Optimizing feedlot placement weights using simulation-based mathematical programming

by

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Abstract

This thesis develops a mathematical programming model to determine the optimal feeder placement weight that maximizes net returns in commercial feedlot operations. Feedlot profitability is affected by numerous biological and economic variables that include feed efficiency, yardage costs, health risks, mortality, feeder cattle purchase prices, and carcass-based revenue. Linear programming has been implemented within the industry before, but linear programming is rarely used to directly model how placement weight influences profitability over a defined feeding period. This study addresses that gap by integrating a flexible mathematical framework with real-world data and biologically informed performance data.

The model simulates feeding outcomes across a range of initial weights while incorporating price slides, dressing percentage, feed-to-gain efficiency, mortality rates, and culling probabilities. Feeder cattle prices and grid-based carcass discounts are included to reflect the real-world market profits that feedlots could experience. The results of this analysis provide feedlot operators with a decision-support tool that can capture the trade-offs between animal growth and economic constraints. The results demonstrate how market-based carcass valuation can incentivize particular feeding durations. By offering a replicable and data driven optimization tool, this thesis contributes practical insights to feedlot decision-making and expands the agricultural economic literature on production modeling.

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Dedication

To my fiancée and family, whose unwavering support and sacrifices have shaped my academic journey. Your dedication and encouragement have made this possible.

Preface

This thesis is the culmination of my academic journey in agricultural economics, shaped by both my classroom experiences and my own experience within the cattle industry. The objective of optimal feedlot placement weight emerged through my own observations of industry challenges, especially when considering balancing profitability with biological constraints. Every hurdle that I experienced throughout the research process offered an opportunity to learn and better the result of the project. I hope that this study contributes not only to academic literature, but also to real-world applications for feedlot operators seeking to make data-informed decisions.

Chapter 1 - Introduction

The U.S. beef industry is vital to the national agriculture economy, generating approximately $143.9 billion in retail value in 2022 alone (USDA-ERS, 2023). Within the industry, feedlot operations play a key role by converting feeder cattle into fed cattle to supply the consumer market. As of January 1, 2025, there were approximately 26,105 feedlots operating in the United States. Of these, 2,105 maintain capacities of 1,000 head or more, accounting for 82.7% of the total on-feed inventory and 87.2% of all feedlot marketing during 2024 (American Angus Association, 2025). Despite the large number of feedlots in the United States, the feedlot industry is highly concentrated among a small subset of large-scale operations. Feedlots with capacities exceeding 50,000 head make up 3.8% of the large-scale category, and they handle 34.8% of the entire national inventory and 35.1% of total fed cattle marketing. Over 50% of all U.S. feedlot inventory and marketings are controlled by feedlots with capacities above 32,000 head, even though these operations account for 6.9% of the large-scale category (American Angus Association, 2025). These values highlight the scale-driven nature of modern feedlot production. Understanding this structural distribution is essential when designing a decision-making tool and economic model that align with the realities of the industry.

Feedlot managers face many challenges in optimizing cattle growth and maximizing net returns. This is particularly true when the market experiences fluctuating feed costs, environmental constraints, and volatility within both the fed and feeder cattle markets. One of the most important decisions is determining the optimal final weight at which cattle should be marketed. This decision directly affects growth performance, feed efficiency, and ultimately profitability.

The viability of any feedlot operation depends on the balance between feed conversion efficiency, growth performance, and market conditions. The decision to feed cattle up to or before a certain weight can either increase revenue through greater carcass yield or reduce profitability due to diminishing marginal feed efficiency and rising input costs. External factors such as changing consumer preferences, climate variability, and feed ingredient availability force managers to pursue efficient solutions to their problems.

Traditionally, feedlot operators rely on historical data, market conditions, and experience-based judgment to determine the optimal final weight for finishing cattle. However, developments in data analytics, mathematical programming, and economic modeling provide opportunities for a more structured approach to these decisions. By developing a mathematical programming function that optimizes net feeding returns based on final weight as the decision variable, this study seeks to contribute a practical and data-driven approach to improve feedlot profitability.

Objective

The primary objective of this study is to develop an economic model that determines the optimal placement weight for cattle on a finishing ration in feedlot operations within the state of Kansas. This model will incorporate key variables such as feed conversion ratios, average daily gain, feed costs, and market prices. By integrating economic principles with mathematical programming techniques, this study aims to identify the weight ranges that maximize net returns per head under varying production and market conditions. The specific goals of this study are to: construct a mathematical programming model that optimizes net feeding returns and evaluate how different placement weights impact profitability and feedlot performance.

This study holds implications for both academic research and industry applications. It contributes to the field of agricultural economics by applying optimization techniques to a real-world problem in livestock production. For industry participants, the findings of this study can lead to more efficient resource allocation, improved economic outcomes, and enhanced sustainability in feedlot operations. Academically, this thesis contributes to the overall research by developing a simulation optimization model that identifies the most profitable feedlot placement weights. A simulation that can be updated and refined by future academics. With rising feed costs and increasing environmental pressures, optimizing feedlot operations is crucial to the industry.

To achieve the objective, this study will employ a combination of quantitative modeling and economic analysis. The core methodology will involve creating a mathematical programming function that considers the placement weight as the decision variable. The function will integrate empirical data on feed conversion ratios (FCR) across different final weights, average daily gain (ADG) at various exit weights, feed cost fluctuations, and market price variations for finished cattle. While developing an optimization model presents significant benefits, several challenges need to be addressed as well. Data availability and variability present obstacles, as feed conversion efficiency and market conditions fluctuate over time and by region. This necessitates a flexible model capable of accommodating the diverse scenarios that feedlot managers face across that United States. Furthermore, while mathematical models provide theoretical optimization, their adoption by feedlot managers depends on ease of use, interpretability, and alignment with existing decision-making processes. To mitigate these challenges, this study incorporates real-world data and industry insight to refine the model's practical use.

Thesis Outline

The organization of this thesis will be as follows: Chapter 2 will provide a review of the relevant literature pertaining to linear programming and feedlot profitability while Chapter 3 will describe the optimization methodology and provide the empirical model. Chapter 4 will report the data and sources; Chapter 5 will describe the results. Finally, Chapter 6 will discuss the conclusions and summarize the limitations and discuss future recommendations for research.

Chapter 2 - Literature Review

This chapter will begin with discussing linear programming and its roots in small-scale agricultural applications. Over time, it has evolved into a key resource for agricultural operations across the globe. Next, an overview of the economic drivers of feedlot profitability by examining core factors such as feed purchases, yardage expenses, health considerations, and marketing decisions. The chapter will conclude with a brief discussion on how the research and findings from this study will contribute to the future beyond the works published before.

Linear Programming

Linear programming, a specialized branch of mathematical programming, focuses on optimizing outcomes under linear constraints and objectives. Initially, agricultural economists used linear programming to devise feed-mix or ration-balancing models on a relatively small scale. This approach and use were straightforward, but very influential in the industry for the years to come. However, researchers recognized that the methodology of linear programming could be expanded to study more holistic planning. These new models were able to evaluate how the ratio of different crops and livestock production interacted with a farm's limited operation portfolio.

A defining feature of linear programming is its ability to encode the real-world limitations of an operation in the form of constraints. Constraints may include acreage limitations for crops being planted, minimum production requirements for certain feed ingredients, labor availability during specific seasons, or capital constraints on borrowing limits. By accounting for these constraints directly within the model, linear programming offers a structured means for farmers to decide on operation's combination to maximize net returns for example. The success of linear programming in these early iterations of application set up the method for more specialized uses across the agricultural sector.

As industry and computing power grew, the method needed to be expanded as well. Many processes in agriculture are non-linear such as biological processes. Processes like marginal feed efficiency prompted researchers to adapt and approximate these processes with piecewise linear segments. Price and yield uncertainties lead to the development of stochastic linear programming and robust optimization methods. In an industry like agricultural production, the variables of operation unfold over time. The weight of an animal, costs and availability of feed, and market prices continuously evolve and change. Single-period linear programming models are thus limited in their ability to guide decisions that would stretch over days, weeks, or months. Seeing this limitation, the integration of temporal dimensions led to dynamic linear programming.

In recent years, the use of a dynamic linear programming model can be seen in the cull cattle sector of research within the industry. Erol et al. (2024) noted that cow-calf operations make culling decisions regularly after weaning or at pregnancy-check time. A producer that culls an animal must decide to replace or leave that animal unreplaced; while a cow retained must be fed, bred, and managed until the next culling routine. Because the choices made within a given time reshape the structure of the herd, culling cattle is a fundamental dynamic problem. A static model would ignore how the culling rate affects the outcome of subsequent costs and revenues. A key feature in Erol et al.'s model is that each cow transitions through age classes and reproductive states. These states are then governed by probabilities of conception, survival, and culling. A dynamic linear programming model enforces linkage constraints so that the number of cows in each age or fertility category at the start of a period must match the number of retained cattle from the previous period. Overall, this study illustrates how and why dynamic linear programming captures essential features of livestock decision-making that simpler, static methods are unable to capture.

Despite the growing sophistication of emerging machine-learning and simulation approaches (Feuz et al., 2021), linear programming remains a foundational and practical tool in agricultural decision-making. The transparent structure, ability to handle constraints, and proven track record make linear programming an enduring option for optimizing resource allocation and profitability in agriculture.

Feedlot Profitability

Feedlot operations aim to convert feeder cattle into market-ready animals as efficiently as possible. However, profitability is hinged on numerous independent variables. Key cost considerations include feeder cattle purchase price, feed and yardage costs, interest and capital costs, mortality and morbidity risk, and marketing endpoints (Erol et al., 2024; Feuz et al., 2021). Recent works emphasize that integrating both biological performance metrics (e.g., average daily gain, mortality risk) and economic drivers (e.g., feed prices, interest rates) is critical for modeling the final profit outcomes of finishing cattle.

Major cost drivers within an operation include feeder purchases, feed and yardage, as well as interest. Acquiring feeder cattle constitutes a large capital outlay. Rising feeder cattle prices increase break-even costs, especially if these cattle have higher health risks and potentially higher mortality (Dennis et al., 2018). Feeder cattle purchases are typically the largest single cost in finishing cattle, with small changes in efficiency (pounds of feed per pound of gain) markedly altering margins. Yardage costs, covering feedlot overhead and labor, also accumulate daily

(Erol et al., 2024). Many feedlots rely on borrowed capital for cattle and feed purchases. Consequently, the longer cattle are fed, or bigger the feeder purchase expense, the higher the interest burden.

