SCIENTIFIC Publishing Limited

Intelligent Agriculture

https://ojs.ukscip.com/index.php/ia/index

ARTICLE

A Mixed Integer Linear Programming Model for Livestock Planning

Joaquín Pablo Tempelsman* , *Javier Marenco *

Escuela de Negocios, Universidad Torcuato Di Tella, Buenos Aires C1428BCW, Argentina

ABSTRACT

In this work, we propose a mixed integer linear programming formulation for the strategic planning of a livestock operation over a multi-period horizon. The model aims to optimize the overall revenue of the operation while explicitly accounting for the complex biological, operational, and economic constraints inherent to livestock breeding systems. These constraints include herd dynamics, breeding and replacement decisions, capacity limitations, resource availability, and time-dependent production factors. The proposed formulation provides a structured and transparent decision-support framework that captures the dependencies between planning periods and supports long-term strategic decision-making. To assess the effectiveness and robustness of the model, extensive computational experiments are conducted across multiple scenarios and parameter settings that reflect realistic operational conditions. The results are benchmarked against a contesting model that represents the heuristic-based decision rules currently applied by company managers. The numerical results demonstrate that the model consistently adapts to diverse scenarios, outperforming the existing heuristics in terms of revenue and resource utilization. Moreover, the solutions obtained are interpretable and aligned with managerial intuition, which facilitates their practical adoption. Overall, the proposed approach shows strong potential as a systematic tool to support and improve livestock operation planning and management decisions.

Keywords: Mixed Integer Linear Programming; Livestock Planning; Decision Support Systems

*CORRESPONDING AUTHOR:

Javier Marenco, Escuela de Negocios, Universidad Torcuato Di Tella, Buenos Aires C1428BCW, Argentina; Email: javier.marenco@utdt.edu

ARTICLE INFO

Received: 30 August 2025 | Revised: 23 October 2025 | Accepted: 26 October 2025 | Published Online: 14 November 2025
DOI: https://doi.org/10.54963/ia.v1i2.1944

CITATION

Tempelsman, J.P., Marenco, J., 2025. A Mixed Integer Linear Programming Model for Livestock Planning. Intelligent Agriculture. 1(2): 61–76. DOI: https://doi.org/10.54963/ia.v1i2.1944

1. Introduction

In recent years, the intensive use of technology has been the main variable of change in multiple industries. Agriculture has also been a fertile ground for innovation, particularly if we consider the Argentine context. Since the 1990s, the increasing use of technology has made it possible to increase the yield per hectare, bringing it closer to the international production efficiency levels year after year. Nevertheless, although livestock activities have benefited from impressive technological advances in genetics and health management, less attention has been paid to optimal planning and general management.

In this work, we are interested in bridging this gap by building a prescriptive solution for a livestock farming company based in the Santa Fe Province, Argentina. The objective is to design a data-driven method to guide the company management in optimizing central parts of their operation that currently are being handled by a combination of past experience-based knowledge and future expectations (which is the usual case in most livestock companies in Argentina). By adopting a data-based decision-making process, the goal is not only to improve revenue but also build a flexible tool that allows the company to make better-informed managerial decisions. Working towards a prescriptive integration would allow the company to adapt faster and learn from changing scenarios influenced by local and foreign market prices, trade regulations, and weather conditions, among other variables.

The necessity of this transition is evidenced by the performance gap between current heuristic-based decision-making and optimization-based approaches. Preliminary analysis of the company's historical data reveals that current manual planning strategies often deviate significantly from the theoretical optimum. In our specific case study comparisons, the proposed model identified potential revenue increases of 22.9% in short-term scenarios and up to 41.1% in long-term planning instances compared to the baseline heuristic. These figures quantify the "efficiency cost" of the current reliance on experience-based estimation in a market characterized by high price volatility.

The central contribution of this work is the development of a prescriptive mixed integer linear programming (MILP) framework tailored to the operational decisions of livestock companies in Argentina. Unlike previous regional studies that focus on macro-resource allocation like land use [1] or transport logistics [2], this paper addresses the granular, tactical planning of the herd's biological life cycle over a long-term horizon. The model considers local market prices over time, local currency exchange rate, and breeding cycles, among other business dimensions. The novelty resides in an integrated solution that simultaneously balances the expansion of reproductive stock and optimal sale timing under strict biological constraints and macroeconomic volatility. This shifts the focus from static resource management to dynamic asset optimization, offering a scalable tool to transition from intuition-based heuristics to systematic, data-driven decision-making. In this work, we also propose a validation strategy, run benchmarks, and analyze the solutions proposed by the model.

The remainder of this work is organized as follows. Section 2 presents similar previous works from the literature, focusing on similar applications in South America. Section 3 presents a review of the livestock operation and the planning decisions that will be included in the model presented in Section 4. Section 5 reports our experience with the model on data from the mentioned company, assessing the potential impact of the introduction of this model. Section 6 presents a detailed analysis of two particular instances, in order to gain more knowledge of the business behavior proposed by the model. Finally, Section 7 closes the paper with final comments and lines for future research.

2. Literature Review

The use of MILP models [3] in the field of agricultural production has a long history worldwide, starting from the pioneering work by Wilton et al. in 1974 [4]. Complete surveys of applications of operations research techniques to crop-livestock production systems have been given by Heidari et al. [5] and Sharma et al. [6], and we refer the reader to these surveys for a comprehensive description of this field.

A similar model to the one presented in this work is developed by Hlavatýa et al.[7], in order to explore the impact of subsidies on the profitability of a beef farm. To this end, a multi-period linear programming formulation is presented, whose main decisions involve the acquisition and selection of heifers for fattening and breeding. A thorough study is performed on a number of scenarios, in a similar way to what is performed here.

A nonlinear model for a dairy farm in New Zealand is presented by Doole et al.[8]. The model considers residual mass, pasture utilization, and intake regulation as key management decisions. Experiments with real data allow the authors to conclude that the model is applicable in practice, and can help identify pragmatic strategies in order to reduce greenhouse gas emissions. Furthermore, Bhamare[9] applies operations research techniques to feed formulation, genetic optimization, and disease control. An integrated approach including multi-modal operations was presented by Popa et al.[10], applying the proposed approach to Romanian ports over the Black Sea.

The integration of crop and livestock has been considered in several previous works. Mixed integer linear programming techniques have been proposed for this issue[11], although with no inter-temporal considerations. A linear mathematical model to optimize the business activities of a dairy farm with crop-livestock integration is presented by Gameiro et al.[12], while also considering social and environmental aspects. The authors apply this model to data from a company in Brazil and conclude that this model could be a relevant tool for decision-making within this kind of company.

The optimization of land allocation between livestock and agricultural activities is considered by Ras et al.[1]. The proposed model allocates land to activities limited by available resources, maximizing the obtained profit. Agro-industrial activities are defined at different sub-stages. The model solution proposes to double the land allocated to livestock production and to adopt a new specialized activity related to weight gain that was not being considered at that time. The model constraints involve costs, risk, and sustainability, among other considerations.

