uFT[1]	0.38	0.31	0.35	0.09[b]	-0.04[a]
uREA[2]	0.33	0.59	0.22	0.06[a]	-0.04[a]

[1] uFT= Final ultrasound 12-13th rib fat thickness, cm.
[2] uREA= Final ultrasound *Longissimus dorsi* muscle area, cm^2.
[a] Correlation was not different from zero at $P > 0.05$.
[b] Correlation tended to differ from zero at $P < 0.10$

Table 5.6. Pearson correlation coefficients of model-predicted traits and selected performance and carcass traits for finishing calves

	DMR	FFM	FFG	R:G	PID
DMI	0.82	0.66	0.80	-0.01[a]	0.49
ADG	0.91	0.35	0.94	-0.75	-0.36
$BW^{0.75}$	0.73	0.90	0.61	0.36	0.04[a]
cFT[1]	0.48	0.48	0.43	0.35	-0.07[a]
cREA[2]	0.29	0.07[a]	0.24	-0.11[b]	-0.14

[1] cFT= 12-13th rib fat thickness, cm.
[2] cREA= *Longissimus dorsi* muscle area, cm^2.
[a] Correlation was not different from zero at $P > 0.05$.
[b] Correlation tended to differ from zero at $P < 0.10$.

Both R: G and PID were negatively correlated with ADG. This was such that selection for more efficient animals would result in an increase in ADG, which may favor larger, faster growing animals. Although the relationship was slightly stronger in this analysis, Arthur et al. (2001b) also noted a negative relationship between RFI with expected feed intake calculated from French feeding standards. As the authors discuss, this relationship was not unexpected, as unlike RFI with expected feed intake calculated from the linear regression of DMI on ADG and $BW^{0.75}$, RFIinra and in this case PID are not automatically independent of BW and ADG. Fan et al. (1995) found a similar relationship when expected feed consumption was calculated using NRC (1984). A negative correlation was also found between PID and $BW^{0.75}$, and was slightly weaker than that reported by both Arthur et al. (2001b) and Fan et al. (1995). This was such that more efficient steers as defined by PID had larger BW and higher ADG. On the other hand, R: G was weakly positively correlated with BW, such that more efficient steers had lighter BW. As DMR is calculated based on BW, gain, and composition, it is highly dependent on these traits. When DMR is used as an expected feed intake measure for use in efficiency calculations, the resultant trait is confounded with BW and gain. This means that selection for more efficient cattle using an efficiency trait such as PID may result in a corresponding selection for an increase in BW and gain. Further research is needed to examine this relationship.

Correlations between the two model-predicted efficiency measures and body composition measures were not different from zero at $P > 0.05$. However, there was a tendency of having a weak positive correlation between R: G and uFT. This suggests that the selection for more efficient animals using either efficiency measure would not affect carcass composition.

The R: G was negatively correlated, although weakly, with DMI. This was in contrast to the relationship between observed DMI and observed FCR reported by Arthur et al. (2001a), who noted a weak positive relationship between the two traits. PID, however, was positively correlated with DMI. The relationship between PID and DMI was similar to that reported by Arthur et al. (2001b).

In the finishing database, strong positive correlations were also noted between DMR and ADG and BW, as was the case with the growing calves. The relationship between DMR and ADG was similar to that reported by Tedeschi et al. (2006). Similar correlations were found between carcass composition, as indicated by carcass FT and *longissimus dorsi* muscle area, and DMR as those between DMR and ultrasound measures of body composition in the growing database, with the relationships with FT slightly higher in finishing steers, and the relationship with REA slightly lower in finishing steers. The relationships between FFM and FFG and carcass composition were also very similar to those reported in the growing steers, with the exception of FFM and REA, which was not different from zero.

