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Optimizing the pork supply chain: A model integrating feed production and pig farming with outsourcing and subcontracting costs

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Abstract

This study introduces a mathematical model designed to optimize the vertically integrated pork supply chain by addressing key cost factors, including pig farming, feed production, and outsourcing. The model integrates pig fattening and feed production stages, incorporating essential cost components to synchronize farming schedules with feed production plans while minimizing total costs. Computational experiments, using data from an empirical study of Thailand's vertically integrated pork supply chain, were conducted to evaluate the model's efficiency and sensitivity under varying farm sizes and planning horizons. The results demonstrate that the model effectively identifies optimal solutions for shorter planning periods (up to 14 months). However, extended planning horizons and larger farm sizes significantly affect solution times and the quality of feasible solutions. These findings provide valuable insights and practical strategies for pork production companies seeking to enhance cost efficiency and improve supply chain sustainability. Future research should focus on developing advanced heuristics and exploring additional supply chain dynamics within integrated environments.

Keywords: Vertically integrated supply chain, Pig fattening operations, Feed production, Pork industry

1. Introduction

The global demand for pork has increased significantly over recent decades, driven by rising incomes and population growth [1]. This demand has fueled the expansion of modern industrial farming, leveraging advanced technologies in feed production, balanced diets, veterinary care, vaccinations, and management techniques to enable the efficient conversion of feed into lean meat [2]. Vertical integration, a key modern practice, allows large corporations to divide operations into specialized stages, including breeding, farrowing, nursery, and fattening [3].

The fattening process is a crucial stage, constituting roughly 40% of the life cycle of a market pig and heavily relying on resources, particularly feed consumption [4]. Feed costs account for approximately 60-70% of production expenses, with feed conversion rates ranging from 3.2 to 4.0 pounds of feed per pound of pork produced [5]. This underscores the substantial financial vulnerability of pork producers to fluctuations in feed prices [6].

This research investigates key operational stages within a vertically integrated pig production system, with particular emphasis on the pig growth (fattening) phase and associated feed manufacturing processes. Pig farming operations are carried out under contractual arrangements with an integrator, facilitating coordination and alignment with overarching supply chain goals. Feed is primarily manufactured in-house and formulated to satisfy the nutritional needs of pigs across different growth phases. In cases where internal production capacity is inadequate, supplementary feed is sourced from external suppliers.

The primary aim of this study is to optimize decision-making across interrelated stages of a vertically integrated pork production system. Pig farms are required to strategically plan their production schedules over a defined planning horizon to ensure a steady supply of pigs that meet market specifications during periods of peak demand. Concurrently, the integrator must determine optimal production quantities for various feed formulations corresponding to different growth phases and assess the volume of feed to be procured externally when in-house production capacity is inadequate.

This paper presents a mathematical optimization model designed for the vertically integrated pork supply chain. It extends the framework introduced by [7] by integrating additional cost considerations, including initial subcontracting expenditures for farms, internal feed production costs, and expenses related to external feed procurement. These cost elements, emphasized by [8] as central to the industry's economic structure, significantly influence operational and financial performance. The model is applied to data derived from a real-world case study of a pork production network in Thailand.

The findings of this research provide valuable insights into enhancing the sustainability of pork supply chains and offer practical strategies for pork production companies to optimize their operations. Figure 1 illustrates the overall configuration of the vertically integrated pork production system considered in this study. It shows the sequential flow through the breeding, farrowing, nursery, and fattening stages, followed by meat processing and distribution to the market. Central to this structure is a feed mill responsible for producing feed used during the fattening phase; additional feed may be outsourced when internal capacity is insufficient. This visual

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framework highlights the interdependence between farming operations and feed supply, underscoring the need for integrated decision-making across all stages. The paper is structured as follows: a literature review, a detailed problem description with underlying assumptions, the mathematical formulation of the model, computational experiments, a numerical example, results and discussion, and concluding remarks.

