Evolutionary Computation Targeting Market Fat Specifications In Beef Steers

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EXTENDED ABSTRACT

Increasing the efficiency and profitability of beef production through targeting market specifications for fat and weight are important industry issues. Typically, young animals are drafted into pens within a feedlot situation, and then grown out until they reach a marketable size. There are considerable price penalties for animals which do not achieve the set weight and fat depth specifications.

The Cooperative Research Centre (CRC) for Beef Genetic Technologies in Armidale is promoting the use of systems models to better manage the overall production of marketable animals. In this study, the Davis Growth Model was adopted for the simulation of a feedlot scenario. This model simulates the growth, composition and fat distribution of beef cattle over time. A typical mixed-breed cohort of 306 animals was taken as the intake to the feedlot, and growth was then simulated for 60 to 140 days. The overall value of the carcasses and the variable feedlot operational costs were estimated, and the gross margin calculated as the difference between these.

The optimal gross margin for the single (non-segregated) herd was $237.19 per animal, which occurred at 84 days on feed. Whilst this value initially seems attractive, note that all of the fixed costs of feedlot operations have not yet been included.

Segregating this herd by breed type into separate feedlot pens, and growing each pen to its respective optimal days on feed, resulted in relatively little improvement (0.5%) in the average gross margin. However, segregation by initial liveweight allowed the pens to be marketed at a wider range of times, and this increased the overall gross margin by 2.2%. These results indicate that, across the breed types used in this study, initial size has more of an influence on ultimate profitability than actual breed.

Evolutionary computation is a biologically-inspired optimisation technique, based on simulated natural selection. Given our animal intake data and feedlot model, differential evolution (a particularly efficient and robust evolutionary algorithm) was used to seek the optimal allocation of animals to pens, as well as days on feed for each pen. Despite the size and complexity of the potential search-space, this efficient algorithm repeatedly converged to the global optimum for this system, in less than two hours of computation time. The best allocation was somewhat related to initial weight, but also incorporated the interacting aspects of breed, frame size, and initial body condition and fat depth. This optimal allocation resulted in a gross margin of $244.27 per animal, which is a 3.0% improvement over the base management scenario, and worth about $2,200 for this particular intake of animals.

This study demonstrates that feedlot scenario modelling can profitably be used to investigate the likely outcomes of alternate management strategies. Also, it is shown that formal economic optimisation is a useful and logical extension, and for this we recommend differential evolution as a proven robust optimisation algorithm. Future CRC research will include simulating more of the 'real-world' feedlot management options, after consultation with feedlot operators.

INTRODUCTION

As with many primary production systems, beef producers face the combined pressures of increasing costs and decreasing returns. Carcass prices are determined by a strict weight and fat grid, and it is essential that producers turn off a high proportion of their animals in the highest price windows. This is usually best achieved by finishing animals on a grain-mix diet in a feedlot situation, and here different management options and strategies are available.

This study uses a proven simulation model of steer growth to set up a typical feedlot scenario. Alternate management strategies are investigated, and their effects on overall gross margin estimated. Differential evolution, a notably robust and efficient variant of evolutionary algorithms (Mayer et al. 2005) is employed to seek out the optimal solution for this scenario.

1. FEEDLOT MODEL

1.1. Davis Growth Model

The dynamic Davis Growth Model (DGM; Oltjen et al. 1986, Sainz and Hasting 2000, McPhee et al. 2007) simulates the growth, composition and fat distribution in beef cattle. The concepts of cellular hyperplasia and hypertrophy are an integral component of these fat deposition models. The net synthesis of total body fat (kg) is calculated as net energy available after accounting for maintenance and protein synthesis. Total body fat (kg) is then partitioned into four fat depots (intermuscular, intramuscular, subcutaneous, and visceral) and then converted to carcass characteristics: intramuscular fat (IMF) in kilograms (kg) of fat to IMF as a percentage, subcutaneous fat (kg) to 12/13th rib fat depth (mm), and visceral fat (kg) to kidney, pelvic, and heart fat (%). Each of the fat depots is derived by a first order differential equation and empirical equations convert the fat in kilograms into their respective carcass characteristics. The amount and quality of feed intake determines the increases in these various body depots, on a daily basis.

