INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

WILEY

INTERNATIONAL TRANSACTIONS IN OPERATIONAL RESEARCH

Intl. Trans. in Op. Res. 00 (2020) 1–24
DOI: 10.1111/itor.12861

Integrated planning decisions in the broiler chicken supply chain

Alfaima L. Solano-Blanco[a], Jaime E. González[b], Luis O. Gómez-Rueda[c], Jhon J. Vargas-Sánchez[d] and Andrés L. Medaglia[a,*]

[a] *Centro para la Optimización y Probabilidad Aplicada (COPA), Departamento de Ingeniería Industrial, Universidad de los Andes, Cra. 1 Este No. 19A – 40, Bogotá, D.C., Colombia*
[b] *Department of Mathematics and Industrial Engineering, Polytechnique Montréal, 2900 Boulevard Édouard-Montpetit, Montréal, QC H3T 1J4, Canada*
[c] *Producción y Logística (PyLO), Departamento de Ingeniería Industrial, Universidad de los Andes, Cra. 1 Este, No. 19A – 40, Bogotá, D.C., Colombia*
[d] *Estadística y Métodos cuantitativos, Departamento de Ingeniería Industrial, Universidad del Magdalena, Carrera 32, No. 22 – 08, Santa Marta D.T.C.H., Colombia*
E-mail: al.solano@uniandes.edu.co [Solano-Blanco]; jaime.gonzalez@polymtl.ca [González]; lo.gomez10@uniandes.edu.co [Gómez-Rueda]; jvargass@unimagdalena.edu.co [Vargas-Sánchez]; amedagli@uniandes.edu.co [Medaglia]

Received 24 December 2019; received in revised form 25 May 2020; accepted 29 July 2020

Abstract

In the poultry industry, the meat market requires a careful coordination of the broiler chicken supply chain comprising breeders, hatcheries, farms, slaughterhouses, wholesale, and retail vendors. Aside from the inherent challenges of coordinating a supply chain, animal husbandry systems face additional complex tasks. The lack of integrated decisions within the poultry chain could lead to a production plan that (a) does not comply with the biosecurity standards required in meat production for human consumption at the farms; (b) violates the production and inventory capacities at the slaughterhouses; and (c) does not meet the demand of customers. To streamline the supply chain, we propose a mixed-integer linear programming model that supports production planning and scheduling decisions in broiler chicken production facilities. In addition, we embedded the mixed-integer programming model in a rolling-horizon scheme to improve scalability and to avoid the myopic effect of time-indexed optimization models that put too much emphasis on a specific time period. We present the results of a case study in a poultry company in Santa Marta (Colombia), where we reach profit improvements that range from 7% to 57% with a reduction in inventory costs that range from 30% to 60%, while simultaneously meeting stringent technical, tactical, and biosecurity constraints.

Keywords: poultry supply chain; mixed-integer linear programming; production planning; lot-sizing decisions; decision support system; rolling horizon

*Corresponding author.

Published by John Wiley & Sons Ltd, 9600 Garsington Road, Oxford OX4 2DQ, UK and 350 Main St, Malden, MA02148, USA.

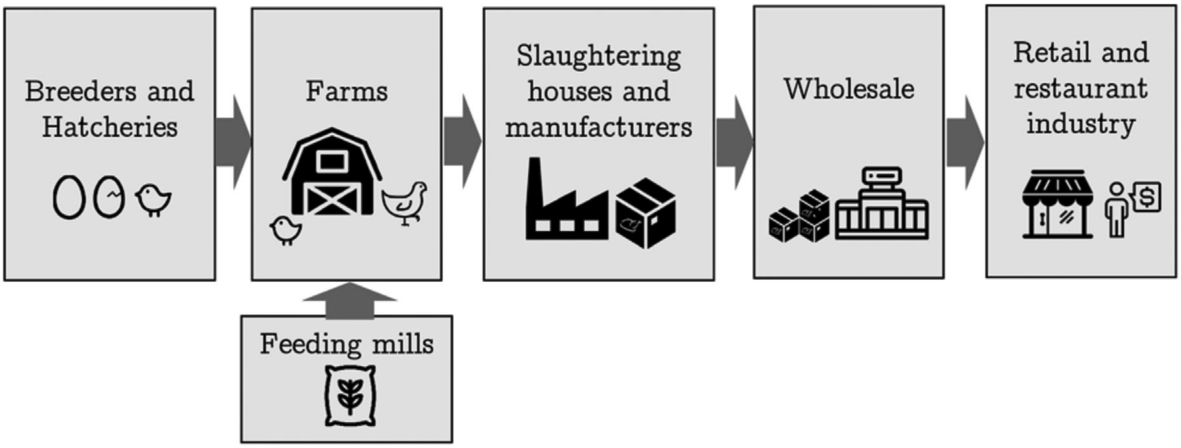


Fig. 1. Broiler chicken meat supply chain.

1. Introduction

In 2018, the poultry sector produced 123.9 million tons of poultry meat leading the market with a 36% of the global meat production (FAO, 2019b). In the same year, it was the most consumed meat in the world and its demand shows an increasing trend of over 1% per year (OECD and FAO, 2019). This trend can be explained by a shift in the preference of customers and the accessibility over other competing types of meat such as pork or beef.

Within the poultry sector, the chicken meat production system has the largest share. *Broiler chickens* are especially raised for meat production and have been enhanced by breeding over decades. These breeds represent less costs for farmers, as they show high food-meat conversion rates that make them grow quickly with less food (Zuidhof et al., 2014). In 2017, broiler chicken meat production accounted for 89% of the world's poultry production (FAO, 2019a). Moreover, production and demand of broiler chicken meat products increased by 7% (about 7000 metric tons) in the last five years (USDA, 2019). Therefore, meeting the demand of broiler chicken meat is essential to guarantee food security and any effort to increase the efficiency of its supply chain contributes to global economic growth.

The structure of the broiler chicken supply chain and its degree of integration vary among countries and firms. Such a structure has changed throughout the years favoring large-scale vertically integrated operations of the supply chain (Narrod et al., 2008). Figure 1 shows the general structure of this agri-chain. At the beginning of the chain, breeders and hatcheries produce batches of day-old chickens that are sent to farms. Once in the farms, day-old chickens are floor-raised on litter (e.g., made from rice hulls) at open structures known as grow-out houses. Chickens are grain-fed, with feed provided by mills, until they reach slaughter weight targeted in terms of animal age (i.e., six weeks). Slaughterhouses then receive these mature chickens from farms and turn them into multiple products for wholesalers, which then distribute them to retailers and customers.

In developing countries, the majority of poultry production is offered by small-to-medium-sized enterprises (SMEs). For instance, in Colombia, poultry SMEs represented 58% of the sector in the period between 2013 and 2017 (Rivera-Godoy and Rendón-Perea, 2019). In a context of growing markets and a more intensive and industrialized production, such SMEs must develop strategies to enhance their competitiveness (Mcleod et al., 2009). One plausible plan is the integration of the supply chain, which, in the poultry sector, implies the collaboration between farms and meat processing facilities. Such cooperation can provide either a vertical integration of large companies with farms or contractual relationships where farms supply services to integrators (OECD, 2018). On the other hand, intensification is another strategy that improves economies of scale in SMEs (Robinson et al., 2011) by lowering costs and allowing access to better technology and management practices. In any case, such strategies increase the complexity of the operations and quantitative analytical methods are then required to make better decisions.

Hence, integrated production planning in the broiler chicken supply chain requires a careful coordination to guarantee not only profitability and high-quality standards but also animal welfare (Allender and Richards, 2010; Tonsor and Olynk, 2011). Good living conditions assure biosecurity measures (Siekkinen et al., 2012; Van Limbergen et al., 2018), prevent and control diseases in birds, and enable sustainable practices (Leinonen and Kyriazakis, 2016), which lead to environmentally and economically viable systems.

For a mid-term (i.e., 6- to 12-month) production plan at the farm level, managers must make several tactical and interweaved decisions. Primarily, they must determine the batch size of chicken lots arriving from hatcheries; and the allocation of these lots to grow-out houses of different sections or farms with varying capacities, while meeting biosecurity constraints. In addition, if the operation in the slaughterhouse is integrated with the farm operation, the production plan should adjust to both the forecast demand of broiler meat products and the slaughterhouse capacity to fulfill the stock policies. At the end, managers are required to produce a profitable plan that keep financial and environmental costs under control.

The planning complexity in the broiler chicken supply chain provides fertile ground for the use of operational research (OR) to support decisions in this agricultural system. Since the early 1950s, OR-based approaches have been applied in agricultural systems to solve decision problems facing large-scale, social, and environmental complexities (Carravilla and Oliveira, 2013). Plà-Aragonés (2015), Weintraub and Romero (2006), Higgins et al. (2010), Bjørndal et al. (2012), and Kusumastuti et al. (2016) have reviewed applications of OR in agriculture to manage resources and to solve planning problems in crops and meat industries using techniques such as linear programming (LP), simulation, risk analysis, stochastic programming, and metaheuristics, among others.

Several applications of OR in the meat sector have been developed for the pig industry. Plà-Aragonés and Rodríguez-Sánchez (2015) and Khamjan et al. (2013) focused on the transportation of pigs to the slaughterhouse considering decisions at the farm level. Rodríguez-Sánchez et al. (2012) modeled tactical decisions at sow farms to produce piglets for the pig supply chain. Nadal-Roig and Plà (2014) developed a production planning tool based on LP for a multiperiod multisite pig production system. Finally, Albornoz et al. (2014) presented a mixed-integer linear program for pork production and cutting that focuses on the slaughterhouse operation.

Some researchers have employed OR techniques to enhance the poultry industry competitiveness. For instance, Taube-Netto (1996) developed an integrated production planning system for a leading Brazilian company. The author used a modular system to determine lot sizes, allocation decisions, slaughtering operations, and shift plans. Although the article presents an overview of the methodology, it does not cover the details of the models. It is worth noting that the sheer size of the company and the integrated structure does not fit most poultry firms in the industry. Oliveira and Lindau (2012) proposed a scheduling methodology for the collection of chickens at the farm level to reduce the waiting times of birds before their transportation to a slaughterhouse with capacity constraints. For egg-laying chickens, which are raised for egg production (not meat consumption), Boonmee et al. (2015) used a hybrid clustering heuristic to minimize transportation distances and to avoid mixing hen ages allocated in the same cages. Later, Boonmee and Sethanan (2016) developed a mixed-integer linear programming (MILP) model for solving small instances of a lot-sizing problem (i.e., with a planning horizon (PH) of up to 20 weeks) and then a particle swarm optimization approach to tackle larger instances. More recently, Brevik et al. (2020) presented an MILP model for the integration in the broiler chicken industry with an emphasis on the connection between hatcheries and farms. The authors also presented rolling-horizon (RH) heuristics to efficiently solve the instances due to the computational burden of the MILP model.