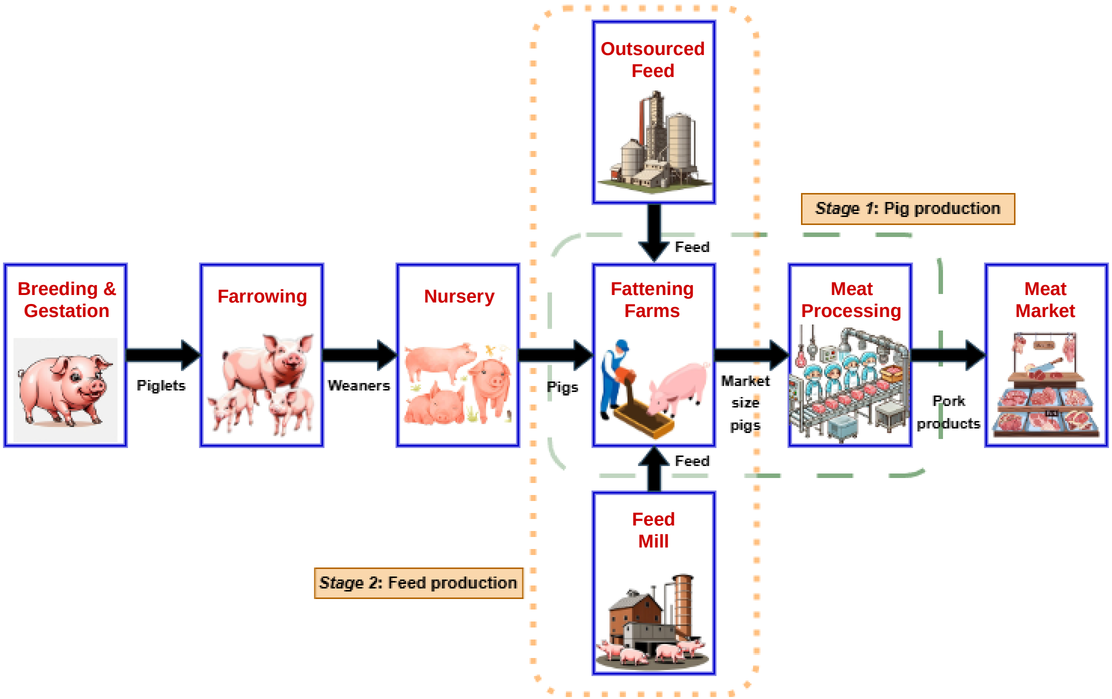

Figure 1 Configuration of a Vertically Integrated Pork Production System

2. Literature reviews

A review of the literature [9] reveals a notable gap in research concerning supply chain models tailored specifically to the pork production sector. This scarcity is largely due to the complexity of quantifying various factors, including environmental impacts, animal welfare, pork quality, and product perishability. Similar to other agri-food sectors, the pork industry experiences greater variability and uncertainty compared to the manufacturing sector. Despite these challenges, there has been growing interest in applying quantitative methods to livestock supply chains in recent years.

One recent study by [7] proposed a three-echelon pork supply chain model that includes a feed production facility, contract farms, and a pork processing unit. The study employed a Lagrangian-based heuristic to generate efficient pig farming schedules and feed production plans. A notable challenge addressed in this model is the long lead time inherent in pig production, which significantly affects supply chain efficiency. In a related investigation, Solano-Blanco et al. [10] examined an integrated production system for broiler chickens, highlighting the significance of strategic coordination between production farms and processing facilities in enhancing overall operational efficiency. Their approach integrated a two-stage stochastic model for managing production and inventory decisions under uncertainties in animal growth, alongside a mixed-integer linear programming formulation designed to optimize resource allocation and the acquisition of fattening inputs. A key insight from their analysis was the significant influence of variability in chicken weight gain on supply chain performance; however, feed intake, one of the primary cost drivers, was not incorporated into the model framework.