In this dataset, R: G was not correlated to observed DMI, which was similar to the results of Tedeschi et al. (2006). The relationship between PID and DMI was positive, and slightly higher than that reported by Tedeschi et al. (2006). Both R: G and PID were negatively correlated with ADG, with the relationship between R: G and ADG being stronger and both were similar to values of Tedeschi et al. (2006). The relationship between PID and BW was not different from zero. This was in contrast to the results of Arthur et al. (2001b) and Fan et al. (1995), who reported a negative correlation between

BW and similar traits. Although calculated in a somewhat similar manner, the authors of the previous studies calculated the expected feed intake from French feeding standards, and the NRC (1984), which does not involve the same equations used to calculate DMR by the CVDS.

The relationships between the two model-predicted efficiency measures and body composition differed from that reported in the growing database. The R: G was positively correlated with FT, and tended to be negatively and weakly correlated with REA. There was no relationship between PID and FT, but a negative relationship with PID and REA. These differences may be due to the large amount of variation between studies in carcass composition. The steers in study 4 were much leaner than steers in the other four studies, and had much larger REA. This difference in composition may be attributed partially to breed type, as steers in study 4 were a British Continental cross, while steers in study 1 and 3 were purebred British and steers in study 2 were Brahman influenced.

Model-Predicted Traits and Observed Efficiency Measures

Pearson correlation coefficients for model-predicted traits and observed efficiency traits are presented in tables 5.7 and 5.8 for growing and finishing steers, respectively. The PID as predicted by the CVDS model was able to explain 48% of the variation in RFIx in the growing database and 33% in the finishing database. This was slightly lower than the correlation reported by Tedeschi et al. (2006) for finishing steers, with an r = 0.84. The correlation in the growing database was similar to the relationship reported by Arthur et al (2001b), with a correlation between RFI calculated from regression and by French feeding standards of 0.70.

The RFIx was not correlated with DMR in either the growing or finishing databases. This was consistent with the results of Tedeschi et al. (2006). The RFIx was not correlated with any of the other model-predicted traits in either database. Tedeschi et al. (2006) found that R: G was weakly correlated with RFI, which differs from these findings.

Table 5.7. Pearson correlation coefficients of model-predicted traits and efficiency traits in growing calves

	DMR	FFM	FFG	R:G	PID
RFIx	0.01[a]	0.01[a]	0.02[a]	0.05[a]	0.69
FCR	-0.64	0.07[a]	-0.74	0.87	0.91
PEG	0.44	-0.12	0.52	-0.70	-0.95
KR	0.80	-0.05a	0.89	-0.94	-0.66

[a] Correlation was not different from zero at $P > 0.05$.
[b] Correlation tended to differ from zero at $P < 0.10$.

Table 5.8. Pearson correlation coefficients of model-predicted traits and efficiency traits in finishing calves

	DMR	FFM	FFG	R:G	PID
RFIx	0.04[a]	0.03[a]	0.04[a]	0.06[a]	0.57
FCR	-0.45	0.30	-0.58	0.80	0.80
PEG	0.37	-0.30	0.49	-0.71	-0.89
KR	0.80	-0.16	0.87	-0.89	-0.44

[a] Correlation was not different from zero at $P > 0.05$.
[b] Correlation tended to differ from zero at $P < 0.10$.

The FCR was negatively correlated with DMR and FFG in both the growing and finishing databases, with slightly stronger correlations in the growing database. In the growing database, the relationship between FCR and FFM was not different from zero, while in the finishing database, a weak positive correlation was found between these two traits. The FCR was strongly correlated with both R: G and PID in both databases, with slightly higher correlations in the growing database. This was in agreement with the relationships reported by Tedeschi et al. (2006) and Arthur et al. (2001b).

The PEG was negatively correlated with FFM, R: G, and PID in both databases. As PEG describes the efficiency of weight gain net of feed required for maintenance, this negative relationship with FFM was expected, as it was represented in the denominator of this ratio. The relationships between PID and PEG were slightly stronger than the relationship between PEG and RFIinra reported by Arthur et al. (2001b). The PEG was positively correlated with both DMR and FFG in both databases, with slightly stronger correlations in the growing database.