Langemeier, Schroeder, and Mintert (1992) reinforce these observations with empirical data, demonstrating the fed cattle and feeder cattle prices together accounted for more than 70% of the variation in feedlot profits across weight categories. In several placement groups, fed cattle price alone explained over 50% of profit variation, confirming that market conditions drive profitability more than internal performance metrics.

Health and mortality costs also directly influence that potential profitability outcome for a feedlot operation. Morbidity directly diminishes weight gain, worsens feed conversion, and raises health related expenditures on the herd. Mortality yields no revenue and renders prior feed and yardage investments unrecoverable (Feuz et al., 2021). Chronic poor performance or "railers" may need to be culled at a discount, further cutting profits to the operation. Dennis et al. (2018) detailed how administering antimicrobials to newly arrived, high-risk cattle (often seen at lighter weights) can significantly lower mortality from respiratory diseases. The use of "arrival metaphylaxis" is widely used across U.S. feedlots to mitigate potential health breaks. The economic simulations show that removing this tool can result in significant financial losses. As emphasized by Feuz et al. (2021), animals that become repeatedly ill incur higher treatment costs, lower average daily gain, and reduced carcass quality. The negative ripple effect on feedlot returns can be significant enough that many operations rely on proactive strategies such as early detection analytics (Feuz et al., 2021) or metaphylaxis (Dennis et al., 2018) to reduce the incidence and severity of illness. Despite the importance of biological performance indicators, Langemeier et al. (1992) found that average daily gain and feed conversion combined explained less than 15% of profit variation. This supports the thesis's emphasis on cash-market variables and simplifies the simulation focus on key economic drivers as opposed to biological variation.

Contribution to Literature

This study advances the uses of linear programming techniques within feedlot operations. While earlier works have explored the use of linear programming in agriculture-ranging from health management and ration development to feedlot profitability-research directly linking feedlot profitability to cattle placement weights remain limited. By combining a dynamic linear programming approach with real-world data such as yardage, mortality risk, and feeder cattle purchase cost, this research provides a more practical framework for guiding decision-making that feedlot operators must do every day. The result is a more systematic framework that offers insights, helping producers weigh profitability against the biological and economic risks that change across the feeding period.

Beyond its methodological contributions, this thesis expands the empirical understanding of feedlot performance by evaluating how initial placement weight affects net returns over a feeding period. By encoding placement weights as a decision variable, the simulation quantifies how placement weight interacts with later outcomes. This allows feedlot operators and researchers to better isolate the trade-offs associated with lighter or heavier placed cattle under real world market conditions.

This study contributes fresh insights on the extent to which animal weights, culled animals, and market-based strategies can influence net feeding returns. While previous research has addressed feedlot profitability and ration efficiency, few studies have directly evaluated how initial placement weight, mortality-adjusted returns, and grid pricing interact over time.

Additionally, the treatment of culled animals is often excluded or simplified in many models. The findings not only offer producers a robust tool for planning and adjustment but also close the gaps between the existing literature and current issues that producers are focused on. By bridging these gaps, this study aims to start down the path for more targeted research and practical adoption of dynamic linear programming within the beef industry’s evolving economic environment.

Chapter 3 - Methodology

This chapter outlines the methodological framework used to identify the optimal feeder cattle entrance weight within a commercial feedlot. The analysis begins with the conceptual framework based on foundational economic principles, where net returns are modeled as a function of revenue and expenses ensnared by biological performance and market conditions. The theoretical foundation establishes the economic relationship that is necessary to frame the overall optimization problem in a pragmatic manner.

Building further on the conceptual model, the empirical framework translates the theoretical relationships into a system of equations that reflect the operational truths of feedlot management. Drawing from structure developed by Dennis et al. (2018), the empirical section of this methodology incorporates real-world variables such as feed efficiency, dressing percentage, mortality risk, and carcass-based pricing to simulate the dynamic of cattle performance and profitability over the duration of a feeding period. Key assumptions related to feeder cattle price slides, daily gain patterns, yardage, and health costs are embedded in this structure to ensure applicability for modern feedlot systems.

The chapter concludes with a description of the coding strategies used to implement the model in Python. Core computational tools and optimization routines from the SciPy and NumPy libraries are employed to functionalize the model. These tools enable the application of nonlinear optimization techniques under real-world biological and economic constraints. The codebase also supports dynamic calculations of weight gain, feed consumption, and cost accumulation, thereby facilitating the simulation and optimization of the production scenarios.

Conceptual Framework

The objective of this thesis is to identify the entry weight that maximizes net feeding returns for steers in a feedlot setting. At the core of this analysis is the economic principle that profit (π) is the difference between total revenue and total expenses. Conceptually, this relationship can be represented as:

$$\pi = f\big(Revenue(Market, Cull), Expenses(Feeder, Yardage, Feed, Health, Interest)\big)$$

Revenue is primarily determined by the final selling weight of the steer and the market price at the time of the sale when adjusted on a grid-based selling system. Because the final weight is fixed in this model, revenue is a function of the market price received per pound, adjusted for shrinkage and potential mortality. In addition, this model allows for the inclusion of cull cattle revenue in the case of non-fatal health issues or early removals from the pen. Although this component is expected to contribute marginally under the assumption of the standard feedlot operations.

Expenses include variable costs, including some that are held constant throughout the feeding period, associated with an operation's feeding period. Feeder cattle purchase price is the most significant cost the operations face and vary with weight due to price slides in the market. Feed costs are determined by average daily gain, feed conversion ratios, and the number of feeding days required to reach a desired final weight at which to market fed cattle. Yardage and health costs are treated as constant costs (i.e., a per head charge) during operation. Interest costs are based on the value of the feeder animal and accumulated over the feeding period to reflect the time value of capital.

The framework recognizes that cattle entering at lighter weights generally gain weight more rapidly, but require more feeding days, resulting in higher yardage, feed, and interest costs. Heavier placement weight calves finish faster but come with higher purchase prices and slower gains. These biological dynamics are modeled in conjunction with cost components to determine the optimal combination of entry weight and days on feed that maximizes net profit.

Empirical Framework

Building on the simulation framework developed by Dennis et al. (2018), this study constructs an optimization model designed to identify the optimal weight and days on feed to maximize the net feeding returns for a steer entering a commercial feedlot operation. While Dennis et al. (2018) focused on evaluating the value of metaphylaxis programs for high-risk cattle, the empirical structure of their research serves as a strong foundation for feedlot profitability modeling. This thesis adapts many of the equations, but repurposes them toward a different objective: determining the most economically efficient points, weights, and days on feed, to start cattle in a finishing program.

The model developed in this study treats entry weight and days on feed as the decision variables. The change of the traditional feeding model shifts the focus towards the front-end of cattle production decisions to reflect both economic and biological trade-offs in real-world feeding operations. To support this objective, the model includes core components such as feeder purchase costs with a weight-based price slide, feed costs that evolve through a daily time step model, yardage, interest, and health costs, and mortality risk. Revenue is calculated on a carcass basis, adjusting for shrink, dressing percentage, price discounts/premiums when applicable, and accounting for revenue from culled animals.

Objective and Core Equations

(1) max $NFR(W_i, DOF) = Rev(W_i, W_{final}) - FDRC(W_i) - Yard(DOF) - FC - HC - IC(W_i, DOF)$

Subject To:

(2) $W_{final} = W_i + [ADG(W_i) \cdot DOF] \leq 1800$

(3) $600\, lbs \leq W_i \leq 900\, lbs$

(4) $140\, days \leq DOF \leq 220\, days$

(5) $FDRC(W_i) = FRPP(W_i) \cdot W_i$

(6) $FRPP(W_i) = (\beta_0 + \beta_1 W_i + \beta_2 W_i^2 + \beta_3 W_i^3 + \beta_4 P_{CORN} + \beta_5 (W_i \cdot P_{CORN}) + \beta_6 P_{FED})/100$

(7) $W_{Shrunk} = W_{final} \cdot (1 - Shrink)$

(8) $Carc_{wt} = W_{Shrunk} \cdot Dress$

(9) $P_{Lbs} = (BaseCWT - DiscCWT)/100$

(10) $MarketRev = Carc_{wt} \cdot P_{Lbs} \cdot [1 - MORT(W_i) - CULL]$

(11) $CullRev = CULL \cdot W_{CULL} \cdot P_{CULL}$

(12) $Rev = MarketRev + CullRev$

(13) $Yard(DOF) = 0.39985 \cdot DOF$

(14) $IC(W_i,\, DOF) = [0.5 \cdot (Yard(DOF) + FC(W_i,\, W_{1800}) + HC) + FDRC(W_i)] \cdot DOF \cdot \frac{IR}{365}$

(15) $W_{t+1} = W_t + ADG(W_t)$

(16) $ADG(W_t) = \max(1.87392923,\, 5.42337165 - 0.001(W_t))$

(17) $AFC(W_i) = 5.82 + 0.007 \cdot (W_{final,1800} - W_t)$

(18) $Feed_t = ADG(W_t) \cdot AFC(W_t)$

(19) $W_{final} = W_i + \sum_{t=1}^{DOF} ADG(W_t)$

(20) $[TotalFeed = \sum_{t=1}^{DOF} ADG(Wt) \cdot AFC(Wt)]$

(21) $FC = TotalFeed \cdot FEED$

(22) $$MORT(W_i) = \begin{array}{l} \{0.0272,\ 400 \leq W_i < 600,\} \\ \{0.0197,\ 600 \leq W_i < 700,\} \\ \{0.0135,\ 700 \leq W_i < 800,\} \\ \{0.0094,\ 800 \leq W_i < 900,\} \\ \{0.0072,\ W_i \geq 900\} \end{array}$$

Table 1 provides the definitions of variables used in this study. The objective function (equation 1) measures net feeding returns by subtracting all relevant costs from total revenue. The second equation (2) links final weight to the decision maker's choice of placement weight (W_i) and days on feed (DOF), while also enforcing a maximum upper limit for the end weight of a steer to not exceed 1,800 pounds. Equations (3) and (4) further constrain W_i to remain between 600 pounds and 900 pounds as well as ensuring DOF does not fall outside of 140 days and 220 days, respectively.