Nadal-Roig et al. [11] proposed a comprehensive analysis of vertically integrated pig production systems involving multiple farms, focusing on the influence of market price uncertainty on production planning decisions. Similarly, Villalba et al. [12] proposed a decision-making framework that integrates simulation techniques with multi-objective optimization to support comprehensive planning within sheep farming systems. Prior studies, such as the work by [13], introduced quantitative models for the poultry supply chain, emphasizing farm selection across different chicken growth phases using heuristic methods based on Lagrangian relaxation principles. Likewise, [14] tackled the challenges of multi-period planning in pig fattening and pork processing by applying dynamic programming methods to manage inventory according to weight-based pig classifications. Additionally, [15] investigated operational issues such as farm scheduling and labor allocation, employing an Adaptive Large Neighborhood Search (ALNS) method to maximize profitability within defined planning horizons, thereby contributing a robust strategy for managing scheduling complexity in livestock production environments. The study by Moryadee [16] addresses dairy supply chain optimization using mixed-integer linear programming. The research integrates production planning, inventory control, and transportation decisions, demonstrating practical optimization of milk production, purchasing, inventory management, and distribution activities.

Other relevant studies on integrated supply chain optimization include Taghikhah et al. [17], who employed a systems-based modeling approach for agro-food supply chains, integrating consumer behavior, supply chain operations, and sustainability. Using agent-based and system dynamics modeling, they explored the interactions among farmers, processors, and consumers in promoting organic farming. Gholamian and Taghanzadeh [18] developed an integrated wheat supply chain network model incorporating long-term supplier selection, silo locations, and transportation logistics. Their mixed-integer linear programming model optimizes wheat distribution and production decisions, significantly reducing transportation costs. Kogler et al. [19] analyzed cost-saving strategies in wood supply chains, examining the impact of coordinated procurement, integrated logistics, and truck payload optimization on supply chain efficiency. Using a mixed-integer programming model, they quantified potential cost reductions and highlighted the benefits of supply chain integration. Chakraborty et al. [20] developed a multi-item integrated supply chain framework that explicitly accounts for product perishability and stock-dependent demand, making it highly applicable to agri-food and livestock supply chains, where perishability and demand uncertainty pose significant operational challenges.

3. Problem statement

This research examines a vertically integrated supply chain managed by a single company, comprising two primary stages: pig fattening and feed production. The pig fattening stage involves multiple subcontracted farms operating under the supervision of the company. The feed production stage is centralized, with a single feed mill responsible for supplying feed to all farms. Pigs are raised through a six-period growth cycle to achieve market-ready size, after which they are transported to a meat processing plant in response to demand.

The primary objective of this research is to secure production continuity aligned with downstream processing requirements while minimizing costs across the supply chain. Under contractual agreements, the company oversees the operations of pig farmers and produces feed internally, tailoring it to the nutritional needs of pigs at different growth stages. When internal feed production capacity is insufficient, the company procures additional feed from external suppliers. This combined pig and feed production strategy ensures flexibility in meeting the nutritional requirements of pigs while maintaining cost efficiency.

4. Mathematical formulation

4.1 Model notation

Table 1 summarizes the sets, indices, parameters, and decision variables utilized in the formulation of the proposed optimization model.

Table 1 Definitions of Model Elements: Sets, Indices, Parameters, and Decision Variables