For the more efficient modelling of our standard feedlot scenario, the DGM was first run on an individual-animal basis to simulate final body weight (kg), carcass weight (kg) and P8 fat depth (mm). This was done for a grid of defined inputs, namely frame size (3 to 8) by condition score (1 to 6) by initial body weight (350 to 450 kg, in increments of 10) by time on feed (60 to 140 days, in increments of 5). Parameters which were fixed for these DGM simulations included sex (steers), implantation status (implanted with a hormonal growth promotant), metabolisable energy intake of the feed (12.0 MJ/kg dry matter), and dry matter intake of the animals (2.8% of bodyweight per day). The inputs and outputs from these DGM runs thus consisted of a 6x6x11x17 matrix, which is subsequently referred to in the text as the DGM grid. For all the model and optimisation runs, outputs for the intermediate input parameter values were estimated (where needed) by linear interpolation within this grid. All simulations were run on a Sun Unix workstation, under Fortran 90.

1.2. Input Data

A typical feedlot intake was compiled from a cohort of animals from the Beef CRC ‘Regional Combinations’ trial (McKiernan et al. 2005). These animals are typical of steers entering into feedlot situations. Seven breed types were represented, namely Limousin, Charolais, Red and Black Wagyu, and three types of Angus – selected for high retail beef yield (RBY), high intramuscular fat (IMF), or high for both traits. There were 586 animals in the initial data set, but we excluded those with incomplete data, frame sizes less than 3 (the lowest value in our grid), and intake weights greater than 420 kg (these were considered too heavy for our minimum of 60 days on feed). This left an intake for the simulated feedlot scenario of 306 animals, with a mean liveweight of 385 kg and P8 fat depth of 4.2 mm. There were 27 to 63 animals per breed. Basic economics were incorporated by assuming a base-price of $1.80 per kg liveweight for animals at feedlot entry, labour, medicine and freight costs of $32 per head, feed costs of $250 per tonne, 8% p.a. interest on purchase and feed costs, a transaction levy of $3.50 per head, and by adopting a commercial (confidential) carcass price-grid based primarily on P8 fat depth and carcass weight. Overheads and fixed costs have not been included, so gross margin only is estimated, on a per-animal basis for consistency.

In general animals in feedlots remain in their initially allocated pens, because it takes several days to establish their social structure, and any disruption is detrimental to production. Different pens can be managed separately, most importantly they can be drafted off and sent to slaughter on different days. One management option is to allocate the animals to different pens according to breed. This assumes the different breeds will tend to show different growth paths, and thus be ‘market-ready’ at different times. A commonly-used alternative is to allocate animals to different pens according to their initial liveweights, with the obvious expectation that the heavier groups will be marketable sooner.

1.3. Management Strategy Scenarios

In the 'base scenario', the 306 steers were managed in the simulated feedlot as one mob. Predicted carcass characteristics and gross margins were estimated for the full range (60 to 140) of days on feed, and the highest value of the gross margin noted.

For the second scenario, animals were segregated according to breed, requiring seven different pens (some feedlots have more pens, and others less). The optimal slaughter date was estimated separately for each pen, again via complete enumeration of all days on feed.

The third scenario segregated the animals by initial liveweight. For consistency, seven pens were again used, with equal numbers of animals per pen.

In the fourth scenario, the animals were grouped according to their likely end-market specifications over time. To achieve this we utilised an optimisation routine, to search for the best allocation of animals to pens. Again, seven pens were allowed, but no restrictions were placed on the numbers in each. This is not an unrealistic scenario, as feedlots do tend to have combinations of smaller and larger pens. The optimisation method is outlined in the following section.

2. OPTIMISATION

2.1. Evolutionary algorithms

Evolutionary algorithms (Michalewicz and Fogel 2000) are a class of optimisation methods which are inspired by nature, and include genetic algorithms, evolution strategies and evolutionary programming. In each, 'parents' are formed, corresponding to a genetic representation of different combinations of the management options for the system under study. Each 'parent' is then assigned a 'fitness value', which is usually taken as the resultant profitability of the system under that particular management combination. The better ('fitter') parents are selected for breeding, and usually their 'offspring' (being combined versions of their management options) will be superior to either. Random mutation is introduced to avoid 'genetic stagnation'. Then the 'offspring' replace the 'parents', and this process is repeated for the next generation.