Similar approaches have been conducted previously for other agricultural endeavors with multi-period models. The optimization of multi-period transport and harvest in the context of the Brazilian sugarcane industry is studied by Aliano Filho et al.[2]. The proposed model solves over a multi-period planning horizon, scheduling for machinery and transport vehicles deployment subject to constraints representing available resources, expected demand, crop yield, weather conditions, and work schedules. Frank[13] seeks to maximize the resources provided by the "Pampa Húmeda" region in Argentina. By evaluating per capita supply for 20 food products, this work studies how to allocate resources in order to maximize production. Further models have been developed for agricultural scenarios, including the forest supply chain[14], use of water[15], fresh tomatoes[16], hydroponic crop planning[17], rotation planning[18], and harvesting decisions[19]. Applications considering logistics operations in agriculture have also been proposed[20,21].

3. The Operation

In this section, we will describe the livestock operation through one complete cycle, starting in September when the newborns are bred yearly. Depending on the decisions taken, the cycle can last up to almost two years until completed if animals are selected to be sold at the highest weight category. During this process, cattle will mature in groups or batches, gaining weight and increasing their maintenance cost month by month. Typically, at a certain age, the animal will reach a weight category in which it can be sold on the local market for a price per kilo attained. There are three weight categories defined at a full weight of approximately 165 kg, 300 kg, and over 391 kg.

Yearly breeding will be enabled by reproductive stock composed of previously separated female cows and bulls. Female cows for this purpose are selected at approximately 11 months of age. They will start breeding at two years old, every year, until they are sold in a special category for reproductive older stock. Reproductive female cows typically perform between one and seven reproductive cycles before being sold.

We will define Class 1 as all male stock, Class 2 as female stock and Class 3 as female stock selected for reproduction. Only Class 2 (female) cows can be transferred to Class 3 at 11 months of age. This process is described in **Figure 1**. Time advances left to right, starting at breeding.

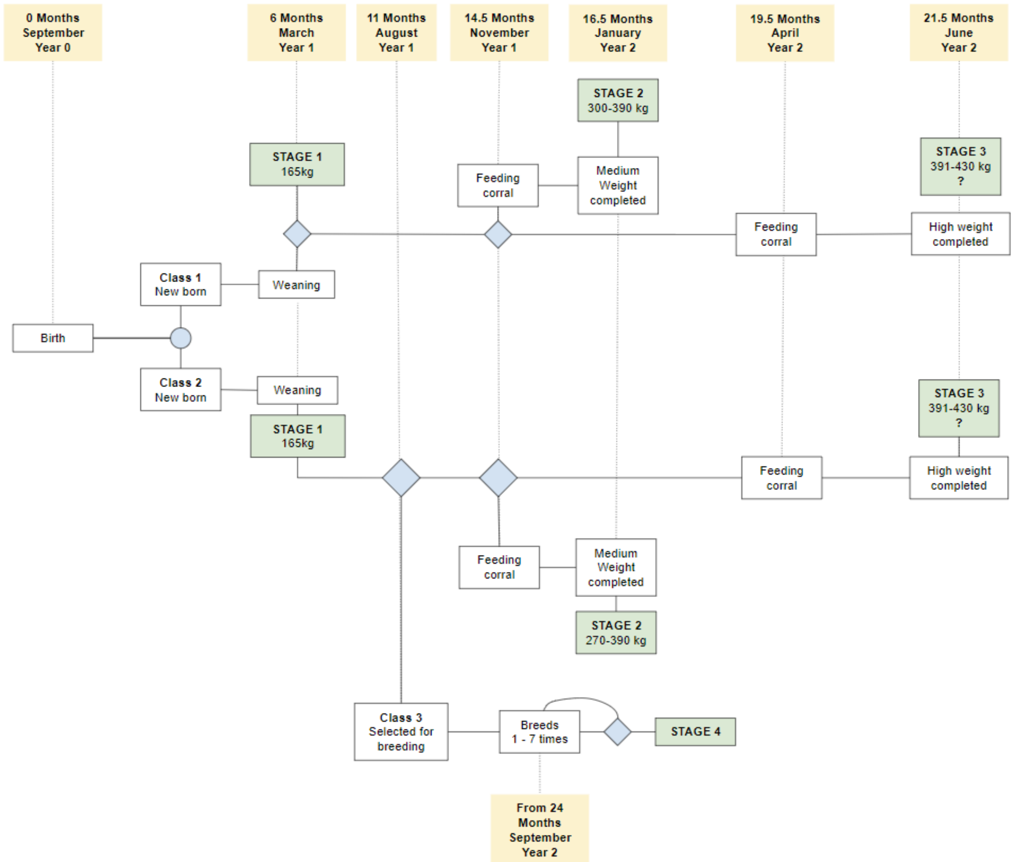

Figure 1. Livestock cycle business decision tree.

Female cows assigned to reproduction give birth in August, yearly. This is aligned with the beginning of spring as higher temperatures have a positive impact on the early development of the newborns. Six months later, both male and female newborns are ready to be separated from their mother (weaning), the moment in which they can be sold (Stage 1) or raised in the local premises.

Sales are possible at four different stages. The price for each animal is defined by its weight multiplied by the price per kilo in the category in which the animal is being sold. Stage 1 corresponds to newborns between six and eight months old, as soon as they are separated from their mother. Stage 2 corresponds to the middleweight category between 16 and 18 months old. Stage 3 corresponds to the highest weight category between 30 and 36 months of age. Finally, Stage 4 represents female cows assigned for reproduction, which can be sold at any age and time.

For the medium and high weight category, cattle are raised and fed on an open grass-fed field until 30 days before being sold, when they are moved into the feeding corral. Weight gain per day increases, resulting in a higher maintenance cost during this month. If cattle are sold in the medium-weight category, they reach complete weight between 16 and 17 months. The high weight category is reached between the months 30 and 36, depending on when it's moved to the feeding corral. Once cattle are moved into the feeding corral, they do not go back to open-grass feeding.

Only for the female cattle, during the 11th month of life, the operation decides how many female cows are permanently assigned to reproductive stock. The main difference is that reproductive stock will remain in open-grass feeding until sold, having less overall maintenance cost than the other classes. All reproductive stock females will give birth every year starting at two years of age, with an average 86% success rate. Years later, at the end of their life cycle, they can be sold at Stage 4, for a specific market price given by half the price per kilo of the female middleweight category.

4. The Model

We introduce in this section the MILP model capturing the operation described in the previous section. A MILP formulation was selected over alternative probabilistic or machine learning (ML) approaches due to the nature of the constraints governing the system. While ML methods excel at predictive tasks (e.g., forecasting prices), the core challenge here is prescriptive: the herd must adhere to strict, non-negotiable biological rules, such as gestation periods, aging rates, and category transitions. Also, a MILP approach ensures that the obtained solutions are operationally feasible since all constraints are satisfied, a feature that may not be attainable with descriptive models.

The model is based on the following sets.

