A Many-Objective Optimization Approach for Weight Gain and Animal Welfare in Rotational Grazing of Cattle

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Abstract

The "multidimensional" nature of the concept of welfare is reflected in the definition proposed by the World Organization for Animal Health (OIE), according to which an animal is in a satisfactory state of welfare when it is healthy, comfortable, and well-fed, can express its innate behavior, and does not suffer pain, fear, or distress. Many of these aspects, in the real context of a cattle farm, are not considered, and most of the farmers' decisions are based on their experiences. In this proposal, we establish a many-objective optimization model for rotational grazing allocation based on six objectives that consider cattle weight gain and travel, as well as their welfare. The model is solved using the NSGA-III algorithm, and its performance is evaluated using a simulation study of 90 days of rotational grazing in which it is compared with the traditional grazing strategy. Average weight gains of up to 36.7 kg per animal are achieved at the end of the three months of simulated grazing using the proposed model. The results indicate that the allocation model generates an average weight gain that is statistically greater than that generated by the traditional rotation method but also guarantees improved animal welfare, the main contribution of our approach.

keywords: Many-objective Optimization, Artificial Intelligence, Precision Livestock Farming, Animal Welfare, Rotational Grazing

1 Introduction

The concept of animal welfare includes three elements: the proper functioning of the organism (which implies, among other things, that the animals are healthy and well-fed), the emotional state of the animal (including the absence of negative emotions such as chronic pain and fear), and the possibility of expressing some normal species-specific behaviors [1].

According to the so-called principle of the five freedoms, the welfare of an animal is guaranteed when the following five requirements are met [2]: the animal does not suffer from thirst, hunger, or malnutrition because it has access to drink water and is provided with a diet adequate to its needs, the animal does not suffer physical or thermal stress because it is provided with a suitable environment, including shelter from inclement weather and a comfortable resting area, the animal does not suffer pain, injury or disease thanks to adequate prevention and/or rapid diagnosis and treatment, the animal can exhibit most of its normal behavioral patterns because it is provided with the necessary space and adequate facilities, and is housed in the company of other individuals of its species, and the animal does not experience fear or distress because the necessary conditions are guaranteed to avoid mental suffering. The principle of the five freedoms constitutes a very useful practical approach to the study of welfare, and especially, to evaluate these aspects on livestock farms and during the transport and slaughter of farm animals.

On the other hand, one way of feeding cattle is using rotational grazing; this type of grazing has been used in livestock farming for many years, and has been recognized as a more efficient and sustainable alternative to continuous grazing [3]. Rotational grazing is a strategy used by livestock farms, dividing their land into smaller plots through the use of electric or wire fencing. Its main objective is to achieve a balance between pasture supply and the nutritional needs of livestock [4]. In situations where the same amount of pasture is available, rotational grazing allows a greater number of cattle to be maintained, resulting in higher productivity [3]. In addition to natural factors, overgrazing is one of the main causes of degradation of rangeland ecosystems [5]. Rotational grazing presents itself as a reasonable option to combat overgrazing, as it helps to increase rangeland productivity and improve ecosystem functionality. Generally, the periods of occupancy, rest, and allotment in rotational grazing are determined based on the subjective experience of livestock farmers [6]. High-quality forage management together with animal welfare are some of the current limitations on cattle farms highlighted in a recent systematic review of the literature [7].

1.1 Related Works

Depending on the number of objectives, an optimization problem is referred to as single-objective, multi-objective, or many-objective [8]. When a multi-objective problem has a large number of objectives (usually more than 4) it is classified as a many-objective optimization problem [9,10]. With respect to the many objectives optimization problem, Raoui *et al.* [11] proposed to address the problems of high-demand and low quality in perishable food distribution through a customer-centric mathematical model that considers delivery times, destination times, and customer priorities. They use a heuristic approach called General Variable Neighborhood Search, which generates multiple solutions and ranks them according to the decision maker's preferences. The results show that this approach generates high-quality solutions and allows different rankings according to the decision maker's profiles. The scientific contributions include the ability of general variable neighbourhood search to generate high quality and efficient generation of many candidate solutions. However, the study lacks environmental features, such as CO2 emissions reduction in the proposed model.

Jafar *et al.* [12] described a common problem in watershed management, where the complexity of water resource systems, the difficulty of high-dimensional modeling, and computational efficiency challenges limit the ability of decision-makers to combine environmental flow objectives (e.g., water quality) with social flow objectives (e.g., hydropower, or water supply). They developed a watershed management decision support tool called Optimum Social-Environmental Flows with Auto-Adaptive Constraints. This approach integrates nine socio-environmental objectives and 396 decision variables into a watershed management model of the Diyala River basin in Iraq. Their contribution is to use evolutionary optimization algorithms, such as the e-DSEA algorithm and the Borg MOEA, to address the complexity of reservoir and catchment management in terms of non-linearity, considering dynamic characteristics. However, their mathematical optimization model does not use characteristics such as lake water inflow, and reservoir water inflow, among others.

Chikumbo *et al.* [13] addressed the land use optimization problem for a large farm, considering 14 objectives including economic, environmental, and social aspects. They used a modified non-dominant sorting genetic algorithm II (NSGA-II), and the solution was represented as a hyperspatial Pareto frontier, which was collapsed into a two-dimensional visualization using a hyperradial visualization approach. Their contributions include the development of a transdisciplinary approach that integrates an innovative epigenetics-based multi-objective optimizer, the incorporation of uncertainty in search space data, and decision-making through visualization of the three-dimensional exchange space. The approach allowed decision-makers to intuitively select a compromise solution based on their preferences under uncertainty. Nevertheless, the study does not focus on specific regions of the Pareto frontier in the process of searching for desired solutions.

White *et al.* [14] developed a model that optimizes pasture and nutritional management to examine the environmental impact of beef production. White *et al.*'s model integrated modules that calculate (1) environmental impact from cradle to the farm gate, (2) diet cost, (3) pasture growth, and (4) willingness to pay. Their contribution was to use different objectives, including the minimization of the cost of the diet, and the minimization of the environmental impact metrics regarding the baseline value, among others. However, more accurate pasture simulation models should be used to accurately simulate the heterogeneity of the landscape.

Raizada *et al.* [15] used multi-objectives to develop alternative land use plans to optimize four objective functions: maximizing (1) farm income, (2) employment (3) nutritional security and (4) forage production, and minimizing (1) soil loss (2) watershed level loss, to guarantee a sustainable animal population. The main contribution of this work is the use of modeling methods and paradigms in multi-criteria decision analysis for natural resource management. They also incorporated temporal and spatial environmental data. Addis *et al.* [16] developed a profit optimization model for a silage supplementation scenario. They employed linear programming to identify the optimum carrying capacity of cattle and sheep, the most profitable slaughter ages of cattle, the number of prime lambs (sold to meat processing plants), and the reserve lambs sold (sold to other farmers for finishing). The contribution is the use of optimization to maximize resource allocation efficiency by identifying the optimum number of cattle and sheep that can be managed within the available feed resources, considering strategies such as early finishing of cattle and selling the majority of sheep at their best time. This study lacks research on pasture quality management, the use of breeding cows, and the assessment of uncertainty and risk in model decisions.

Zhai *et al.* [17] proposed a drone mission planning algorithm, which combines Genetic Algorithms and Particle Swarm Optimization, treating the planning problem as a Multi-Objective Optimization problem. Through simulations, they demonstrated the feasibility of the approach in achieving efficient mission planning and optimal resource allocation. Their main contribution is to use a multi-agent system where components, such as UAVs, are considered autonomous agents. Validation through simulations, such as the "precise pesticide spraying" task, supports the effectiveness of the approach by demonstrating the ability to generate optimal mission planning strategies, considering aspects such as expected profit, energy consumption, and equipment loss.

Li *et al.* [18] developed an integrated modeling framework based on the water-energy-food nexus to maximize agroforestry-livestock system performance under uncertain water supply conditions. Using a multi-objective programming approach and empirical frequency analysis for different water supplies. The model addressed the complex interrelationship between energy and material conversion processes on agricultural, forestry, and grazing lands. Their contributions include a systematic analysis of energy flows and material conversion, consideration of trade-offs between economic benefits, efficiency of multiple energy use, and environmental and ecological benefits. Michalak *et al.* [19] approached the multi-objective optimization of neural models to make decisions on vaccine distribution in a scenario of disease spread between farms, pastures, and other locations. Three neural models were analyzed: multilayer perceptrons, classical recurrent neural networks, and short- and long-term memory networks, whose weights were optimized using the MOEA/D algorithm.

Chen *et al.* [20] proposed an optimization model-based evaluation method for configuring integrated crop-livestock systems to improve agricultural sustainability. The Optimization Model-based Energy Evaluation method combines an energy analysis with a non-dominated genetic algorithm NSGA-II programming model. Using economic energy efficiency, environmental energy efficiency and energy sustainability indexes, sustainable development is evaluated. The contribution of this work is the definition of theoretical guidance for quantitative resource allocation in integrated farming systems.