Feeder Cattle Purchase and Price Slide

The feeder cattle purchase costs (equation 5) are found by multiplying the feeder price slide (FRPP(W_i)) by the calf's placement weight (W_i). Equation (6) defines a regression model that was run outside of the simulation using historical market data. The estimate coefficients from the regression are then embedded into the simulation framework. Baldwin et al. (2021) outlines how feeder prices typically adjust downward (or upward) with changes in arrival weight, while also acknowledging how feed and fed-cattle markets can influence these premiums and discounts. This is done by encapsulating both a cubic polynomial term for W_i and relevant commodity feeder-cattle valuations. Dividing by 100 converts the polynomials results from \$/cwt to \$/lb. Consequently, heavier or lighter cattle see systematic shifts in their per-pound purchase costs, closely reflecting the patterns that Baldwin et al. (2021) documented for stocker or feeder operations in typical market conditions.

Carcass Weight and Revenue

In feedlot production, the final live weight alone does not determine the ultimate value of the cattle at the time of slaughter. Instead, slaughter plants pay for saleable carcasses; thus, equation (7) applies shrink and a dressing percentage before computing for revenue. In practice, shrink reflects the weight loss due to transportation of per-slaughter handling. Even after shrink, only a portion of the live weight becomes saleable (muscle, fat, bone). Thus, equation (8) incorporates a *Dress* variable to account for the percentage of saleable weight after slaughter.

Once a dressed carcass weight is established ($Carc_{wr}$), most packers use a grid based selling system to determine final payment. The base grid price is typically stated in terms of $/cwt of the carcass, then premium and/or discounts apply depending on weight range, yield grade, or quality grade. In this study we only focus on weight-based discounts as seen in equation (9). The term *BaseCWT* is a $/cwt price representing the "ideal" carcass, and *DiscCWT* is a weight driven discount in $/cwt. The conversion to $/lb occurs by dividing *BaseCWT* – *DiscCWT* by 100.

Since not every head of cattle placed into a feedlot will survive or remain healthy enough to market, the model incorporates this using equation (10). The term [1 – $MORT(W_i)$ - CULL] is the proportion of the cohort that makes it to harvest as fed cattle. Higher mortality or a larger fraction of chronically ill cattle (culled early or railed) reduces the number of animals contributing to carcass value.

Some cattle do not finish due to chronic illness or other issues. A small percentage of the cohort, represented by CULL, is sold at a reduced weight (W_{CULL}) and discounted price (P_{CULL}). This model adjusts for this scenario through equation (11). Because these animals typically exhibit poor body condition or are otherwise not suitable for finishing, packers pay significantly less for them. Thus, partial revenue is received by feedlot operators to offset removing these steers from the final harvest.

The overall revenue from harvested cattle can be observed by equation (12), adding together the revenue from fed cattle sent to market and the partial revenue received from cull cattle. Through this, the model calculates total gross revenue for that cohort.

Yardage and Interest Costs

For many feedlot operation budgets, yardage is an overhead charge on a per head, per day basis. It covers a multitude of fixed and partially fixed expenses that do not directly scale with feed usage. Equation (13) represents the daily yardage charge ($) multiplied by total DOF for the cattle. This ensures that longer feeding periods experience higher yardage costs for the cohort.

Interest costs capture the opportunity cost of investing in cattle, feed, and other inputs over the entire feeding duration. The model spreads the annual interest rate across the fraction of the year that cattle are on feed. By multiplying the sum of the variables *Yard, FC, HC,* and *FDRC* by *DOF*(IR/365)*, the model annualizes the interest but only applies the interest costs to the total DOF duration. This approach acknowledges that not all costs are incurred immediately on the first day of feeding, but also that capital is incrementally committed over time.

Daily Weight Gain and Feed Usage

Weight gain in feedlot cattle does not increase at a consistent rate during the duration of the feeding period. Rather, growth slows as steers approach heavier weights. Equation (15) integrates a daily update rather than a single constant average daily gain value for the feeding period. This better reflects the dynamic relationship that daily gain has with cattle in a feedlot. In equation (15), W_t represents that cattle's weight on day t. Each additional day that a steer is present within the feedlot, the daily weight updates. This structure allows each day's growth to be directly influenced by the steer's live weight on that day, meaning the biological efficiency and rate of gain for the steer is adjusted daily. Lighter cattle will gain more quickly as opposed to heavier cattle. To model the diminishing returns of weight gain in cattle feeding, equation (16) implements a simple linear decline in daily gains. This equation ensures that the W_t increases daily, but does not allow for the average daily gain to fall below 2.0 lbs/day.

Feed consumption varies as animals grow in a feedlot. Heavier animals usually require more feed per pound of gain when compared to their lighter cohort members, demonstrating the lower marginal efficiency for weight gain that heavier cattle experience. Each day, the feed that is consumed for each pound of gain is calculated using equation (17). The term ($W_{final,1800} - W_t$) increases as W_t remain relatively low. This implies higher cumulative feed requirements. Within equation (17), 5.82 and 0.007 represent pounds of feed per pound of gain and an incremental factor, respectively, during the duration of the feeding period (Fox et al., 2001). The incremental factor refers to the additional pounds of feed required per pound of gain for each unit increase in the steer's weight. This approach illustrates the broad idea that feed efficiency deteriorates as cattle grow closer towards finishing weight. Multiplying a specific day by that same day's feed per pound of gain is shown by equation (18). Summing over all days in the feeding period produces the total feed usage.

Final Weight, Total Feed, and Feed Cost

From the daily gain model, final weight (W_{final}) results from summing each day's daily gain to the animal's weight from the prior day. By summing the daily incremental gain (equation

19), in contrast to a single average ADG*DOF expression, this study more accurately tracks how weight increases during the feeding period. Equation (19) accounts for changes in variations in gain caused by differing body condition, day-to-day feed intake, and diminishing returns when feeding heavier cattle.

In parallel, equation (20) sums all the daily feed usage to compute the total amount of feed consumed during the feeding period. Each day's feed intake is determined by multiplying that day's average daily gain by a feed per pound of gain factor $AFC(W_t)$. Because $AFC(W_t)$ often increases with weight, daily feed usage will also grow over time. Offsetting the fact that *ADG* might decline as the animal gets heavier. Summing over the full *DOF* provides a comprehensive measure of total feed consumption. Rather than a single average feed conversion for the entire feeding period, the model calculates an incremental consumption day-by-day.

After determining the total feed consumption, calculating feed cost, *FC* (equation 21), is relatively straightforward. The value of *FEED* reflects the average cost of the feed ration. If the ration changes, one could model a time-varying feed price or keep a single blended rate that approximates the diet during the feeding process. *TotalFeed* can become large for heavier cattle when a large *DOF* is experienced. Thus, small changes in the feed price can substantially affect the profitability of feedlot operations. This underscores that the daily approach can lead to a better understanding and estimate of final feed costs.

Mortality Rate

In cattle feeding operations, mortality directly reduces the number of cattle that can be marketed and sold, affecting every level of the supply chain. Unlike costs that scale with time, an animal's death results in the complete loss of all previous investments made towards that animal.

Many large-scale observational studies confirm that lighter animals entering a feedlot tend to experience higher levels of mortality, often due to younger age, weaker immune systems, or increased stress upon arrival (Vogel et al., 2016).

Mortality represents an essential component within a feedlot operation's profitability. To capture an accurate mortality risk at various incoming weights, a report by Vogel et al. (2016) is incorporated into this research (Elanco Animal Health, Greenfield, IN). In that study, the authors conducted a broad assessment of commercial feedlot records across multiple U.S. operations. Lighter weight cattle are significantly more prone to fatal illnesses, while heavier or yearling-weight cattle demonstrate lower mortality risks.

A piecewise mortality function is created and used in equation (22) that corresponds to the distinct weight brackets provided by Vogel et al. (2016). In applying the probabilities of mortality for each weight range, we assume that each mortality percentage captures a cumulative possibility of death by the end of a feeding period. This piecewise approach uses a single average for the entire feeding period as opposed to a daily re-evaluation of potential mortality chance. Despite only using a single average, it ensures that the model maintains ease of use and captures overall feedlot losses for evaluating net returns under varying entrance weights and days on feed.

Table 1. Description of Variables used in the Model

W_i	The entrance weight of the cattle upon arrival at the feedlot.
DOF	The total number of days the cattle are fed before marketing.
W_{final}	The live weight of the cattle at the end of the feeding period.
$ADG(W_i)$	A function describing how many pounds per day cattle gain, depending on their weight.
$NFR(W_i, DOF)$	Objective function representing total revenue minus costs, to be maximized.
Rev	Composed of market revenue from carcass weight plus any cull revenue.
FC	Total feed consumed (lbs) multiplied by the feed price ($/lb).
HC	A fixed charge on a per-head basis covering veterinary, pharmaceuticals, etc.
$FDRC(W_i)$	Price of feeder cattle based on initial weight, using the feeder price slide.
$FRPP(W_i)$	A regression-based formula (cubic polynomial) that incorporates initial weight, corn price, and fed-cattle price.
P_{CORN}	Market price of corn, used in the feeder price slide and feed cost considerations.
P_{FED}	Market reference price for fed cattle.
Yard(DOF)	A per-head, per-day overhead charge multiplied by the days on feed.
$IC(W_i, DOF)$	Financing charge on feeder purchase cost plus half of feed, yardage, and health costs over the feeding period.
$MORT(W_i)$	Piecewise function giving the proportion of cattle expected to die based on initial weight.
CULL	A proportion of chronically ill cattle removed from the cohort prior to finishing.
W_{Shrunk}	Final live weight minus the shrink value, accounting for transportation or handling losses.
$Carc_{wt}$	Shrunk weight multiplied by the dressing percentage.
Dress	The proportion of the shrunk live weight that becomes saleable carcass.
BaseCWT	The starting point on a carcass grid before applying discounts/premiums.
DiscCWT	The amount subtracted from BaseCWT based on the carcass weight ranges.
P_{Lbs}	Base carcass price minus discounts, converted from $/cwt to $/lb.
MarketRev	Carcass weight multiplied by the carcass price, adjusted for mortality and cull proportions.
CullRev	Revenue from selling the cull proportion at a lower weight and price.
W_{CULL}	The assumed average weight of chronically ill cattle when removed from the feedlot.
P_{CULL}	The per-pound value assigned to cull cattle.
TotalFeed	Sum of daily feed usage, each day's feed intake = ADG* feed per lb of gain.
FEED	Cost of the feed ration on a per-pound basis.
$AFC(W_t)$	A factor that increases as cattle grow heavier.
Shrink	A proportion of live weight lost due to transportation/handling.
$Feed_t$	The amount of feed consumed on day t.