Sets	
T	Set of discrete time periods considered in the planning horizon.
F	Set of all available feed formulations produced during *Stage 2*.
M	Set of contracted pig farms operating in *Stage 1*.
P	Set of defined production phases in *Stage 1*, (representing the growth stages pigs undergo from initial entry to market weight (total of 6 phases).
Indices	
t, u	Indices representing individual time periods within the planning horizon.
p	Index corresponding to the production phases in the pig growth cycle.
f	Index denoting specific feed formulations.
m	Index referring to pig farms.
Parameters	
h	Cost incurred per period for holding a pig (*Stage 1*).
$\hat{h}$	Cost per unit per period for holding feed inventory (*Stage 2*).
s_m	Initial setup or subcontracting cost associated with farm *m*.
$\hat{s}_f$	Setup cost for initiating production of feed formulation *f*.
c_f	Unit production cost associated with feed formulation *f*.
r_f	Unit cost incurred when feed formulation *f* is procured externally.
A_{mfut}	Binary parameter to enforce that feed formulation *f* for farm *m* in period *t* cannot be produced before the farm begins operation in period u. A value of 1 indicates feasibility; 0 otherwise.
L_m	Capacity or size of farm *m*, representing the number of pigs it can raise.
D_t	Demand for pigs in period *t*.
w_f	Quantity of feed formulation *f* consumed per pig per period.
K	Maximum production capacity of the feed mill per period.
G	A sufficiently large positive constant used in constraint modeling.
Decision Variables	
X_{mt}	Binary variable indicating whether farm *m* starts production in period *t* (1 if yes; 0 otherwise).
Y_{mft}	Binary variable equal to 1 if feed formulation *f* is produced for farm *m* in period *t*; 0 otherwise.
Z_{ft}	Binary variable equal to 1 if feed formulation *f* is produced in period *t*; 0 otherwise.
Q_t	Number of pigs produced in period *t* (*Stage 1*).
I_t	Ending inventory of pigs carried into period *t* (*Stage 1*).
$\hat{I}_{ft}$	Ending inventory of feed formulation *f* at the end of period *t* (*Stage 2*).
$\hat{D}_{ft}$	Required amount of feed formulation *f* in period *t*.
$\hat{Q}_{ft}$	Quantity of feed formulation *f* internally produced in period *t* (*Stage 2*).
R_{ft}	Quantity of feed formulation *f* procured from external suppliers in period *t* (*Stage 2*).

4.2 Mathematical formulation

The following mixed-integer linear programming (MILP) model is developed to capture the key decision-making processes across pig farming and feed production stages in the integrated supply chain.

$$\text{Minimize} \quad Z_{LP} = \sum_{m \in M} \sum_{t \in T} (s_m X_{mt} + h I_t) + \sum_{f \in F} \sum_{t \in T} \left(\hat{s}_f Z_{ft} + \hat{h} \hat{I}_{ft} + c_f \hat{Q}_{ft} + r_f R_{ft} \right) \tag{4.1}$$

Subject to

$$Y_{mft} = \sum_{u \in T} A_{mfut} X_{mu} \qquad ,\forall m \in M, \forall f \in F, \forall\, t \in T \tag{4.2}$$

$$\sum_{p \in P} X_{m,t+p-1} \leq 1 \qquad ,\forall m \in M, \forall t \in \{t | t \leq |T| - |P|\} \tag{4.3}$$

$$\sum_{t \in T} X_{mt} \geq 1 \qquad ,\forall m \in M \tag{4.4}$$

$$\sum_{t \in \{t | t \geq |T| - |P| + 2\}} X_{mt} = 0 \qquad ,\forall m \in M \tag{4.5}$$

$$Q_t = \sum_{m \in M} L_m X_{m,t-|P|} \qquad ,\forall t \in \{t | t > |P|\} \tag{4.6}$$

$$I_t = I_{t-1} + Q_t - D_t \qquad ,\forall t \in \{t | t \geq |P| + 1\} \tag{4.7}$$

$$\widehat{D}_{ft} = w_f \sum_{m \in M} L_m Y_{mft} \qquad ,\forall f \in F, \forall t \in T \tag{4.8}$$

$$\hat{I}_{f,t} = \hat{I}_{f,t-1} + \hat{Q}_{ft} + R_{ft} - \widehat{D}_{ft} \qquad ,\forall f \in F, \forall t \in \{t | t \geq 1\} \tag{4.9}$$

$$\sum_{f \in F} \hat{Q}_{ft} \leq K \qquad ,\forall t \in T \tag{4.10}$$

$$\hat{Q}_{ft} \leq G Z_{ft} \qquad ,\forall f \in F, \forall t \in T \tag{4.11}$$