- The set $T = \{1, \ldots, maxPeriods\}$ represents discrete time periods, from 1 to a maximum period, in which decisions about cattle management are made. Throughout the model definition, we shall use the subscript "*t*" to refer to elements from this set. We also introduce the set $AP \subseteq T$ to denote the periods included within the month of August, and $NAP = T - AP$ to represent the non-August periods.
- The set $E = \{1, \ldots, maxAge\}$ encompasses the possible ages of animals. We shall use the subscript "e" to refer to elements from this set. The set $sell_1 \subseteq E$ specifies the ages at which Stage 1 cattle can be sold, whereas the set $sell_{23} \subseteq E$ specifies the ages at which Stage 2 and Stage 3 cattle can be sold.
- The set $C = \{1, 2, 3\}$ represents the considered classes of cattle. Class 1 represents male stock, Class 2 denotes female stock, and Class 3 characterizes female stock selected for reproduction. Similarly, we shall use the subscript "c" to refer to elements from this set.

Besides these sets, the model takes as input data the following parameters.

- For every $t \in T$, $e \in E$, and $c \in C$, the parameter $cost_{tec}$ defines the maintenance cost associated with animals of class c and age e in the period t. If a discount rate is applied in the model, we assume $cost_{tec}$ to include such a discount.
- For every $t \in T$, $e \in E$, and $c \in C$, the parameter $price_{tec}$ specifies the selling price of animals of class c and age e in the period t. Similarly, if a discount rate is applied in the model, we assume $price_{tec}$ to include such a discount.
- For every $t \in T$, the parameter $sellCost_t$ specifies a fixed sales cost for the period t, if any sales are performed in this period, for each class and age. Similarly, we assume any discount factor to be included in the value of this parameter.
- For every $e \in E$ and $c \in C$, the parameter $initialStock_{ec}$ specifies the number of existing animals of class c and age e at the initial period.
- The parameter $preg_{rate}$ provides the mean pregnancy success rate for female breeding.
- The parameter $minsell_{12}$ represents the minimum selling required quantity for Class 1 and Class 2 per period, if any sales are performed in that period. Similarly, the parameter $maxsell_{12}$ represents the maximum selling quantity allowed in that period.

In order to state the model, we introduce the following variables.

- For every $t \in T$, $e \in E$, and $c \in C$, the variable x_{tec} represents the available stock (in number of animals) of class c and age e in the period t.
- For every $t \in T$, $e \in E$, and $c \in C$, the variable y_{tec} represents sales of animals of class c and age e in the period t.
- For every $t \in T$ and $e \in E$, the variable w_{te} represents the number of animals of age e transferred from Class 2 to Class 3 in the period t.
- For every $t \in T$, the variable n_t represents the number of births in the period t.
- For every $t \in T$, the binary variable s_t takes the value 1 if sales occur in the period t, and takes the value 0 otherwise.

The goal of the model is to maximize profit, calculated as the sum of revenue from sales minus the maintenance cost and fixed costs associated with sales. Hence, the following expression provides the objective function to be maximized.

$$\sum_{t\in T}\sum_{e\in E}\sum_{c\in C}(price_{tec}y_{tec} - cost_{tec}x_{tec}) - \sum_{t\in T} sellCosts_t$$

We now state the model constraints. The first trivial constraints are the non-negativity constraints for the continuous variables.

$$x_{tec} \geq 0 \quad \forall t \in T, \forall e \in E, \forall c \in C \tag{1}$$

$$y_{tec} \geq 0 \quad \forall t \in T, \forall e \in E, \forall c \in C \tag{2}$$

$$w_{te} \geq 0 \quad \forall t \in T, \forall e \in E \tag{3}$$

$$n_t \geq 0 \quad \forall t \in T \tag{4}$$

We now state the flow conservation constraints. Constraints (5), (6), and (7) set up the logical relationship between present, past, and future stock for all three classes. We define the current stock as the available stock on the previous period minus the previous period's sales and transfers.

$$\begin{gathered} x_{te1} = x_{t-1,e-1,1} - y_{t-1,e-1,1} \\ \forall t \in T, \forall e \in E, e > 0 \end{gathered} \tag{5}$$

$$\begin{gathered} x_{te2} = x_{t-1,e-1,2} - y_{t-1,e-1,2} - w_{t-1,e-1} \\ \forall t \in T, \forall e \in E, e > 0 \end{gathered} \tag{6}$$

$$\begin{gathered} x_{te3} = x_{t-1,e-1,3} - y_{t-1,e-1,3} + w_{t-1,e-1} \\ \forall t \in T, \forall e \in E, e > 0 \end{gathered} \tag{7}$$

The following group of constraints limits the possible sales within the time horizon. Constraints (8) and (9) demand that if sales occur, they must be at least $minsell_{12}$ and at most $maxsell_{12}$ for both Class 1 and Class 2. Constraint (10) forbids sales in the final period, this avoids last-period sales that could comply with end stock requirements. Constraint (11) binds sales to be less than or equal to the existing stock.

$$\sum_{e\in E}\sum_{c\in C, c\neq 3} y_{tec} \geq minsell_{12}s_t \quad \forall t \in T \tag{8}$$

$$\sum_{e\in E}\sum_{c\in C, c\neq 3} y_{tec} \leq maxsell_{12}s_t \quad \forall t \in T \tag{9}$$

$$y_{maxPeriods,e,c} = 0 \quad \forall e \in E, \forall c \in C \tag{10}$$

$$y_{tec} \leq x_{tec} \quad \forall t \in T, \forall e \in E, \forall c \in C \tag{11}$$

The following group of constraints specifies stock movements. Constraint (12) sets the initial stock in the corresponding variables. Constraint (13) restricts the end stock of animals in Class 3 to be at least the same levels as the initial stock of Class 3 for all ages. Constraint (14) repeats constraint (13) for a subset of less than 30-month-old breeding cows, ensuring that the business cycle is possible in the future while the proportion of younger cows in Class 3 remains relatively stable. This allows for mitigating the "end of the world" effect in this temporally-constrained model, which could make myopic decisions in the last periods since there are no further periods to consider.

$$x_{0ec} = initialStock_{ec} \quad \forall e \in E, \forall c \in C \tag{12}$$

$$\sum_{e\in E} x_{0e3} \leq \sum_{e\in E} x_{maxPeriods,e,3} \tag{13}$$

$$\sum_{e\in E: e<30} x_{0e3} \leq \sum_{e\in E} x_{maxPeriods,e,3} \tag{14}$$

We now specify constraints related to transfers between classes. Constraint (15) binds transfers to be less than or equal to the available stock minus sales in that period. Constraint (16) forbids transfers in the initial period, in order to control unwanted behavior. Constraint (17) forbids transfers for all ages except age 11.

$$w_{te} \leq x_{te2} - y_{te2} \quad \forall t \in T, \forall e \in E \tag{15}$$

$$w_{0e} = 0 \quad \forall e \in E \tag{16}$$

$$w_{te} = 0 \quad \forall t \in T, \forall e \in E, e \neq 11 \tag{17}$$

Finally, we specify constraints related to births. Constraint (18) forbids births in the initial period, in order to avoid unwanted behavior. Constraint (19) enables births for each existent breeding cow over 23 months of age, $pregRate$ animals from Class 1 and Class 2 will be added to the stock in that period for each birth-ready cow. Constraint (20) forbids births in months other than August. Constraint (21) binds the age-zero stock to be defined only by births except in the initial period, and we assume that the births of male and female cows are equiprobable. Finally, constraint (22) specifies that no Class 3 births are allowed.