Castonguay *et al.* [21] et al. developed a multi-objective optimization tool for livestock production, addressing economic and environmental objectives in agriculture and animal husbandry. Using advanced techniques, such as high granularity spatial optimization, the model evaluates trade-offs between reducing greenhouse gas emissions and minimizing production costs in beef production. Finally, Shahin *et al.* [22] used multi-objective optimization algorithms and IoT data mining, to calculate farm-level greenhouse gas emissions. They proposed optimized feeding schedules to mitigate emissions. The application is based on a case study on a dairy farm and is positioned as a valuable tool for sustainable emissions management in livestock production.

In relation to some recent works that study the relationship between crop/feeding optimization versus animal health, Erinle *et al.* [23] presented a review of the applicability and impact of fruit pomaces in poultry nutrition. They concluded that the utilization of plants and/or their by-products, like fruit pomaces, has important advantages. They have a rich nutritional composition and phytochemical profile, and are ready availability and a pocket-friendly cost. Particularly, fruit pomaces contain protein, dietary fiber, and phenolic compounds, and thus, can be used by the poultry industry as a substitute for antibiotics and some conventional feedstuff. Also, Mallick *et al.* [24] proposed a linear programming technique to minimize the feed cost for small-scale poultry farms. This approach uses locally available feed ingredients to formulate the broiler feed mix. The dietary nutrient requirements for broilers are determined from the prescribed standard specifications by international standard institutions and sixteen feed ingredients were used to formulate the optimal feed mix, minimizing the total cost of the feed mix subject to the essential nutrient constraints. Alqaisi *et al.* [25] proposed a static linear programming approach for the sustainable feed formulation for crop farmers and livestock producers. The diet formulation defines nutritional and economic feed optimization considering the interaction between feed components over time and the volatile global feed prices.

The work of Han *et al.* [26] proposed a simulation of the system dynamic of herbivorous animal husbandry in agricultural areas. They studied the development of herbivorous animal husbandry, and the balance of livestock-grassland as a constraint. The system designs the development strategy to optimize the herbivorous animal husbandry and the feed planting industry. They found that without any development strategy, the inertia of the system is subject to factors such as the scale of female livestock and epidemic diseases, among other factors. The paper of Dooyum *et al.* [27] presented the problem of feed formulation in the context of the livestock industry as a hard (NP-hard) problem. The feed formulation is defined by specifying the nutritional requirements as rigid constraints to find a feasible cost-effective formulation. They modified the conventional problem with a tolerance parameter to allow the relaxation of constraints and used the differential evolution technique, a type of evolutionary algorithm, to solve the problem.

Gharehchopogh et al. [28] define a population evolution strategy to help the multi-population evolution algorithm improve its global optimization ability and avoid local optimum. They compare this approach with five state-of-the-art variants and seven basic metaheuristic algorithms over 30 benchmark functions. The paper [29] introduces a binary multi-objective dynamic Harris Hawks Optimization (HHO) applied to Botnet Detection in IoT. They improve HHO with a mutation operator to obtain better performance over other machine learning approaches.

As can be seen in the review of the literature, the many-objective models that have been proposed have been dedicated to solving problems such as food distribution, watershed management, land use, or pasture and nutritional management, among others. On the other hand, multi-objective optimization models have been proposed to optimize livestock that can be managed within available food resources and maximize the performance of the agroforestry-livestock system under uncertain water supply conditions, among others. That is to say, there are no works that propose many-objective models that allow, in addition to improving the fattening of livestock, their welfare.

1.2 Contributions

The focus of this work is on the use of beef production variables for optimal grazing decisions while maintaining animal welfare, with a focus on autonomous or semi-autonomous beef production that can be included in autonomous cycles of data analytics tasks (ACODAT) [30, 31]. The ACODAT is a great help in corrective decision-making because it generates knowledge to determine decisions that favor the performance of beef production [32, 33]. Specifically, the objective of this work is to define a dynamic optimization model for the daily allocation of lots of animals to pastures, which can be included in an autonomous system for managing the production process of cattle fattening. Thus, this paper presents a rotational-grazing assignment model that seeks to maximize animal weight gain based on the best quality forage and animal welfare. The main contributions of this work are:

- The definition of a many-objective optimization model for rotational livestock grazing that considers livestock fattening and their welfare.
- The definition of a set of objective functions that describe animal welfare.

This work is organized as follows. Section 2 introduces the assignment mathematical model used in this work. Section 3 shows our approach through different case analyses in meat production. After, Section 4 compares this work with previous work. Finally, Section 5 presents the conclusions and future works.

2 Our Approach

Rotational grazing involves dividing a farm into multiple paddocks, some of which are grazed while others are left to rest [34] (see Figure 1). By reducing the total grazing area and evenly distributing the cattle, this method ensures that forage is consumed uniformly, making it possible to assign different herds to various paddocks [35].

An assignment problem, on the other hand, involves assigning resources to carry out tasks, with the aim of fulfilling specific goals such as maximizing benefits or minimizing costs [36–38]. Thus, the problem of rotational grazing can be viewed as an assignment problem, where the relationship between the resource and the task is equivalent to the correlation between the herds and paddocks in the assignment model.

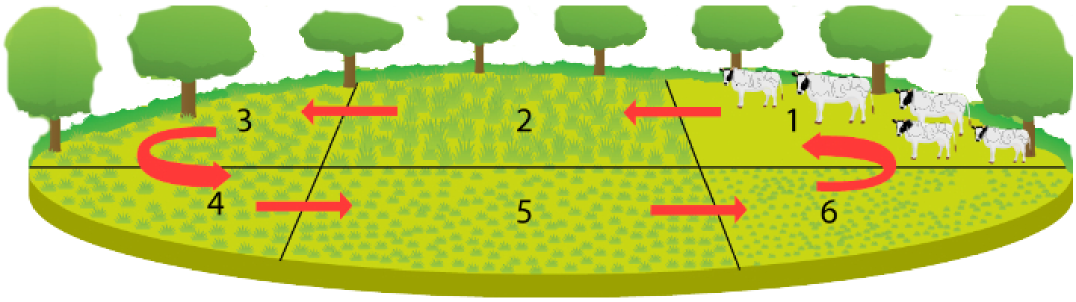


Figure 1: A graphical representation of a rotational grazing system (*Source:* Own elaboration).

This paper proposes a new approach to rotational livestock grazing that takes into consideration animal welfare by means of a mathematical model of many-objective optimization. Thus, what makes our approach novel are mainly two components: the proposal of indices to measure the animal welfare of cattle, which does not exist in the literature reviewed; and the proposal of an optimization model that in addition to maximizing animal weight gain, optimizes animal welfare by maximizing or minimizing the proposed welfare indices.

Specifically, we propose a dynamic optimization model for the daily allocation of animal lots to paddocks. The optimization is guided by six objectives associated with the weight gain of the animals, the walking distance of the cattle when they are moved from one paddock to another, and indices of their welfare such as food availability, temperature, noise, and space of each paddock. The optimization process consists of evaluating the conditions of each paddock on a daily basis and assigning cattle to paddocks in order to maximize cattle weight gain and animal welfare. Each optimization run takes into account the needs of each lot and calculates the estimated number of days each lot should remain in its respective paddock. The reasons for the proposals of welfare indices and the proposed mathematical model of rotational grazing are detailed below.

2.1 Animal welfare in our approach

The five animal freedoms are a set of principles that establish the necessary conditions for animal welfare [39]. Animal welfare freedoms consist of:

- Freedom from hunger and thirst: Continuous access to water and high-quality feed is fundamental to animal welfare.
- Freedom from discomfort: Prevention and treatment of discomfort are essential to ensure animal welfare.
- Freedom from pain, injury, and disease: Early detection and treatment of illness and injury are essential to ensure animal welfare.
- Freedom from fear and distress: Handling, transport, and slaughter of animals should be conducted in a manner that minimizes stress and distress to the animals.

- Freedom to express normal behavior: It is important to provide an environment that allows animals to express their natural behavior, such as foraging for food and water, moving freely, and socializing with other animals of their species.

These freedoms are fundamental to animal welfare, and their fulfillment is essential to ensure the health and well-being of animals. It also improves the quality of animal products for human consumption [40].

In this paper, we propose a mathematical optimization model that includes objectives aimed at increasing animal welfare by maximizing or minimizing variables that measure paddock conditions that are directly related to the freedoms described above. In addition to the weight gain and the distance traveled by the animals, it is proposed to assign herds to paddocks optimizing the following variables: the amount of available forage, noise level, temperature, and available space. The optimization of these conditions together allows for rotational grazing that, in addition to increasing the weight of the cattle, also seeks to improve animal welfare.