$$I_t, Q_t \geq 0 \qquad ,\forall t \in T \tag{4.12}$$

$$\hat{I}_{ft}, \widehat{D}_{ft}, \hat{Q}_{ft}, R_{ft} \geq 0 \qquad ,\forall f \in F, \forall t \in T \tag{4.13}$$

$$X_{mt} \in \{0,1\} \qquad ,\forall m \in M, \forall t \in T \tag{4.14}$$

$$Y_{mft} \in \{0,1\} \qquad ,\forall m \in M\ , \forall f \in F, \forall t \in T \tag{4.15}$$

$$Z_{ft} \in \{0,1\} \qquad ,\forall f \in F, \forall t \in T \tag{4.16}$$

The formulation begins with the objective function (4.1), which seeks to minimize the total cost incurred across the supply chain. This encompasses the initial subcontracting costs associated with activating farms, the holding costs for mature pigs at the farming stage, setup costs related to initiating feed formulation processes, procurement costs for externally sourced feed, and inventory holding costs for excess feed stored at the feed mill. Constraint (4.2) defines the dependency between the initiation of farm operations and the timing of feed production, ensuring that feed formulation f for farm m in period t is permitted only if the corresponding farm has commenced operations by that time. Constraint (4.3) ensures that each farm progresses through all specified pig production phases before initiating a subsequent production cycle. Before starting a subsequent production cycle. Constraint (4.4) ensures that every farm initiates at least one production cycle within the defined planning horizon. To ensure feasibility, Constraint (4.5) restricts farm activation to time periods that allow adequate time for completing the full production cycle. Constraint (4.6) computes the number of pigs reaching market weight in each period, based on the farm's capacity and the start time of production. Constraint (4.7) captures the pig inventory dynamics, maintaining a balance between incoming matured pigs and outgoing demand. Feed demand is calculated through Constraint (4.8), which quantifies the required amount of each feed formulation based on farm-specific consumption rates. Constraint (4.9) governs the feed inventory balance at the feed mill, ensuring accurate tracking of production, procurement, and usage over time. Constraint (4.10) imposes an upper limit on the total feed production in each period, ensuring that aggregate production does not exceed the feed mill's operational capacity. Constraint (4.11) links production quantities to setup decisions, ensuring that a formulation is only produced if the associated setup decision has been made. Constraints (4.12) and (4.13) ensure the non-negativity of all continuous decision variables. Finally, Constraints (4.14), (4.15), and (4.16) define the binary nature of key decisions, specifically whether a farm initiates production in a given period and whether a feed formulation is scheduled for production.

5. Computational experiments

To evaluate the performance of the proposed model, a series of computational experiments were carried out using multiple case studies. These case studies were constructed using simulated data that reflect operational characteristics of the pork production system in Thailand, as referenced in [12]. Each case study consisted of five simulated instances, with varying demand patterns for fully grown pigs across the planning horizon. The proposed optimization model was applied to solve each instance, and computations were executed until either an optimal solution was identified, or the pre-defined time limit of 7,200 seconds was reached. In scenarios where optimality could not be achieved within the time constraint, the best feasible solution obtained was documented, along with the corresponding optimality gap, expressed as the percentage deviation from the theoretical lower bound.

All computational experiments were executed on a computer powered by an Intel i7 processor (3.60 GHz) with 16 GB of RAM. The mathematical model was developed and solved using the LINGO v.13 optimization platform [21]. The following subsections present a detailed overview of the case configurations and an analysis of the corresponding computational outcomes.