$$n_0 = 0 \quad \forall c \in C \tag{18}$$

$$n_t = \sum_{e \in E : e \geq 24} pregRate x_{te3} \quad \forall t \in AP \tag{19}$$

$$n_t = 0 \quad \forall t \in NAP \tag{20}$$

$$x_{t0c} = \frac{n_t}{2} \quad \forall t \in T : t > 0, \forall c \in C : c \neq 3 \tag{21}$$

$$x_{t03} = 0 \quad \forall t \in T \tag{22}$$

We implemented the model in the ZIMPL modeling language [22], which provides a clean and straightforward environment for translating the model constraints into an input accepted by a MILP solver. We used the SCIP solver [23] for solving the instances. According to our experience, this machinery was sufficient for solving all the considered instances with optimality within acceptable running times.

5. Experimental Results

In this section, we will describe two strategies designed to analyze and validate the model solutions, with the objective of understanding whether the proposed model adds business value, in which scenarios it works, and how it adapts to changes in settings. The main metric we are going to study is the total revenue, while also considering other dimensions such as changes in stock allocation, sales distribution, reproduction, and transfers.

Our first benchmark strategy attempt was to map real past business decisions and replicate the same input settings for the solver, get the revenue obtained from both, and compare for multiple time windows. This strategy failed to ensure comparability between past business decisions and decisions proposed by the model, since it was not possible to precisely replicate the input data and the assumptions made by the company when these decisions were made. However, there were three noteworthy lessons obtained from the process, which are interesting from a modeling standpoint.

- End of the world. As the solver optimizes for the modeled time period, it will tend to sell all possible stock (including reproductive) stock before or during the last period. This can lead to noise and unwanted conclusions. To deal with this, buffer extra periods were added to the model experiment to delay this "end of the world" effect and have sound conclusions for the original periods. This was complemented by manually calculating the experiment revenue before the buffer periods are reached, in order to ensure the robustness of the conclusions.
- Age translation. In the last period, all business-side stocks exist in a specific category, which has a selling price and an associated cost, and there are no "in between" quantities in the business stock report. Differently, the model will usually end with some stock units at an age that has no price associated and thus cannot be sold directly (especially when adding buffer periods). In order to tackle this situation, we "move" this stock to the nearest selling stage and use that price and cost, sometimes upward the lifecycle and sometimes downward depending on which one is closer.
- Solver-informed prices. Future prices are unknown to the business owners so decisions are made based on expected future prices. The solver instead optimizes knowing the prices for all periods, which is an advantage when compared against human past choices. To cover this, solver-informed prices would be generated by a simple forecasting model.

Due to these facts in the preceding list, we resort to the following experimental comparison with the strategies currently in use at the company. We synthesized day-to-day business decision making into general heuristics that can be abstracted into model constraints, thus enabling us to compare this setting with an unrestricted solver in a more elegant benchmark with fewer or none comparability issues. After discussing with the business owners, they could describe three rules that represent how they usually manage their stock and sales flows, namely:

> *"For all female newborns during the exercise, 30% is sold at early stage (Stage 1), 30% is sold between Stages 2 and 3, and the remaining 40% is saved for reproduction".*

These rules are represented by the following constraints.

$$70.3\frac{n_t}{2} = \sum_{e \in sell_1} y_{t+e,e,2} \qquad \forall t \in AP : t + 6 < maxPeriods \tag{23}$$

$$0.3\frac{n_t}{2} = \sum_{e \in sell_{23}} y_{t+e,e,2} \qquad \forall t \in AP : t + 16 < maxPeriods \tag{24}$$

$$0.4\frac{n_t}{2} = w_{t+11,11} \qquad \forall t \in AP : t + 11 < maxPeriods \tag{25}$$

Constraint (23) asks that 30% of the female births are sold at Stage 1, whereas constraint (24) asks 30% of these births to be sold at Stages 2 and 3. Finally, constraints (25) ask 40% of the female births to be assigned to Class 3. This way, we are able to mimic within the model the decisions taken by the company, in order to perform a fair comparison between the two strategies. We call the baseline model to the model composed by constraints (1)–(25), whereas the model given by constraints (1)–(22) will be called the free model. As the baseline model is more restricted than the free model, we will always expect the optimal value of the free model to be higher than the optimal value of the baseline model. The key will be in understanding both the magnitude of the difference and how that difference is obtained regarding business calls. We will restrict both models to finish the exercise with the same amount or more of reproductive class as received during the initial period. This enforces both models to avoid a solution that won't allow the business to keep running in the future.

The decision to use a model based on the company's current heuristics as the primary benchmark, rather than comparisons with other optimization approaches, responds to the objective of validating the empirical impact of the solution on the business in a "fair" setting. Since the decisions taken by the company may be affected by external considerations not present in the model, a direct comparison may be unfairly biased in favor of the MILP model. Instead, the proposed comparison can be interpreted as the identification of an "optimization gap" with respect to current practices, namely a reflection of the efficiency gains with respect to manual practices in a clean setting.

We defined a set of 24 instances based on a grid of settings that allows us to evaluate the model's impact in multiple scenarios. Instances are given by specific settings on which we are going to compare the results for the free model with the results for the baseline model. **Table 1** provides details on these instances and on the obtained solutions. The columns in this table contain the following information.

- Instance: Instance name.
- Start month: The month of the year in which the instance begins.
- Periods: Number of periods (months) between start and end date.
- Fixed prices: Represent whether the selling prices remain constant during all periods, or if the prices come from a multi-period forecast instead. This setting allows us to assess the decisions without the influence of price variations.

Table 1. Instance settings with the obtained results.

Instance	Start Month	Periods	Fixed Prices	Discount Factor	Free Model Objective	Baseline Model Obj.	Relative Impact
Instance 1	January	24	No	0%	138,960	135,881	2.3%
Instance 2	June	24	No	0%	214,763	174,783	22.9%
Instance 3	January	24	No	0%	155,077	147,267	5.3%
Instance 4	January	36	No	0%	180,379	157,766	14.3%
Instance 5	January	42	No	0%	275,843	201,437	36.9%
Instance 6	January	48	No	0%	239,279	206,043	16.1%
Instance 7	January	24	Yes	0%	276,975	245,771	12.7%
Instance 8	June	24	Yes	0%	419,392	341,765	22.7%

Table 1. *Cont.*

Instance	Start Month	Periods	Fixed Prices	Discount Factor	Free Model Objective	Baseline Model Obj.	Relative Impact
Instance 9	January	24	Yes	0%	386,107	358,127	7.8%
Instance 10	January	36	Yes	0%	383,903	313,586	22.4%
Instance 11	January	42	Yes	0%	492,248	367,824	33.8%
Instance 12	January	48	Yes	0%	506,185	395,788	27.9%
Instance 13 (FP)	January	120	No	0%	442,013	313,385	41.0%
Instance 14 (FP)	January	120	Yes	0%	2,377,258	1,191,302	99.6%
Instance 15 (FP)	January	24	No	0%	49,024	46,298	5.9%
Instance 16 (FP)	January	48	No	0%	93,886	73,026	28.6%
Instance 17 (FP)	January	72	No	0%	134,147	94,211	42.4%
Instance 18 (PI)	January	24	No	0%	134,479	131,268	2.4%
Instance 19 (PI)	January	120	No	0%	263,325	203,497	29.4%
Instance 20 (FC)	January	24	No	0%	136,680	133,469	2.4%
Instance 21 (DF)	January	120	No	0.5%	211,947	181,929	16.5%
Instance 22 (DF)	January	120	No	1%	203,385	181,270	12.2%
Instance 23 (DF)	January	24	No	0.5%	132,194	129,222	2.3%
Instance 24 (DF)	January	24	No	1%	132,982	130,119	2.2%

Note: Own elaboration, objective function values rounded to thousands.