By simulating the processes of evolution and natural selection, evolutionary algorithms have consistently proven to be most efficient and robust. This has been shown for both general (Fogel 1995, Bäck et al. 1997) and agricultural systems - Appendix 1 of Mayer (2002) lists 35 agricultural examples which had appeared in the literature to that date, and many more have subsequently been published. Whilst many different variants of evolutionary algorithms are available, studies have demonstrated that the exact form is not critical – for many problems, any version of an evolutionary algorithm will tend to outperform the alternative optimisation techniques. Similarly, the choice of operational parameters for the evolutionary algorithm does not appear to be critical, as most combinations do seem to work well in practice.

2.2. Differential Evolution

Differential evolution (DE), as introduced in Storn and Price (1997) and expanded in Price et al. (2005), is a notably simple, efficient and robust variant of evolutionary algorithms. DE has successfully been used in the optimisation of a number of agricultural systems (López Cruz et al. 2003, Mayer et al. 2005, Groot et al. 2007). In contrast with many of the more complex versions, DE can be programmed in about 20 lines of pseudo-C code, as listed in Storn and Price (1997). Similarly, DE has only three operational parameters, whereas some other evolutionary algorithms require a more comprehensive range of parameters to define operations such as parent selection strategy, recombination, mutation, and replacement method.

The first of DE's operational parameters is the population size, namely how many genetic 'parents' are used. Price and Storn (1997) recommended a population size of 5 to 20 times the dimensionality of the problem. However, this may be excessive, as research with alternate real-value evolutionary algorithms has shown best results with factors between 1.5 and 2 (Mayer 2002). Values in this lower range could be more efficient, by not carrying an excessive number of population members.

The second of the key operational parameters is the crossover rate (CR), which defines the genetic operation of recombination. Storn and Price (1997) suggest a CR value of 0.1 for a thorough (but slow) optimisation, to 1.0 for speedier (but riskier) convergence. Previous evolutionary algorithm studies have shown that most forms of recombination work well, across quite a wide range of rates, so the recommended value of 0.5 (Storn and Price 1997) would appear an adequate choice.

The mutation rate is the third key operational parameter. Studies have shown that low (around 0.01) to high (towards 1.0) mutation rates can all be effective (Mayer, 2002). DE has no user-specification for the mutation rate; instead it is taken as (1 – CR). Hence using CR of 0.5 also gives a mutation rate of 0.5, which again appears a reasonable choice. Mayer et al. (2001) show that the exact form of mutation used is less critical than ensuring that some version is actually present, to drive exploration. DE's innovative version of mutation (Storn and Price 1997) ensures self-adaptation of the mutation amounts as the optimisation progresses. This arithmetical form allows both intermediate and extrapolative mutation, depending on the defined scaling factor (F). Storn and Price (1997) recommended a value of F of between 0.4 and 1, with 0.5 as a good initial choice. Investigations with DE (B.P. Kinghorn, unpublished) have found that 'pulsing' F to a larger amount every few generations has the effect of assisting the optimisation process, as it introduces extrapolative mutation.

Under the terminology of Price et al. (2005), we have adopted the standard and robust DE/rand/1/bin. Different versions of this basic configuration have been tested, and in practice, most have worked well. As with most evolutionary algorithms, DE incorporates the key processes of recombination and mutation. Theoretical and empirical investigations (Michalewicz and Fogel 2000) have shown that these processes have a synergistic effect.

2.3. Feedlot Model Optimisation

As described, our feedlot scenario forms quite a difficult problem. There are 313 options to optimise, being the days on feed for each of the seven pens, plus the actual pen allocation for each of the 306 animals. This results in an optimisation across 313 dimensions, with a potential search-space of the order of 10^{270}. Previously, the most difficult optimisation we have tried was a 70-dimensional herd dynamics model with a search-space of 10^{120} (Mayer et al. 2005). That particular optimisation took 9 months (using the same workstation) to converge to the global optimum, which was found after 37 million runs of that much more complex model.

In the current feedlot study, the key operational parameters adopted for DE were a population size of 100 (500 was initially used, but this proved to be inefficient), CR of 0.5, and F of 0.5 intermittently spiking up to 5.0. Initial runs allowed up to 10^8 generations, but this proved excessive so the limit was subsequently set to 10^6.