5.1 Case-study information

This research investigates a vertically integrated pork production system in Thailand, with particular emphasis on the pig fattening and feed manufacturing stages. The study is grounded in empirical data reflecting real-world supply chain operations and includes farms of diverse scales, categorized as small, medium, and large, with capacities spanning from 100 to 1,500 pigs. These farms incur differing initial subcontracting costs. The pig fattening period lasts six months, and the holding cost for a fully grown pig at the farm is 337 units per pig per year if the pigs are not sold to the market immediately. Throughout the fattening period, three feed formulations, designated A1, A2, and A3—are required to meet the pigs' nutritional needs. Each feed formulation is consumed for two consecutive months before switching to the next. The initial inventory for each feed formulation is zero.

Feed manufacturing is centralized at a single facility, which has a monthly production capacity of 192,000 kilograms. The associated inventory holding cost for feed stored at the mill is estimated at 3.5 monetary units per kilogram per month. Feed production costs vary by formulation, with unit production costs of 14.15, 15.92, and 17.69 units per kilogram for feed formulations 1, 2, and 3, respectively. When feed is outsourced, the cost is 15% higher than the in-house production cost.

Experiments were conducted using scenarios with 6, 9, 12, and 15 farms of various sizes over planning horizons of 12, 14, 16, and 18 months to optimize production plans. The objective was to align farm operations with feed production to minimize total costs under specific operational configurations while ensuring demand fulfillment. These experiments provide a basis for evaluating the performance of the proposed model and its effectiveness in optimizing supply chain operations.

5.2 Numerical example

To demonstrate the practical application of the proposed optimization model, this section provides a numerical example based on the case study introduced in Section 5.1. The example features twelve farms, comprising four small, four medium, and four large-scale operations, with specific capacities outlined in Table 2. The planning period covers 12 months, and the corresponding demand for market-ready pigs is presented in Table 3.

The results generated from Stage 1 include the scheduling decisions for pig farming activities (Figure 1), along with production volumes and inventory levels across all farms (Table 3). In Stage 2, the model outputs encompass the demand, production quantities, inventory levels, and externally sourced volumes for feed formulations A1, A2, and A3, as detailed in Tables 4 through 7. These findings illustrate the operational flow of the proposed model and offer insight into its underlying decision-making mechanisms.

Table 2 Farm size (pigs)

Farm	1	2	3	4	5	6	7	8	9	10	11	12
Farm Size	180	157	195	249	451	442	410	416	1,066	1,243	1,295	1,271

5.2.1 Pig farming schedule, pig production, and inventory

The pig farming schedules, as illustrated in Figure 2, are staggered to meet the demand for market-ready pigs while aligning production cycles with market requirements, thereby avoiding resource constraints and overproduction. By adjusting the start times of farming operations across various farms, the model ensures a continuous supply throughout the planning horizon. Larger farms are optimally utilized during peak demand periods, whereas smaller farms contribute to maintaining supply consistency during periods of lower demand. Additionally, the schedule is synchronized with the feed production plan to optimize feed inventory and minimize both production and outsourcing costs. As shown in Table 3, pigs are ready for market after a six-period fattening period. During the middle of the planning horizon, pig inventory is built up, while minimal inventory levels are maintained toward the end of the planning horizon.