Coding Strategies

This study requires four lines of code to implement dynamic linear programming models within Python. The first of these, *import math,* brings the entire Python math module into the script. This module contains fundamental mathematical functions and constants, specifically functions involving trigonometric functions, pi, and exponential functions. By importing the entire module, this allows one to access any of these functions using dot notation. Next, *from math import sqrt specifically* imports the square root functions from the math module.

The line *import numpy as np* imports NumPY, provides data structures and functions for handling large, multi-dimensional arrays and matrices. This is useful for vectorized operations, numerical methods, and linear algebra tasks. Finally, *from scipy.optimize import minimize* imports the minimize function from SciPy's optimization subpackage. This function is typically used to find the minimum of a scalar function of one or more variables, under various constraints and bounds when needed. All of the above functions and the code itself can be found from *Python Software Foundation (Python (Version 3.12.4) [Software].*

Chapter 4 - Data

Details regarding the data sources, parameter values, and assumptions used to support the optimization model developed in this thesis are detailed in the chapter below. The data represents a combination of empirical averages, economic benchmarks, and published performance figures for feedlot steers.

The central objective of this study is to replicate the economic and biological environment of a Kansas-based finishing operation as closely as possible. Therefore, the data includes a wide array of components including feeder cattle pricing mechanisms, feed efficiency metrics, carcass valuation structures, mortality probabilities, yardage and interest costs, and health management assumptions. Each subsection in this chapter describes the origin, justifications, and application of these variables within the model. Where appropriate, values were translated from source materials into functional equations or input parameters to allow for dynamic simulation across a range of entry weights and DOF.

Data Selection and Valuation Assumptions

This study analyzes data from steers rather than including both steers and heifers. The decision to isolate solely into steer data stems from the biological and economic differences between steers and heifers. These differences can introduce variability in feedlot performance, average daily gain, feed efficiency, carcass outcomes, and many other factors. Steers typically have higher growth rates and finish at heavier weights when compared to heifers, making steers more representative of the typical feeding model in many commercial feedlots. By focusing only on steers, this study ensures consistency across the parameters used, thereby reducing heterogeneity in the data. Allowing the optimization framework to more accurately isolate and quantify the key drivers of feeding profitability - namely feeder purchase costs, feed efficiency, yardage expenses, health risks, interest, and carcass-based revenue outcomes.

This analysis evaluates feedlot profitability using cash market prices. Although most commercial feedlots today manage market risk by using futures contracts or other hedging mechanisms, the use of cash market prices, both for feeder cattle purchases and fed cattle sales, allows for a straightforward evaluation of net feeding returns without the added complexity of individual contracts for risk management strategies. This allows the model to focus directly on biological performance and feeding economics rather than introducing assumptions about risk management strategy or market timing. In doing so, the optimization more clearly highlights the economic incentives for choosing entry weights and feeding durations under specific market conditions.

Only choice-graded beef product prices are used when estimating revenue and pricing details. Choice products are the most marketed and produced within the beef industry in the United States, representing the largest share of total fed cattle that are marketed. Relying only on choice-grade prices allows this study to provide a consistent reference point for direct and practical comparisons of net feeding returns across a variety of feeding strategies.

Data Description and Parameterization

Price Slide Development and Carcass Revenue

To estimate the purchase cost of feeder cattle based on their respective initial weights, this study used a price slide equation adapted from Baldwin et al. (2021). This approach is commonly referred to as a price slide that incorporates both a cubic polynomial in animal weight and market driven variables such as corn and fed-cattle prices as seen in equation (6).

All prices and historic data were obtained from the Livestock Marketing Information Center (LMIC): 1) feeder cattle prices: Kansas Auctions Summary , Feeder Steers – Medium and Large frame #1, monthly price, years 2020 through 2024, 2) corn price: Kansas Feedlot Performance and Feed Cost Summary, Feed Costs (mid-month average), monthly average prices, years 2020 through 2024, and 3) Fed Cattle Price: Monthly Weighted Average Slaughter Cattle – Negotiated (Kansas), monthly average price ($/cwt), years 2020 through 2024.

The feeder cattle price slide regression developed in this thesis does not include lagged price terms or account for potential autocorrelation in the feeder cattle market. Instead, this regression relies on simultaneous values of feeder weight, corn prices, and fed cattle futures to estimate purchase price. This does introduce a naïve assumption: that current market variables fully reflect the information relevant to price information. In practice, feeder cattle prices often exhibit temporal dependencies and can be influenced by past market behavior, seasonal patterns, or delayed responses to commodity price shifts. The absence of lagged variables means that the model may not fully capture cyclical pricing dynamics or the expectation-driven nature of cattle procurement decisions. While this approach simplifies the estimation, it aligns with the objective of capturing broad price trends.

The primary data used for the carcass discount valuations come from the USDA Livestock, Poultry, and Grain Market News Division in St. Joseph, MO. These market updates provide current schedules for discounts for "non-ideal" carcass weights. Table 2 outlines the weight ranges that correspond to the different discounts that are used and applied throughout this research.

The core of the pricing structure is a base carcass price of $327.08/cwt. This value is provided by LMIC, Monthly Weight Average Slaughter Cattle–Negotiated for Kansas, Dressed and Delivered Steers for March 1, 2025. This figure represents the "ideal" carcass market value under typical yield and quality conditions. Packers then use discounts based on the dress weight. To align with typical feeding timelines, feeder cattle prices used in this analysis were taken from the month of September, reflecting the expected purchase period for cattle marketed in March.

Table 2. Carcass Grid Pricing (Discounts)

Weight Categories	$/cwt
400-500 lbs.	$29.29
500-550 lbs.	$22.64
550-600 lbs.	$11.57
600-900 lbs.	$0.00
900-1000 lbs.	$1.07
1000-1050 lbs.	$5.00
1050 lbs. and up	$15.45

Source: USDA Livestock, Poultry, and Grain Market News Divisions, St. Joseph, MO. Monday March 17, 2025

Using USDA's St. Joseph Market News provides a snapshot for a specific date. Discounts can vary by region, plant, and time of year reflecting shifts in consumer demand, packer supply chain logistics, and seasonal trends within the industry. Regardless, the base carcass price and weight brackets for dress carcasses provide a practical baseline for feedlot operators in the state of Kansas. In real-world negotiations, some operators could encounter narrower or broader discounts, but the principle that lighter or heavier dressed carcasses are penalized by packers.

Health Cost

Among the variety of health challenges that can present themselves during a feeding period, bovine respiratory disease (BRD) is the most prevalent condition seen in feedlots throughout the United States. The USDA's National Animal Health Monitoring System (NAHMS) published their findings from the *Feedlot 2011 Part IV: Health and Health Management* report, which provides insight into the probability and cost of managing BRD in a feedlot setting.

According to the study, feedlots with a capacity between 1,000 and 7,999 head of cattle reported a 95.6% probability of having at least one case of BRD among cattle placed during a feeding period (USDA-NAHMS, 2013). The high probability of infection of BRD in mid-sized feedlot operations illustrates the need for preventative and therapeutic protocols as a necessary part of feedlot management. The same study reports that the average cost to treat a single case of BRD was $23.60 per head (USDA-NAHMS, 2013). In this thesis, the $23.60 per head value is used to represent health cost within the relevant cost structure equations. With the high level of prevalence of BRD, we assume that all cattle are getting pre-treated for BRD within this simulation. Making the $23.60 health cost a constant cost across all iterations of the model.

Dressing Percentage and Shrink Percentage

According to Saner and Buseman (2024), the average dressing percentage for finished steers is approximately 63%. This estimate is derived from typical market ready cattle. Although dressing percentage can vary based on genetics and feeding regimens, the benchmark of 63% represents a practical industry standard for economic modeling purposes. For this thesis, the 63% dressing percentage will be used to convert final weights into dressed carcass weight to calculate revenue when using a carcass pricing scenario. Maintaining a consistent dressing percentage allows for a clearer evaluation of how other variables affect overall profitability.

To follow standard industry performance evaluations, a 4% pencil shrink is applied to the final carcass weight for finished cattle. According to *Focus on Feedlots* December 2024 report, the closeout figures used in the summary data "usually sold FOB the feedlot with a 4% pencil shrink" (Waggoner, 2024). This standard ensures comparability across feedlots and maintains modeling consistency.

Feed to Gain, Incremental Factor, and Average Daily Gain

To represent a typical feed conversion efficiency for finishing cattle, we utilize a baseline feed-to-gain ratio of 5.82 pounds of dry matter per pound of live weight gain (Fox et al., 2001). This value was reported under conventional feedlot conditions. This value represents a consistent and realistic benchmark for evaluating feed efficiency and simplifies analysis across a variety of production scenarios.

As cattle in a feedlot get larger, they will require more feed to gain an additional live weight pound. To account for this decline in feed efficiency as steers get larger, we incorporate an incremental adjustment factor on 0.007 pounds to the base feed-to-gain value of 5.82 pounds. This means that for every additional day that a steer remains in a feedlot, the value of 0.007 will be added to 5.82 pounds to account for the increasing feed demand for gain as the steer gets larger. The support for this value is also found in Fox et al. (2001), where feed-to-gain ratios ranged from 5.18 for low performing cattle and 6.76 for high performing heavy crossbred cattle. The value of 0.007 introduces a conservative and linear means of monitoring the decline in feed efficiency when real-world data are not available or varies from operation to operation.

Zinn et al. (2008) evaluates commercial feedlot performance data from over 9,600 pens of steers across 15 different feedlots in the United States and Canada. They reported average daily gain values ranged between 2.46 kilograms and 0.85 kilograms during the duration of the observed feeding periods. By converting into pounds, 5.43 pounds and 1.87 pounds, respectfully, these values are incorporated into the average daily gain model. Because steer live weight and daily gain have an inverse relationship, this study employs a subtraction of 0.001 pounds every day that a steer is fed to represent the decrease in daily gain as live weight is increased.

Yardage and Interest Rates

To estimate the daily yardage costs, data from Day et al. (2025) is used, which presents pen-level feedlot performance data divided between weight and sex. They calculated yardage by dividing the total yardage cost per head by the total days on feed for each of the subgroups and then compiling an average across all of these groups. This approach concluded with a daily yardage cost of $0.39985 per head per day.

Dennis et al. (2018) reported an interest rate of 0.05 within their research paper. The equation that this thesis uses to calculate the total interest cost is modified from Dennis et al. (2018) therefore will be using the same value of 0.05 to represent the annualized interest rate within this study.

Cull Cattle Valuations

To account for the possibility of cull cattle being a part of a feedlot cohort during a feeding period. Dennis et al. (2018) found through their research that 1.4% of cattle placed on feed will need to be removed from the cohort before the marketing period for a multitude of reasons. This value will serve as a benchmark for modeling cull rate in commercial feedlots; specific operations will be able to tailor this value to their operation.