3. RESULTS AND DISCUSSION

Simulated growout for the single herd produced results as expected. Average carcass weights and P8 fat depths increased almost linearly with time, from 291 kg and 15.2 mm at 60 days, to 334 kg and 23.1 mm at 140 days. At 60 days on feed only a proportion of these animals were in the highest pricing window. This increased with time, and at 84 days on feed the herd reached its optimal overall gross margin, of $237.19 per animal. This value forms the 'minimal management' benchmark for this feedlot scenario. After 84 days, proportionately more animals entered into the over-fat categories, but the major factor affecting profitability was that the extra feed and other costs overwhelmed further gains in the marketable carcass weights. Hence, the overall gross margin for the herd steadily declined after this.

Segregation by breeds into separate pens improved the overall average gross margin slightly, to $238.30 per animal, an increase of 0.5%. This was achieved by accommodating the somewhat different growth patterns between breeds, as shown in Figure 1.

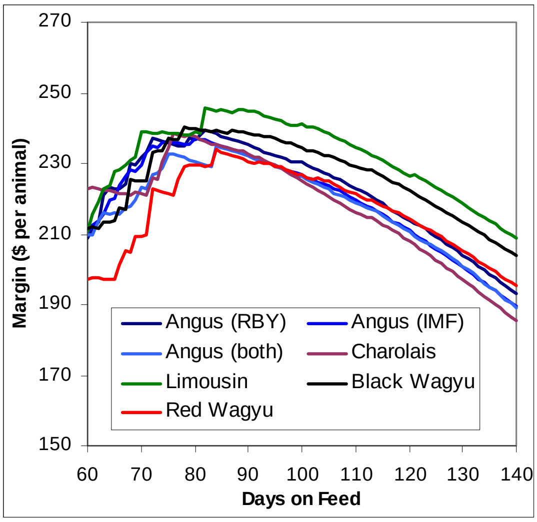

Figure 1. Gross margins against days on feed, for seven pens allocated by breeds.

As expected, Limousin had the lowest average P8 fat (13.0 mm at 60 days to 20.3 mm at day 140), and high-IMF Angus the highest (16.5 to 24.8 mm respectively). Red and Black Wagyu had the lowest carcass weights throughout. Amongst the other breeds, at 60 days Charolais were heaviest followed by Angus and then Limousin, but at 140 days this order had reversed to Limousin, Angus and then Charolais. These breed interactions between growth and fat deposition result in the observed different patterns in gross margins across time for these breeds (Figure 1). Optimal time on feed ranged between 76 and 84 days, depending on the breed. Limousin was clearly the most profitable breed for this scenario (at $245.84 per animal), and Red Wagyu the least ($233.89 per animal).

Segregation by initial liveweight proved to be a better option, with an overall gross margin of $242.48 per animal, which is a 2.2% improvement over the base scenario. Again, these simulated results provided no real surprises. The initial separation in liveweights was maintained across the growth paths, as were the P8 fat patterns – the lighter animals had lower P8 throughout. As Figure 2 shows, the pen with the heaviest animals was ‘market-ready’ at 60 days (and maybe even earlier, but this was outside our set scenario). The other groups then reached their respective highest price windows approximately in sequence, with the exception of the 3rd-lightest group which showed a curious double-hump. The second of these was that group’s actual optimum, and these animals took 94 days on feed to reach this. These results indicate that factors other than just initial liveweight are important in determining overall profitability.

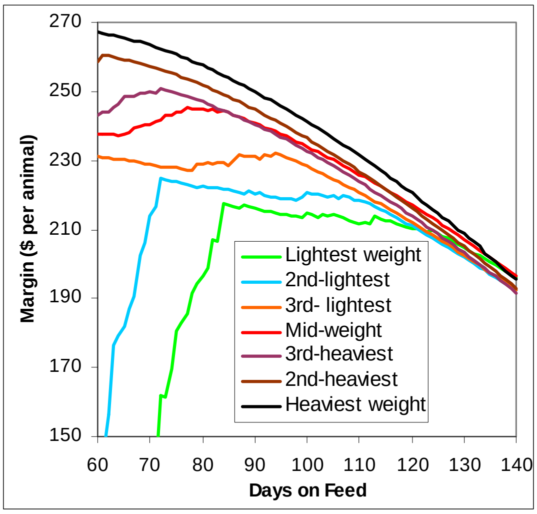

Figure 2. Gross margins against days on feed, for seven pens allocated by initial liveweights (lightest to heaviest).