The literature lacks work on integrated production planning and scheduling in the broiler chicken supply chain where farms and slaughterhouses are tightly coordinated. This paper aims to fill this gap by extending the work outlined by the authors in BigDSSAgro held in Valparaiso (Chile) in 2019 (Solano-Blanco et al., 2020). This work presents an optimization-based decision support tool that tackles strategic, tactical, and operational decisions in a poultry company with integrated operations among its farms and slaughterhouse facilities.

The remaining structure of the paper is as follows. Section 2 presents the integrated production planning problem for broiler chickens. In Section 3, we present the MILP model that provides a production plan. Section 4 presents the case study. Section 5 presents both computational experiments on different instances of a Colombian poultry company with vertical integration (farm and slaughterhouse) and a comparative analysis using a rolling-horizon heuristic and a sensitivity analysis on the demand. Finally, Section 6 concludes the paper and outlines future work.

2. The broiler chicken production problem

We study the broiler chicken supply chain where production and inventory decisions are made by the same decision maker at the farm, slaughterhouse, and wholesale level. The hatcheries and feed manufacturers are suppliers of day-old chicken and chicken feed, respectively. These sourcing options have sufficient capacity, provided purchase orders are sent to suppliers with enough time in advance. In general, hatcheries expect purchase orders six months ahead of time so they can plan and adjust their production of day-old chicken lots. Therefore, a decision support tool for planning poultry operations is critical to run efficiently, this supply chain and negotiating economic deals with hatcheries and feeding mills.

In this vertically integrated context, decisions made at the farm level have a tremendous impact and propagate throughout the whole supply chain. Specifically, the lot sizing and assignment of day-old chicken lots to grow-out houses have a cascade effect in the poultry chain. Such resource allocation decisions must consider not only the operational conditions in the farm but also the capacity of the slaughterhouse and the demand of chicken meat products at the wholesale level. Thus, the coordinated flow of material and information between these echelons of the poultry supply chain makes production planning a challenging problem for any company.

Fig. 2. Life cycle of the broiler chicken in a grow-out house.

Figure 2 shows the typical life cycle of the broiler chicken under consideration. Operations at the farm begin with the arrival of day-old chicken lots. These lots are allocated in grow-out houses where they stay until completing their life cycle and are taken to the slaughterhouse. In the grow-out houses, chickens are provided with water, food, and a controlled microclimate. The first two weeks are crucial since mortality and food-meat conversion rates are particularly high. If chickens are confined to a high density (chickens/m^2), their stress levels increase while their conversion rate and meat quality decrease (Estevez, 2007). Overcrowding can even cause a significant increase in mortality rates, yet lower densities increase costs of chicken raising.

Meeting biosecurity measures improve animal welfare and guarantee meat quality for human consumption. For this reason, it is of utmost importance that broiler chickens allocated at the same grow-out house have the same age, so vaccines can be scheduled accordingly. By doing so, there are lower chances of proliferation of diseases, which can greatly affect the whole farm and its surroundings. Since chickens are mainly affected by airborne diseases or through tools used by employees, it is advisable to have homogeneous and separated lots. Consequently, poultry farms are often geographically divided into smaller areas called *sections* comprising grow-out houses located nearby. Figure 3 shows an example of a case of a farm with 11 grow-out houses distributed into five sections.

Confining chickens into sections is a good poultry farming practice. Aside from avoiding cross-contamination, which is a major biosecurity concern, sections can also increase productivity. Since the idea is that grow-out houses in one section are filled with day-old chicken in the shortest possible time, nearby chickens are going to reach their slaughter weight roughly at the same time. When the slaughter time comes, it then requires less effort to load trucks and ship chickens to the slaughterhouse. Once chickens leave the farm, cleaning and sanitation processes start simultaneously at all grow-out houses of the same section, so to get ready for a new production cycle as early as possible. These processes require a rest period where no chicken lots are assigned to the section.

In the meat market, consumers value freshness and short storage times. A good coordination between farm and slaughterhouse operations often translate into low inventories and cost reductions. A good flow of information allows for a smooth reaction to demand fluctuations and to adjust operations to avoid under- or oversupply. Slaughterhouses store chicken meat products in compartmentalized cold rooms that operate based on the inventory levels and their safety stock. In practice, if inventory levels are kept low, close to the safety stock, product freshness is guaranteed and storage costs reduced.

In summary, an efficient broiler chicken supply chain relies on coordinated farm, slaughterhouse, and wholesale operations. Given the farm layout (i.e., distribution of sections and grow-out houses),

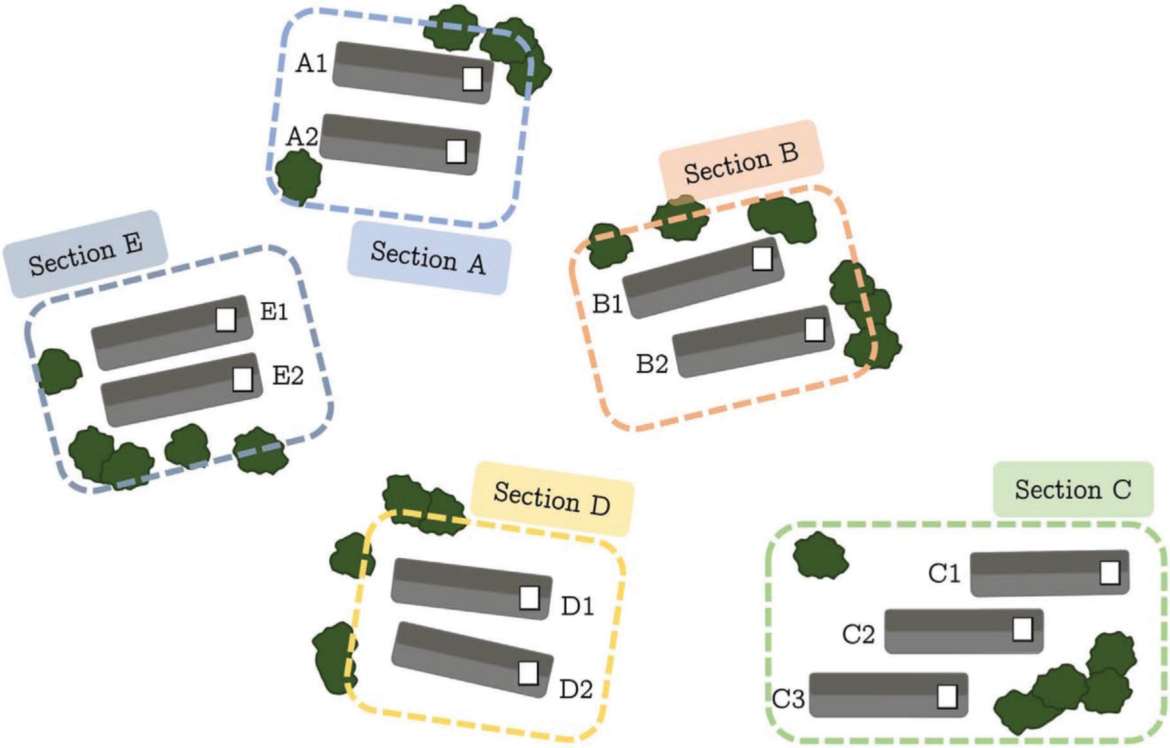


Fig. 3. Example of a farm with 11 grow-out houses distributed into five sections.

the broiler chicken production problem consists of determining the size of day-old chicken lots to order from hatcheries and the grow-out house assignment at the farm, so to maximize the company's profit along the PH. The plan must meet the demand of chicken meat product at the wholesale level as well as operational and biosecurity constraints in the farm and slaughterhouse. The longer the PH the better, as better decisions can be spread taking advantage of seasonal demand and better sourcing deals.

3. Optimization model for the broiler chicken production problem

We propose an MILP model to solve the broiler chicken production problem. The MILP model aims at providing optimal production and inventory decisions for the farm and the slaughterhouse, while observing the demand from the wholesale level and operational constraints. The model will be described using the order of Fig. 4, which zooms in on Fig. 1. Table 1 summarizes the notation used in this section.

The model definition is as follows. Let $\mathcal{T}$ be the set of weeks in the time horizon and $\mathcal{J}$ the set of ages of broiler chickens (in weeks). Let $\mathcal{H}$ be the set of grow-out houses and $\mathcal{H}^0$ the subset of grow-out houses that are occupied (i.e., not available) at the beginning of the PH. Let $\mathcal{S}$ be the set

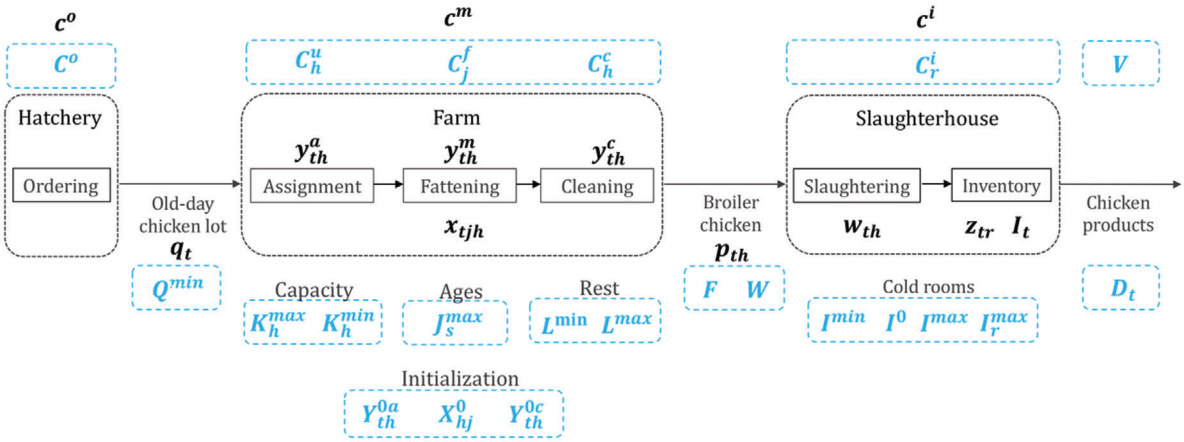


Fig. 4. Schematic notation of the model following the flow of the supply chain.

of sections in the farm and $\mathcal{H}_s$ be the subset of grow-out houses of section $s \in \mathcal{S}$. Finally, let $\mathcal{R}$ be the set of walk-in cold rooms at the slaughterhouse.

