Decision-support tool for global allocation of dairy sire semen based on regional demand, supply constraints, and genetic profiles

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ABSTRACT

An artificial insemination (AI) company seeks to allocate semen units globally by balancing perceived demand with uncertain product supply, in what is an arduous subjective process. This study aimed to objectivize this process by providing a user-friendly linear programming model to allocate bulls’ semen units to regions for the next trimester sales period based on maximum revenue, and to describe the features and outcomes of this model when applied to a sample bull herd and global demand scenario reflective of a leading AI company. The objective function of maximizing revenue was calculated by summing the product of units allocated by bull and region with purchase prices assigned by bull and region. Constraints considered were regional demand for overall units, regional preferences for specific genetic traits, bulls’ production capacity, and percentage of bulls’ units allocated to a single region. A sensitivity analysis was performed to identify the effects of variables and constraints on total revenue. Production, sales, and bull demographic data from 2018 to 2021 from a leading AI company were used to establish base values and build a sample herd of 61 bulls and 5 global regions. The case study provided a maximum revenue of $8,287,197 in semen sales per trimester, with 634,700 units allocated. Of the 61 bulls in the case study, 9 were not allocated to any region. The most limiting constraint was regional demand, which resulted in a surplus of 274,564 units not allocated. A sensitivity analysis confirmed this finding, with the largest shadow prices assigned to regional demands, and indicated that a single unit increase in regional demand would add up to $14.84 in total revenue.

Key words: linear program, allocation, sperm production

INTRODUCTION

Global dairy genetics companies seek to allocate product globally to balance customers’ demands with uncertainty in product availability. The process of allocating future product is subject to factors such as regional demand (total quantity and genetic profile preferences), quantity of bulls’ units produced or available from inventory, bulls’ health status and countries’ import regulations, and the company’s supply and inventory constraints. Many internal and external factors and competing interests create a highly subjective and complicated allocation problem, which US AI companies struggle with 3 times per year, coinciding with the Council on Dairy Cattle Breeding (Bowie, MD) genetic evaluations of US dairy cattle. There is potential benefit to AI companies in making this process more objective and streamlined, such as with a decision-support tool.

Allocation problems are not new to the dairy industry. Linear programs (LP) have been used to model allocation problems involving dairy farms (Cabrera, 2010; Wu et al., 2019; Bellingeri et al., 2020) and dairy processing plants (Kerrigan and Norback, 1986; Banaszewska et al., 2013). For example, Benseman (1986) developed a time-staged LP to find the most profitable daily production schedule of powder, casein, cheese, and butter products. The nature of dairy product allocation and resource optimization is comparable to dairy bulls’ semen product allocation, with raw biological products from cattle that can be destined for different end-products and markets. In the AI industry, LP and mixed-integer programs (MIP) have been used to model the optimal portfolio of sires for dairy herds (McGilliard and Clay, 1983a,b; Erba et al., 1991; McConnel and Galligan, 2004). McConnel and Galligan (2004) used an MIP to model the effects of semen quantity price discounts on the lowest cost portfolio of sires from 3 AI companies. Although LP and MIP have been used in the AI industry, to our knowledge, there has not been an analysis of global product allocation considering differing regional demands and bulls’ semen production capacities.
Therefore, the objectives of this study were to (1) provide a user-friendly LP model to allocate bulls’ semen units to global regions for the next trimester sales period based on maximum revenue; and (2) to describe the features and outcomes of this model when applied to a sample herd and global demand scenario that are reflective of a leading AI company.

**MATERIALS AND METHODS**

**Programming Approach**

The LP optimization model was defined as follows:

\[
\text{max } Z = C'X,
\]

subject to \( AX \geq, =, \text{ or } \leq B, \)

\( X \geq 0, \)

where \( Z = \) maximum revenue generated from the sale of semen units to regions; \( C' = \) matrix of objective function coefficients \( [e.g., \text{ price of unit by bull (b) and region (r)}] \); \( A = \) matrix of technical coefficients; \( B = \) vector of constraints \( [e.g., \text{ units available, demand}] \); and \( X = \) decision variables \( [e.g., \text{ bulls’ units per region}] \). An MIP has the added constraint that all variables in \( X \) (number of units) are integers: \( X \in \mathbb{Z} \).

Revenue is calculated as the summed product of bulls’ units per region by price per bull and region:

\[
\text{Revenue} = \sum_{\text{regions}} \left( \sum_{\text{bulls}} \left( \text{units}_{r,b} \times \text{price}_{r,b} \right) \right).
\]

**Model and Figure Creation**

The problem was set in an Excel Workbook (Microsoft Corp.) and the model solved using the Analytic Solver platform with a standard LP/quadratic engine (Frontline Systems Inc.). Figures were generated using Tableau (2020 4.13; https://www.tableau.com/).