Each of these indicator variables is associated with one or more freedoms. For example, access to food helps animals not go hungry, i.e., the more food available, the less hungry the animals are, so the variable "Amount of Forage" is strongly and positively related to freedom from hunger and thirst. However, the amount of forage is also positively associated, albeit less strongly, with the freedom of cattle to express their normal behavior, which includes foraging for food and water. Additionally, access to feed allows the animal to eat properly and get the nutrients it needs, which decreases the risk of disease.

Table 1 shows the strength and direction (positive or negative) of the relationship between the proposed target variables and the freedoms that guarantee animal welfare. The variable Distance traveled is also included. Weight gain is not included in the table because it is related to animal mass gain and not to animal welfare.

Table 1: Relationship between objective variables and animal freedoms.

	Freedom from hunger and thirst	Freedom from discomfort	Freedom from pain	Freedom from fear and distress	Freedom to express normal behavior
Distance travelled		Moderate (-)	Weak (-)	Strong (-)	
Quantity of forage	Strong (+)		Weak (+)		Moderate (+)
Space		Moderate (+)		Weak (+)	Strong (+)
Noise level		Strong (-)	Weak (-)	Moderate (-)	
Temperature		Strong (-)	Weak (-)	Weak (-)	

A positive relationship (+) between the target variable and animal freedom indicates that the higher the value of the variable, the better the welfare condition of the animal. Therefore, the objective variables that have a positive relationship with the freedoms must be maximized and those with a negative relationship must be minimized. For example, if the noise level is too high, then it can generate discomfort in the animals, increase stress, cause distress, and even make them sick. Therefore, the variable "Noise level" has a negative relationship with the absence of discomfort, pain, fear, and distress. Thus, one of the objectives is to minimize the noise level. This is formalized mathematically in section 2.2, where the proposed mathematical optimization model is described.

In the literature reviewed, there are no parameters or criteria for measuring the animal welfare of cattle in grazing systems. Our work is the first to propose metrics to quantify the animal welfare of cattle.

It is good to recognize that the analysis that we have just done about animal freedoms and how to model them can lead to certain conflicts that will be analyzed in future works. For example, the transfer of a batch of cattle from one pasture to another motivated by the weight gain that the animals can acquire if the pasture to which they are transferred has better pasture conditions (quantity and quality), can lead to weight loss of the animal due to fat loss caused by walking and changing feeding places (can cause stress to the animal). Furthermore, the quantity and quality of forage in paddocks are not necessarily positively related to temperature, noise, or spaces, so a paddock with good forage conditions may also have very poor comfort conditions. Thus, it is possible that in some cases, the weight gain of livestock conflicts with animal welfare during the grazing process. That is why it is interesting to approach the problem of rotational grazing as a multi-objective problem that allows analyzing these objectives individually, in groups or globally, and add new ones that consider these possible conflicts.

2.2 Proposed many-objective optimization model

Let n and m be the total number of herds and the total number of paddocks in the grazing system, respectively. In real life, n is less than or equal to m. However, classically in operations research is assumed that an assignment model must always be balanced in order to be solved [41]. This assumption will be used in this work. Therefore, in the case where the number of herds is less than the number of paddocks, fictitious herds are virtually created in order to make n and m equal. When the model is implemented in real life, then the paddocks with fictitious herds assigned are empty paddocks. Thus, the mathematical formulation is based on the assumption that the system is balanced and that rotational grazing is performed for p days. Then, the binary decision variable x_{ij}^t is defined to indicate if the herd i is assigned to the paddock j at time t (days), with $i, j = 1, 2, \ldots, n$ and $t = 1, 2, \ldots, p$.

This paper proposes a many-objective optimization model composed of six objectives corresponding to the weight gain and movements of the animals, and to the five animal freedoms. The first objective is to maximize the total weight gain of the animals due to the allocation of the flocks to paddocks at each time t. The mathematical function representing this objective is given by equation 1.

$$Maximise \;\; Z_1 = \sum_{i=1}^{n} \sum_{j=1}^{n} G_{ij}^t x_{ij}^t \tag{1}$$

where G_{ij}^t is the weight gain to be obtained by herd i in paddock j estimated at time t.

The second objective is to minimize the total distance traveled by the animals when moving from one paddock to another each time they are moved during the defined rotational grazing period, which can be three months or one year, for example.

The mathematical function is given by equation 2, in which D_{ij}^t is the distance in meters between paddocks i and j at a time t to move herd k between these paddocks.

$$Minimise \;\; Z_2 = \sum_{k=1}^{n} \sum_{i=1}^{n} \sum_{j=1}^{n} D_{ij}^t x_{ki}^t x_{kj}^{t-1} \tag{2}$$

For animal welfare, Table 2 describes the mathematical notation used for objective variables representing the levels of animal freedom. Since it is desired to maximize the available amount of food and space but to minimize noise and temperature levels, then the mathematical functions for these objectives are given by equations 3-6.

Table 2: Animal welfare index variables.

Variables	Description
FI_{ij}^t	Forage Index of allocation of herd i to paddock j at time t.
SI_{ij}^t	Space Index of allocation of herd i to paddock j at time t.
NI_{ij}^t	Noise Index of allocation of herd i to paddock j at time t.
TI_{ij}^t	Temperature Index of allocation of herd i to paddock j at time t.

$$Maximise\ \ Z_3 = \sum_{i=1}^{n}\sum_{j=1}^{n} FI_{ij}^t x_{ij}^t \tag{3}$$

$$Maximise\ \ Z_4 = \sum_{i=1}^{n}\sum_{j=1}^{n} SI_{ij}^t x_{ij}^t \tag{4}$$

$$Minimise\ \ Z_5 = \sum_{i=1}^{n}\sum_{j=1}^{n} NI_{ij}^t x_{ij}^t \tag{5}$$

$$Minimise\ \ Z_6 = \sum_{i=1}^{n}\sum_{j=1}^{n} TI_{ij}^t x_{ij}^t \tag{6}$$

The amount of forage available within a paddock j at a time t does not depend on the herds assigned to it. However, it is important to take into account the nutritional needs of the animals when assigning a herd to a paddock since it influences the amount of weight the animals can gain. Since nutritional need depends directly on the weight of the animal, then we propose to calculate the forage index by means of the expression 7, which measures the amount of forage (in mass units) available per unit of weight (in mass units) of the herds of animals. In other words, this index indicates the amount of forage available per unit of weight of cattle

$$FI_{ij}^t = \frac{TF_j^t}{W_i^t}, \qquad \forall i, \forall j, \forall t \tag{7}$$

where TF_j^t is the total amount of forage within paddock j at time t, and W_i^t is the total weight of the animals in herds i at time t.

For the space index, it is necessary to take into account the space occupied by the herd, which depends on the size of the animals, which in turn is directly related to the weight. Thus, denoting the area of the paddock j as A_j, the space index is calculated with the expression 8, which represents the amount of space available per unit weight of livestock.

$$SI_{ij}^t = \frac{A_j^t}{W_i^t}, \qquad \forall i, \forall j, \forall t \tag{8}$$

On the other hand, we consider that the noise and temperature sensation experienced by the animals is positively related to their size and to the number of animals in the herds. Therefore, as a first approximation to the measurement of noise level and temperature indices of the allocation of a herd i to a paddock j, we propose the equations 9 and 10, where N_j^t and T_j^t are the noise and temperature levels of paddock j at time t, respectively. They indicate the noise level and temperature level of each paddock boosted by the stocking rate (total weight) of each lot. Thus, taking the noise index as an example, the assignment of a specific lot of cattle to a specific paddock has an associated noise index that corresponds to the noise level of the paddock boosted by the stocking rate of the lot.

$$NI_{ij}^{t} = N_j^t \cdot W_i^t, \qquad \forall i, \forall j, \forall t \tag{9}$$

$$TI_{ij}^{t} = T_j^t \cdot W_i^t, \qquad \forall i, \forall j, \forall t \tag{10}$$

The parameters $TF_j^t, W_i^t, A_j, N_j^t$ and T_j^t are read from system information or estimated at time t.