The integrated operation starts with the day-old chicken lot orders that arrive every week to the farm. The number of day-old chickens in the lot should be greater than a minimum order quantity parameter Q^{min}. The lot is then assigned to one or more grow-out houses $h \in \mathcal{H}$, considering its minimum and maximum occupancy, which are the parameters K_h^{min} and K_h^{max}, respectively. Chicken lots of different ages can be assigned to grow-out houses of the same section $s \in \mathcal{S}$, but the difference between lot ages can be at most J_s^{max} weeks. After chickens are sent to the slaughterhouse, grow-out houses need to be cleaned and rested during at least L^{min} weeks; on the other hand, a grow-out house cannot be idle for more than L^{max} weeks. In the first weeks of the PH, the values of some variables have to be fixed using the parameters Y_{th}^{0a} for assignments, X_{hj}^0 for fattening, and Y_{tk}^{0c} for cleaning.

The chicken lot that arrives to the slaughterhouse is diminished by the mortality rate F. Chickens are slaughtered and the yield is given by the parameter W. The chicken product is then stored in cold rooms. In the first week, there is an inventory of I^0 at the slaughterhouse; then, at any given time, there should be a minimum safety stock given by I^{min}. The parameters I_r^{max} and I^{max} represent the maximum inventory capacity of every cold room $r \in \mathcal{R}$ and of the slaughterhouse, respectively. The demand is known for every week and it is denoted by the parameter D_t. The parameter C^o denotes the unitary ordering cost of day-old chickens. Parameters C_h^u and C_h^c are the fixed costs of using and cleaning a grow-out house, respectively. The cost C_h^u includes mostly salaries and supplies to workers; and the cost C_h^c includes disinfection and sanitization supplies. The parameter C_{tj}^f is the unitary cost of maintaining (fattening) chickens of age $j \in \mathcal{J}$ in week $t \in \mathcal{T}$ and includes the cost of feed and vaccines. In general, in the poultry cost structure, the feed costs account roughly for 70% of the operation cost, thus C_{tj}^f is modeled with finer detail to capture cost variations per week along the PH. Finally, parameter V_t denotes the revenue per unit of chicken product on week $t \in \mathcal{T}$.

The model decides with variable q_t the size of the day-old chicken lot that arrives on week $t \in \mathcal{T}$. For the farm operation, binary variables y_{th}^a, y_{th}^m, and y_{th}^c decide whether a grow-out house $h \in \mathcal{H}$

Table 1
Summary of the notation used in the mathematical model

Sets	
$\mathcal{T}$	Set of weeks in the time horizon (ordered set)
$\mathcal{J}$	Set of ages (in weeks) of broiler chickens
$\mathcal{H}$	Set of grow-out houses
$\mathcal{H}^0$	Set of grow-out houses occupied at the beginning of the PH (i.e., not available)
$\mathcal{S}$	Set of sections in the farm
$\mathcal{H}_s$	Set of grow-out houses of section $s \in \mathcal{S}$
$\mathcal{R}$	Set of walk-in cold rooms at the slaughterhouse (ordered set)
Parameters	
Q^{min}	Minimum order quantity of day-old chickens for each week (chickens)
K_h^{min}	Minimum number of chickens in grow-out house $h \in \mathcal{H}$ (if used) (chickens)
K_h^{max}	Maximum number of chickens in grow-out house $h \in \mathcal{H}$ (if used) (chickens)
J_s^{max}	Maximum difference of chicken ages allowed in section $s \in \mathcal{S}$ (weeks)
L^{min}	Minimum number of weeks for cleaning, sanitizing, disinfecting, and resting of a grow-out house (weeks)
L^{max}	Maximum number of weeks for resting of a grow-out house (weeks)
Y_{th}^{0a}	1, if the grow-out house $h \in \mathcal{H}$ can be assigned on week $t = 1, \ldots, \lvert\mathcal{J}\rvert - 1$; 0, otherwise
Y_{th}^{0c}	1, if the grow-out house is resting on week $t = 1, \ldots, L^{min}$; 0, otherwise
X_{hj}^{0}	The number of chickens of age $j \in \mathcal{J}$ that occupy grow-out house $h \in \mathcal{H}$ on the first week (chickens)
F	Mortality rate of a chicken lot (dimensionless)
W	Unitary yield of slaughtered chickens (kg/chicken)
I^{min}	Minimum inventory of chicken product (kg)
I^{max}	Maximum inventory of chicken product (kg)
I_r^{max}	Maximum inventory in cold room $r \in \mathcal{R}$ (kg)
I^0	Inventory of chicken product at the beginning of the planning horizon (kg)
D_t	Demand of chicken product on week $t \in \mathcal{T}$ (kg)
C^o	Unitary ordering (purchasing) cost of a day-old chicken (\$)
C_h^u	Fixed weekly cost of using grow-out house $h \in \mathcal{H}$ (\$)
C_{tj}^f	Unitary weekly cost of fattening a chicken of age $j \in \mathcal{J}$ on week $t \in \mathcal{T}$ (\$)
C_h^c	Fixed weekly cost of cleaning, sanitizing, and disinfecting grow-out house $h \in \mathcal{H}$ (\$)
C_r^i	Fixed weekly cost of carrying inventory using cold room $r \in \mathcal{R}$ (\$)
V_t	Revenue per kilogram of chicken product for week $t \in \mathcal{T}$ (\$/kg)
Variables	
q_t	Size of the day-old chicken lot that arrives on week $t \in \mathcal{T}$ (chickens)
y_{th}^a	1, if the grow-out house $h \in \mathcal{H}$ receives a day-old chicken lot at week $t \in \mathcal{T}$; 0, otherwise
y_{th}^m	1, if a lot of chickens with age greater than one week is maintained at grow-out house $h \in \mathcal{H}$ in week $t \in \mathcal{T}$; 0, otherwise
y_{th}^c	1, if the grow-out house $h \in \mathcal{H}$ is being cleaned in week $t \in \mathcal{T}$; 0, otherwise
x_{thj}	The number of chickens of age $j \in \mathcal{J}$ that occupy a grow-out house $h \in \mathcal{H}$ in week $t \in \mathcal{T}$ (chickens)
w_{th}	Quantity of chicken product from chickens of the grow-out house $h \in \mathcal{H}$ slaughtered in week $t \in \mathcal{T}$ (kg)
z_{tr}	1, if the cold room $r \in \mathcal{R}$ is being used on week $t \in \mathcal{T}$; 0, otherwise
I_t	Quantity of chicken product that is kept on inventory in the cold rooms at the end of week $t \in \mathcal{T}$ (kg)
Auxiliary variables	
c^o	Cost of ordering (\$)
c^m	Cost of farm operation (\$)
c^i	Cost of inventory management (\$)

should be assigned with day-old chickens, maintained with chickens of other ages, or cleaned in a given week $t \in \mathcal{T}$, respectively. The variable x_{thj} keeps track of the amount of chickens that are in grow-out house $h \in \mathcal{H}$ in week $t \in \mathcal{T}$ with age $j \in \mathcal{J}$. Variable p_{th} denotes how many chickens leave grow-out house $h \in \mathcal{H}$ in week $t \in \mathcal{T}$ to be slaughtered; while variable w_{th} keeps track of the chicken product (in kg) after the slaughtering. Variable z_{tr} decides whether to operate a cold room $r \in \mathcal{R}$ on week $t \in \mathcal{T}$, while variable I_t keeps track of the inventory of chicken product stored in the cold rooms on week $t \in \mathcal{T}$. Finally, the auxiliary variables c^o, c^m, and c^i are a convenient way to account for the total ordering, maintenance, and inventory costs, respectively. The proposed MILP follows:

$$\max \quad z = \sum_{t \in \mathcal{T}} V_t \cdot D_t - [c^o + c^m + c^i] \tag{1}$$

subject to

costs:

$$c^o = \sum_{t \in \mathcal{T}} C^o \cdot q_t \tag{2}$$

$$c^m = \sum_{t \in \mathcal{T}} \sum_{h \in \mathcal{H}} \left[\left(C_h^u \cdot (y_{th}^a + y_{th}^m) + C_h^c \cdot y_{th}^c \right) + \sum_{j \in \mathcal{J}} C_{tj}^f \cdot x_{thj} \right] \tag{3}$$

$$c^i = \sum_{t \in \mathcal{T}} \sum_{r \in \mathcal{R}} C_r^i \cdot z_{tr}; \tag{4}$$

ordering:

$$q_t \geq Q^{min}, \quad t = 1, \ldots, |\mathcal{T}| - |\mathcal{J}| + 1 \tag{5}$$

$$q_t = \sum_{h \in \mathcal{H}} x_{th1}, \quad t = 1, \ldots, |\mathcal{T}| - |\mathcal{J}| + 1; \tag{6}$$

assignment of grow-out houses:

$$y_{th}^a + \sum_{t' = t + J_s^{max} + 1}^{t + |\mathcal{J}| - 1} y_{t'h'}^a \leq 1, \quad t = 1, \ldots, |\mathcal{T}| - |\mathcal{J}| + 1; h, h' \in \mathcal{H}_s; s \in \mathcal{S} \tag{7}$$

$$x_{th1} \geq K_h^{min} \cdot y_{th}^a, \quad t \in \mathcal{T}, \ h \in \mathcal{H} \tag{8}$$

$$x_{th1} \leq K_h^{max} \cdot y_{th}^a, \quad t \in \mathcal{T}, \ h \in \mathcal{H} \tag{9}$$

$$x_{thj} \geq K_h^{min} \cdot y_{th}^m, \quad t \in \mathcal{T}, \ h \in \mathcal{H}, \ j \in \mathcal{J} \tag{10}$$

$$x_{thj} \leq K_h^{max} \cdot y_{th}^m, \quad t \in \mathcal{T}, \ h \in \mathcal{H}, \ j \in \mathcal{J} \tag{11}$$

$$y_{th}^a + y_{th}^m + y_{th}^c \leq 1, \quad t \in \mathcal{T}, \ h \in \mathcal{H}; \tag{12}$$

sanitation of grow-out houses:

$$K_h^{max} \cdot y_{t'h}^c \geq x_{th|\mathcal{J}|}, \quad t = 1, \ldots, |\mathcal{T}| - 1; \quad t' = t+1, \ldots, \min(t + L^{min}, |\mathcal{T}|); \quad h \in \mathcal{H} \tag{13}$$