- Discount factor: Time-value-of-money discount factor to all periods within the variant. This represents scenarios where economic decisions are evaluated on a consistent present-value basis.
- Free model objective: Optimal objective function for the free model, i.e., the model that is not restricted by the business heuristic constraints (23)–(25).
- Baseline model objective: Optimal objective function for the baseline model, i.e., the model restricted by the business heuristic constraints (23)–(25).
- Relative impact: Percentage difference between the optimal objective function of the free and the baseline models.

The following three minor settings apply to some of the instances and are specified close to the instance name in **Table 1**.

- Forecasted prices: Instances including "FP" near their name utilize forecasted prices as part of the data inputs from January and later. To forecast the prices, we used a detrended Holt-Winters model (no trend). This allows us to run experiments on more periods beyond our existing price data.
- Fixed cost for sales. Instances including "FC" in their name have sales fix cost increased from 10 to 100. This scenario could represent an increase in cattle transportation to the selling market.
- Pregnancy index. Instances including "PI" in their name have the pregnancy index modified from 86% to 70%, representing a case where breeding cows is harder. This would impact required transfers to comply with business sustainability restrictions, among other factors.
- Discount factor. Instances including "DF" in their name include a nonzero discount factor.

In the proposed experiments, the solver explores a search space ranging from 21.497 variables in the 24-period instances to 104.057 variables in the 120-period instances. As mentioned previously, running times to optimality are acceptable. We now explore the results on these instances.

Objective function. As a first result, we are interested in the relative difference between the objective function for the baseline model (i.e., constrained with the heuristic business rules) and the free model. The results reveal a minimum positive impact of 2% and a maximum of 96% with a median value of 22.4%. Excluding the outlier exhibited on Instance 14, we can interpret that the positive impact revolves around 0% to 40%.

Evidence shows that longer runs appear to establish a bigger impact, with a Pearson correlation coefficient between relative impact and number of experiment periods of 0.83. **Figure 2** contains one line plot per instance showing the objective function absolute difference cumulative sum between the two models. The line over zero means that the free model is accumulating a higher value at that specific period on the horizontal axis. This representation can provide a sense of how each model competes on a period-to-period basis in order to maximize revenue. With the exception of Instance 15, there is always a subset of periods where the baseline variant accumulates more revenue, to be later surpassed by the free variant. This indicates a pattern of delaying present revenue into later periods.

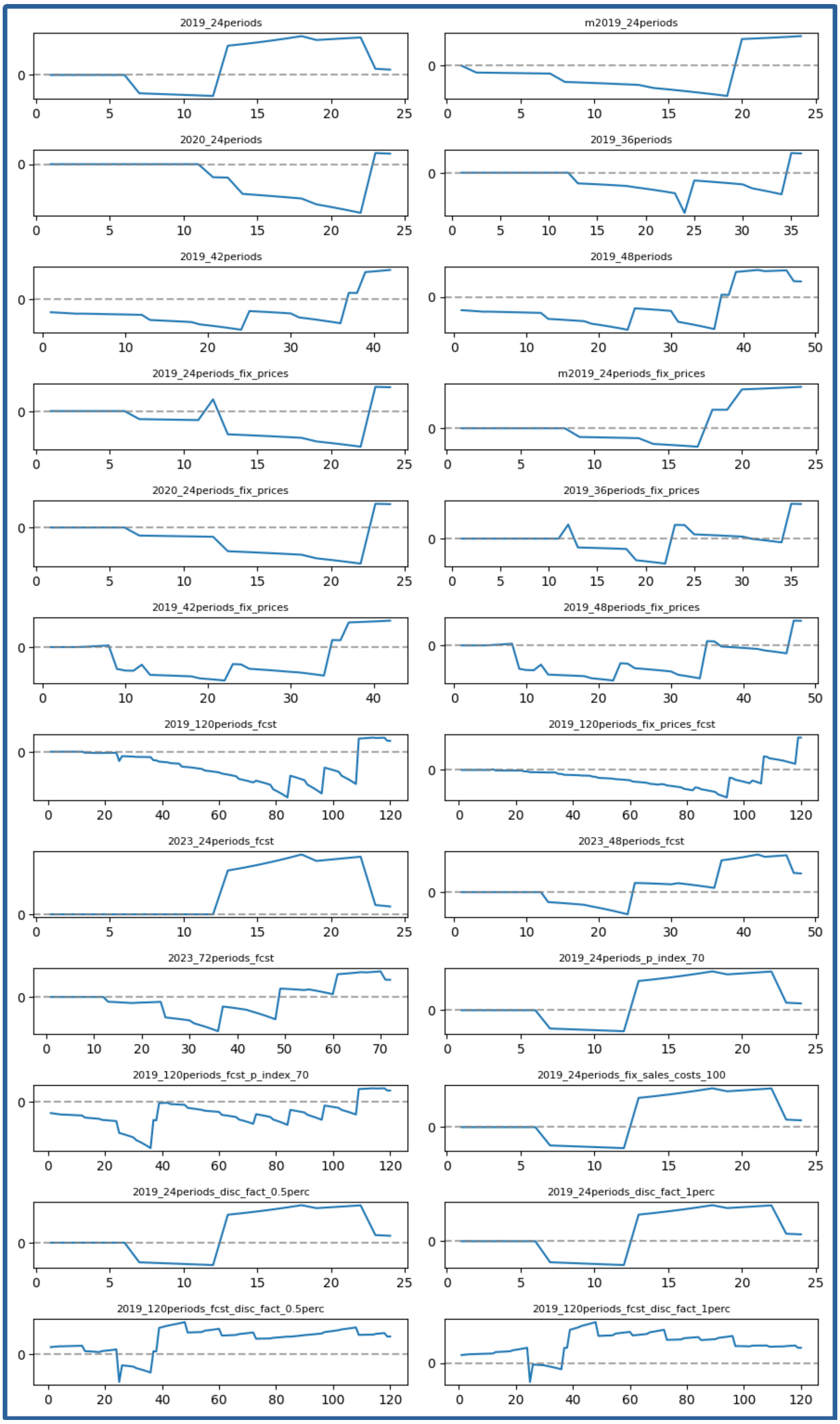

Figure 2. Objective function cumulative absolute difference between variants per instance through periods.