Similar correlations between KR and the model-predicted traits were found in both databases, with the exception of FFM, which was not correlated with KR in the growing database. The correlation between DMR and KR was similar to that reported by Tedeschi et al. (2006). As KR increased, a greater ADG relative to maintenance requirement was represented, as KR was the ratio of ADG to $BW^{0.75}$. A strong negative correlation was found between KR and R: G. This was as expected due to the fact that the numerator of the KR was the denominator of R: G. Tedeschi et al (2006) found similar strong correlations between these two traits, although a slightly stronger relationship was noted in this analysis. KR was also negatively correlated with PID although the relationship was not as strong as with R: G, and the relationship was slightly stronger in the growing database.

CHAPTER VI

CONCLUSIONS

Feed costs represent the largest expense in beef production, and Individual Cattle Management Systems (ICMS) have been suggested to improve profitability. The Cattle Value Discovery System (CVDS) was developed to predict growth and feed requirements of individual cattle fed in groups based on animal, diet, and environment information (Tedeschi et al., 2006). This evaluation of the CVDS: (1) examined the accuracy of the model's prediction of DMR for cattle fed in groups (2) examined the model's sensitivity to diet ME values (3) compared the model's prediction of DMR to actual DMI of individual animals and (4) evaluated the use of several model-predicted feed efficiency measures.

The first evaluation of the CVDS model involving pen-fed Santa Gertrudis steers revealed that accurate prediction of individual DMR of pen-fed cattle was possible, with an average mean bias of 2.43% for both steers and heifers. This suggested that the CVDS model may be a useful tool to successfully implement ICMS, although further research may be needed to improve inconsistencies in mean bias of DMR prediction. The sensitivity analysis of dietary ME values revealed that the model tends to consistently over- and under-predict DMR when the ME values are under- and over-estimated respectively. However the ranking of pens was not affected by this mis-estimation of diet ME, which suggests that the CVDS prediction of DMR may also have utility in the prediction of feed inputs for genetic evaluation.

The second evaluation of the CVDS also evaluated the model's prediction of feed required for pen fed steers from several research trials. Both methods (mean body weight and dynamic iterative model) of CVDS were highly accurate and precise in allocating feed to pens of steers fed diverse type of diets and environmental conditions. The DIM model was slightly more accurate. Both methods tended to over-predict DMR slightly when pens consumed more than the average of the database. The decomposition of the MSEP revealed that a greater proportion of error was random when the dynamic model was used rather than mean BW, suggesting that more information might be needed to account for more of the variation in dry matter intake. A larger proportion of error was attributed to mean and systematic biases when the mean BW method was used, suggesting that further improvements in the equations are needed. Further work is needed to decrease mean and systematic bias when using the mean BW method, and to account for more random variation in the dynamic model. These results suggested that CVDS using either the mean BW method or the DIM model can accurately and precisely allocate feed to cattle fed in pens. For this reason, CVDS may be a useful tool in ICMS programs.

The meta-analysis of CVDS predictions for growing and finishing steers revealed that the model was able to account for 64% and 67% of the variation in observed DMI for growing and finishing steers, respectively. However, future work is needed to account for more of the animal variation in DMI. The two model-predicted efficiency measures, R: G and PID, were strongly to moderately correlated with their observed efficiency counterparts. In growing and finishing steers, R: G was able to account for 76% and 64% of the variation in observed FCR. Strong correlations were also found between RFIx and PID, suggesting that there may also be some similarity on these two measurements.

These three analyses support the results of Tedeschi et al. (2006), Guiroy et al. (2001), and Tedeschi et al. (2004) who concluded the CVDS was able to account for a large portion of the variation in observed DMI. The authors also concluded that the CVDS may be a useful tool in ICMS, by allocating feed to individual cattle fed in group pens based on animal performance and diet information.

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VITA

Name: Brandi Marie Bourg

Address: Department of Animal Science
Texas A & M University
College Station, Texas 77843-2471

Email Address: bbourg@tamu.edu

Education: B.S., Animal Science, Louisiana State Univeristy, 2005
M.S., Animal Science, Texas A&M University, 2007