$$\sum_{t'=t}^{t+|\mathcal{J}|+L^{max}-1} y_{t'h}^a \geq 1, \quad t = 1, \ldots, |\mathcal{T}| - |\mathcal{J}| - L^{max} + 1; h \in \mathcal{H}; \tag{14}$$

farm initialization (variable fixing):

$$x_{thj} \leq 0, \quad t = 1, \ldots, |\mathcal{J}| - 1; \; h \in \mathcal{H} \;\middle|\; h \notin \mathcal{H}^0; \quad j = t+1, \ldots, |\mathcal{J}| \tag{15}$$

$$y_{th}^c \geq Y_{th}^{0c}, \quad t = 1, \ldots, L^{min}; \; h \in \mathcal{H} \;\middle|\; Y_{th}^{0c} = 1 \tag{16}$$

$$y_{th}^a \leq Y_{th}^{0a}, \quad t = 1, \ldots, |\mathcal{J}|; \; h \in \mathcal{H} \tag{17}$$

$$x_{1hj} = X_{hj}^0, \quad h \in \mathcal{H}^0, \; j \in \mathcal{J} \;\middle|\; X_{hj}^0 > 0; \tag{18}$$

fattening:

$$x_{thj} = x_{t+1,h,j+1}, \quad t = 1, \ldots, |\mathcal{T}| - 1; \; h \in \mathcal{H}; \; j = 1, \ldots, |\mathcal{J}| - 1 \tag{19}$$

$$x_{th1} = 0, \quad t = |\mathcal{T}| - |\mathcal{J}| + 1, \ldots, \mathcal{T}; \; h \in \mathcal{H}; \tag{20}$$

slaughterhouse:

$$w_{th} = (1 - F) \cdot W \cdot x_{th|\mathcal{J}|}, \quad t \in \mathcal{T}, h \in \mathcal{H}; \tag{21}$$

freezing rooms:

$$I_t \geq I^{min}, \quad t \in \mathcal{T} \tag{22}$$

$$I_t \leq I^{max} \cdot z_{t1}, \quad t \in \mathcal{T} \tag{23}$$

$$I_t - \sum_{r'=1}^{r-1} I_{r'}^{max} \leq \left(I^{max} - \sum_{r'=1}^{r-1} I_{r'}^{max} \right) \cdot z_{tr}, \quad t \in \mathcal{T}; \; r = 2, \ldots, |\mathcal{R}|; \tag{24}$$

sales:

$$\sum_{h \in \mathcal{H}} w_{1h} + I^0 = D_1 + I_1 \tag{25}$$

$$\sum_{h \in \mathcal{H}} w_{th} + I_{t-1} = D_t + I_t, \quad t = 2, \ldots, |\mathcal{T}|; \tag{26}$$

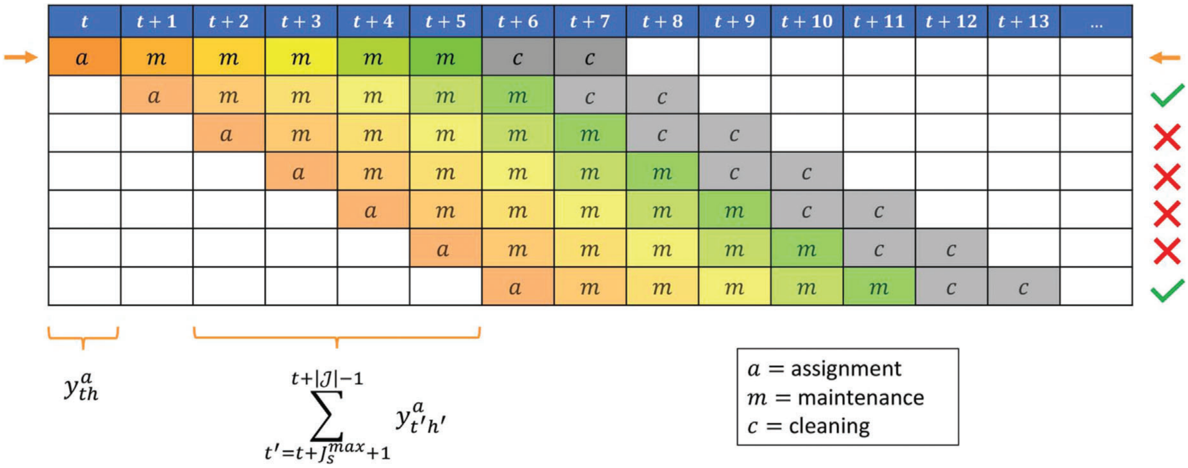


Fig. 5. Graphical representation of constraint (7), which enforces a maximum allowed age difference between lots.

variable definition:

$$x_{thj} \in \mathbb{Z}^1_+; \quad t \in \mathcal{T}, h \in \mathcal{H}, j \in \mathcal{J} \tag{27}$$

$$y^a_{th}, y^m_{th}, y^c_{th} \in \{0, 1\}; \quad t \in \mathcal{T}, h \in \mathcal{H} \tag{28}$$

$$w_{th} \geq 0; \quad t \in \mathcal{T}, h \in \mathcal{H} \tag{29}$$

$$z_{tr} \in \{0, 1\}; \quad t \in \mathcal{T}, r \in \mathcal{R} \tag{30}$$

$$q_t \in \mathbb{Z}^1_+; \quad t \in \mathcal{T} \tag{31}$$

$$I_t \geq 0; \quad t \in \mathcal{T} \tag{32}$$

$$c^o, c^m, c^i \geq 0. \tag{33}$$

The model maximizes profit (1) by subtracting to the sales income, the costs of fattening and slaughtering operations (2)–(4) along the PH. The group of constraints (5) assures that the order size at any given week is larger than or equal to the minimum order size. Since the last lot considered should be ready for slaughtering at the end of the PH, we can only order until period $|\mathcal{T}| - (|\mathcal{J}| - 1)$. The set of constraints (6) assigns the day-old chicken of the arriving lot to the grow-out houses every week.

The set of constraints (7) guarantees that the age difference within a section is less than or equal to the maximum allowed. For the sake of clarity, Fig. 5 illustrates this constraint through an example with $|\mathcal{J}| = 6$ and $J^{max}_s = 1$. Let the first row represent an assignment at grow-out house h in week t, then the constraint checks for the other grow-out houses h' in the same section s, that the maximum difference between ages of chickens in that section is one week. This indicates that we can assign chickens in that section on $t + 1$ but not on $t + 2, \ldots, t + 5$.

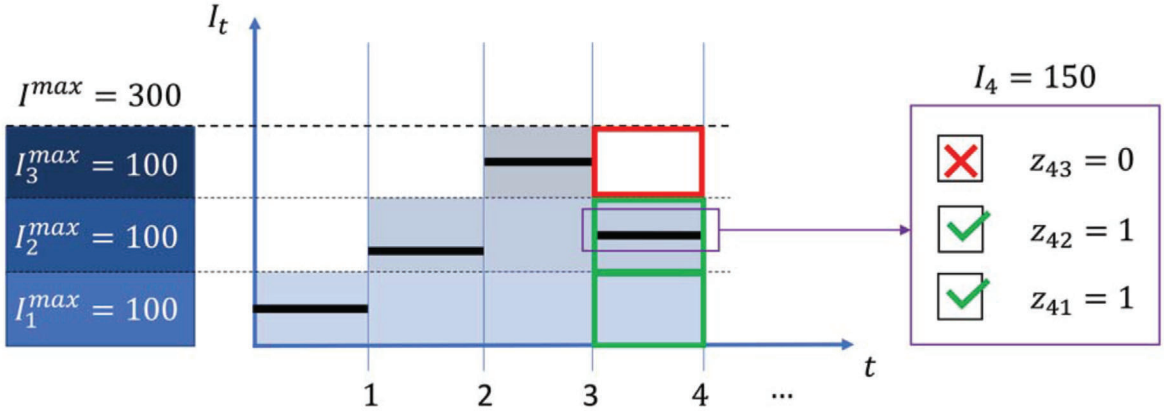


Fig. 6. Graphical representation of the inventory and cold rooms management modeled through constraint (24).

Constraints (8) and (10) guarantee that if a grow-out house is used, the amount of assigned chickens should satisfy a minimum occupancy level. Constraint groups (9) and (11) assure that the amount of chickens assigned is less than or equal to the maximum capacity of the grow-out houses. If a grow-out house is being used, new chicken assignments are possible after it is freed from the current lot and sanitized. Constraints (12) guarantee that at a given time period a grow-out house could be either receiving chickens, maintaining chickens, being cleaned, or idle.

For sanitation purposes, the set of constraints (13) enforces a minimum number of weeks of cleaning for each grow-out house just after a lot of chickens has been sent to the slaughterhouse. The constraint group (14) assures that any grow-out house should not exceed L^{max} weeks of cleaning and resting after the fattening stage.

The set of constraints (15) assures that in the first weeks, the model does not assign chickens older than t. For instance, the model forbids to maintain chickens three-week old in the second week of the PH. Constraints (16) assure the resting period of grow-out houses in the first weeks that is fixed with parameter Y_{th}^{0c}. The set of constraints (17) guarantees that no more grow-out houses can be assigned to a section in the first weeks if this assignment violates the biosecurity conditions with parameter Y_{th}^{0a}. Constraint group (18) assigns chickens of different ages in the first week according to the initial assignment conditions of the farm. In summary, constraints (15)–(18) allow us to initialize the model with a snapshot of the current conditions in the farm.

We model the chicken life cycle with constraints (19) assuring that, when assigned, chickens are going to grow through the weeks until they reach the slaughter weight (at age $|\mathcal{J}|$). Constraints (20) guarantee that there are no more assignments of chickens in the farm in the last weeks of the PH because they would not reach maturity. The set of constraints (21) guarantees that the number of chickens that leave the grow-out house are converted to kilograms of chicken meat product accounting for the mortality rate.

In the slaughterhouse, chicken meat products are stored in walk-in cold rooms. Constraint group (22) enforces the minimum weekly inventory. Constraints (23) assure that the first cold room is always in operation. Constraints (24) guarantee that cold rooms are activated depending on the inventory levels. Figure 6 shows an illustrative example with three cold rooms, each one of them with a capacity of 100 kg, and an inventory in the fourth period of $I_4 = 150$. For this case, the first two cold rooms should be operating and the third cold room should be powered off, so variables z_{41} and z_{42} will take the value of 1, while variable z_{43} will take the value of 0.