When cattle are culled from the cohort, they can still be sold but command a lower price. A cull cattle price of $1.114 per pound value is assigned to cull cattle when sold (Horton et al. (2025). This price will help to reflect the value that culled cattle have while not being as valuable as cattle that are fed through to the marketing period. In conjunction with the price per pound that cull cattle receive, the weight of those animals is also an important factor in the overall value of the animal. Dennis et al. (2018) reported that the average weight of culled steers is equal to 861 pounds. This weight paired with the price per pound that is given by Horton et al. (2025) allows the model to assign an overall estimated value for culled cattle in feedlot operations.

Table 3. Model Variables Values and Sources

Variable	Value	Source
ADG(W_i)	Equation (16)	Zinn et al. (2008)
HC	\$23.60/Head	USDA-NAHMS, 2013
FRPP(W_i)	Equation (6)	Baldwin et al. (2021)
P_{CORN} and FEED	0.0689 (\$/lb)	LMIC – National Corn Price
P_{FED}	\$163.38 (\$/cwt)	LMIC-Monthly Live Cattle Futures
Yard(DOF)	0.39985 (\$/day)	Day et al. (2025)
IR	0.05	Dennis et al. (2018)
MORT(W_i)	Equation (22)	Vogel et al. (2016)
CULL	0.014 or 1.4%	Dennis et al. (2018)
Dress	63%	Saner & Buseman, 2024
BaseCWT	\$327.08	LMIC – Monthly Weighted Average: Kansas: Dressed Delivered Steers
W_{CULL}	861 lbs	Dennis et al. (2018)
P_{CULL}	0.62 (\$/lb)	Erol et al. (2024)
Shrink	0.04 or 4.0%	Waggoner, 2024
lbs of Feed/lb of Gain	5.82 lbs	Fox et al. (2001)
Incremental Factor	0.007 lbs	Fox et al. (2001)

Chapter 5 - Results

This chapter presents the key findings from both the feeder cattle price slide regression and the optimization model. The first section will evaluate the statistical results of the price slide regression, which estimates the per-pound purchase price of feeder steers as a function of entry weight and key market variables. The model uses a cubic polynomial to capture the nonlinear pricing behavior across weight classes and incorporates market interactions to improve overall accuracy.

The second section reports the results of the optimization model designed to determine the profit-maximizing placement weight and feeding duration. Outputs include optimal placement weight, days on feed, average daily gain, final live weight, mortality rate, and maximized net returns per head. These results reflect the interaction of biological performance and market-driven costs and revenues, while adhering to the imposed constraints.

Price Slide Regression Results

The linear, quadratic, and cubic forms of the weight terms were found to not be significant on their own. However, the inclusion of these terms is needed to capture the nonlinear shape of price discounts across the weight brackets from Table 2. The negative coefficient of –0.413 suggests that as placement weight increases the price of the feeder will decrease in return. The quadratic coefficient is represented by a positive coefficient of 0.00017, introducing curvature into the price slide. This curvature reduces the rate of price decline as moderate weights. Similar to the weight coefficient, the cubic term is small negative value, ensuring that price will eventually flatten or experience a downward turn at heavier weights.

Corn price coefficient is reported as highly significant at a value of –13.25. The negative relationship confirms that as corn prices (a large component within feed costs) increase, the price of feeder cattle will decrease as producers project lower net margins. The interaction of weight and corn price was also significant to the regression. This positive interaction suggests that as corn prices rise, the negative price impact is greater for heavier cattle. Those heavier cattle would require more feed during the finishing period. The model implies a fixed discount for feed costs as well as a scaling penalty based on weight and feed price to better align with feeder purchase decision-making. Fed cattle futures indicated that for every $1.00/cwt increase in expected finished cattle prices, the feeder cattle price would also increase by $1.79/cwt.

The regression model used to estimate feeder cattle prices shows an overall 93.4% of explained variation based on the variables used. The high explanatory power supports the validity of using the cubic price slide established by Baldwin et al. (2021) to capture both the biological and market-based dynamics that affect feeder price determination.

Table 4. Price Slide Regression Output

Variables	Coefficients	P-Value
Intercept	183.5270*	0.0160
Weight	-0.4120	0.2290
$Weight^2$	0.0002	0.7308
$Weight^3$	-0.0000	0.9745
Corn Price	-13.2500***	0.000
Weight * Corn Price	0.0087**	0.0020
Fed Cattle Price	1.7920***	0.0000
$R^2 = 0.934$	N = 360	

*** indicates statistical significance at the 0.01 level.
** indicates statistical significance at the 0.05 level.
* indicates statistical significance at the 0.1 level.

Model Output Results

The optimization framework identified the profit-maximizing placement weight strategy for feeder cattle entering a finishing ration under defined marketing and production constraints. The model found the optimal entrance weight to be 704 lbs combined with an optimal feeding duration of 166.10 days (Table 5). Cattle entering at this mid-range weight level avoid elevated health risks often associated with lighter calves while still maintaining substantial gain potential during the finishing period. The 704 lbs placement weight falls within the 600-to-900-pound entry weight constraint, imposed to reflect real-world purchase weights. Similarly, the optimal DOF rests within the bounds of 140 through 220 days, validating the biological feasibility of the strategy.

At the placement weight, the model predicts an ADG of 4.72 pounds per day. This average daily gain is derived from a function tied to placement weight, emphasizing the model's consideration of diminishing marginal gain. This leads to a final live weight of 1,488 lbs at the time of the marketing period. We see that this final weight is higher than the LMIC average weight reported in the same time frame of 1,378lbs. When this final weight is adjusted by the 4% pencil shrink followed by the 63% dressing percentage leads to a dressed weight within the 600-to-900-pound range which incurs no discounts based on the grid-based selling strategy found in Table 2. The avoidance of carcass weight-based discounts plays a crucial role in optimizing revenue. The modeled mortality rate for this cohort based on the entry weight is equal to 1.35%. This reflects the relatively low health risks associated with placing cattle above the lightweight, high-risk threshold. This placement weight indicates a favorable balance between growth potential and animal health performance.

Maximized net returns were reported at $119.42 per head, reporting the difference between the total adjusted revenue and all variable costs – including feeder purchase, feed, yardage, health, interest charge, and lost revenue from mortality. The figure shows the financial value of making placement weight decisions based on flexible modeling as opposed to fixed values. The magnitude of this return demonstrates that thoughtful optimization of feeder placement and duration of feeding periods can yield meaningful financial gains.

In summary, these results affirm the thesis hypothesis: optimal placement weight is not static, but depends on the interaction between feed costs, market prices, health risk, and biological efficiency. By identifying a specific weight and feeding duration that jointly maximize net returns the model provides actionable insights for feedlot managers seeking to enhance profitability under real-world constraints.

Table 5. Optimization Model Output Results

Parameters	Results
Optimal Placement Weight	704.32 lbs
Optimal Days on Feed	166.10 days
Average Daily Gain	4.72 lbs/day
Final Live Weight	1,488.10 lbs
Mortality Rate	1.35%
Maximized Net Returns	$119.42

Table 6 provides a detailed breakdown of the revenue and cost components associated with the optimal feeding strategy identified by the model. The market revenue for finished cattle totaled to $2,823.64 per head, with an additional $18.72 per head generated from culled animals. The largest expense, as expected, was feeder cattle purchase amounting to $1,849.79. Followed by feed costs of $728.48 for the duration of the feeding period. Yardage and health costs remained relatively minor at $66.41 and $23.60 per head. With interest cost associated with capital investment over the feeding period being equal to $54.69 per head.

This budget reinforces the key finding of the analysis; profitability is highly sensitive to feeder cattle prices and feed efficiency. Both of which contribute massively to the overall cost structure of a feedlot operation. The inclusion of cull revenue, while minor, illustrates the model's capacity to capture real-world instances that affect feedlot profitability. Overall, the budget confirms the economic feasibility of the optimized placement weight and feeding duration while providing a transparent framework that can be adapted to other scenarios or integrated into decision-support tools for producers.

Table 6. Budget Breakdown ($/head)

Parameters	Results
Market Revenue	$ 2,823.64
Cull Revenue	$ 18.72
Feeder Purchase Cost	$ 1,849.76
Yardage Cost	$ 66.41
Feed Cost	$ 728.48
Health Cost	$ 23.60
Interest Cost	$ 54.69

Sensitivity Analysis

To evaluate how entry weight and days on feed interact on overall profitability, a sensitivity analysis was conducted across seven different fixed placement weights ranging from 600 to 900 pounds. For each placement weight, net returns were simulated over a range of DOF from 140 to 220 days, in five-day increments. The results are illustrated in Figure 1. The x-axis represents days on feed, while the y-axis captures the net returns per head with each line within the graph corresponding to a specific placement weight.

The graph reveals important patterns that align with the core findings of the optimization model presented in the earlier chapters. Initially, across all of the potential placement weights, net returns rise before eventually declining in later DOF positions. This reflects the trade-offs between gains in carcass value and increasing feed, yardage, and interest costs. Heavier placement weights, such as 850 and 900 pounds, reach their profitability peaks earlier in the feeding period due to slower ADG and diminishing marginal feed efficiency. In contrast, lighter placement weights continue gaining profitability over longer feeding periods but at the cost of lower peak value and greater exposure to mortality and cost accumulation.

Figure 1 underscores the economic advantage of targeting placement weights that strike a balance between growth potential and operational efficiency. The optimal curve appears to occur between 700 and 750 pounds, which aligns closely with the model's identified optimum as described in earlier chapters. These curves achieve the highest net return while maintaining a relatively wide range, suggesting flexibility in DOF decisions without substantial economic loss. This insight can be valuable for feedlot operators seeking to adapt to real-world variability in market timing or pen space availability.

Furthermore, the structure of the graph offers validation for the diminishing returns that arise from prolonged feeding. As feeding durations increase, the upward slope of net returns flattens or even reverses. This is particularly true for cattle that are placed at heavier weights. This supports the emphasis on marginal efficiency and biological constraints of finishing cattle within this thesis. As cattle approach their maximum gain ability, additional feeding days lead to rapidly increasing feeding costs with minimal additional revenue.