**Case Study and Data Description**

Production data, sales records, health events, and bull demographics of Holstein bulls at 2 collection facilities were obtained from a commercial AI company (ABS Global Inc.). Institutional Animal Care and Use Committee or similar approval was not required for this data analysis and simulation study, as there were no animal procedures.

**Regions.** Five global regions were designated based on the company’s recommendation regarding geographic location, production type, and current regional marketing practices. Regions were designated A through E. Country-level sales data from 2018 to 2021 were aggregated at the regional level. Sales data obtained from the company did not include the actual per unit price received for each bull’s semen in a specific country. Rather, a blended price was available for all bulls sold to the country in that bulk order transaction, which reflected the average price per unit across all bulls in the order; this tended to dilute variation in prices per unit of different bulls, especially when high-value and low-value bulls were grouped in the same order.

**Bull Herd.** A sample herd was selected from bulls available for sale between April and December 2020. To ensure each region was represented in the sample herd, 15 bulls from each region with the highest number of units sold were chosen. Once duplicate bulls were removed, 56 unique bulls remained.

An important consideration in the allocation problem is country-specific regulations preventing the sale of semen from specific bulls in certain locations. For example, roughly 10% of US Holstein bulls do not meet health standards for importation into the European Union (EU; European Commission, 2016). Of the 56 bulls originally chosen for the case study, only 1 did not meet EU health standards. Therefore, to make the case study more realistic, 5 additional bulls with the most units sold that failed EU health standards (HT bulls) were added, resulting in 61 total bulls for the case study.

**Bull Units Available.** Assuming bulls would be collected twice weekly, an aggregated total sperm value was calculated for the trimester of August–November 2020. An average total sperm packing rate of \( 15 \times 10^6 \) was used to convert total sperm to units available for the trimester.

**Regional Demand.** Regional demand was considered in 2 ways: (1) demand for total units, and (2) desired genetic trait profile of selected bulls. Total unit quantity demand by region was assigned using actual unit quantity sold for the August to November 2020 trimester. The level of sales data does not allow differentiation between company’s supply and demand; for example, we do not know whether a given region would have purchased an additional 10% of product if it had been offered. Therefore, upper and lower bounds were added to the regional demands to provide flexibility in demand and supply. For the 61 bulls considered, demand was 44,000 units in region A, 149,000 units in region B, 145,000 units in region C, 131,000 units in region D, and 108,000 units in region E.
To determine the genetic trait profiles associated with these regional demands, the top 5 bulls (highest units sold) for each region were identified, and their trait profiles were averaged within region. The average values for each trait were compared with those of other regions, and one trait per region was selected based on the traits for which those 5 bulls excelled. The traits that were selected for each region’s strengths were PTA type composite for region A, dairy composite (DairyComp) for region B, PTA milk for region C, feet and legs composite (FLComp) for region D, and cheese yield for region E.

Using 2020 sales data, the percentage of total units each region needed from bulls in the top 25% and bottom 25% for each trait are shown in Table 1. The top 25% serves as a lower bound (i.e., a region can receive more units from bulls ranking among the top 25% for the trait), and the bottom 25% serves as an upper bound (i.e., a region can receive fewer units from bulls ranking among the bottom 25% for the trait).

### Decision Variables and Constraints

The problem is made up of 299 integer decision variables, $\text{Units}_{r,b}$, which is the number of units per bull ($b$) per region ($r$). There are 61 bulls, with 5 regions (305 possible variables) minus 6 HT bulls that were not eligible for one region and were automatically set to 0.

Table 2 summarizes the constraints. The problem consists of 122 functions (including constraints and objectives), 1,991 dependencies (whenever a constraint or objective depends on the decision variable), and 593 simple bounds on the decision variables. To prevent all units from a bull being allocated to a single region, the user can define a percentage ($z$) of units available per bull that can be allocated to a single region (Table 2, constraint 4). The base scenario’s $z = 50\%$ for non-HT bulls and 90% for HT bulls. To accommodate potential deviations from regional demand ($\text{uDemand}$), constraints 5 and 6 provide lower and upper bounds based on percentages ($lt$ and $ut$) defined by the user. These bounds, beyond demand, reflect the potential variation in supply, allowing for under- and oversupply relative to demand, such as would occur if the company were unable to meet the region’s demand or the region were willing to accept product beyond their original demand. The base scenario values were $lt = 90\%$ and $ut = 110\%$. Last, to meet the desired genetic trait profile of bulls for a given region, the number of units a region could receive between 90 and 110% of demanded units.