On the other hand, defining O_{ij}^t as the estimated occupancy time (in days) at time t that a herd i must remain in paddock j to consume the total quality forage, setting g_j^t as the average daily weight gain of an animal in paddock j (influences the type of pasture in the paddock) on the day t (influences the time of year), and defining C_i^t as the number of cattle in the herd i at time t, the total weight gain obtained by a herd of animals if assigned to a given paddock is calculated by the expression:

$$G_{ij}^{t} = O_{ij}^t \cdot g_j^e \cdot C_i^t, \qquad \forall i, \forall j, \forall t \tag{11}$$

The occupancy time of herds in the paddock is calculated using the expression 12, where QF_j^t is the amount of quality forage in paddock j at time t and NR is the daily nutritional requirement of an animal expressed as a fraction of its weight, with $0 \leq NR \leq 1$.

$$O_{ij}^{t} = \frac{QF_j^t}{NR \cdot W_i^t}, \qquad \forall i, \forall j, \forall t \tag{12}$$

The total area of each paddock is an important constraint when making daily allocations. Defining a_i^t as the estimated area of occupancy of the herds i at time t, the inequality 13 must be satisfied.

$$a_i^t \cdot x_{ij}^t \leq A_j, \qquad \forall i, \forall j, \forall t \tag{13}$$

At any time t, each herd must be assigned to a single paddock and each paddock must be assigned to a single herd. These restrictions are represented by the expressions 14 and 15.

$$\sum_{j=1}^{n} x_{ij}^t = 1, \qquad \forall i, \forall t \tag{14}$$

$$\sum_{i=1}^{n} x_{ij}^t = 1, \qquad \forall j, \forall t \tag{15}$$

Finally, equation 16 expresses the constraint corresponding to the binary nature of the decision variable

$$x_{ij}^t \in \{0, 1\}, \;\; \forall i, \forall j, \forall t \tag{16}$$

Since the proposed model considers the evolution of parameters and variables over time, it is a dynamic optimization model. The model must be run daily after updating the information corresponding to the characteristics of the paddocks and cattle herds, such as total forage quantity, forage quality, noise and temperature levels, and animal weight, among other parameters. On each day, an efficient solution to the model is found, which allows an efficient allocation of herds to paddocks, seeking to maximize weight gain but taking into account animal welfare. In this way, depending on the values of the target variables (weight gain and animal welfare indexes), the decision is made to assign each lot of cattle to a specific paddock. The analysis of the proposed model is presented in section 3.

3 Model Evaluation

The effectiveness of the optimization model proposed in this work was analyzed through a simulation of a rotational grazing system. The characteristics of the simulation study conducted are described below.

3.1 Description of Simulation Study

A simulation of a 90-day rotational cattle grazing system was run to evaluate the performance of the proposed mathematical model. Two types of grazing systems are considered, a traditional grazing system that does not use mathematical optimization and a grazing system that uses the optimization model proposed in this work.

Before starting the simulation, parameter values such as the number of cattle herds and the number of paddocks are defined. The characteristics of the paddocks such as location within the farm, area, type of pasture, the amount of forage, and noise and temperature levels, are randomly generated. Likewise, in the case of cattle herds, characteristics such as gender, weight, and age of each animal are randomly produced. For the daily growth of the pasture, the influence of the season of the year, the species of the pasture, and its flowering time were taken into account. On the other hand, at the beginning of the simulation, the farm begins by having all its paddocks with a complete and known quantity of forage, which is made up of quality forage and non-quality forage. In turn, on each day of the simulation, the amount of total forage changes depending on the amount of forage consumed by the livestock, the natural growth of the grass, and the time of year (rainy or dry seasons).

Quality forage corresponds to the part of the pasture that provides the greatest weight gain to the animals due to its nutrients, has the best flavor, and is found in the upper part of the plant. Because of this, the simulation assumes that quality forage is the first thing that animals consume, and therefore, is the first to be depleted during grazing. When the quality forage runs out, the animal proceeds to consume the rest of the forage.

The weight of the animals is updated at the end of each day based on the quantity and quality of forage consumed, their age, gender, weight, and distance traveled when moving from one paddock to another. The parameters that are defined before starting the simulation are presented in Table 3.

The *output variables* are: (1) Final weight of animals, (2) Average weight of animals, (3) Average weight gain of the animals, (4) Final forage of each paddock (quality and non-quality) (5)Average forage (quality and non-quality)

In summary, the discrete event simulator macro-algorithm of the cattle rotation system is shown in Figure 2. The simulator is located at `https://github.com/devraxielh/Simulador_Ganadero`.

Table 3: Parameter identification

	Parameter
General	Number of days to be simulated Number of paddocks
Paddocks	Daily growth rate of the pasture (in percentage units) Plant species Rate of extra increase in the rainy season Rate of loss in the dry season Rate of loss due to flowering Daily weight gain of an animal depending on the quality of the forage Minimum and maximum area of a paddock Minimum and maximum capacity of the paddocks at the beginning of the simulation The measurements of the farm within which the paddocks are randomly located before starting the simulation Initial fraction of the total forage that is quality forage Amount of forage per square meter that grows in a paddock on a rest day after the capacity reaches zero Number of paddocks Area of each paddock (m^2) Location of the paddocks within the farm Forage of each paddock (kg) Number of consecutive days of occupation allowed per paddock Number of days that a paddock must remain unoccupied after the maximum number of consecutive days of occupation allowed
Herds	Number of herds Nutritional requirement, as a percentage of the total weight of a cattle herd that the herd needs to consume daily to increment the weight Minimum and maximum number of animals per herd Weight loss per walk (kg/m) Daily nutritional requirement of an animal

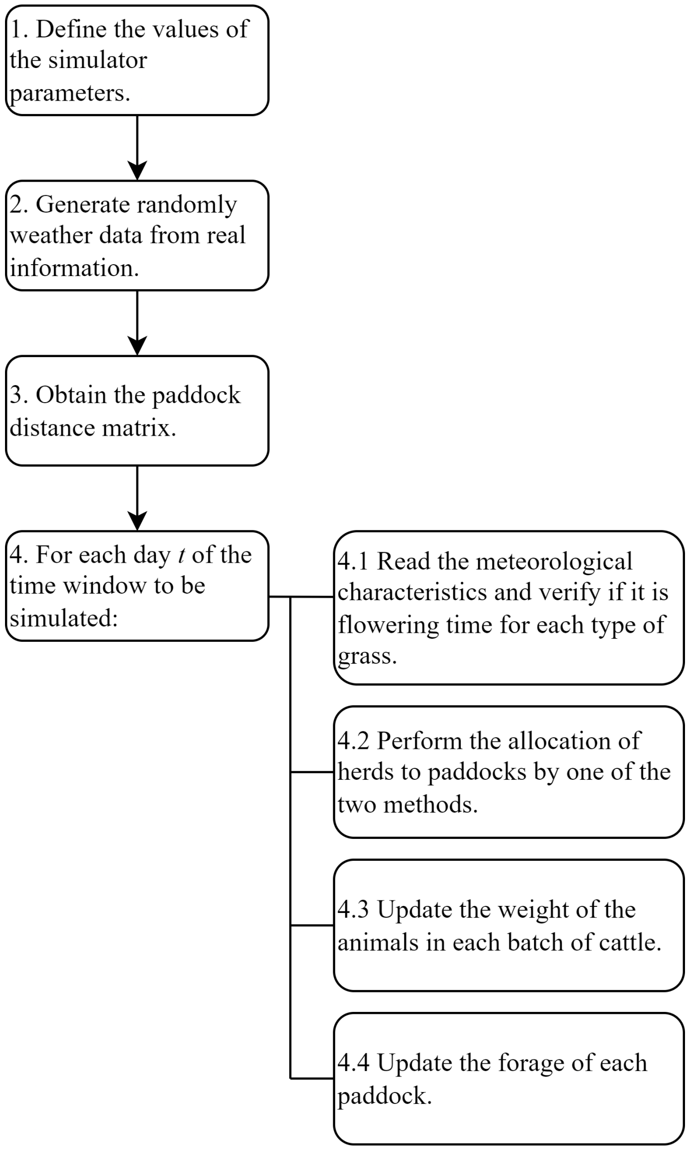


Figure 2: General simulation algorithm flowchart (*Source:* Own elaboration).

The simulation was programmed in R software due to its potential in statistical data analysis but was connected to Python to make use of the Platypus library in which several algorithms are available for the solution of multi-objective and many-objective optimization problems. Since the objective of this work is to innovate in the way of analyzing the rotational grazing problem by including additional objectives for livestock weight gain (classical approach), it is not of interest to compare the performance of algorithms for solving multi-objective optimization models nor to propose a particular heuristic for the solution of the proposed model. Therefore, the NSGA-III evolutionary algorithm was used to solve the optimization model because of its good performance in multi-objective optimization problems according to the literature [20, 21, 38]. Particularly, the computational complexity of the NSGA-III algorithm is $O(n_g n_o n_p^2)$, where n_g is the number of generations, n_g is the number of objectives, and n_p is the population size, but in turn, the objective functions, in our case, depend on the number of livestock herds and paddock. On the other hand, a grid search was carried out to adjust the hyperparameters of the evolutionary algorithm, with which it was determined to use a population of 10 individuals and 10,000 runs, among other optimized parameters.

3.2 Experimental Design

The validation of the proposed optimization model is carried out by means of an experimental design considering three factors: the number of herds/lots, the number of animals per herd and the grazing strategy. The levels of each factor are presented in Table 4. Thus, we have an experimental design with 3x3x2 = 18 treatments, for each of which 6 simulation runs were executed.