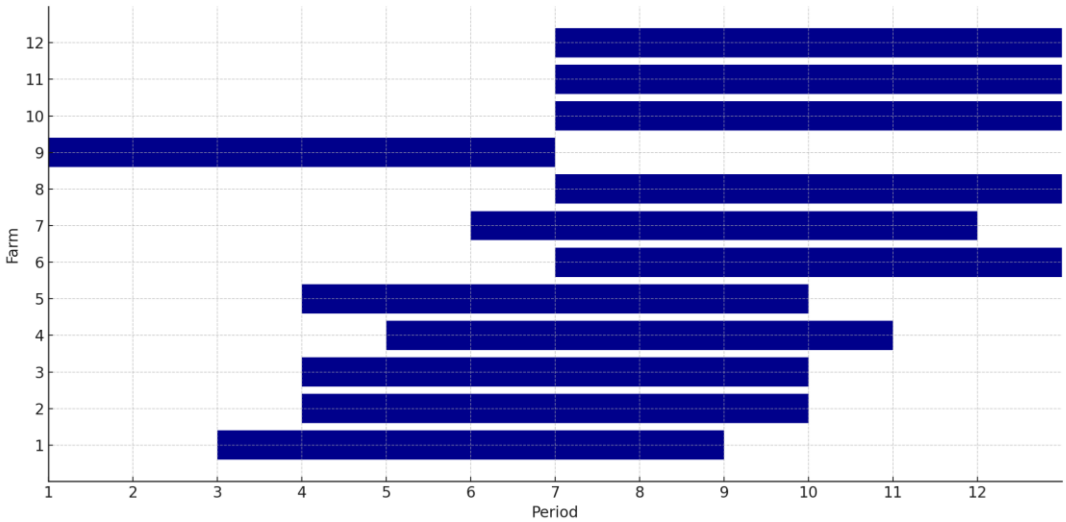

Figure 2 Farming schedule for all 12 farms

Table 3 Pig demand, Number of pigs produced, and Ending inventory (units)

	Farming Period (Month)											
	1	2	3	4	5	6	7	8	9	10	11	12
Demand	-	-	-	-	-	-	740	200	305	750	300	400
Production	-	-	-	-	-	-	1066	0	180	803	249	410
Inventory	-	-	-	-	-	-	326	126	1	54	3	13

5.2.2 Feed production, inventory levels, and outsourced quantity

The proposed model translates the pig production plan in Stage 1 into the demand for feed formulations A1, A2, and A3, as shown in Table 4. The farming schedule in Stage 1 is designed to comply with the feed mill's monthly capacity constraint of 192,000 kg, ensuring that the production quantities of each feed formulation remain within this limit during every period. To manage high-demand periods without exceeding mill capacity, outsourced feed is used as a supplement. For example, Table 7 shows that outsourcing peaks for A3 during the final months of the planning horizon. Conversely, during periods 5 and 6, when the demand for A1, A2, and A3 is relatively low, excess capacity is used to build up inventory for future use, as shown in Table 6. In terms of setup costs, Table 5 demonstrates that the model minimizes these costs early in the planning horizon by producing only A1 when it is not immediately needed. Similarly, near the end of the planning horizon, the model reduces setup costs by avoiding the production of A1 and A2 formulations when they are not required.

Table 4 Feed Demand (1,000 kg.)

Feed	Farming Period (Month)											
Formulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
A1	36.8	36.8	6.2	33.9	36.3	22.7	202.1	171.4	0.1	4.5	0.2	1.1
A2	-	-	72.0	72.0	12.2	66.4	97.9	54.9	342.8	319.5	0.2	1.1
A3	-	-	-	-	87.9	87.9	41.7	91.5	86.9	58.8	419.1	386.1

Table 5 Feed Production Quantity (1,000 kg.)

Feed	Farming Period (Month)											
Formulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
A1	36.8	36.8	6.2	33.9	59.0	-	122.9	45.6	-	-	-	-
A2	-	-	72.0	72.0	12.2	95.2	69.1	54.9	105.1	133.2	-	-
A3	-	-	-	-	120.8	96.8	0.0	91.5	86.9	58.8	192.0	192.0

Table 6 Feed Inventory Quantity (1,000 kg.)

Feed	Farming Period (Month)											
Formulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
A1	-	-	-	-	22.7	-	-	-	-	-	-	-
A2	-	-	-	-	-	28.8	-	-	-	-	-	-
A3	-	-	-	-	32.9	41.7	-	-	-	-	-	-

Table 7 Feed Outsourced Quantity (1,000 kg.)