### Market Pricing

Sales data from 2018 to 2020 for the 61 sample bulls were summarized as price per unit by region and averaged by bins corresponding to 50 points in lifetime net merit (NM$)$ (Supplemental Table S1; http://dx.doi.org/10.17632/5yy9wwjh6.1; Quick, 2022).

### Company-Imposed Supply Constraint

To prevent one region from receiving all available units from a given bull, a company may impose a constraint on the percentage of a bull’s total units allowed to a single region. In this case study, individual regions were limited to 50% of a bull’s total units, except for HT bulls, which were limited to 90% of total units for an eligible region.

To model the supply range on the overall units obtained by a region, upper and lower bounds of the regional demand were modeled. In the base scenario, a region could receive between 90 and 110% of demanded units.

### Table 1.

<table>
<thead>
<tr>
<th>Traits</th>
<th>Region A</th>
<th>Region B</th>
<th>Region C</th>
<th>Region D</th>
<th>Region E</th>
</tr>
</thead>
<tbody>
<tr>
<td>Top 25%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Milk</td>
<td>0.00</td>
<td>0.18</td>
<td>0.41</td>
<td>0.37</td>
<td>0.29</td>
</tr>
<tr>
<td>Cheese yield</td>
<td>0.17</td>
<td>0.29</td>
<td>0.37</td>
<td>0.26</td>
<td>0.39</td>
</tr>
<tr>
<td>Type</td>
<td>0.35</td>
<td>0.33</td>
<td>0.23</td>
<td>0.25</td>
<td>0.23</td>
</tr>
<tr>
<td>FLComp</td>
<td>0.26</td>
<td>0.21</td>
<td>0.25</td>
<td>0.23</td>
<td>0.24</td>
</tr>
<tr>
<td>DairyComp</td>
<td>0.28</td>
<td>0.32</td>
<td>0.24</td>
<td>0.17</td>
<td>0.21</td>
</tr>
<tr>
<td>Bottom 25%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Milk</td>
<td>0.43</td>
<td>0.22</td>
<td>0.24</td>
<td>0.18</td>
<td>0.18</td>
</tr>
<tr>
<td>Cheese yield</td>
<td>0.28</td>
<td>0.22</td>
<td>0.26</td>
<td>0.37</td>
<td>0.19</td>
</tr>
<tr>
<td>Type</td>
<td>0.25</td>
<td>0.23</td>
<td>0.22</td>
<td>0.34</td>
<td>0.28</td>
</tr>
<tr>
<td>FLComp</td>
<td>0.18</td>
<td>0.22</td>
<td>0.31</td>
<td>0.31</td>
<td>0.30</td>
</tr>
<tr>
<td>DairyComp</td>
<td>0.24</td>
<td>0.17</td>
<td>0.28</td>
<td>0.43</td>
<td>0.33</td>
</tr>
</tbody>
</table>
Sensitivity Analysis

To obtain a sensitivity report from Analytic Solver, the constraint of integer decision variables was removed. Effects of decision variables and constraints on the objective function were tested. Reduced costs measure the change in objective function per unit increase in a decision variable; nonzero values occur when the variable value is equivalent to a lower or upper bound. Shadow price measures change in objective function per unit increase in the constraint’s bound. If the shadow price is zero, the constraint is nonbinding. Allowable ranges that reduced costs and where shadow prices remain constant were examined.

RESULTS AND DISCUSSION

Base-Case Herd Statistics

Units available per bull ranged from 1,368 to 33,672, with an average of 14,906. Total units available for allocation was 909,264. The total unit demand across the 5 regions was 577,000. The 90 to 110% bounds on demand created a supply range from 519,300 to 634,700 units. Price per unit was assigned based on bull’s NM$.

Base-Case Model Results

The revenue achieved in the optimal solution was $8,287,197.15. The total number of units allocated was 634,700, leaving 274,564 units not allocated. The unit quantities supplied to specific regions reached the upper bounds of regional demand constraints and were 48,400 units for region A, 163,900 for B, 159,500 for C, 144,100 for D, and 118,800 for E (Table 3). Based on the sensitivity analysis, it would take an upper bound of 140% above the regional demand to activate other constraints. In this example, an upper bound of 140% above regional demand would keep region B from reaching the upper bound, because the trait constraint of the bottom 25% of sires for the desired trait profile would become the limiting constraint.