Table 4: Factors and levels of the experimental design.

Factor	**Level**
Number of herds	1, 4, 15
Number of animals per herd	2, 10, 50
Grazing strategy	Traditional Rotational grazing, Rotational grazing using our optimization model.

The traditional rotational grazing strategy consists of a grazing system in which animal lots are periodically rotated within the farm taking into account the number of days that each paddock must remain unoccupied for pasture recovery, the estimated forage of the unoccupied paddocks, the distances between paddocks that the animals must travel, the area of the paddocks and the size of the lots (number of animals and their weight). For example, on some farms, it is decided by default that animal lots remain in each paddock to which they are assigned for 30 consecutive days. After this time, it is decided to move the lot to a paddock with the largest amount of forage and as close as possible to simplify the process of transporting the animals. In general, the allocation of lots to paddocks is based on the perception of the decision-maker, is not guided by a formal optimization strategy, and does not take into account animal welfare.

On the other hand, the rotational grazing strategy using the optimization model is based on a daily execution of the mathematical model after reading or calculating the levels of the system state variables such as animal weight, paddock forage, location of the cattle herds, etc. The proposed model is solved using a many-objective optimization problem-solving algorithm. The algorithm finds a set of effective solutions called the Pareto front. Since the priority is the weight gain of the animals, the effective solution of the Pareto front that has the highest value in the objective variable Total Weight Gain is selected as the best solution. Based on this selected solution, an allocation of lots to paddocks is made to optimize the weight gain of the animals and to take care of animal welfare. Depending on the allocation obtained by the model, some lots remain in the paddock where they are located and others are moved to another paddock. Then, the system state variables are updated. Nevertheless, if higher priority is given to animal welfare, then the solution chosen as the best would mean a different allocation. Thus, depending on the order of priority given to the objectives, different allocations of lots to paddocks can be obtained.

Regarding water for livestock, according to experts, the usual is that in the design of the pastures, farmers ensure that they provide the necessary water to the animals in each of them so that the animals can satisfy this need at the time they require it. Thus, in the simulation process it is assumed that on the farm where rotational grazing is carried out, the animals have access to sufficient water to satisfy their needs in any pasture. Therefore, this work does not include parameters or variables related to water availability or consumption. The rest of the simulation parameters are the same for all the design treatments (combinations of factor levels), and their values are presented in Table 5. The selection of these parameters was defined with the advice of farmers and zootechnical professionals from Finca El Rosario (Montería, Colombia), who are experts in rotational grazing of cattle in the Colombian tropics. Several consultation meetings were held with these experts in which it was determined that these parameters are the most influential in the rotational grazing process according to their experience.

Particularly, forage quality has a great impact on cattle weight gain [42]. Now, the amount of quality forage in the pasture depends on factors such as type of grass, proportion of young leaves [43], height of the plant [44], or season of the year [45], among others. Thus, to simulate the positive impact that quality forage has on the weight gain of livestock, the increase in the animal's weight gain when consuming quality forage with respect to the consumption of non-quality forage was assumed to be a higher percentage than varies between 10% and 25%, depending on the type of grass and the season of the year. These values were suggested by the consulted experts, who considered them reasonable values based on their experience in the behavior of grasses used in the Colombian tropics.

Following the procedure described in subsection 3.1 and the guidelines in subsection 3.2, the experiments carried out in this work are easily reproducible, and allow the addition of new variables or factors that can be considered important or influential in rotational cattle grazing.

Table 5: Simulation parameters

Parameter	**Value**
Simulated rotational grazing days	90
Number of paddocks	30
Minimum area of a paddock (m^2)	45000
Maximum area of a paddock (m^2)	55000
Minimum capacity of a paddock (kg of grass)	3000
Maximum capacity of a paddock (kg of grass)	3500
Minimum noise level (decibels)	30
Maximum noise level (decibels)	80
Minimum temperature (degrees Celsius)	30
Maximum temperature (degrees Celsius)	45
Maximum number of consecutive days a paddock can be occupied consecutively.	3
Ideal number of days a paddock should remain unoccupied after being used.	25
Forage (kg/m^2) that grows in one day in a paddock after it has been completely consumed.	0.08
Fraction of total forage that is quality forage	0.3
Minimum initial weight of an animal (kg)	370
Maximum initial weight of an animal (kg)	530
Weight loss per walk (kg/m)	0.00001
Fraction of weight gain that is in addition to the average gain for quality forage	0.15
Daily nutritional requirement of an animal (percent of its weight)	11%
Prime rate of daily growth of grass (forage)	12%
Increase in forage due to rainfall gain	12%
Decrease in forage due to drought loss	4%
Decrease in forage due to flowering loss	3%

3.3 Experimental Results

Since the main objective of interest is to maximize animal weight gain, the model performance metric used in the experimentation is the average animal weight-gain (AWG), which is useful for comparing the two grazing strategies considered in the simulation study. The AWG allows measuring the average amount of weight gained by the animals due to grazing during the study time since it calculates the average weight difference of the animals between the last day of grazing and the first day of grazing. The AWG is calculated as follows:

$$AWG = \frac{1}{N}\left(\sum_{k=1}^{N} W_{fk} - \sum_{k=1}^{N} W_{0k}\right) \tag{17}$$

where W_{0k} and W_{fk} are the weights of the animal k at the beginning and end of the simulation, respectively, and N is the total number of animals.

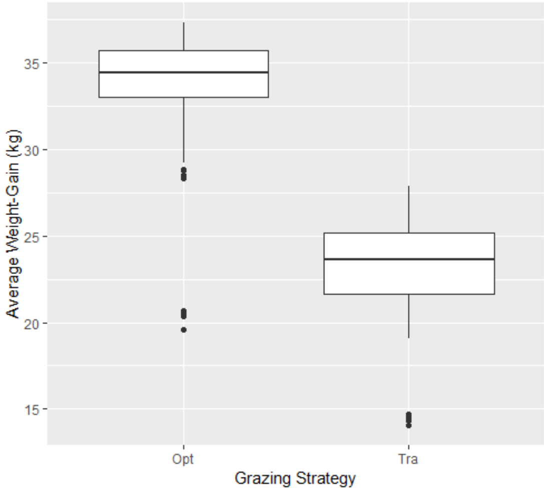
Figure 3-(a) shows the box plots of the AWG obtained for the two grazing strategies evaluated without discriminating the number of cattle lots or the number of animals per lot. According to the diagrams, in general, the grazing strategy using the proposed optimization model (Opt) achieves an average weight gain (with a mean of 32.73 kg and standard deviation of 4.9 kg), higher than the traditional grazing strategy (Tra) (with a mean of 22.82 kg and standard deviation of 3.7). However, a greater presence of outlier data is also observed in the grazing strategy with optimization, specifically in the lower tail, indicating greater variability.

However, it is necessary to compare the performance of the rotational grazing strategy using the optimization model with traditional rotational grazing in different scenarios. Figures 3-(b), 3-(c) and 3-(d) show the AWG box plots of each grazing strategy for the simulated scenarios, where H1, H4 and H15, represent the cases of 1 herd, 4 herds and 15 herds, respectively, and A2, A10, and A50 denote the cases of 2 animals, 10 animals and 50 animals per herd, respectively. It is observed that in each of the scenarios considered in the experimental design, the optimization model produces higher AWG values than traditional grazing, showing superior performance in the task of generating animal weight gain. The arithmetic mean and standard deviation of the AWGs (in kg) of the simulation runs are presented in Table 6. For cases where the number of herds is 1 or 15, a decreasing trend in the mean AWG is observed as the number of animals increases. This is an expected result since an increase in flock size has a negative impact on feed availability, so animals consume less feed and gain less weight.

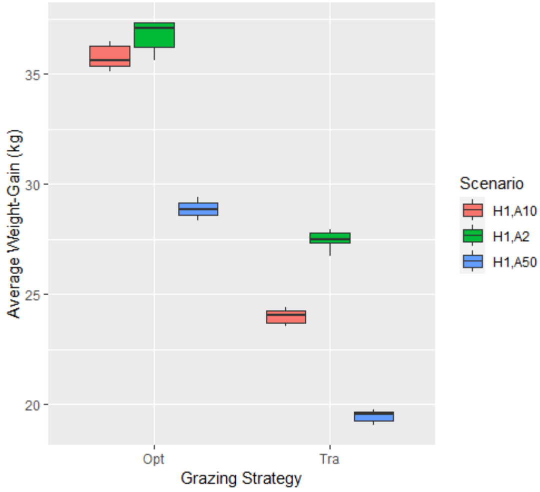
Table 6: Mean and standard deviation of AWGs (in kg) of the simulation replicates.