As expected, the DE optimisation algorithm performed consistently and reliably. Four randomly-generated replicate optimisation runs all converged to about the same gross margin, of $244.27 per animal, which is a 3.0% increase over the base scenario. This is now assumed to be the global optimum for this particular scenario, but will obviously change with different animals, prices, feed types, etc. All the replicate optimisations converged prior to 400,000 generations (which equates to 40 million individual model runs), and these took less than two hours of computational time. Whilst the gross margins of the replicates were all about the same, the allocation patterns of the animals were not. This is probably due to the reasonably wide optimal pricing window, along with the similar performance of some of the pens, allowing some groups of animals to drift between similar pens without affecting the economic outcome.

Figure 3 shows the animal allocation pattern for the best replicate. The other replicates were reasonably similar to this. One pen (number 3) had the highest number of animals, made up primarily of the heavier (Figures 4 and 5) and fatter (Figure 6) animals. This single pen contained more than half of the Angus animals, with the rest distributed across the other six pens. Pen 2 contained animals which were a little lighter and had less fat than those in pen 3. These two ‘heaviest’ pens had the largest gross margins ($251.80 and $250.80 per animal respectively), with these occurring notably earlier than for the other pens (Figure 7).

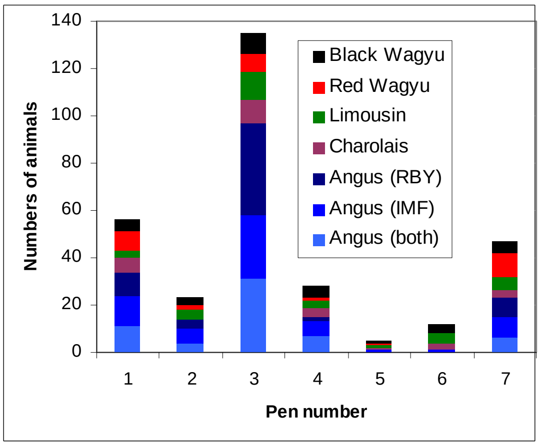

Figure 3. Distribution of the numbers of animals by breeds, for the seven pens allocated according to DE’s optimal solution.

With proportionately more Limousin, pen 6 contained the ‘later-maturing’ animals, and took the longest (89 days) to reach its optimum. Despite this, its optimal value of $244.90 per animal was third only to the two early-maturing pens. Pens 1, 4 and 7 performed quite similarly economically, with gross margins ranging between $234.00 and $237.40 per animal. These three pens had similar weights throughout (Figure 5) but showed some discrimination regarding fat depth (Figure 6). The fatter animals assigned to pen 1 took 72 days to reach optimal market condition, whereas pen 7 took 84 days. Pen 5 contained the ‘poor performers’, having the lowest weights and fat depths throughout, and this resulted in an average gross margin of only $231.70 per animal.

The patterns displayed in these figures are no doubt due to interactions between the initial weights, frame sizes and condition scores, the weight and fat gains over time, feed and other costs, and the proportions of animals achieving the various pricing windows. These interacting effects can be difficult to interpret, but investigative 'what-if' simulations should give some understanding of the various mechanisms involved. We intend conducting these in consultation with key industry personnel, to investigate and address these issues. These exercises should also provide valuable learning exercises into the potential uses of simulation models for these industry experts.

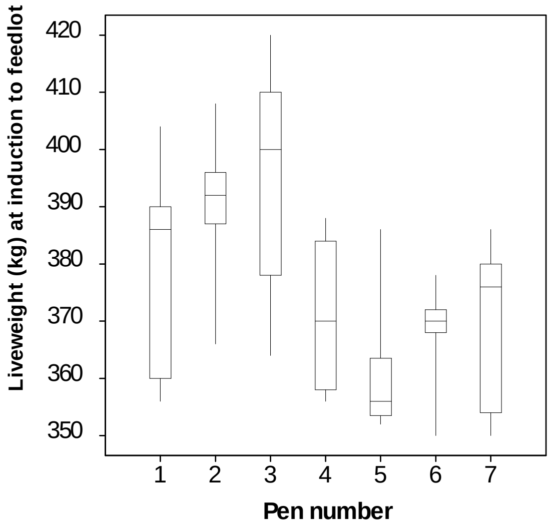

Figure 4. Boxplot distributions (mean, inter-quartile distance and range) of initial liveweights (kg), for the seven pens allocated according to DE's optimal solution.