Revenue difference emerges during the second half of all instances. The transition from negative to positive occurs mostly in the last 20% of the periods. This highlights that these periods are highly relevant in shaping the global impact within each instance. We can conclude that the free model accumulates less revenue during the first half of the experiments, which is then surpassed by the revenue in the second half, making a positive difference over the baseline model. This is probably related to higher upfront costs related to increasing reproductive stock towards a higher return rate in future periods.

Sales. We now explore how sales are solved for. According to the obtained results, there is a general exchange between selling more at Stages 1, 2, and 3, with a counterpart of selling less at Stage 4. This means that the baseline model is selling more reproductive stock (at a lesser price) than the free model. This can be explained because heuristic rules consistently assign 30% of female newborns to reproductive stock. This stock exceeds the requirement to at least maintain the reproductive stock given in the initial period by the end of the instance. This excess enables sales of reproductive stock to increase revenue (even at a reduced price compared to the other stages).

There are two instances that don't follow this rationale and make more Stage 4 sales, both being the 120-period instances. Apparently, with enough reproduction cycles (one per year) available during the instance duration, a positive impact on revenue can be obtained by increasing reproductive stock as it increases future sales. This potentially compensates for revenue loss from reduced selling prices for reproductive stock sold at Stage 4.

In summary, there is a clear difference between how sales are conducted. As a first conclusion, we can observe that Stage 4 sales are lower except for the two longer instances. A second conclusion is that the number of considered periods in the instance may impact sales composition, so it is advisable to consider as many periods as possible.

Transfers. We now explore transfers, i.e., the quantity of Class 2 (female) stock that is transferred into Class 3 stock (reproductive). This change can be performed at the 11th month of age only and is irreversible. The results for most instances show a decrease in transfers ranging between 25% to 100%. In the cases where no transfers are performed, this must be aligned with no Stage 4 sales to fulfill the sustainability restriction. In correlation with the sales analysis, the only two instances that show increased transfers are the longer 120-period instances, from a 50% increase to doubling the number of transfers. We can establish that more periods in the instance are correlated with more transfers. The Pearson correlation coefficient between both variables is 0.9263.

Pregnancy index. Reducing the pregnancy index has a negligible effect on short-horizon instances but leads to a 28.3% reduction in relative performance in long-horizon variants. A lower pregnancy rate decreases the expected return on investment of transfers to the reproductive class by extending the number of breeding cycles required to recover the associated maintenance costs. Consequently, the optimal policy shortens the effective planning window over which reproductive stock expansion remains profitable. The breakeven threshold at which the model abandons reproductive accumulation in favor of a liquidation-oriented strategy is anticipated to approximately period 40, compared to period 80 under the equivalent higher pregnancy index variant, resulting in an earlier transition toward short-term sales decisions without further increases in reproductive stock.

Discount factor. The discount factor introduces an incentive for earlier sales by reducing the present value of long-term inventory accumulation strategies, particularly in long-horizon variants. While its impact on short-term scenarios is negligible, the relative lift in long-term variants is significantly reduced. This behavior proposes a more realistic representation of long-term optimization in economies exposed to high inflation like Argentina, where future revenues are heavily discounted. As the discount factor increases, strategies exhibit a stronger bias toward early liquidation over delayed, higher-priced sales.

6. Analysis of Specific Instances

In this section, we will review the results for two specific instances, with the objective of gaining further knowledge of the behavior of the proposed solutions. We first consider Instance 8, a 24-period instance that starts in June (the first winter month in the Southern Hemisphere) for which the free model makes fewer transfers than the baseline model.

Figure 3 compares the free variant above to the baseline variant below. The height of barplots represents stock maintained per period, horizontally divided into three blocks, one per class. The color darkness represents stock age. This plot gives us a perspective on how stock decisions are made on a period-to-period basis for each class.

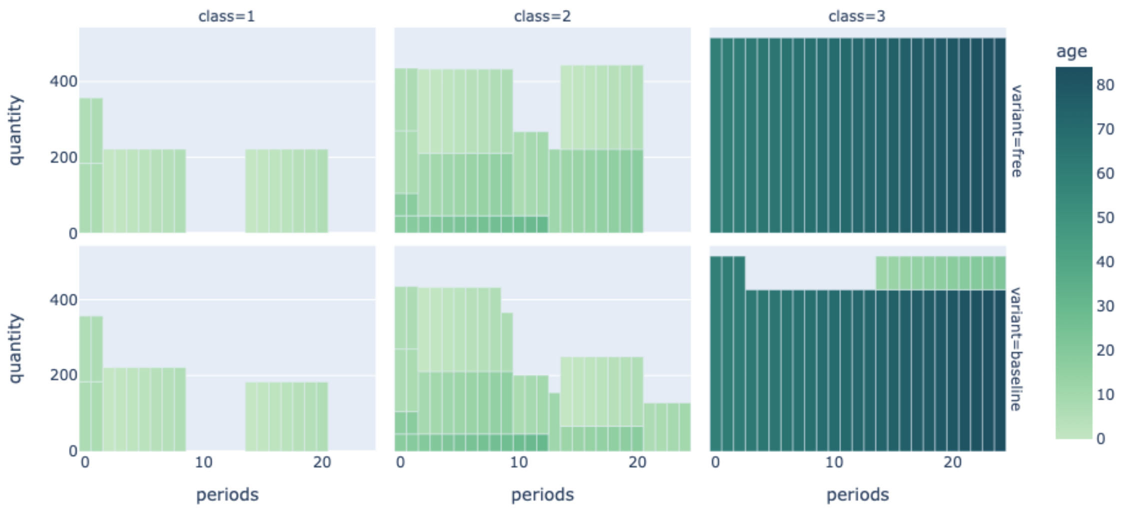

Figure 3. Stock per period, class and age per variant for Instance 2.

This instance shows two interesting aspects that are worth mentioning. The first aspect is given by the fact that the baseline model ends with unsold Class 2 stock, which is a loss of potential revenue. This can be explained by the newborn sales composition restrictions that the baseline variant enforces.

In this instance, we have two breeding windows at periods 2 and 14. All generated newborns from the second breeding period are sold at Stage 1 at the free model as there is not enough time to reach any other selling stage, regardless of the profit that each stage could generate. The baseline model is only allowed to sell 30% of newborns at Stage 1, ending with 155 units of unsold Class 2 stock. This generates a profit loss to the baseline model compared to the free model.

The second relevant aspect that stands out is the baseline model selling 88.58 units of reproductive Class 3 stock in the second period. The model does not wait until the second enabled breeding window at period 14 to make those sales since the cost to maintain potentially generated newborn stock and higher Class 3 maintenance costs until period 14 is higher than the newborn's selling value at Stage 1, for 30% Class 2 and 100% Class 1. Hence, it is better not to breed stock at all if the variant is only allowed to sell 30% of female stock, as the maintenance costs are higher than the obtained revenue.