### Table 2. Summary of constraints within the linear programming model

<table>
<thead>
<tr>
<th>Constraint description</th>
<th>Constraint type</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Integer decision variables</td>
<td>Value type</td>
</tr>
<tr>
<td>Positions decision variables</td>
<td>Lower bound</td>
</tr>
<tr>
<td>Bulls’ total units cannot exceed production capability</td>
<td>Upper bound</td>
</tr>
<tr>
<td>Bull’s units per region cannot exceed user defined percent (z)</td>
<td>Upper bound</td>
</tr>
<tr>
<td>Region’s total units above lower threshold (lt) based on demand</td>
<td>Lower bound</td>
</tr>
<tr>
<td>Region’s total below upper threshold (ut) based on demand</td>
<td>Lower bound</td>
</tr>
<tr>
<td># units region needs of bulls in top 25% each trait</td>
<td>Lower bound</td>
</tr>
</tbody>
</table>

1r = region; b = bull; uAvail = units available; uDemand = units demanded by region; t = trait; t75Demand = regional demand for bulls of top 25% of trait; t25Demand = regional demand for bulls of bottom 25% of trait.

### Table 3. Number of bulls and units per bull allocated to each region in the optimized solution in the base scenario and sensitivity report of the upper bound constraints on regional total demand

<table>
<thead>
<tr>
<th>Constraint name (no. of bulls)</th>
<th>Average (SD) units from assigned bulls</th>
<th>Final value (units)</th>
<th>Shadow price (USD)</th>
<th>Constraint RH side (units)</th>
<th>Allowable increase (units)</th>
<th>Allowable decrease (units)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Region total A (n = 11)</td>
<td>4,400 (3,757)</td>
<td>48,400</td>
<td>10.86</td>
<td>48,400</td>
<td>306</td>
<td>1,270</td>
</tr>
<tr>
<td>Region total B (n = 26)</td>
<td>6,304 (4,103)</td>
<td>163,900</td>
<td>6.20</td>
<td>163,900</td>
<td>7,003</td>
<td>1,270</td>
</tr>
<tr>
<td>Region total C (n = 27)</td>
<td>5,907 (3,537)</td>
<td>159,500</td>
<td>14.84</td>
<td>159,500</td>
<td>126</td>
<td>475</td>
</tr>
<tr>
<td>Region total D (n = 20)</td>
<td>7,205 (6,721)</td>
<td>144,100</td>
<td>10.77</td>
<td>144,100</td>
<td>915</td>
<td>1,717</td>
</tr>
<tr>
<td>Region total E (n = 11)</td>
<td>5,657 (3,276)</td>
<td>118,800</td>
<td>10.85</td>
<td>118,800</td>
<td>915</td>
<td>5,582</td>
</tr>
</tbody>
</table>

Final value is the assigned value for the optimized solution, and shadow price is the change in objective function per unit increase in the constraint’s bound. Constraint right-hand (RH) side is the value of the constraint’s bound. Allowable increase and decrease are the values for which the final value can be altered without changing the shadow price.
The numbers of bulls assigned to each region under the optimal solution were 11, 26, 27, 20, and 21, for regions A through E, respectively (Table 3). Of the bulls allocated, the average (SD) of units allocated per region was highest for market D, at 7,205 (6,721), and lowest for market A, at 4,400 (3,757). Despite the large differences in demand between regions, the numbers of units allocated per bull by region were similar, and the numbers of bulls per region drove differences in total units allocated.

Nine bulls were not allocated to any region, 14 bulls were assigned to 1 region, 26 bulls to 2 regions, 9 bulls to 3 regions, and 3 bulls to 4 of the 5 available regions. In other words, 9 bulls would be collected but not needed to meet demand. Beyond this example, Gorr et al. (A. Q. Gorr, V. E. Cabrera, J. Meronek, and K. A. Weigel; unpublished data) showed that 49% of bulls would be recommended for culling based on negative net present value relative to others in the herd. The current and previous studies suggest that opportunities exist within the AI stud to reduce the number of bulls collected, thereby decreasing production costs without losing revenue, while still meeting market demands. The present study also supports the transition of AI companies’ marketing campaigns to those based on promotion types of bulls (i.e., groups of bulls with similar genetic trait profiles) rather than individual bulls. Genomic evaluations have enabled the selection and marketing of young bulls, shortening the generation interval faster than in the pregenomic era (Ruiz-López et al., 2018). This selection pressure has shortened the productive life of bulls, as newer and genetically superior bulls replace them, perhaps solidifying the relevance of marketing teams of bulls rather than the bull itself. The NM$ bins of bulls not allocated were 550 (5 bulls) or 450 (4 bulls). These bulls tended to be in the lowest 25% or middle 50% for nearly every trait except PTA milk (4 bulls were among the top 25% for PTA milk), and they had an average of 19,023 (5,741) units available for allocation. In summary, bulls not selected for allocation were of average or below average genetic merit but were above average for semen production.