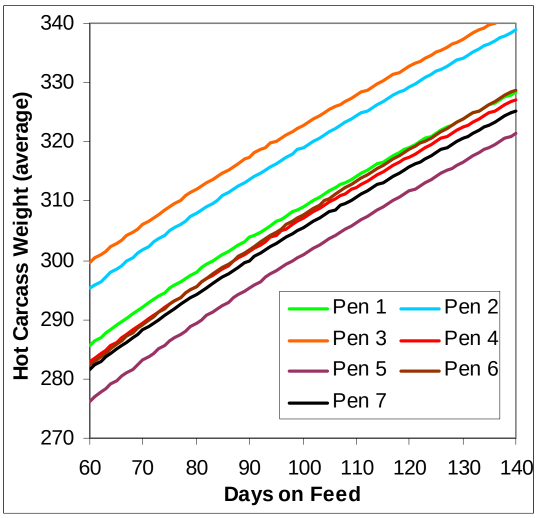

Figure 5. Carcass weights (kg) against days on feed, for the seven pens allocated according to DE's optimal solution.

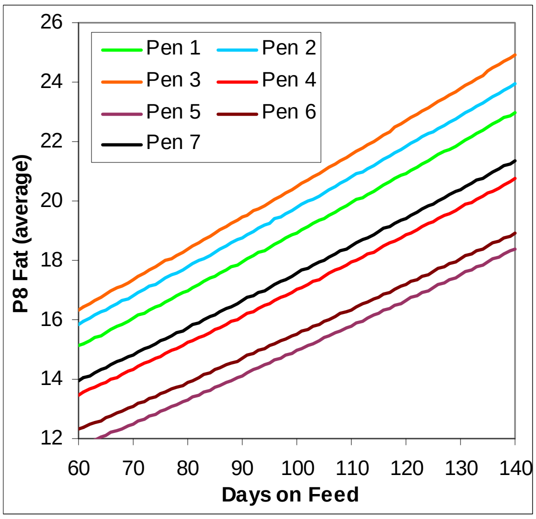

Figure 6. Average P8 fat depth (mm) against days on feed, for the seven pens allocated according to DE's optimal solution.

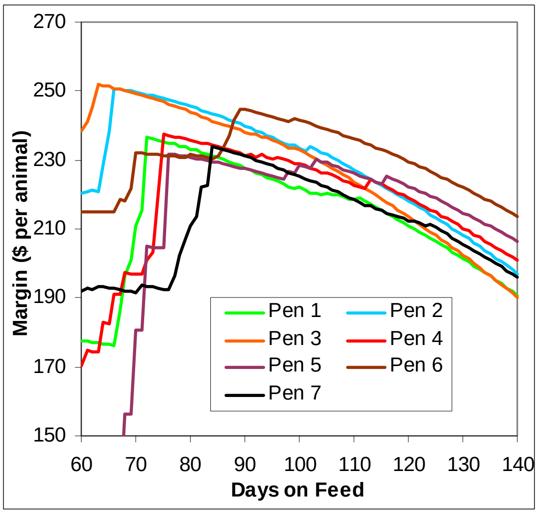

Figure 7. Gross margins against days on feed, for the seven pens allocated according to DE's optimal solution.

Overall, the results of these alternate management strategies, particularly the DE optimisation, were successful. Against the base-line 'minimal management' scenario, segregation by breeds lifted the gross margin by 0.5%, whereas segregation according to initial liveweight resulted in a 2.2% increase. Allocation of animals via DE's optimal strategy raised the gross margin by 3.0%, which is worth about $2,200 for this intake of animals.

4. FUTURE RESEARCH

In subsequent simulations, more real-world management options will be incorporated, after consultations with feedlot managers. For example, 'managerial intervention' can be applied at one or more times, to draft-off some of each pen and let the rest grow out to better specifications, along the lines of Walmsley (2007). Despite increased labour costs here, this could prove to be more optimal. However, with a higher number of input options to investigate, these optimisations will become more lengthy and difficult.

5. CONCLUSION

This study showed that feedlot scenario modelling can profitably be used to investigate the likely outcomes of alternate management strategies. Here, economic optimisation can be a useful and logical extension. Again, differential evolution has proven to be a robust optimisation technique, consistently and efficiently finding the global optimum of this system.

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