Finally, with constraints (25) for the first week and (26) for the remaining ones, we guarantee that the inventory of meat (chicken product) at the end of a time period is given by the initial inventory, plus the newly slaughtered chicken coming from the farm, minus the demanded chicken product at the sales points. Constraints (27)–(33) define the nature of the decision variables.

4. Case study: a vertically integrated poultry supply chain in Santa Marta (Colombia)

We applied the proposed optimization model using real data from a medium-sized company in Santa Marta (Colombia) called Pollos Altair. The company handles 80,000 chickens at any given time in the farm and a daily production of more than 2,000 chickens in the slaughterhouse. The company was involved in the model definition phase providing constant feedback and reality checks. Some of the critical and practical requirements, explicitly asked by the company management, consisted in handling biosecurity constraints, initial conditions, and maximum resting times in grow-out houses, among other conditions. The model was refined through an iterative process with periodic meetings with the company's management.

The company provided 30 months of data records (from January 2016 to June 2018) on the farm scheduling and slaughterhouse operations. Jointly with the company, we estimated parameters such as, but not limited to, costs, allowed chicken density, inventory limits, size of day-old chicken lots, and chicken-to-meat conversion rates. To estimate demand, we used production and inventory levels and a forecast based on historic data.

The company sends in advance its yearly poultry production plan to the hatchery. This information flow allows the hatchery to align its production plan and improve the supply chain performance from the supplier end. However, during the year, the plan is updated every six months and the company is allowed to make minor modifications to the plan three months in advance of the housing date. For benchmark purposes, we created four instances with 3-, 6-, 9-, and 12-month PHs from two datasets with records starting in December 2016 and December 2017 labeled as `Altair01` and `Altair02`, respectively.

To illustrate the model inputs, let us consider a smaller instance depicted in Fig. 7. It represents the state of the farm with 11 grow-out houses distributed in five sections at the beginning of the PH. Note that some sections (e.g., Section C) have allocated lots of chicken of different ages. Within sections, chickens of one or two consecutive ages are allowed to coexist. Also, if a grow-out house is empty, it could be either idle or being cleaned. After solving the model, the company aims for a detailed production plan at the farm and the inventory management decisions at the slaughterhouse, which could lead to the best possible profit while meeting all business constraints.

5. Computational results and analysis

We implemented the model using Pyomo 5.6.2.dev0 (Hart et al., 2017) library for Python 3.7 and Gurobi 9.0.2 as the MILP solver (Gurobi Optimization, 2020). We ran all experiments on a 7th

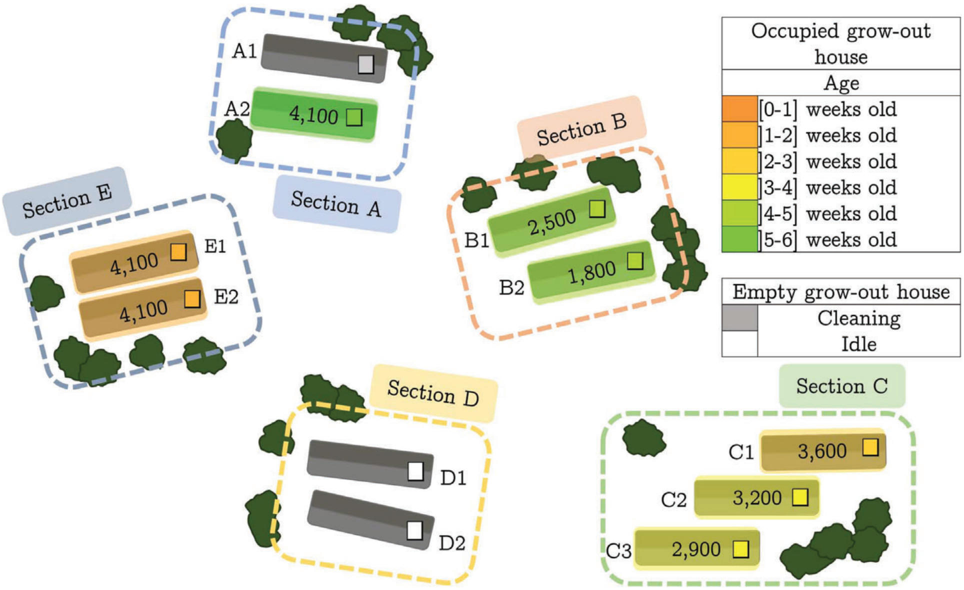


Fig. 7. Illustrative example of the farm with 11 grow-out houses distributed in five sections.

Generation AMD A10 2.40 GHz computer with 8 GB RAM, 10 processors (4 CPU + 6 GPU cores) and 64-bit architecture on Windows 10. We set the solver parameters to use at most four threads; and the termination criteria was either a time limit of 84,600 seconds (1 day) or an optimality gap of 1%, 3%, 5%, and 10% for the 3-, 6-, 9-, and 12-month instances, respectively.

5.1. Decision support system

We developed a Microsoft (MS) Excel-based decision support system to communicate the output of the models to the farm managers and to facilitate the implementation of the model's output. Figure 8 represents a 13-week (three-month) schedule for the farm operations of the illustrative example shown in Fig. 7. The columns in the table represent weeks, while rows represent a combination of section (A, B, C, D, or E) and grow-out house sequence (1, 2, ...). Observing a given column, we could know the current state of the farm for a given week. For instance, observing column "01," we note that in the first week grow-out houses A1 and D1 are idle; 4100 chicken at grow-out house A2 are ready to be sacrificed; and an incoming lot of 2068 day-old chickens from the hatchery is allocated to grow-out house D2. If we focus on a row, for instance D2, we see what happens to the grow-out house along the PH. Note that the incoming lot of chickens in grow-out house D2 is raised and gets ready to be slaughtered in week 6. Then, the grow-out house gets cleaned in weeks 7 and 8, and becomes idle starting from week 9. This output was produced with Visual Basic for Applications (VBA) automation in MS-Excel and helped us communicate the proposed production plan to the farm managers. Based on this output, they quickly checked if the results were coherent and helped us discuss model changes.

Grow-out house		Week 01	02	03	04	05	06	07	08	09	10	11	12	13
A	A1			4,100	4,100	4,100	4,100	4,100	4,100					
A	A2	4,100			4,100	4,100	4,100	4,100	4,100	4,100				
B	B1	2,500	2,500				4,100	4,100	4,100	4,100	4,100	4,100		
B	B2	1,800	1,800			3,634	3,634	3,634	3,634	3,634	3,634			
C	C1	3,600	3,600	3,600	3,600			4,100	4,100	4,100	4,100	4,100	4,100	
C	C2	3,200	3,200	3,200			2,663	2,663	2,663	2,663	2,663	2,663		
C	C3	2,900	2,900	2,900				3,331	3,331	3,331	3,331	3,331	3,331	
D	D1		4,100	4,100	4,100	4,100	4,100	4,100						
D	D2	2,068	2,068	2,068	2,068	2,068	2,068							
E	E1	4,100	4,100	4,100	4,100	4,100			4,100	4,100	4,100	4,100	4,100	4,100
E	E2	4,100	4,100	4,100	4,100	4,100			2,239	2,239	2,239	2,239	2,239	2,239

Occupied grow-out house
Age
[0-1] weeks old
]1-2] weeks old
]2-3] weeks old
]3-4] weeks old
]4-5] weeks old
]5-6] weeks old

Empty grow-out house
Cleaning
Idle

Fig. 8. Illustrative example: a 13-week schedule for the farm (weeks in columns; grow-out houses in rows). Colors in cells represent the age of chicken lots.

s	First Cycle							
1	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	D - D2	-	Fri, Jan 4 2019	400	5.17	2068	Sun, Feb 10 2019	Fri, Feb 15 2019
	Previous Inventory	6231	Estimated demand	6000	Total	2068	Inventory	4243
2	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	D - D1	-	Fri, Jan 11 2019	296	13.85	4100	Sun, Feb 17 2019	Fri, Feb 22 2019
	Previous Inventory	4243	Estimated demand	5200	Total	4100	Inventory	6998
3	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	A - A1	-	Fri, Jan 18 2019	440	9.32	4100	Sun, Feb 24 2019	Fri, Mar 1 2019
	Previous Inventory	6998	Estimated demand	8500	Total	4100	Inventory	6454
4	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	A - A2	2	Fri, Jan 25 2019	200	20.50	4100	Sun, Mar 3 2019	Fri, Mar 8 2019
	Previous Inventory	6454	Estimated demand	8200	Total	4100	Inventory	6210
5	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	B - B2	2	Fri, Feb 1 2019	400	9.09	3634	Sun, Mar 10 2019	Fri, Mar 15 2019
	Previous Inventory	6210	Estimated demand	10100	Total	3634	Inventory	3160
6	Grow-out house	Rest	Lot arrival	Area (m2)	Bird/m2	Quantity	Min slaughtering date	Max slaughtering date
	B - B1	3	Fri, Feb 8 2019	400	10.25	4100	Sun, Mar 17 2019	Fri, Mar 22 2019
	C - C2	2	Fri, Feb 8 2019	400	6.66	2663	Sun, Mar 17 2019	Fri, Mar 22 2019
	Previous Inventory	3160	Estimated demand	13200	Total	6763	Inventory	3082

Fig. 9. Illustrative example: tactical visualization of the 13-week schedule.

Figure 9 shows the second representation of the schedule shown in Fig. 8, which allows farm managers to communicate with employees in charge of implementing the model's output. In Fig. 9, the solution for the illustrative example is translated into a tactical format that includes relevant information per week, including the assigned grow-out house, date of arrival, area, density, quantities of chickens, range of dates for slaughtering, demand, and inventory. Another output of the decision support system is a chart of the inventory level at any given time of the PH (depicted in Fig. 10). Note that the optimization process pushes down inventory, fulfilling the minimum requirement level and using as few cold rooms as possible.