Number of herds	Number of animals per herd	Opt	Tra
1 herds	2 animals	36.73 (0.75)	27.46 (0.43)
	10 animals	35.75 (0.58)	23.98 (0.35)
	50 animals	28.85 (0.40)	19.46 (0.28)
4 herds	2 animals	34.84 (0.66)	26.19 (0.68)
	10 animals	35.63 (0.60)	21.97 (0.63)
	50 animals	33.43 (0.40)	24.88 (0.47)
15 herds	2 animals	35.19 (0.94)	23.22 (0.87)
	10 animals	33.85 (0.52)	23.79 (0.62)
	50 animals	20.38 (0.43)	14.42 (0.21)

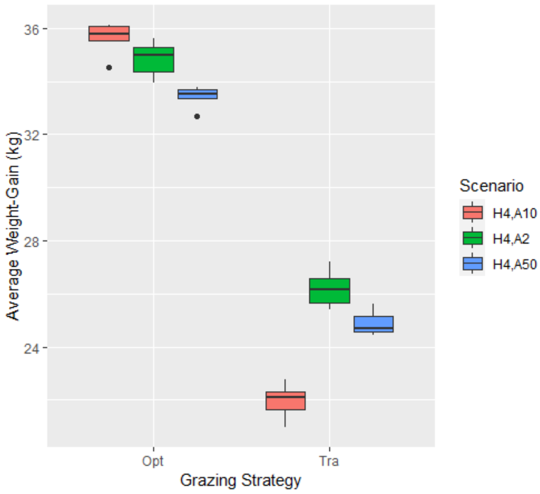
According to these results, the proposed optimization model for rotational grazing



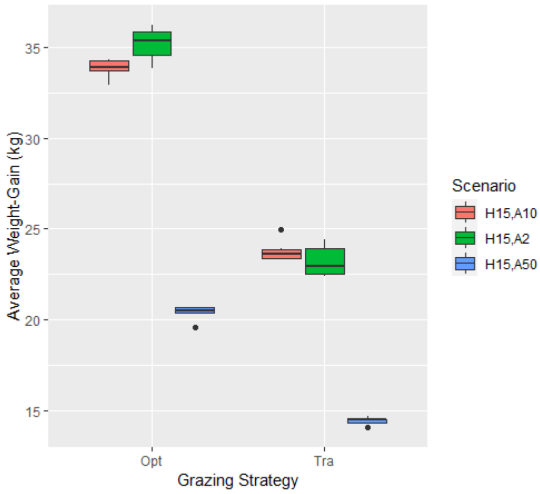
(a) General boxplot.



(b) Herds: 1; Animals: 2,10,50.



(c) Herds: 4; Animals: 2,10,50.



(d) Herds: 15; Animals: 2,10,50.

Figure 3: Boxplots of the AWG obtained for the grazing strategies for each scenario (*Source:* Own elaboration based on simulation results).

presents on average a higher average weight gain than that achieved by rotational grazing performed in the traditional way. The statistical verification of these assertions is presented in section 3.5.

3.4 Discussion about the Obtained Pareto Front

It is possible to find an optimal solution in single-objective optimization problems, but in the case of multi-objective problems, it is not possible to determine a single optimal solution for all the objectives because they are in conflict, i.e., improving one of them implies making others worse [20, 21, 38]. This situation justifies the concept of the Pareto front [15], which is the set of optimal solutions with the best compromises between the different objective functions.

On the other hand, heatmaps are frequently used for visualizing the objectives of a multi-objective problem with respect to individual solutions. They show the interaction between these two elements as a color of varying intensity. Thus, the heatmaps provide a 2D visualization of how the objectives interact for any solution as well as how each objective interacts with a given solution. Figure 4 shows the heatmaps of the six objectives (each column represents a goal: Z_1= Weight gain; Z_2= Distance traveled (Dist); Z_3= Food (Forage), Z_4= Space, Z_5= Noise and Z_6= Temperature (Temp)) and the solutions in our Pareto front. The variation in color intensity provides a clear visual cue on how the variables vary with respect to each other in each solution. Specifically, Figure 4 shows the heatmaps for the Pareto optimal points for one of the scenarios of our problem (15 herds and 10 animals) for different simulation days. This method allows the visualization of the behavior of the objectives in each Pareto solution.

The results show that with more days of simulation, solutions begin to prevail in the Pareto Front where the profit objective is the most relevant (see Figure 4.c). Thus, it is possible to stand out that with more days of simulation, solutions are achieved on the Pareto front that greatly degrade animal welfare goals. Figure 4.c shows that the weight is one of the more relevant variables (more intensive color in many solutions). Also, the Pareto solutions that are in the lower part of Figure 4.c combine with good values the objectives of animal welfare, but it is seen that for this, they degrade the goal of weight gain. In Figure 4.c, there are also solutions where all the objectives are degraded, and the only one that prevails with a good value is weight gain. In general, improving that objective may imply a worsening of animal welfare. But it is possible to achieve solutions that improve that objective without degrading those of animal welfare (for example, see solutions from the middle to the top of Figure 4.c).

On the other hand, it is possible to see that there is at least one Pareto solution where each objective reaches its best value (more intense color). No solutions are found that successfully achieving an animal welfare objective, degrades the rest of the animal welfare objectives (they are compatible with each other). In summary, in this analysis of the Pareto front is observed that the greater the number of days of grazing, the weight gain objective becomes more relevant. That is, the longer the grazing time, there are more solutions on the Pareto front where weight gain becomes more important than animal welfare. On the other hand, we see that welfare objectives do not degrade each other. In other words, the weight gain goal is in conflict with the animal welfare goals, while the latter are not in conflict with each other.

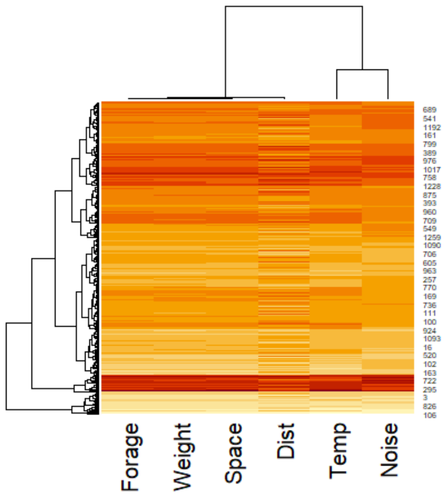
This type of analysis can help decision makers find an appropriate solution from the Pareto-optimal set. Finally, the most suitable solution will be obtained considering aspects of the environment/business, such as the current conditions of the farm, the meat market, and possible future improvements in each of them, among other things.

3.5 Quality analysis

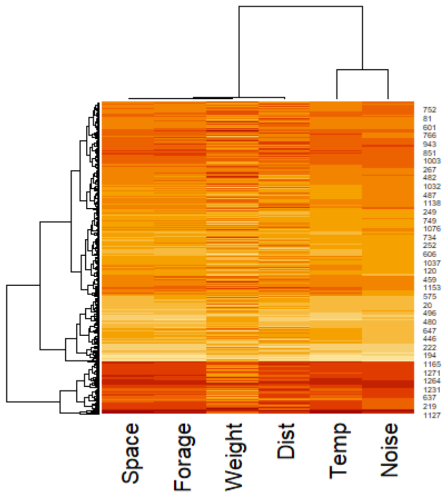
To test statistically whether there are significant differences in AWG between treatments (simulation scenarios), an effects model is fitted with the results of the experimental design described in section 1. With such a model for the analysis of variance, we intend to model linearly the effects that the combinations of simulation scenarios have on the weight gain metric. Thus, the model of the effects is given by:

$$AWG_{ijkr} = \mu + h_i + a_j + s_k + (ha)_{ij} + (hs)_{ik} + (as)_{jk} + (has)_{ijk} + \varepsilon_{ijkr}, \qquad (18)$$

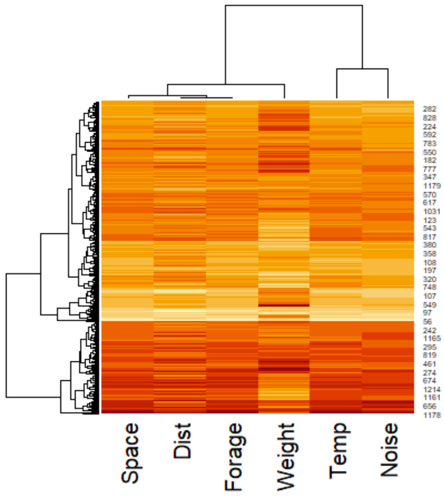
where AWG_{ijkr} is the average animal weight-gain of the $ijkr$-th observation, r the index of the simulation replicate, μ the overall average effect, h_i the effect of the i-th level of the Number of herds factor, a_j the effect of the j-th level of the factor Number of animals per herd, s_k the effect of the k-th level of the factor Grazing strategy, $(ha)_{ij}$ the effect of the interaction between h_i and a_j, $(hs)_{ik}$ the effect of the interaction between h_i and s_k, $(as)_{jk}$ the effect of the interaction between a_j and s_k, $(has)_{ijk}$ the effect of the interaction



(a) Day 30.