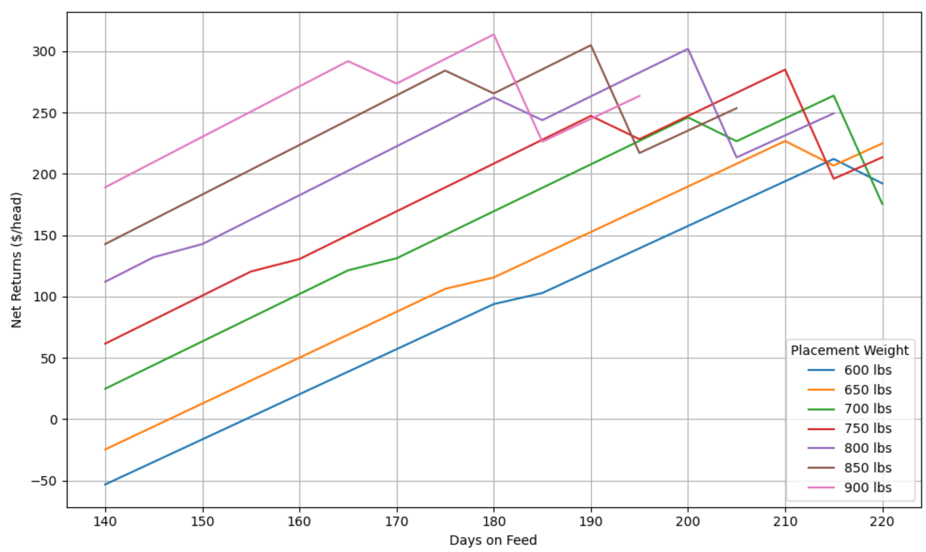

Figure 1. Net Returns over DOF for Different Placement Weights

Figure 2 presents the sensitivity of net returns to varying corn prices, in relation to the optimal weight value found previously in this thesis. Net returns show only marginal changes across most of the corn price range suggesting resiliency in profitability when moderate increases in feed costs occur (corn prices). However, a large jump in net returns is observed as corn prices exceed \$0.084 per pound. Indicating a potential nonlinear impact or a shift in the optimal placement and feeding duration combination. The results suggest that while feed costs are important, the model's structure and compensating margins from market revenue can partially absorb cost increases until a certain threshold in passed.

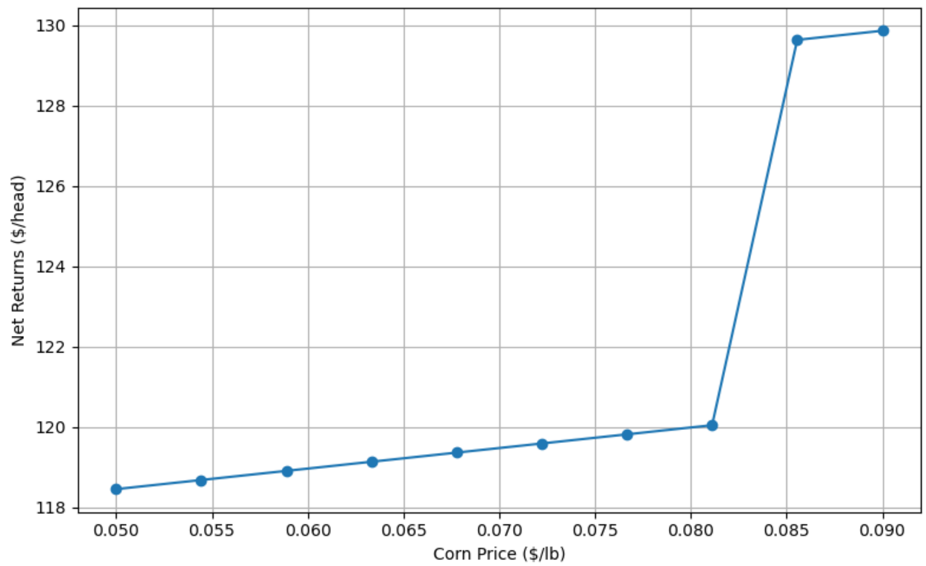

Figure 2. Net Returns over Corn Price

Figure 3 reveals a vast decline in net returns as the price of fed cattle increases from \$150 to \$180 per cwt. The net returns for this analysis were calculated in terms of the optimal weight found in this thesis. This result could be considered counterintuitive, but the inverse trend is driven by the interaction between placement weight and the price slide formula. As fed prices rise, the feeder price also increases due to the regression-based feeder price equation. This inflates the purchase cost of calves more aggressively than it raises revenue, thus reducing profits. Figure 3 demonstrates a crucial dynamic in cattle feeding: when input prices are tightly linked to output markets, margin compression can occur in favorable conditions.

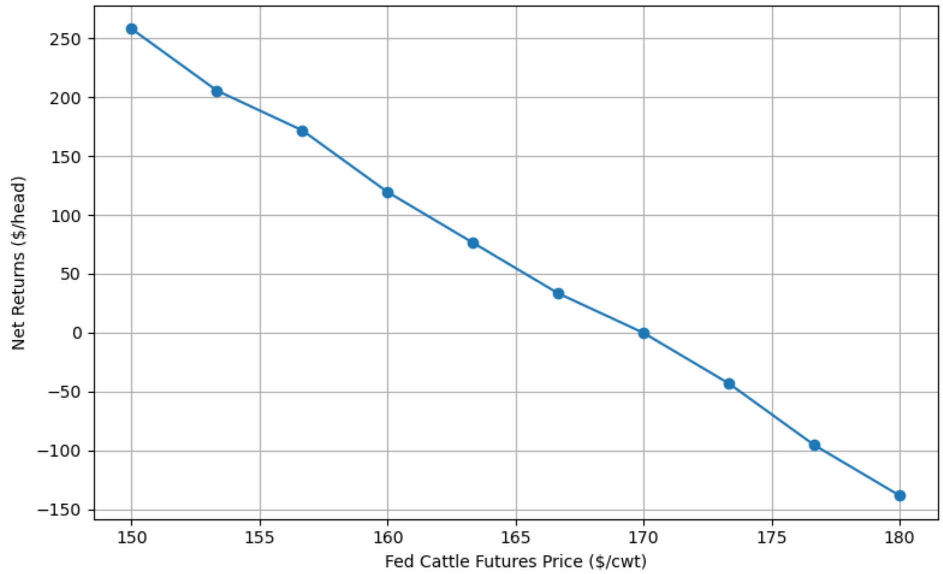

Figure 3. Net Returns over Fed Cattle Price

Figure 4 displays the effects of changing the dressing percentage of cattle carcasses from 60% to 66% that exit the feedlot at the optimal finishing weight calculated previously. As expected, net returns increase somewhat linearly with improvements in dressing percentages. A higher dressing percentage increases the proportion of the live animal that is converted into saleable carcass weight, directly boosting market revenue while leaving input costs unchanged. This graph highlights how carcass yield efficiency has a substantial impact on profitability, especially under grid-based selling systems. Improvements in dressing percentages could stem from genetic selection, improved management, or ration formulation, providing actionable strategies for enhancing profitability outside of market conditions.

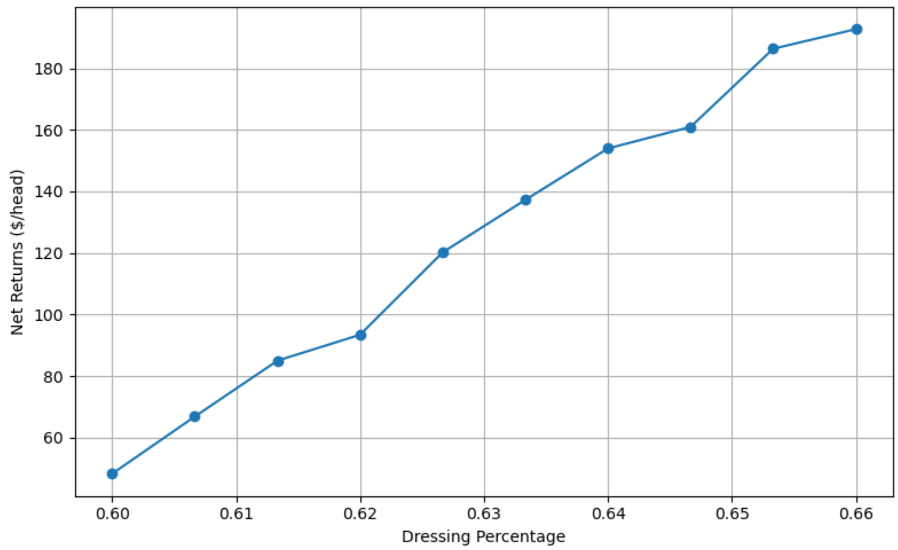

Figure 4. Net Returns over Dressing Percentage

Collectively, these sensitivity analyses reinforce the importance of considering both production efficiency and market dynamics when designing feeding strategies. While corn price exhibits moderate impact with a nonlinear inflection, dressing percentage offers clear economic leverage, and fed cattle price introduces margin risks due to its correlation with feeder prices. These insights validate the importance of embedding dynamic relationships in feeder pricing and market behavior within feedlot models and suggest opportunities for future research exploring joint sensitivities or stochastic simulation.

Conclusions

This thesis developed and implemented a dynamic optimization model to determine the profit-maximizing entrance weight and feeding period duration for steers in a commercial feedlot setting. By implementing biological, economic, and operational realities into the simulation framework, this study offers a structured decision-making tool that supports informed placement strategies in beef production systems. Grounded by industry benchmarks and empirical data, the model demonstrates how placement weight and days on feed interact to influence feed efficiency, mortality risk, carcass discounts, and ultimately, net returns.

The core findings confirm that optimal entrance weight is not static, but depends on changes within cattle market conditions, feed costs, and animal performance parameters. Specifically, the model identifies 704 pounds as the ideal entrance weight under the defined conditions, with an optimal feeding duration of approximately 166 days. This strategy balances rapid early-stage weight gain with a relatively low mortality risk, while positioning final carcass weight within the ideal grid range to avoid market discounts. The resulting net return of $119.42 per head underscores the economic value of precises, data-driven placement decisions.

In addition to providing actionable insights for feedlot managers, this thesis contributes to academic literature by advancing the use of dynamic linear programming within cattle feeding systems. Unlike many prior studies, this model treats entrance weight and days on feed as the core decision variables as opposed to just exit weight. This slight shift more so reflects how producers/managers make initial purchase and placement decisions, rather than focusing solely on marketing outcomes. The model captures a broader set of tradeoffs that must be evaluated by linking feeder cattle purchase price, feed conversion, yardage, mortality, and interest to the front-end of feeding decisions.