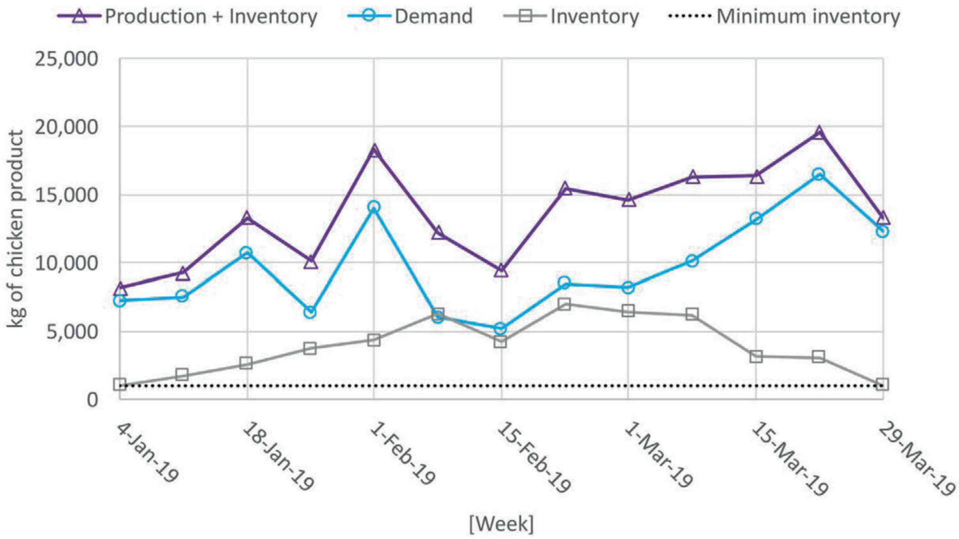


Fig. 10. Illustrative example: evolution of the production and inventory levels along the planning horizon.

Table 2
Summary of results for the benchmark instances in terms of size (horizon, variables, and constraints), quality (gap), and performance (time)

Dataset	Planning horizon (months)	Variables	Constraints	Improvement (%)	Gap (%)	Time (seconds)
Altair01	12	14,353	36,885	42.8	≤10%	6456.8
	9	10,765	27,213	36.5	≤5%	2903.8
	6	7177	17,541	40.0	≤3%	63.5
	3	3589	7869	57.0	≤1%	1.4
Altair02	12	14,353	36,885	28.3	≤10%	7690.4
	9	10,765	27,213	22.8	≤5%	2895.5
	6	7177	17,541	19.0	≤3%	187.9
	3	3589	7869	6.7	≤1%	0.4

5.2. *Quality and performance assessment*

Table 2 summarizes the computational results for the two sets of instances. Column 1 presents the name of the dataset (family of instances). Column 2 shows the length of the PH. Columns 3 and 4 present the number of variables and constraints in the resulting MILP model for each instance, respectively. Column 5 presents the improvement of the MILP solution against the housing and slaughtering plan used by the company. Column 6 presents the optimality gap used as termination criterion. Column 7 presents the computational time in seconds to reach the target gap in Column 6. More importantly, for all instances there is a significant improvement that ranges from 7% to 57%, against the manual plan of the company. Although the model is hard to solve, the optimizer found high-quality solutions for the 3-, 6-, 9-, and 12-month instances in less than 2 seconds, 4

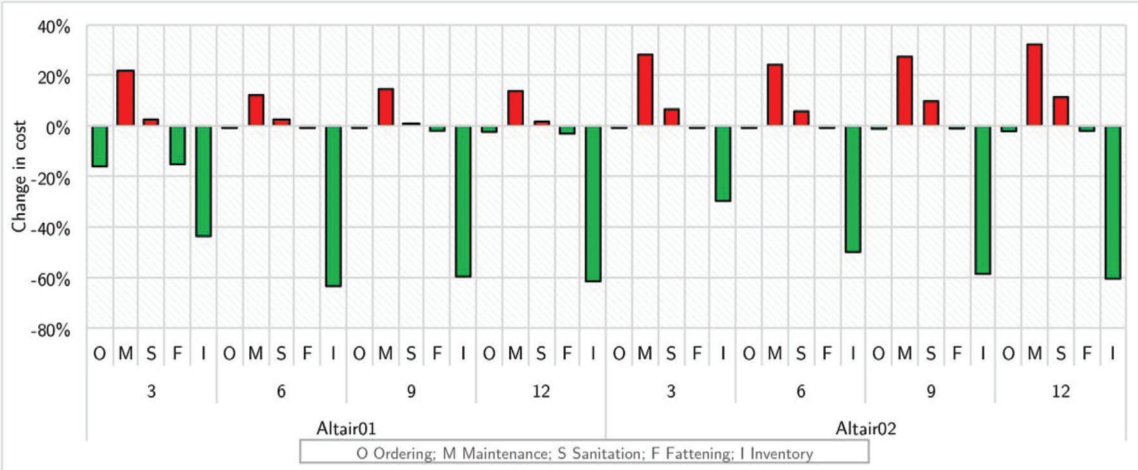


Fig. 11. Breakup of cost variation against the manual plan for all benchmark instances.

minutes, 50 minutes, and 2.2 hours, respectively. These times are acceptable due to the strategic and tactical level of the decisions.

To understand what drives the significant improvements against the manual planning approach, we delved into the cost structure of the solutions for the benchmark instances. Figure 11 shows the relative cost variation against the manual approach, breaking up the costs for each instance of each dataset (family of instances). Note that cost reductions come mostly from a better inventory management. To a less extent, these cost savings come from ordering and fattening decisions. The reduction in inventory costs ranges from 30% to 60%; while the reduction in ordering and fattening costs reaches up to 3% and 4%, respectively. This means that less chicken is bought and fattened, and ultimately kept in inventory. These cost improvements come at the expense of higher housing and cleaning costs. However, it is worth highlighting that for some instances we found that the original production plan violated the biosecurity standards, which is understandable because they are very hard to meet manually. For example, the original 12-month production plans that the company executed for the periods included in the `Altair01` and `Altair02` datasets had 16% and 23% of assignments violating biosecurity conditions, respectively. On the contrary, the model did not allow biosecurity violations, shifting the company away of an overly expensive risk exposure.

5.3. Rolling-horizon heuristic

In general, time-based optimization models present a myopic behavior in the last time periods of the PH. As the foresight is restricted to the last time period of the calendar, decisions are made without considering future periods beyond the end of the PH. In our case study, such behavior shows in Fig. 10 by model decisions carrying the inventory to the lowest possible level at the end of the PH. This low inventory and farm configuration at the end are less than ideal as they put the company at risk as initial conditions are harsh for future planning cycles (i.e., next optimization run).

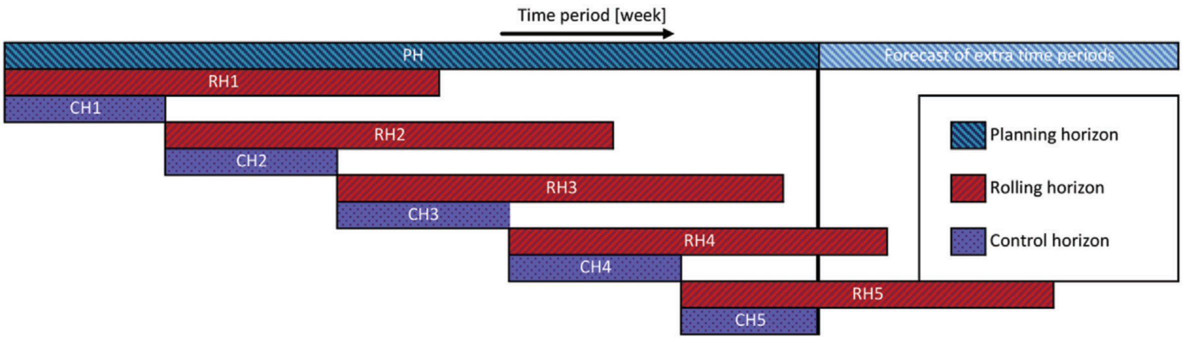


Fig. 12. Representation of the rolling-horizon approach.

A common practice in industry to address this problem is to feed the model with a forecast of additional time periods under an RH approach (Sethi and Sorger, 1991). The idea behind the RH is to make decisions for a (long) PH by solving a series of linked smaller optimization models with shorter planning cycles (Sahin et al., 2013). Although an RH approach yields a heuristic solution for the long PH, it is suitable for addressing the myopic behavior, scalability, and even stochastic demand scenarios (Silvente et al., 2015).

For the implementation of the RH approach we define (a) the (long) PH; (b) the shorter equally sized RH for each of the smaller MILP models; and (c) a control horizon (CH), which is a fraction of the RH where the smaller MILP models build (fix) part of the final solution for the PH. The RH approach iteratively solves smaller MILP models as follows. First, we solve a smaller MILP over the first RH and save the decisions of the first periods over the CH. The state of the system at the end of the first CH is used to initialize the model for the second RH. This process continues by sliding the RH over the PH, solving smaller MILP models over RH, and fixing the solution for the CH. At the end, to cover all the PH with the CH, the last RH needs to extend over additional dummy time periods. Figure 12 shows schematically an example of the RH approach with a PH of 6 months (26 weeks), RH of 3 months (13 weeks), and CH of 5 weeks (except for the last one).

To test the benefits of the RH approach, we solved the instances with the longer 9- and 12-month PHs for the `Altair01` and `Altair02` datasets, using 13-week RH. Figure 13 compares the RH heuristic against the MILP (henceforth called the *single-run MILP*) in terms of solution quality and computing time. On the left axis, the clustered columns show the improvement of the single-run MILP and the RH heuristic compared against the manual housing and slaughtering plan used by the company. On the `Altair01` dataset, the improvements for the single-run MILP for the 12- and 9-month horizon are 42.8% and 36.5%, whereas the RH heuristic improves the manual plan by 24.3% and 14.4%. Similarly, on the `Altair02` dataset, the improvements for the single-run MILP for the 12- and 9-month horizon are 28.3% and 22.8%, whereas the RH heuristic improves the manual plan by 12.9% and 4.7%. However, the better improvements of the single-run MILP come at a computational price. On the right axis (in logarithmic scale), the markers show the time in seconds for the single-run ($\times$) and the RH ($+$). On the `Altair01` dataset, the solution time for the single-run MILP for the 12- and 9-month horizon are 6456.8 and 2903.8 seconds, respectively, whereas the RH heuristic takes just 14.9 and 7.3 seconds. Similarly, on the `Altair02` dataset, the solution time for the single-run MILP for the 12- and 9-month horizon are 7690.4 and 2895.5 seconds, respectively,

Fig. 13. *Summary of results of the rolling horizon for the benchmark instances in terms of improvement and performance (time).*

whereas the RH heuristics only takes 4.6 and 3.9 seconds. Thus, on the computational side, an advantage of the RH heuristic is that it takes less than 15 seconds to solve, whereas a single-run MILP can take a few hours.