(b) Day 60.



(c) Day 90.

Figure 4: Heatmap of the 6 objectives in the solutions on the Pareto front for the scenario of 15 herds and 10 animals (*Source:* Own elaboration based on simulation results).

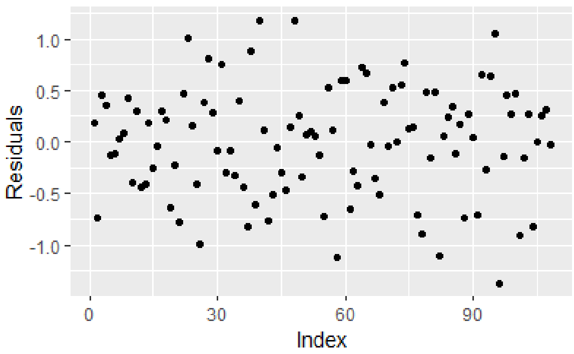
between h_i, a_j and s_k, with $i = 1, 2, 3$; $j = 1, 2, 3$; $k = 1, 2$ and $r = 1, 2..., 6$.

Note: The significance level for the hypothesis testing performed in this section is $\alpha = 0.01$.

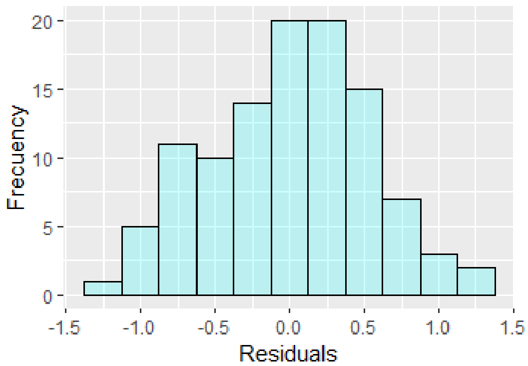
3.5.1 Statistical verification of the optimization model

To be confident in the analysis of variance, it is necessary that the assumptions of the statistical model, which correspond to independence, normality, and homogeneity of variance of the errors, are met. In Figure 5, are presented: the plot of the residuals in their time order (a), the histogram of the residuals (b), and the plot of the residuals against the fitted values of the response variable (c). In Figure 5 (a) there is no increasing or decreasing trend in the values of the residuals over time, moreover, the dispersion remains stable. Therefore, it is suspected that the errors are independent. On the other hand, the histogram (5 (b)) shows a clear bell shape with great symmetry, but a disturbance is observed in the left tail of the distribution. Thus, it appears that the errors possess a

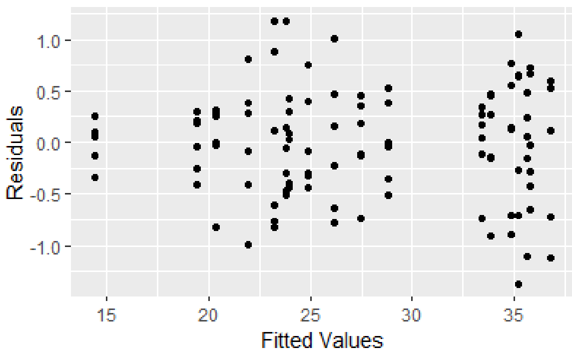
Normal distribution, but this needs to be confirmed. As for the homogeneity of variances, in Figure 5 (c), the variability of the residuals is not shown to be stable, which suggests that the homoscedasticity assumption is not met. In summary, Figure 5 indicates that the errors are independent, normally distributed with homogeneous variance.



(a) Independence



(b) Normality



(c) Homocedasticity

Figure 5: Validation of ANOVA assumptions (*Source:* Own elaboration based on simulation results).

To formally validate compliance with the assumptions of independence, normality, and homogeneity of variances, the Durbin-Watson, Shapiro-Wilk and Bartlett statistical tests were performed, respectively. The p-values obtained when performing the tests were 0.3432, 0.7549, and 0.2397, respectively, which are greater than the significance level $\alpha = 0.01$ previously defined. Therefore, it is formally verified that the effects model meets the assumptions and the Analysis of Variance can proceed.

3.5.2 Analysis of variance (ANOVA)

Table 7 presents the hypotheses tested in the analysis of variance and their respective P-values, which are all less than the 0.01 significance level. This indicates that all the null hypotheses are rejected so that sufficient statistical evidence was found to affirm that there are differences between the effects of the levels of the factors on the mean weight gain of the animals. In particular, the rejection of hypothesis number 3, which corresponds to the comparison of the effects between grazing strategies, shows that there are significant differences between the effects of traditional rotational grazing and rotational grazing based on the proposed optimization model.

Table 7: ANOVA hypothesis testing results of the model.

Hypothesis H_0	Description of hypothesis	P-Value
$h_i = 0, \ \forall i$	The effects of the levels of the Number of herds factor are equal to zero.	$< 2.2e-16$
$a_j = 0, \ \forall j$	The effects of the levels of the Number of animals in the herds are equal to zero.	$< 2.2e-16$
$s_k = 0, \ \forall k$	The effects of the levels of the Grazing strategy are equal to zero.	$< 2.2e-16$
$(ha)_{ij} = 0, \ \forall i,j$	There is no interaction between the Number of herds and the Number of animals in the herds.	$< 2.2e-16$
$(hs)_{ik} = 0, \ \forall i,k$	There is no interaction between the Number of herds and the Grazing strategy.	0.001357
$(as)_{jk} = 0, \ \forall j,k$	There is no interaction between the Number of animals in the herds and the Grazing strategy.	$< 2.2e-16$
$(has)_{ijk} = 0, \ \forall i,j,k$	There is no interaction between the Number of herds, the Number of animals in the herds and Grazing strategy.	$< 2.2e-16$

Since it was found that there are significant differences between the effects of the factor levels and that there is interaction between some of them, multiple comparison tests are performed. In this case, the Tukey HSD (Honestly Significant Difference) test was performed, and the results are presented in Table 8. The third column of the table shows the groups of means resulting from the Tukey test. If two scenarios have the same letter, it signifies that the means of the AWGs are statistically equal. For example, scenarios 1 and 2 belong to the **a** group, so there is no significant difference in the AWG means. The same is true for scenarios 2 and 4, which belong to the **b** group, but scenarios 1 and 4 do not share any letters, then their AWG means have significant differences. Since the scenarios are ordered in descending order according to the value of the mean AWG, it is observed that the use of the optimization model generates a significantly higher weight gain than that achieved without using it in any scenario. These results show that the rotational grazing strategy using the proposed optimization model produces a statistically higher mean weight gain than the traditional grazing strategy.

Table 8: Results of Tukey HSD test.

N°	**Scenario**	$\overline{AWG}$ **(kg)**	**Group**
1	H1, A2, Opt	36.73	a
2	H1, A10, Opt	35.75	ab
3	H4, A10, Opt	35.64	ab
4	H15, A2, Opt	35.19	b
5	H4, A2, Opt	34.84	bc
6	H15, A10, Opt	33.85	cd
7	H4, A50, Opt	33.43	d
8	H1, A50, Opt	28.86	e
9	H1, A2, Tra	27.46	f
10	H4, A2, Tra	26.19	g
11	H4, A50, Tra	24.88	h
12	H1, A10, Tra	23.98	hi
13	H15, A10, Tra	23.79	hi
14	H15, A2, Tra	23.22	i

15	H4, A10, Tra	21.97	j
16	H15, A50, Opt	20.38	k
17	H1, A50, Tra	19.46	k
18	H15, A50, Tra	14.42	l

4 Comparison with Previous Works

In this section, we propose several criteria to compare previous studies related to animal grazing optimization with our approach. These criteria are:

- ***Criterion 1:*** The study proposes a mathematical optimization model applied to Precision farming processes.
- ***Criterion 2:*** The study approaches the rotational grazing problem by means of an optimization model using many objectives.
- ***Criterion 3:*** The study takes into account the welfare of animals through their freedoms.

Criterion 1 is relevant because it allows addressing the problem in a quantitative and systematic way, using advanced tools and techniques of Precision farming to find optimal solutions. Criterion 2 is important because rotational grazing involves managing multiple variables and objectives, such as maximizing livestock weight and optimizing pasture utilization. A multi-objective approach allows these different aspects to be considered and balanced more effectively, helping farmers take actions that benefit both the productivity and sustainability of the system. Finally, criterion 3 is critical because animal welfare is an increasingly important aspect of livestock production. Consideration of animal freedoms, such as the freedom to move, behave naturally, and avoid stressful situations, can significantly improve the living conditions of animals. The integration of these criteria allows finding solutions that promote both productivity and animal welfare. In Table 9, a qualitative comparison with related studies is made, based on previous criteria.