Limitations

Reliance on aggregated industry averages as opposed to pen-level or proprietary feedlot data represents a primary limitation of this thesis. All values used throughout this model are derived from published articles, extension reports, USDA surveys, and other academic literature. This leads to generalized benchmarks rather than showcasing the day-to-day variability that takes place on individual feedlot operations. For example, cull cattle proportion, average daily gain, and dressing percentages are averages that do not reflect varying practices, genetics, or risk environment of any one commercial operation. Future research that incorporates operational records would improve the accuracy of the model for specific operations moving forward.

Average Daily Gain

While the ADG function used in this study provides a weight-dependent estimate of growth performance, it assumes a uniform relationship between entry weight and rate of growth across all cattle. This approach does not capture the full biological complexity and individual variability observed in real-world feedlot settings. ADG can be influenced by numerous factors including genetics, diet composition, environmental conditions, management practices, and stress levels. By basing ADG solely on initial placement weight using a declining linear function, the model overlooks how daily gains may fluctuate throughout the duration of the feeding period due to physiological and nutritional responses.

The model enforces a minimum ADG threshold to avoid unrealistic values, which introduces an artificial floor that does not reflect true biological outcomes for underperforming animals or high-risk groups. This limitation can lead to overestimated weight gain for cattle placed at suboptimal weights or under unfavorable conditions during the feeding period. Without incorporating pen-level or stochastic data, the ADG estimates are best viewed as deterministic averages rather than precise forecasts. Future versions of the model could benefit from the integration of variable ADG distributions or time-dependent gain functions based on real-world feedlot performance data to enhance realism and improve predictive power.

Biological and Production

The model treats cattle performance as homogeneous, assuming that all animals placed at a given entrance weight will achieve the same average daily gain, final weight, and feed conversion efficiency. In reality, cattle performance is highly variable, based on genetics, management, weather, and pen conditions. By using weight-based equations for average daily gain and feed conversion, the model captures biological trends but does not account for the variability within the cohort, outliers, or stochastic shocks relating to weather extremes or disease outbreaks. Furthermore, mortality is applied as a static fraction based on entry weight, rather than dynamically linked to days on feed or time-specific risk factors. Potentially causing the model to underestimate or overestimate economic losses from death in specific situations.

Using fixed percentages for shrink rate as well as dressing percentage across all final weights could cause an issue. While widely accepted across the industry, shrink and dressing percentages can vary and be influenced by cattle breed type, handling practices, environmental stress, and seasonal conditions. Similarly, the model assumes that feed cost per pound of gain can be described by a linear or quadratic adjustment, not fully capturing changes in ration formulation or feeding behavior that may emerge at different body weights during the duration of a feeding period.

This study does not incorporate a quality grading grid (e.g., USDA Choice, Select, or Prime) into the revenue modeling framework. While the use of quality premiums and discounts are used in marketing, their inclusion would require access to data regarding marbling scores, yield grades, and genetic or management factors that are not available for this thesis. Furthermore, modeling quality grade outcomes would introduce large amounts of complexity and variability that would obscure the core economic trade-offs that are tied to placement weight, feed efficiency, and carcass weight. By excluding quality grading grids, the model remains focused on widely observable pricing factors such as carcass weight discounts. This simplification enhances transparency and usability while still offering a valuable framework for optimizing net feeding returns in real-world feedlot settings.

Economic Assumptions

This thesis assumes static market conditions for key variables, including fed cattle prices and grid-based carcass discounts. These prices are held constant across the optimization model and are treated as exogenous inputs. In actual feedlot decision-making, price levels and basis risks can shift over the course of a feeding period. Futures markets may offer hedging tools to reduce risk, but this model does not incorporate the financial or opportunity costs associated with risk management strategies.

Modeling Constraints

Full utilization of the carcass grid pricing system is assumed, but the model does not include quality or yield grade variability. In practice, cattle with identical live weights and days on feed can differ in carcass marbling, fat cover, and muscling. All traits that would directly affect any discounts that a carcass may or may not receive in a value-based marketing system. Without incorporating variability in carcass traits, the model may misconstrue the actual consequences of decisions based on placement weight and days on feed.

Future Research

Incorporating Stochastic and Dynamic Elements

Changing the model from deterministic to stochastic would be highly beneficial in future research. Feedlot operations are characterized by uncertainty and variability in animal performance, commodity prices, weather events, and disease outbreaks. Future work could incorporate stochastic elements, such as simulating average daily gain, mortality, and feed costs as random variables with probability distributions derived from empirical data. A simulation could be used to generate distributions of net returns, allowing for researchers and producers to evaluate not just the expected outcome, but risk exposure.

Reformatting the model from a single-period structure into a dynamic optimized framework would allow for time dependent decision-making. Feedlot managers do not make one decision for the entire duration of a feeding period and maintain it. Managers monitor performance, adjust rations, extend or shorten days on feed, while responding to market conditions. Stochastic dynamic programming could reflect this process by optimizing decisions of multiple time periods while accounting for advanced state variables such as weight, health status, and mortality. Bringing the model closer to the realities of operational management.

Integrating Quality and Yield Grade Prediction

Carcass revenue is not a function solely of weight. Value-based marketing systems apply premiums and discounts on quality grade (e.g., Choice, Prime) and yield grade (1-5), reporting fat cover and muscling. While the current model focuses on carcass weight to determine grid revenue, this approach excludes variation in marbling, backfat thickness, and ribeye area. These factors greatly impact carcass profitability. Future models and research could integrate prediction algorithms for carcass quality and yield outcomes by using regression models or machine learning trained on closeout and carcass data.

Real-World/Proprietary Data Integration

The predictive power of this model could be greatly enhanced using real-world, proprietary feedlot data. Access to closeout reports, treatment logs, daily feed intake data, and carcass quality records would allow future researchers to build empirically grounded response functions for gain, mortality, dressing percentages, and grade performance. Replacing the generalized equations with regression models that reflect the unique management practices, genetics, climate, and feeding choice of a specific operation.

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Appendix A - Python Code

Appendix A displays the code needed to run the mode within the python coding language.

```
import math
from math import sqrt
import numpy as np
from scipy.optimize import minimize

SHRINK = 0.04
DRESS = 0.63
FEED = 0.0689
IR = 0.05

W_f_max = 1800

P_corn = 0.0689
P_Fed = 160.00

W_c = 1200
P_c = 1.114
CULL = 0.014

HC_fixed = 23.60

def FRPP(W_i):
    beta_0 = 183.5270876
    beta_1 = -0.412318202
    beta_2 = 0.000172951
    beta_3 = -7.63735e-09
    beta_4 = -13.25006091
```

```
    beta_5 = 0.008734087
    beta_6 = 1.792934383

    price_cwt = (
        beta_0
        + beta_1 * W_i
        + beta_2 * W_i**2
        + beta_3 * W_i**3
        + beta_4 * P_corn
        + beta_5 * W_i * P_corn
        + beta_6 * P_Fed
    )
    return price_cwt / 100.0

def ADG(W_i):
    return max(1.87392923, 5.42337165 - 0.001 * W_i)

def MORT(W_i):
    if W_i < 400:
        return 0.0272
    elif 400 <= W_i < 600:
        return 0.0272
    elif 600 <= W_i < 700:
        return 0.0197
    elif 700 <= W_i < 800:
        return 0.0135
    elif 800 <= W_i < 900:
        return 0.0094
    elif 900 <= W_i < 1100:
        return 0.0072
    else:
```

```
        return 0.0072

def grid_price(carc_wt):
    base_cwt = 323.68
    if carc_wt < 400:
        discount_cwt = 29.29
    elif 400 <= carc_wt < 500:
        discount_cwt = 29.29
    elif 500 <= carc_wt < 550:
        discount_cwt = 22.64
    elif 550 <= carc_wt < 600:
        discount_cwt = 11.57
    elif 600 <= carc_wt < 900:
        discount_cwt = 0.00
    elif 900 <= carc_wt < 1000:
        discount_cwt = 1.07
    elif 1000 <= carc_wt < 1050:
        discount_cwt = 5.00
    else:
        discount_cwt = 15.45

    final_cwt = base_cwt - discount_cwt
    return final_cwt / 100.0

def revenue_components(W_i, W_f):
    shrunk_live = W_f * (1 - SHRINK)
    carc_wt = shrunk_live * DRESS
    survive_frac = 1.0 - MORT(W_i) - CULL
    price_per_lb = grid_price(carc_wt)
    market_revenue = carc_wt * price_per_lb * survive_frac
    cull_revenue = CULL * W_c * P_c
```

```
    return market_revenue, cull_revenue

def revenue(W_i, W_f):
    market_revenue, cull_revenue = revenue_components(W_i, W_f)
    return market_revenue + cull_revenue

def FDRC(W_i):
    return FRPP(W_i) * W_i

def YC(dof):
    return 0.39985 * dof

def AFC(W_i):
    return 5.82 + 0.007 * (W_f_max - W_i)

def FC(W_i, W_f):
    return FEED * AFC(W_i) * (W_f - W_i)

def IC(W_i, dof):
    return (
        (
            0.5 * (YC(dof) + FC(W_i, W_f_max) + HC_fixed)
            + FDRC(W_i)
        )
        * dof
        * (IR / 365)
    )

def objective(vars):
    W_i, dof = vars
    W_f_calc = W_i + ADG(W_i) * dof
```

```
    net_returns = (
        revenue(W_i, W_f_calc)
        - FDRC(W_i)
        - YC(dof)
        - FC(W_i, W_f_calc)
        - HC_fixed
        - IC(W_i, dof)
    )
    return -net_returns

def final_weight_constraint(vars):
    W_i, dof = vars
    W_f_calc = W_i + ADG(W_i) * dof
    return W_f_max - W_f_calc

bounds = [(600, 900), (140, 220)]
constraints = [{'type': 'ineq', 'fun': final_weight_constraint}]
initial_guess = [700, 150]

result = minimize(
    objective,
    initial_guess,
    bounds=bounds,
    constraints=constraints,
    method="COBYLA",
    options={'maxiter': 2000}
)

if result.success:
    W_i_opt, DOF_opt = result.x
    adg_opt = ADG(W_i_opt)
```

```
    W_f_opt = W_i_opt + adg_opt * DOF_opt
    final_mortality = MORT(W_i_opt) * 100
    shrunk_live_opt = W_f_opt * (1 - SHRINK)
    carc_wt_opt = shrunk_live_opt * DRESS
    max_profit = -result.fun

    market_rev, cull_rev = revenue_components(W_i_opt, W_f_opt)
    feeder_cost = FDRC(W_i_opt)
    yardage_cost = YC(DOF_opt)
    feed_cost = FC(W_i_opt, W_f_opt)
    interest_cost = IC(W_i_opt, DOF_opt)

    print(f"Optimal Entrance Weight:   {W_i_opt:.2f} lbs (600–900)")
    print(f"Optimal Days on Feed:     {DOF_opt:.1f} days (140–220)")
    print(f"Average Daily Gain:       {adg_opt:.2f} lbs/day")
    print(f"Final Weight (live):      {W_f_opt:.2f} lbs (≤ {W_f_max})")
    print(f"Mortality Rate:           {final_mortality:.2f}%")
    print(f"Maximized Net Returns:    ${max_profit:,.2f}\n")

    print("------ Budget Breakdown ------")
    print(f"Market Revenue:           ${market_rev:,.2f}")
    print(f"Cull Revenue:             ${cull_rev:,.2f}")
    print(f"Feeder Purchase Cost:     ${feeder_cost:,.2f}")
    print(f"Yardage Cost:             ${yardage_cost:,.2f}")
    print(f"Feed Cost:                ${feed_cost:,.2f}")
    print(f"Health Cost:              ${HC_fixed:,.2f}")
    print(f"Interest Cost:            ${interest_cost:,.2f}")
else:
    print("Optimization failed:", result.message)
```