For further understanding, we delved into the solution of the single-run MILP solved for the entire PH and compared it against that of the RH heuristic. For illustrative purposes, Fig. 14 shows such differences for the 12-month instance in dataset `Altair01`. Figure 14a shows that the inventory of kilograms of broiler chicken in the RH heuristic is kept low with respect to the single-run MILP, except for the last weeks (50–52). Because the RH heuristic sees more demand on weeks that go beyond the PH, it chooses to keep more inventory to satisfy it. Such protective behavior effectively addresses the short-sighted view of the single-run MILP. At first glance, it also seems that the RH heuristic performs better due to greater savings in inventory costs. Nonetheless, the maintenance cost increases in the RH heuristic because roughly less chickens are assigned to more grow-out houses. This is supported by Fig. 14b, which shows the number of six-week-old chickens for every week and by Fig. 14c, which shows the number of grow-out houses that hold six-week-old chickens. For example, in week 11, though the amount of birds in both single-run MILP and RH heuristic are very similar, the number of grow-out houses needed by the RH heuristic to allocate the chickens is larger. In total, 13 more grow-out houses are used by the RH heuristic for this instance, thus increasing the fixed costs in comparison to the single-run MILP.

Lastly, we evaluated financially the implementation of the RH heuristic in the company. Even though the improvement by the RH heuristic is lower than the single-run MILP, the return on investment (ROI) with one year of use is at least 11%. To compute this ROI, we considered the benefits expressed by the gains against the hand-based solution and the cost of a commercial solver license, equipment, and salaries to run the project for that year. In summary, this optimization-based decision support system is self-sustainable and pays off.

5.4. Demand sensitivity analysis

Demand is a critical parameter in any production planning system and this is no exception for the broiler chicken supply chain. Fortunately, the decision support tool allows the company to

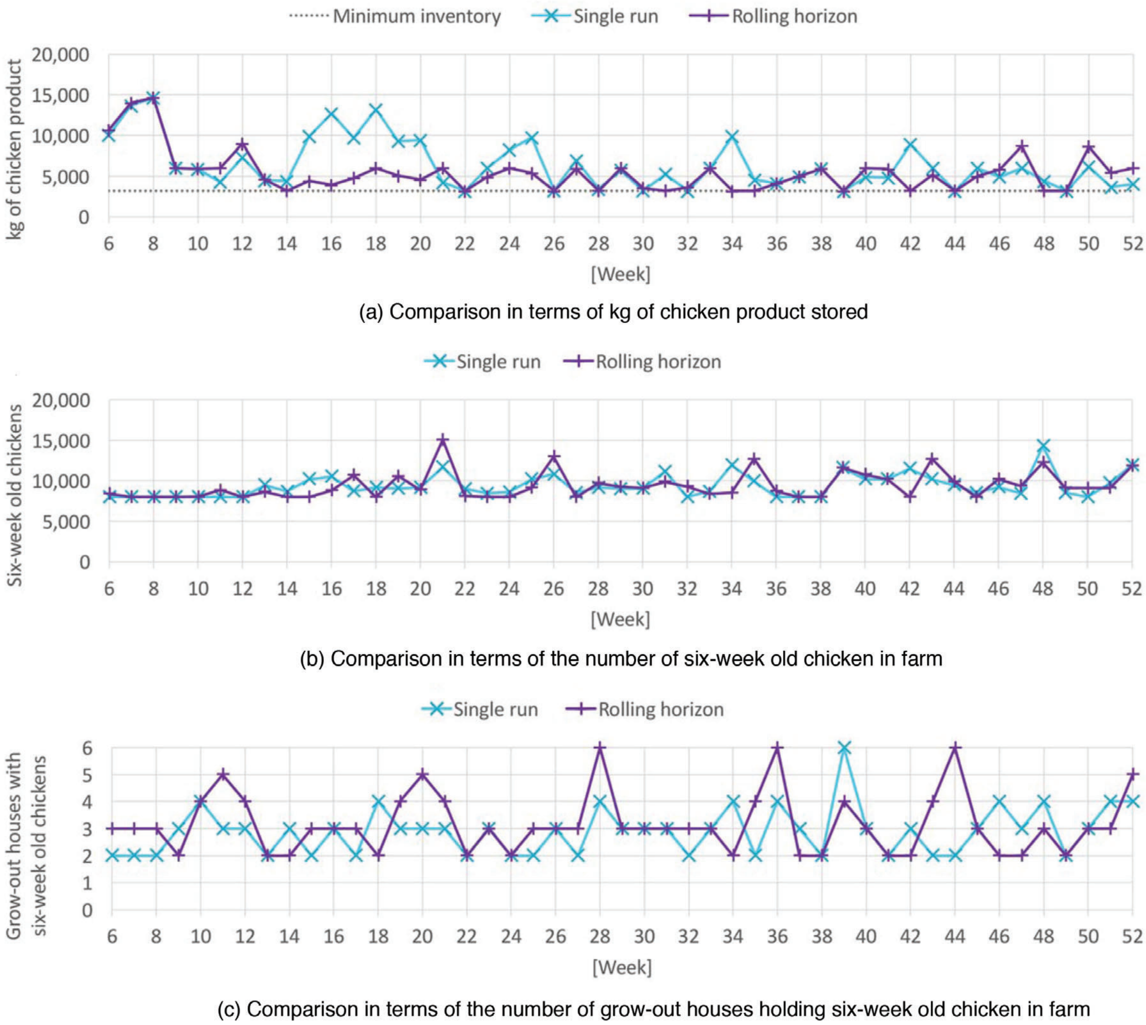
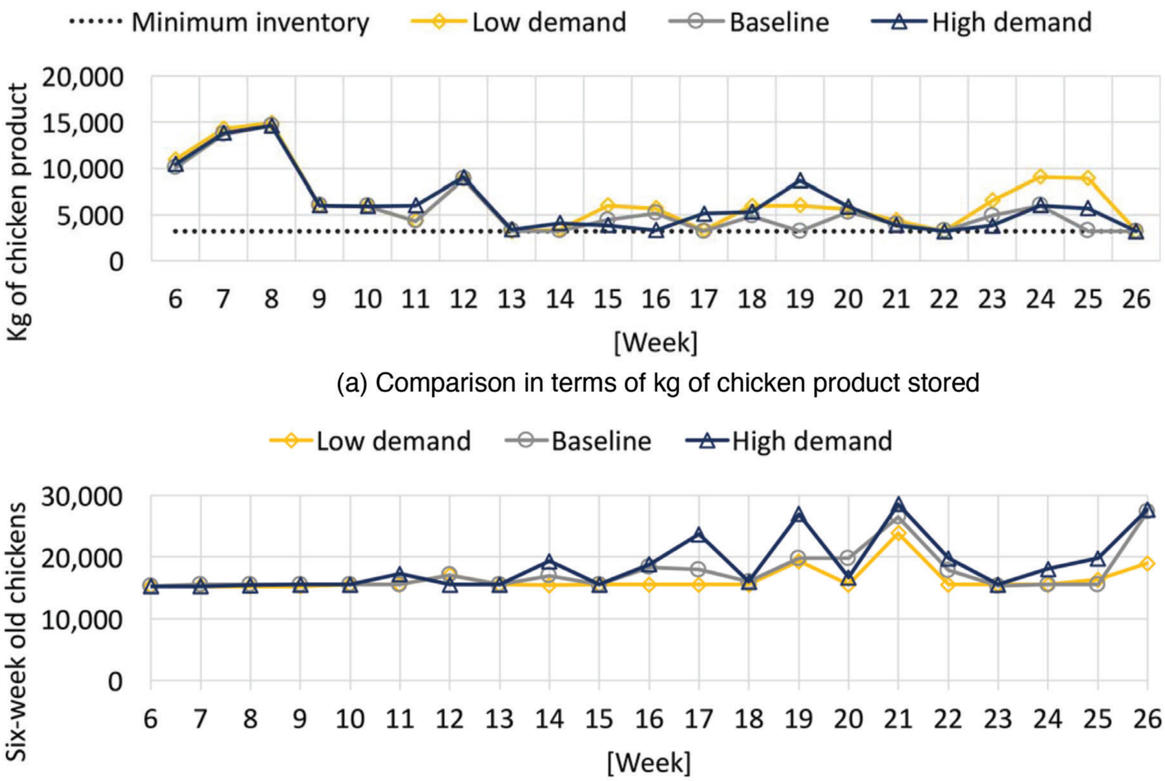


Fig. 14. Weekly comparison between the single-run MILP and the rolling-horizon heuristic for the 12-month instance of dataset `Altair01`.

explore different "what-if" scenarios to measure the impact on profit as demand fluctuates. Figure 15 shows how the prescriptive actions of the model vary as we change the demand for the six-month instance of dataset `Altair01`. We compare two scenarios (low- and high-demand) against a baseline case (expected demand). The low-demand (high-demand) scenario reduces (increases) by 10% the expected demand (baseline) in the last half of the PH.

Figure 15a and b shows the weekly inventory levels and the number of chickens ready for slaughter, suggested by the MILP for the three scenarios. Under high demand, more chickens are fattened in the farms and inventory is kept under control. In contrast, under a low-demand scenario, less chickens are fattened, but inventories are kept high. Comparing against the baseline case, the high-demand scenario increases profit by 6%, while the low-demand scenario reduces profit by 7%.



(a) Comparison in terms of kg of chicken product stored

(b) Comparison in terms of the number of six-week old chicken in farm

Fig. 15. Weekly comparison between the cases of low, baseline, and high demand for the six-month instance of dataset Altair01.

Although demand is inherently deterministic in the proposed MILP, the decision support tool allows the company to relax this assumption and evaluate different scenarios based on demand changes leading to better informed decisions. As expected, the MILP model conveniently adjusts production plans that are sensitive to demand fluctuations. In addition, the RH heuristic (Section 5.3) provides an effective adaptive strategy to adjust the production plan as more reliable demand estimates unveil. In this way, available demand estimations at the beginning of the PH can be used for an initial aggregate plan and future adjusted demand estimations could be used within a RH heuristic as more accurate data reveals over time.

6. Conclusions

In this paper, we developed an MILP model (single-run MILP) that determines a suitable way to order and assign chicken lots for the integrated operations of farms and slaughterhouses in the broiler chicken supply chain. The model maximizes profit and considers the customer demand observed at the wholesale level, initialization conditions at the farm, homogeneity of chicken ages in sections, the mortality rate of chickens, cleaning times of grow-out houses, and inventory and production decisions at the slaughterhouse. Although these considerations add complexity to the integrated planning of poultry chicken production, the proposed model is capable of solving instances with several grow-out houses and sections in a mid-term PH.