In conclusion, two sources of increased revenue are found that give the free models the means to reach a 22.9% relative revenue increase. The first such source is given by the higher flexibility regarding how to allocate newborn sales on different selling stages. The second source is given by the flexibility in transfer management and business sustainability, represented in maintaining reproductive stock over time while optimizing revenue.

We conclude this section by reviewing the results for Instance 13, a 120-period instance, 10 of them being breeding periods. Contrasting to the other group of 17 shorter period instances, this instance represents one of the two cases where transfers are increased. As before, we report in **Figure 4** the stock per period, for each class.

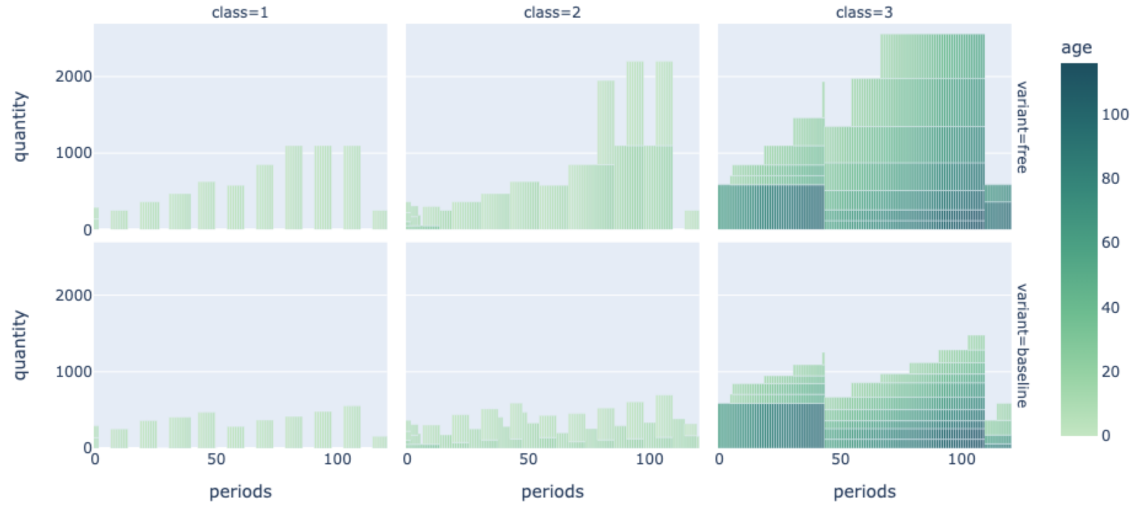

Figure 4. Stock per period, class and age per variant for Instance 13.

Both models exhibit an increase in Class 3 stock over time. Eleven periods prior to the instance ending at period 109, both models sell Class 3 stock, falling back to initial stock levels to comply with the sustainability constraint. The free model obtained a 41.1% revenue increase with respect to the baseline model, and proposes an increase in transfers of 50.42%.

A primary distinction is at the phase at which transfers are allocated. The baseline model steadily increases the reproductive stock by following up with the heuristic rules, assigning 40% of newborn stock to Class 3 every year. The free model surpasses this ratio by rapidly increasing Class 3 allocation at the detriment of Class 2 earlier sales.

The free model continues transferring stock from Class 2 to Class 3 until period 66. Class 3 quantities remain constant until period 109, at which point 61% of the total stock is sold. We could ask why it is optimal to sell Class 3 stock on period 109 if there is one more last breeding window at period 115. The answer lies in the fact that newborn-generated stock for that breeding window hits the age of 5 months by the last period. This is one period away from reaching Stage 1, which occurs between the ages of 6 and 8 months. This makes breeding more, not optimal in the last window. Some amount is proposed by both solutions as a certain amount of Class 3 is required to match the initial Class 3 stock to comply with sustainability constraints. The baseline solution performs more breedings on this last window, caused by a more restricted model regarding transfers.

Class 2 sales in the free model are deferred towards earlier transfers, proposing no sales between period 13 and 85, this choice accelerates the rate at which reproductive stock increases. During the last period, the sales in the free model yielded a significant revenue difference compared to the baseline model. Class 1 sales quantities increase year to year for both models. Higher quantities of maintained reproductive stock also lead to higher male newborns, subsequently translating into more sales.

In summary, contrasting the analysis from shorter duration instances, there is a shift in the proposed solution strategy. Longer instances are giving enough time to redeem the investment made in reproductive stock and capture long-term revenue by performing later higher sales. This is one example of the model's capacity to adapt effectively in response to various settings and input variables, showcasing its flexibility to respond to diverse proposed scenarios. The turning point in making this shift could be generated by a combination of factors. Increasing selling prices, cost reduction, a higher pregnancy rate or a combination of all of them with other inputs can directly reduce or increase the number of periods into reaching this strategy shift.

7. Conclusions

In this work, we propose a MILP model for optimizing livestock planning decisions. We conducted a benchmark analysis for a set of 24 instances, exploring how the proposed solutions solve for a diverse grid of configurations. The experiments show a positive impact on the total profit between 2% and 40% with a median value of 22.4%, excluding an outlier instance of significantly higher revenue. Prioritized selling stages between variants exhibit high variability based on inputs, showing model flexibility upon given inputs. Nevertheless, as the number of periods increases, in general, a greater revenue impact can be achieved.

Baseline levels of reproductive stock allocation are exceeded only in longer instances as time is required for the investment to yield benefits. Instance duration plays a crucial role towards optimal solution being to exceed baseline levels, other relevant model inputs such as price fluctuations directly influence the period in which this shift occurs.

Our evidence indicates that the analytical solution based on optimization techniques can successfully capture the main dimensions of the business problem. The obtained solutions show high adaptability to changing input variables, demonstrating versatility while utilizing explainable strategies that can be used to provide insights to the decision maker into improving their operation. According to our experience, data visualization tools are essential in order to improve the understanding and explainability of the outputs.

Although the model is fundamentally deterministic, its robustness against uncertainty is validated through an exhaustive sensitivity analysis implemented via 24 different scenarios. By varying critical parameters such as price projections (using the Holt-Winters method), pregnancy rates, and fixed costs at different historical moments, the results demonstrate that core strategic decisions remain stable and consistent. This stability suggests that, for the tactical purposes of a livestock company, the deterministic model provides a reliable and explainable roadmap, mitigating the need for more complex stochastic frameworks that could obscure the underlying business logic.

Upon these findings, spending resources and time to refine the model and build an integration as a prescriptive solution emerges as a promising business opportunity. As future research, it would be interesting to consider the following dimensions.