Appendix B - Net Returns over DOF Python Code

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

SHRINK = 0.04
DRESS = 0.63
FEED = 0.0689
IR = 0.05
W_f_max = 1800
P_corn = 0.0689
P_Fed  = 160.00
W_c = 1200
P_c = 1.114
CULL = 0.014
HC_fixed = 23.60

def FRPP(W_i):
   beta_0 = 183.5270876
   beta_1 = -0.412318202
   beta_2 = 0.000172951
   beta_3 = -7.63735e-09
   beta_4 = -13.25006091
   beta_5 = 0.008734087
   beta_6 = 1.792934383

   price_cwt = (
      beta_0
      + beta_1 * W_i
      + beta_2 * W_i**2
```

```
        + beta_3 * W_i**3
        + beta_4 * P_corn
        + beta_5 * W_i * P_corn
        + beta_6 * P_Fed
    )
    return price_cwt / 100.0

def ADG(W_i):
    return max(1.87392923, 5.42337165 - 0.001 * W_i)

def MORT(W_i):
    if W_i < 400:
        return 0.0272
    elif 400 <= W_i < 600:
        return 0.0272
    elif 600 <= W_i < 700:
        return 0.0197
    elif 700 <= W_i < 800:
        return 0.0135
    elif 800 <= W_i < 900:
        return 0.0094
    elif 900 <= W_i < 1100:
        return 0.0072
    else:
        return 0.0072

def grid_price(carc_wt):
    base_cwt = 323.68
    if carc_wt < 400:
        discount_cwt = 29.29
    elif 400 <= carc_wt < 500:
```

```
        discount_cwt = 29.29
    elif 500 <= carc_wt < 550:
        discount_cwt = 22.64
    elif 550 <= carc_wt < 600:
        discount_cwt = 11.57
    elif 600 <= carc_wt < 900:
        discount_cwt = 0.00
    elif 900 <= carc_wt < 1000:
        discount_cwt = 1.07
    elif 1000 <= carc_wt < 1050:
        discount_cwt = 5.00
    else:
        discount_cwt = 15.45
    return (base_cwt - discount_cwt) / 100.0

def revenue(W_i, W_f):
    shrunk_live = W_f * (1 - SHRINK)
    carc_wt = shrunk_live * DRESS
    survive_frac = 1.0 - MORT(W_i) - CULL
    price_per_lb = grid_price(carc_wt)
    market_revenue = carc_wt * price_per_lb * survive_frac
    cull_revenue = CULL * W_c * P_c
    return market_revenue + cull_revenue

def FDRC(W_i):
    return FRPP(W_i) * W_i

def YC(dof):
    return 0.39985 * dof

def AFC(W_i):
```

```
    return 5.82 + 0.007 * (W_f_max - W_i)

def FC(W_i, W_f):
    return FEED * AFC(W_i) * (W_f - W_i)

def IC(W_i, dof):
    return (
        (
            0.5 * (YC(dof) + FC(W_i, W_f_max) + HC_fixed)
            + FDRC(W_i)
        )
        * dof
        * (IR / 365)
    )

weights = [600, 650, 700, 750, 800, 850, 900]
dof_range = range(140, 221, 5)

results = []

for W_i in weights:
    for dof in dof_range:
        ADG_val = ADG(W_i)
        W_f = W_i + ADG_val * dof
        if W_f <= W_f_max:
            net_return = (
                revenue(W_i, W_f)
                - FDRC(W_i)
                - YC(dof)
                - FC(W_i, W_f)
                - HC_fixed
```

```
        - IC(W_i, dof)
    )
    results.append({
        "Placement Weight (lbs)": W_i,
        "Days on Feed": dof,
        "Net Returns ($/head)": net_return
    })

# Convert results to DataFrame and display
df_results = pd.DataFrame(results)
print(df_results)

plt.figure(figsize=(10, 6))
for W_i in weights:
    subset = df_results[df_results["Placement Weight (lbs)"] == W_i]
    plt.plot(subset["Days on Feed"], subset["Net Returns ($/head)"], label=f"{W_i} lbs")
plt.xlabel("Days on Feed")
plt.ylabel("Net Returns ($/head)")
plt.title("")
plt.legend(title="Placement Weight")
plt.grid(True)
plt.tight_layout()
plt.show()
```

Appendix C - Further Sensitivity Analysis Python Code

```
import numpy as np
import matplotlib.pyplot as plt
from scipy.optimize import minimize

SHRINK = 0.04
FEED = 0.0689
IR = 0.05
W_f_max = 1800
W_c = 1200
P_c = 1.114
CULL = 0.014
HC_fixed = 23.60

def FRPP(W_i, P_corn, P_Fed):
    beta_0 = 183.5270876
    beta_1 = -0.412318202
    beta_2 = 0.000172951
    beta_3 = -7.63735e-09
    beta_4 = -13.25006091
    beta_5 = 0.008734087
    beta_6 = 1.792934383

    price_cwt = (
        beta_0 + beta_1 * W_i + beta_2 * W_i**2 + beta_3 * W_i**3 +
        beta_4 * P_corn + beta_5 * W_i * P_corn + beta_6 * P_Fed
    )
    return price_cwt / 100.0

def ADG(W_i):
```

```
    return max(1.87392923, 5.42337165 - 0.001 * W_i)

def MORT(W_i):
    if W_i < 400: return 0.0272
    elif W_i < 600: return 0.0272
    elif W_i < 700: return 0.0197
    elif W_i < 800: return 0.0135
    elif W_i < 900: return 0.0094
    elif W_i < 1100: return 0.0072
    else: return 0.0072

def grid_price(carc_wt, DRESS):
    base_cwt = 323.68
    if carc_wt < 400: discount_cwt = 29.29
    elif carc_wt < 500: discount_cwt = 29.29
    elif carc_wt < 550: discount_cwt = 22.64
    elif carc_wt < 600: discount_cwt = 11.57
    elif carc_wt < 900: discount_cwt = 0.00
    elif carc_wt < 1000: discount_cwt = 1.07
    elif carc_wt < 1050: discount_cwt = 5.00
    else: discount_cwt = 15.45
    return (base_cwt - discount_cwt) / 100.0

def revenue(W_i, W_f, DRESS):
    shrunk_live = W_f * (1 - SHRINK)
    carc_wt = shrunk_live * DRESS
    survive_frac = 1.0 - MORT(W_i) - CULL
    price_per_lb = grid_price(carc_wt, DRESS)
    market_rev = carc_wt * price_per_lb * survive_frac
    cull_rev = CULL * W_c * P_c
    return market_rev + cull_rev
```

```
def FDRC(W_i, P_corn, P_Fed):
    return FRPP(W_i, P_corn, P_Fed) * W_i

def YC(dof):
    return 0.39985 * dof

def AFC(W_i):
    return 5.82 + 0.007 * (W_f_max - W_i)

def FC(W_i, W_f):
    return FEED * AFC(W_i) * (W_f - W_i)

def IC(W_i, dof, P_corn, P_Fed):
    return ((0.5 * (YC(dof) + FC(W_i, W_f_max) + HC_fixed)) + FDRC(W_i, P_corn, P_Fed)) *
dof * (IR / 365)

def optimize_model(P_corn, P_Fed, DRESS):
    def objective(vars):
        W_i, dof = vars
        W_f_calc = W_i + ADG(W_i) * dof
        net_returns = (
            revenue(W_i, W_f_calc, DRESS) -
            FDRC(W_i, P_corn, P_Fed) -
            YC(dof) -
            FC(W_i, W_f_calc) -
            HC_fixed -
            IC(W_i, dof, P_corn, P_Fed)
        )
        return -net_returns
```

```
    def final_weight_constraint(vars):
        W_i, dof = vars
        W_f_calc = W_i + ADG(W_i) * dof
        return W_f_max - W_f_calc

    result = minimize(
        objective,
        [700, 150],
        bounds=[(600, 900), (140, 220)],
        constraints=[{'type': 'ineq', 'fun': final_weight_constraint}],
        method="COBYLA"
    )
    if result.success:
        W_i, DOF = result.x
        profit = -result.fun
        return W_i, DOF, profit
    else:
        return None, None, None

corn_range = np.linspace(0.05, 0.09, 10)
fed_range = np.linspace(150, 180, 10)
dress_range = np.linspace(0.60, 0.66, 10)

corn_results = [optimize_model(p, 160, 0.63) for p in corn_range]
fed_results = [optimize_model(0.0689, p, 0.63) for p in fed_range]
dress_results = [optimize_model(0.0689, 160, d) for d in dress_range]

def plot_sensitivity(x_vals, results, title, x_label):
    profits = [p[2] if p[2] else np.nan for p in results]
    plt.figure(figsize=(8, 5))
    plt.plot(x_vals, profits, marker='o')
```

```
    plt.title(title)
    plt.xlabel(x_label)
    plt.ylabel("Max Net Returns ($/head)")
    plt.grid(True)
    plt.tight_layout()
    plt.show()

plot_sensitivity(corn_range, corn_results, "", "Corn Price ($/lb)")
plot_sensitivity(fed_range, fed_results, "", "Fed Cattle Futures Price ($/cwt)")
plot_sensitivity(dress_range, dress_results, "", "Dressing Percentage")
```