We validated the model with a medium-sized poultry company that operates in Santa Marta (Colombia). The company provided us with real data and manual plans with biosecurity risks (i.e., shorter cleaning times and mixed ages). The results showed potential profit improvements ranging from nearly 7% up to 57%, while still meeting biosecurity standards. As assignment costs may rise due to stringent constraints, inventory costs can be reduced by more than 40%. Therefore, the vertical integration proved to be beneficial as the common goal is achieved with fewer resources.

Additional benefits of using an optimization-based decision support system in this agri-chain come in terms of solution quality, feasibility of the plans, "what-if" analysis on sensitive parameters (e.g., demand), and savings in management time. The model was able to produce a tactical solution for a 52-week PH in less than 2.2 hours; and the plan can be adjusted for a 13-week PH in less than a minute.

Furthermore, we propose an RH heuristic as an alternative to cope with the myopic inventory decisions at the end of the PH and to reduce the computational burden of long-term time-indexed planning models, such as the single-run MILP. The computational experiments show an acceptable trade-off between speed and accuracy comparing the RH heuristic against the single-run MILP model over the year-long PH. The reduction in computational times (from a couple of hours to less than a minute) makes the RH approach a fair alternative if the MILP model for the entire PH becomes hard to solve. Evidently, if resources are available (e.g., commercial solver capability and time), in terms of profit improvement potential it is preferred to use the single-run MILP with the mentioned caveat on the myopic decisions made at the last time periods of the horizon. Alternatively, the fast and scalable RH heuristic is a very good option, competitive against the single-run MILP and superior to the hand-based solution. To relax the deterministic assumptions of the MILP, a sensitivity analysis over different scenarios allows the company to measure the impact on profit to demand fluctuations. Finally, we discuss how the proposed RH heuristic can be used to dynamically adjust the production plan as better demand estimations reveals.

Research currently underway focuses on relaxing some of the deterministic assumptions used herein. As we found the model sensitive to demand forecast, incorporating uncertainty could lead to a more robust planning. In the case study, prices of resources and products are steady because of the year-round availability of resources and the tropical weather without seasons. However, this might not be the case in other regions worldwide. Another source of variation comes from the weight gain of birds that might reach maturity at different weeks. Therefore, addressing fluctuations in demand, resources, prices, and weight gain is certainly an important research line. Finally, the integration with more echelons of the supply chain (e.g., chicken feed suppliers) could increase the profit margin for the companies in this highly competitive meat market.

Acknowledgments

The authors thank the management of *Pollos y Huevos Altair* for providing us a detailed description of the case study and data of its operations. The authors also express their thanks to the financial support received from Universidad del Magdalena at an early stage of this project; and from grant

CI-001/2020 from the Research Office at Universidad de los Andes. Last, but not least, the authors would like to thank the anonymous reviewers who provided insightful comments that greatly improved the paper. As always, any and all errors are fully attributable to the authors.

References

Albornoz, V., González-Araya, M., Rodriguez, S., Albornoz, V.M., Gripe, M.C., Rodríguez, S.V., 2014. A mixed integer linear programming model for planning at operative level in a meat packing plant. 3rd International Workshop on Food Supply Chain, San Francisco, CA.

Allender, W.J., Richards, T.J., 2010. Consumer impact of animal welfare regulation in the California poultry industry. *Journal of Agricultural and Resource Economics* 35, 424–442.

Bjørndal, T., Herrero, I., Newman, A., Romero, C., Weintraub, A., 2012. Operations research in the natural resource industry. *International Transactions in Operational Research* 19, 1–2, 39–62.

Boonmee, A., Sethanan, K., 2016. A GLNPSO for multi-level capacitated lot-sizing and scheduling problem in the poultry industry. *European Journal of Operational Research* 250, 2, 652–665.

Boonmee, A., Sethanan, K., Arnonkijpanich, B., Theerakulpisut, S., 2015. Minimizing the total cost of hen allocation to poultry farms using hybrid growing neural gas approach. *Computers and Electronics in Agriculture* 110, 27–35.

Brevik, E., Lauen, A., Rolke, M.C., Fagerholt, K., Hansen, J.R., 2020. Optimisation of the broiler production supply chain. *International Journal of Production Research*. https://doi.org/10.1080/00207543.2020.1713415.

Carravilla, M.A., Oliveira, J.F., 2013. Operations research in agriculture: better decisions for a scarce and uncertain world. *Agris On-line Papers in Economics and Informatics* 5, 2, 37–46.

Estevez, I., 2007. Density allowances for broilers: where to set the limits? *Poultry Science* 86, 6, 1265–1272.

FAO, 2019a. FAOSTAT statistical database.

FAO, 2019b. Food Outlook—Biannual Report on Global Food Markets. FAO, Rome.

Gurobi Optimization, L., 2020. Gurobi Optimizer Reference Manual. Available at https://www.gurobi.com/wp-content/plugins/hd-documentations/documentation/9.0/refman.pdf.

Hart, W., Laird, C., Watson, J., Woodruff, D., Hackebeil, G., Nicholson, B., Siirola, J., 2017. *Pyomo-Optimization Modeling in Python* (2nd edn), Vol. 67. Springer Science & Business Media, New York.

Higgins, A.J., Miller, C.J., Archer, A.A., Ton, T., Fletcher, C.S., McAllister, R.R.J., 2010. Challenges of operations research practice in agricultural value chains. *Journal of the Operational Research Society* 61, 6, 964–973.

Khamjan, S., Piewthongngam, K., Pathumnakul, S., 2013. Pig procurement plan considering pig growth and size distribution. *Computers & Industrial Engineering* 64, 886–894.

Kusumastuti, R.D., Donk, D.P.V., Teunter, R., 2016. Crop-related harvesting and processing planning: a review. *International Journal of Production Economics* 174, 76–92.

Leinonen, I., Kyriazakis, I., 2016. How can we improve the environmental sustainability of poultry production? *Proceedings of the Nutrition Society* 75, 3, 265–273.

Mcleod, A., Thieme, O., Mack, S., 2009. Structural changes in the poultry sector: will there be smallholder poultry development in 2030? *World's Poultry Science Journal* 65, 2, 191–200.

Nadal-Roig, E., Plà, L.M., 2014. Multiperiod planning tool for multisite pig production systems. *Journal of Animal Science* 92, 4154–4160.

Narrod, C., Tiongco, M., Costales, A., 2008. Global poultry sector trends and external drivers of structural change. FAO Procceedings on "Poultry in the 21st Century." Available at https://pdfs.semanticscholar.org/6e71/1c9aba5cd2080f2bd23db65b9014642cdea9.pdf.

OECD, 2018. Market examinations in Mexico: case study of the chicken meat market 2018. Available at https://www.oecd.org/daf/competition/ENG-WEB-REPORT-Chicken-MeatMarketMexico2018.pdf.

OECD, FAO, 2019. OECD-FAO agricultural outlook. Available at http://www.fao.org/3/ca4076en/ca4076en.pdf.

Oliveira, G.A., Lindau, L.A., 2012. A framework for delivery scheduling in the poultry industry. *Journal of Scheduling* 15, 6, 757–772.

Plà-Aragonés, L.M., 2015. *Handbook of Operations Research in Agriculture and the Agri-Food Industry*. Springer Science+Business Media, New York.

Plà-Aragonés, L.M., Rodríguez-Sánchez, S.V., 2015. Optimal delivery of pigs to the abattoir. *Handbook of Operations Research in Agriculture and the Agri-Food Industry*. Springer, New York, pp. 381–395.

Rivera-Godoy, J.A., Rendón-Perea, J.D., 2019. Sector avícola en Colombia: rendimiento contable y EVA. *Contaduría Universidad de Antioquia* 74, 127–151.

Robinson, T.P., Thornton, P.K., Franceschini, G., Kruska, R., Chiozza, F., Notenbaert, A.M.O., Cecchi, G., Herrero, M.T., Epprecht, M., Fritz, S., You, L., Conchedda, G., See, L., 2011. *Global Livestock Production Systems*. FAO and ILRI, Rome: FAO.

Rodríguez-Sánchez, S.V., Plà-Aragonés, L.M., Albornoz, V.M., 2012. Modeling tactical planning decisions through a linear optimization model in sow farms. *Livestock Science* 143, 162–171.

Sahin, F., Narayanan, A., Robinson, E.P., 2013. Rolling horizon planning in supply chains: review, implications and directions for future research. *International Journal of Production Research* 51, 18, 5413–5436.

Sethi, S., Sorger, G., 1991. A theory of rolling horizon decision making. *Annals of Operations Research* 29, 1, 387–415.

Siekkinen, K.M., Heikkilä, J., Tammiranta, N., Rosengren, H., 2012. Measuring the costs of biosecurity on poultry farms: a case study in broiler production in Finland. *Acta Veterinaria Scandinavica* 54, 1, 12.

Silvente, J., Kopanos, G.M., Pistikopoulos, E.N., Espuña, A., 2015. A rolling horizon optimization framework for the simultaneous energy supply and demand planning in microgrids. *Applied Energy* 155, 485–501.

Solano-Blanco, A., González, J.E., Gomez, L., Vargas-Sanchez, J., Medaglia, A.L., 2020. Aggregated planning in the broiler chicken industry: a case study in Santa Marta (Colombia). In Albornoz, V., Mac Cawley, A. (eds) Proceedings of the III International Conference on Agro BigData and Decision Support Systems in Agriculture. Universidad Técnica Federico Santa María, Valparaíso, Chile, pp. 16–18.

Taube-Netto, M., 1996. Integrated planning for poultry production at Sadia. *Interfaces* 26, 1, 38–53.

Tonsor, G.T., Olynk, N.J., 2011. Impacts of animal well-being and welfare media on meat demand. *Journal of Agricultural Economics* 62, 1, 59–72.

USDA, 2019. Livestock and poultry: world markets and trade. Technical Report, USDA, Washington, DC.

Van Limbergen, T., Dewulf, J., Klinkenberg, M., Ducatelle, R., Gelaude, P., Méndez, J., Heinola, K., Papasolomontos, S., Szeleszczuk, P., Maes, D., 2018. Scoring biosecurity in European conventional broiler production. *Poultry Science* 97, 1, 74–83.

Weintraub, A., Romero, C., 2006. Operations research models and the management of agricultural and forestry resources: a review and comparison. *Interfaces* 36, 5, 446–457.

Zuidhof, M., Schneider, B., Carney, V., Korver, D., Robinson, F., 2014. Growth, efficiency, and yield of commercial broilers from 1957, 1978, and 2005. *Poultry Science* 93, 12, 2970–2982.