Table 9: Comparison with previous works.

	Criterion 1	Criterion 2	Criterion 3
[11]	✓	✗	✗
[12]	✓	✗	✗
[13]	✓	✗	✗
[14]	✓	✗	✗
[15]	✓	✗	✗
[16]	✓	✗	✗
[17]	✓	✗	✗
[19]	✓	✗	✗
[18]	✓	✗	✗
[20]	✓	✗	✗
[21]	✓	✗	✗
[22]	✓	✗	✗
This work	✓	✓	✓

As shown in Table 9, previous studies did not satisfy all the criteria. Specifically, for *criterion 1*, all related research makes use of mathematical optimization models to improve livestock production. Particularly for Criterion 1, Raoui *et al.* [11] proposed a customer-centric mathematical model that considers lead times, and destination times in perishable food distribution. Additionally, Jafar *et al.* [12] proposed an approach that integrates nine socio-environmental objectives and 396 decision variables in a watershed management model of the Diyala River basin in Iraq for agriculture and livestock. Also, Chikumbo *et al.* [13] addressed the problem of land use optimization for a large agricultural farm, taking into account 14 objectives, including economic, environmental, and social aspects. On the other hand, White *et al.* [14] developed a model that optimizes pasture and nutrition management to examine the environmental impact of beef production. Similarly, Raizada *et al.* [15] used multiple objectives to develop alternative land use plans to maximize farm income, employment, and nutritional security, and minimize soil loss. Also, Zhai *et al.* [17] proposed a model of mission planning considering multiple criteria, such as expected profit, energy consumption and equipment loss, and developed an algorithm called MP-PSOGA, which combines Genetic Algorithms and Particle Swarm Optimization.

In addition, Michalak *et al.* [19] used a multi-objective optimization of neural models for vaccine allocation in disease spread scenarios. Also, Li *et al.* [18] defined a multi-objective approach that considers energy and material flows, and addresses economic trade-offs, efficient energy use, and environmental benefits. Furthermore, Chen *et al.* [20] proposed a method that integrates an energy analysis with NSGA-II, evaluating the economic and environmental trade-offs for sustainable development. Besides, Castonguay *et al.* [21] employed advanced spatial optimization techniques to evaluate the trade-offs between minimizing production costs and reducing greenhouse gas emissions in beef production. Additionally, Shahin *et al.* [22] used multi-objective optimization and IoT data mining to quantify greenhouse gas emissions on a dairy farm. Finally, our work focuses on the use of beef production variables to make optimal grazing decisions while maintaining animal welfare.

For *criterion 2*, our work is the only one that addresses the problem of rotational grazing using a multi-objective optimization model. Instead of focusing solely on maximizing productivity, the proposed optimization model takes into account forage quality, which is fundamental to ensure adequate nutrition and optimal weight gain in cattle. By considering forage quality as one of the objectives, the model can help determine the optimal allocation of grazing areas to maximize the supply of high-quality forage, which can have a direct impact on the weight gained by the animals.

Finally, regarding *criterion 3*, our proposal is the only one that focuses on maximizing weight gain using quality forage, which is taken by our model to calculate the occupancy time of a herd in a pasture and the welfare of the animals through their liberties. Therefore our proposal is the only one that takes into account animal welfare.

Using the above-mentioned criteria simultaneously is relevant because they allow addressing the livestock problem from a holistic perspective, considering both efficiency and productivity as well as animal welfare, exploiting all the advances that have been made in precision farming. This will lead to significant improvements in the sustainability and profitability of livestock operations while ensuring the ethical treatment and welfare of animals.

This research distinguishes itself from the existing literature by presenting a novel many-objective optimization model for rotational grazing in cattle farming that uniquely integrates considerations of both forage quality and animal welfare freedoms. Contrary to conventional approaches that often place emphasis on efficiency metrics, this approach employs the NSGA-III algorithm to simultaneously boost animal body mass while safeguarding their health. A 90-day simulation study showing statistically greater average weight gain compared to traditional methods and an improvement in overall animal welfare is what demonstrates the feasibility of our proposal.

This work is significant to the beef production industry as it introduces a rotational grazing model based on mathematical optimization. Unlike conventional practices, this strategy provides a holistic approach by considering both productive efficiency and respect for livestock living conditions. By adopting a many-objectives approach, the model seeks a balance, resulting in more sustainable and ethical meat production. The results suggest that this strategy is superior in all scenarios, for example in situations of farm underutilization as in cases of paddock saturation, offering a more balanced and beneficial approach for the livestock industry.

5 Conclusions and Future Work

A new approach to rotational grazing of cattle based on mathematical optimization was achieved and showed superior performance to the traditional rotational grazing approach with respect to animal weight gain. The mathematical model was evaluated via simulation using an experimental design with which its effectiveness was statistically proven. Metrics were proposed that characterize the decisions of allocating lots to paddocks during the rotational grazing process that allow measuring animal welfare based on the fulfillment of their freedoms. According to the literature reviewed, this work is the first in which metrics are proposed to measure animal welfare in the livestock context, specifically in the grazing process.

Specifically, we have proposed a new approach composed of indices to measure the animal welfare of cattle and the animal weight gain. Our optimization process consists of evaluating the conditions of each paddock on a daily basis and assigning cattle to paddocks in order to maximize cattle weight gain and animal welfare. Particularly, the rotational grazing allocation model proposed in this work would be integrated into an ACODAT for the management of the meat production process as one of its tasks, which would receive information from other ACODAT tasks on the quality of the pasture and the status of the cattle, among other information, and its assignment would be the decision of ACODAT.

Thanks to the many-objective approach, the proposed rotational grazing strategy allows maximizing livestock weight gain while taking care of animal health by maximizing (or minimizing) the proposed metrics associated with animal freedom. This gives a very important added value to the proposal. With the results, it was possible to verify that the proposed model is a significantly superior rotational grazing strategy to the traditional one in any of the evaluated scenarios. Both for cases in which the farm is underutilized and in cases in which the paddocks are saturated.

Thus, the main contribution was to achieve a many-objective model that, in addition to considering the classic objectives of animal fattening, considered animal welfare. For the latter, it was essential to consider the amount of food and space available, as well as the noise levels and temperature of the environment. This modeling allowed us to mainly consider the following freedoms of animals: the freedom to satisfy hunger and thirst, the freedom to engage in normal behavior, and the absence of fear and distress. Other works should be expanded to consider other freedoms related to the absence of discomfort, pain, injury, and illness.

The simulation and experimental design helped to understand the dynamics of the rotational grazing system and to identify variable forms of interaction between factors that influence livestock weight gain. For example, the effect of the season (rainy or dry) on grass growth directly influences the availability and quality of forage in pastures, which in turn has a great impact on livestock weight. Likewise, the distance traveled by the animals when moving lots of cattle to new pastures has a negative effect on the weight of the animals. All this could be observed in the designed simulation environment.

One of the limitations of the proposal is that the average weight gain of the animals is reduced due to the concern for animal welfare. The multi-objective approach leads to a lower weight gain than could be achieved in a single-objective approach to weight gain. Additionally, the metrics proposed to measure animal welfare in rotational grazing are approximations to measures of freedom that can be improved considering other variables of the context (e.g., climatic).

The efficiency of the rotational grazing strategy based on the proposed optimization model was evaluated through a simulation of livestock systems under Colombian tropical conditions. In this context, our approach showed superior performance to the classical grazing strategy. Because of this, our approach will be useful, scalable, and applicable to farms of any size in similar contexts. However, it cannot be assured that its efficiency would have the same quality in grazing systems with very different management practices or significantly different environmental conditions. For example, in grazing systems where water input is a variable or parameter to be modeled because of its variability, the approach proposed in this work would not be easily applicable. To verify the efficiency of our proposal in grazing systems with significantly different management practices, it is necessary to implement the model in a simulation study with parameters according to the context under study.

In future work, the incorporation of this dynamic allocation model into an autonomous cycle of data analysis tasks for monitoring the animal fattening process is natural. The autonomous cycle would allow the automation of the animal fattening/rotation process within the framework of precision livestock farming. Also, this is a dynamic optimization problem, so extensions to the optimization model that consider this aspect should be studied in the future. Finally, our many-objective approach allows adding aspects linked to the sustainability of the production process in future work, incorporating environmental factors as objectives to be achieved, such as the reduction of CO^2 emissions, which will improve the applicability and relevance of the proposed approach.

Acknowledgements

Marvin Jimenez is supported by a PhD grant financed by Universidad EAFIT. All the authors would like to thank the "Vicerrectoría de Descubrimiento y Creación", of Universidad EAFIT, for their support on this research. Also, the authors want to thank the HAMADI 4.0 project, code 22-STIC-06, of the STIC-AmSud regional program, for the support of this work.

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