Figure 1 shows the demand (dark lines) of unit quantity for top 25% and bottom 25% of each trait and the amount assigned from optimal solution (light gray bars). FLComp = feet and legs composite; DairyComp = dairy composite.
higher trait profile bulls to fill regional demand. All but one trait, cheese yield with 3,062 units below, were capped at the upper bound for region B’s bottom 25% demand versus allocated.

**Sensitivity Analysis**

The relaxed LP solution (removal of integer decision variables) received nearly the same optimal revenue, $8,287,197.19. Rounding differences made up the change in units allocated, with 1 unit removed from a bull in market A.

Among the 299 total decision variables, 145 were not bound by a constraint, resulting in a reduced cost of 0. The average reduced cost of the decision variables was $-0.76 \pm 1.85$, indicating that a 1-unit increase would reduce revenue by $0.76. Of the 121 constraints, 77 were not binding. The range of shadow prices was $-2.34$ to $14.84$. The constraints with the largest shadow prices were regional upper bounds for total units demanded (Table 3). For an example of the influence of shadow prices on the objective function, an increase in the final value of region C’s total units by 100 units would result in an increase in revenue of $1,484.
Thirty-one bulls were limited by their semen production capabilities, and more units could have been marketed if available. The number of bulls bound by the percentage of bulls’ units allowed to each region was actively constrained 63 times (twice in region A, 18 times in B, 17 times in C, 11 times in D, and 15 times in E).

Figure 2 shows the allowable value range compared with its final value, as well as the shadow price for all trait/region combinations. When the shadow price is zero, the constraint is nonbinding. Of the 50 regional/trait (top and bottom) constraints, 19 were binding. The upper and lower bounds of these nonbinding constraints demonstrate the number of units needed for that category to change into a binding constraint. When the shadow price is less than 0, adding units will negatively affect the objective function. The top 25% trait demand constraint acted as lower bounds, leading to negative shadow prices. Decreasing the unit quantity of region A in cheese yield would add $2.34 to the revenue, with an allowable increase of 1,118 units (Figure 2, zoomed-in example). When the shadow price is greater than 0, that constraint positively affects the objective function value: adding units above the final value will increase revenue. Bottom 25% had positive shadow prices, as they acted as upper bounds (Figure 3). Adding 1 unit within lower-tiered FLComp bulls for region B would add $2.67/unit to the objective function, with an allowed increase of 776 units. Generally, the final values were close to upper and lower bounds, demonstrating that moderate to large changes in unit quantity for the constraints will change the shadow price and the manner in which the objective function is subsequently affected.

We suggest this tool would be most useful during product allocation discussions if used in tandem with the semen production forecasts of individual bulls (as proposed by Quick et al., 2021) and developing collection schedules for the coming trimester. For instance, the 9 bulls not allocated could be culled if they are not needed to fulfill market demand. The sensitivity analysis would be beneficial for an AI company to negotiate bounds and constraints. For example, a region could request more units from a particular trait profile, and the company could provide the (shadow) price needed for the transaction to be profitable. The

![Figure 3. Allowable ranges [lower (○), upper (□)], final values (+), and shadow prices (×) assigned to each constraint within the bottom 25% trait and region combinations. Traits: PTA of milk, cheese yield, type composite, feet and legs composite (FLComp), and dairy composite (DairyComp).](image-url)

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tool can be modified to meet a company’s goals and marketing schemes, such as allocating groups of bulls, rather than specific bulls, to regions. Computational time should also be considered in the decision-support tool’s practicality. The LP/MIP solver provided results in less than 1 s, making it an efficient tool to utilize during decision-making.

CONCLUSIONS

In this study, we demonstrated that an LP or MIP can be used to allocate semen units regionally, given demand and supply constraints. The LP model allowed for user-defined bounds based on regional demand and bulls’ individual semen production capabilities. This model provides unit quantities by bull provided to each region. Results from the case study demonstrate the feasibility and efficiency of this decision-support tool. A sensitivity analysis confirmed that the case study’s most limiting constraint to the solution was regional demand. This decision-support tool was contained in an Excel workbook, with the Analytic Solver Add-in to model the LP and sensitivity analysis.

ACKNOWLEDGMENTS

Data and financial support for this project were provided by ABS Global Inc. (DeForest, WI). The authors have not stated any conflicts of interest.

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