- Grass feed mixture utilized to feed cattle is produced locally. When depleted, it is then bought from other producers. Outsourcing is generally more expensive and the price can increase more if the market supply is low due to scarce rains or hail falling during the previous harvesting season. This can impact breeding costs and is usually associated with selling at earlier stages of the life cycle (Stage 1) rather than later stages. Opting to reduce production and utilize only in-house grown grass feed reduces price uncertainty but could also negatively impact revenue. Including grass consumption, availability and outsourcing prices would provide a more realistic cost dynamic for the breeding operation.
- Bulls are bought (usually from foreign markets). Decisions and restrictions related to how many bulls are required and their cost to satisfy breeding for all the female classes are not being modeled. We consider that modeling bulls will not pay off the increase in complexity for adding a fourth class to the model and adding more constraints to describe this situation. This could change if we want to consider multiple species, in which case this variable could gain relevance.
- Costs related to infrastructure and hand labor adapting according to the stock being maintained in different age groups. Data related to how costs and labor increase per operation size was not available but would be relevant to gather in future research.
- Local and foreign government policy is constantly changing, affecting how agents decide and project business expected revenue, both short and long term. Examples of government policies implemented in the last ten years range from setting maximum export prices, variable taxes relative to global prices, or enforcing a selling quota to a specific selling stage. Depending on the political orientation of the ruling government, drastically different scenarios are expected to happen given the polarization in

both parties related to commercial policies. These can be a leading factor and one of the central factors in the decision making. Incorporating these externalities into a framework that describes how different scenarios could impact the operation theoretically could be valuable to consider.

In conclusion, we believe that the MILP model proposed in this work is valuable and can be helpful for decision makers in livestock operations. The ability of adapting to multiple scenarios and to incorporate business constraints is key to providing a robust and interpretable solution. According to our experience, there are plenty of business opportunities in this field, and it would be interesting to explore further refinements and lines of research on these topics.

Author Contributions

Conceptualization, J.P.T. and J.M.; methodology, J.M.; software, J.P.T.; validation, J.P.T. and J.M.; data curation, J.P.T.; writing, J.M. Both authors have read and agreed to the published version of the manuscript.

Funding

No funding was received for this research.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

The model implementation and the instances are available upon request from the authors.

Acknowledgments

The authors are grateful to the anonymous reviewers for their detailed and insightful comments, which greatly helped to improve this manuscript and provided further conclusions on the model results.

Conflicts of interest

The authors declare no conflict of interest.

References

[1] Ras, C.H., Marra, R., Tettamanti, M., 2020. Changes in land use between agriculture and livestock farming in a typical establishment in General Pinto, Pradera Pampeana, Argentina, analyzed with linear programming. Agronomía & Ambiente. 40(2), 151–163. (in Spanish)

[2] Aliano Filho, A., Melo, T., Vaz Pato, M., 2020. Tactical planning of sugarcane harvest and transport operations. Schriftenreihe Logistik der Fakultät für Wirtschaftswissenschaften der htw saar (Technical Reports on Logistics of the Saarland Business School). 18. Available from: https://www.ifors.org/wp-content/uploads/2021/09/2020_HTW-Technical-Report-Tactical-planning-of-sugarcane-harvest-and-transport-operations.pdf

[3] Petropoulos, F., Gilbert, G., Aktas, E., et al., 2024. Operational Research: Methods and Applications. Journal of the Operational Research Society. 75(3), 423–617.

[4] Wilton, J., Morris, C., Jenson, E., et al., 1974. A linear programming model for beef cattle production. Canadian Journal of Animal Science. 54, 693–707.

[5] Heidari, M., Turner, I., Ardestani-Jaafari, A., et al., 2021. Operations research for environmental assessment of crop-livestock production systems. Agricultural Systems. 193, 103208.

[6] Sharma, S., Murari, N., Randhawa, Z., et al., 2022. Making agriculture efficient with Operations Research. Journal of Research in Agriculture and Animal Science. 9(11), 6–9.

[7] Hlavatýa, R., Krejcí, I., Houška, M., et al., 2021. Understanding the decision-making in small-scale beef cattle herd management through a mathematical programming model. International Transactions in Operational Research. 30(4), 1955–1985.

[8] Doole, G.J., Romera, A.J., Adler, A.A., 2013. An optimization model of a New Zealand dairy farm. Journal of Dairy Science. 96(4), 2147–2160.

[9] Bhamare, M., 2023. Enhancing livestock management efficiency through Operations Research: Advancements in feed formulation, genetic optimization, and disease control. International Journal of Engineering Applied Sciences and Technology. 8(3), 74–80.

[10] Popa, C., Stefanov, O., Goia, I., 2025. Multimodal

Livestock Operations Analysis Using Business Process Modeling: A Case Study of Romanian Black Sea Ports. Economies. 13(3), 69.

[11] Ghebretsadik, A., 2004. Farm Planning for a Typical Crop-Livestock Integrated Farm: An Application of a Mixed Integer Linear Programming Model [Master's Thesis]. University of Stellenbosch: Stellenbosch, South Africa.

[12] Gameiro, A., Rocco, C., Caixeta-Filho, J., 2011. Mathematical model to optimize a dairy farm characterized by crop-livestock integration: Economic, logistic, social and environmental aspects. In Proceedings of the International Conference on Operational Research, Phuket, Thailand, 21–23 December 2011.

[13] Frank, R.G., 2021. How many people can the Pampas region feed? Anales de la ANAV. LXXII, 72–83. (in Spanish)

[14] Campanella, S.R., Corsano, G., Montagna, J.M., 2018. A modeling framework for the optimal forest supply chain design considering residues reuse. Sustainable Production and Consumption. 16, 13–24.

[15] Gradowczyk, M., Jacovkis, P., Freisztav, A., et al., 1990. Water resources optimization—simulation in Argentina. European Journal of Operational Research. 49(2), 247–253.

[16] Alemany, M.M.E., Esteso, A., Ortiz, A., et al., 2021. Centralized and distributed optimization models for the multi-farmer crop planning problem under uncertainty: Application to a fresh tomato Argentinean supply chain case study. Computers & Industrial Engineering. 153, 107048.

[17] Donmuen, M., Suntinac, A., Arunyanart, S., 2025. A multi-period optimization model for hydroponic crop planning and scheduling in a centralized supply chain. Expert Systems with Applications. 297(Part C), 129362.

[18] Benini, M., Blasi, E., Detti, P., et al., 2023. Solving crop planning and rotation problems in a sustainable agriculture perspective. Computers & Operations Research. 159, 106316.

[19] Gómez-Lagos, J., González-Araya, M., Acosta-Espejo, L., et al., 2024. Supporting tactical harvest planning decisions of major fruits through a multi-objective modeling approach by using exact methods. Expert Systems with Applications. 251, 123929.

[20] Fikry, I., Gheith, M., Eltawil, A., 2021. An integrated production-logistics-crop rotation planning model for sugar beet supply chains. Computers & Industrial Engineering. 157, 107300.

[21] Shadkam, E., Irannezhad, E., 2025. A comprehensive review of simulation optimization methods in agricultural supply chains and transition towards an agent-based intelligent digital framework for agriculture 4.0. Engineering Applications of Artificial Intelligence. 143, 109930.

[22] Koch, T., 2004. Rapid Mathematical Programming [PhD Thesis]. Technische Universität Berlin: Berlin, Germany.

[23] Bolusani, S., Besançon, M., Bestuzheva, K., et al., 2024. The SCIP Optimization Suite 9.0. Zuse Institute Berlin: Berlin, Germany.