Feed	Farming Period (Month)											
Formulation	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
A1	-	-	-	-	-	-	79.1	125.8	0.1	4.5	0.2	1.1
A2	-	-	-	-	-	-	-	-	237.7	186.3	0.2	1.1
A3	-	-	-	-	-	-	-	-	-	-	227.1	194.1

6. Results and discussion

6.1 Computational results and analysis

The computational experiments conducted to evaluate the proposed mathematical model provided valuable insights into optimizing the vertically integrated pork supply chain. The model was tested under various scenarios, including different numbers of farms (6, 9, 12, and 15) and planning periods (12, 14, 16, and 18 months). The results demonstrated both the computational efficiency of the model and its sensitivity to farm sizes and planning horizons. As shown in Table 8, the proposed model successfully found optimal solutions for problems involving up to 16 farms and 16-month planning periods within the 7,200-second time limit.

For shorter planning periods of 12 and 14 months, the model achieved global optimal solutions across all farm sizes, as illustrated in Table 8. However, for longer planning periods of 16 and 18 months, the solution time exceeded the 7,200-second limit. Figure 3 highlights that the solution time increases rapidly with an increase in the number of planning periods. While the solution time also increases with the number of farms, the rate of increase is less pronounced compared to the effect of longer planning periods.

As shown in Table 9, extending the planning horizon beyond 14 months results in a widening gap between the best feasible solution and the lower bound obtained from integer programming, with deviations ranging from 0.56% to 6.51%. This discrepancy tends to increase as both the number of time periods and the number of farms grow. Figure 4 further demonstrates that, in scenarios where an optimal solution was not obtained, the quality of the best feasible solution declined significantly as the planning horizon increased. However, no conclusive pattern was observed regarding the impact of farm quantity on solution quality in cases where optimality was not achieved.

The proposed model extends the framework introduced by [7] by incorporating two additional cost elements: the initial subcontracting cost for farms and the outsourcing cost for feed procurement, factors not previously considered. The inclusion of these components increases the model's computational complexity. As a result, the current formulation can optimally solve instances involving up to 12 farms over a 14-period planning horizon within a computational time limit of 7,200 seconds. In comparison, the model presented in [7] was able to achieve optimal solutions for cases with up to 12 farms and 16 periods under the same time constraint. The reduction in solvable problem size is primarily due to the added complexity introduced by these new cost dimensions.

6.2 Opportunities for future research

Our findings highlight significant cost-saving opportunities arising from integrated optimization strategies, particularly through the simultaneous optimization of decisions related to pig farming and feed production. This observation aligns with Ivanov et al. [22], who reported substantial economic benefits achieved by integrating dairy and biodiesel production via the effective utilization of waste streams. Additionally, Ivanov et al. evaluated environmental impacts by assessing greenhouse gas emissions, underscoring the need for future research that jointly considers environmental and economic outcomes. Another promising direction for future investigation involves explicitly incorporating uncertainty into optimization frameworks to more effectively address potential market disruptions and supply shortages. This recommendation aligns with Mostaghim et al. [23], who emphasized the critical roles of backup facilities and multiple sourcing strategies in enhancing resilience within broiler supply chains. Furthermore, the importance of addressing uncertainty in agricultural optimization is consistent with recent studies such as Sebatjane et al. [24], who highlighted the necessity of robust planning methods for managing variability in agricultural supply chains. Similarly, Urra-Calfuñir et al. [25] illustrated the benefits of scenario-based optimization approaches to mitigate risks associated with demand fluctuations in food production systems. Additionally, the significance of simultaneously considering economic, environmental, and social dimensions in agricultural supply chain optimization is supported by Fikry et al. [26], who demonstrated enhanced overall sustainability through integrated decision frameworks. Lastly, Jabbarzadeh and Shamsi [27] emphasized the value of developing multi-objective optimization models that balance cost efficiency, resilience, and environmental performance, highlighting further opportunities for interdisciplinary research in this field.

Table 8 Solution Time by Number of Farms and Planning Periods

# of Periods	6 Farms (sec.)	9 Farms (sec.)	12 Farms (sec.)	15 Farms (sec.)
12	19	12	8	32
14	1,439	370	822	7,200
16	7,200	7,200	7,200	7,200
18	7,200	7,200	7,200	7,200

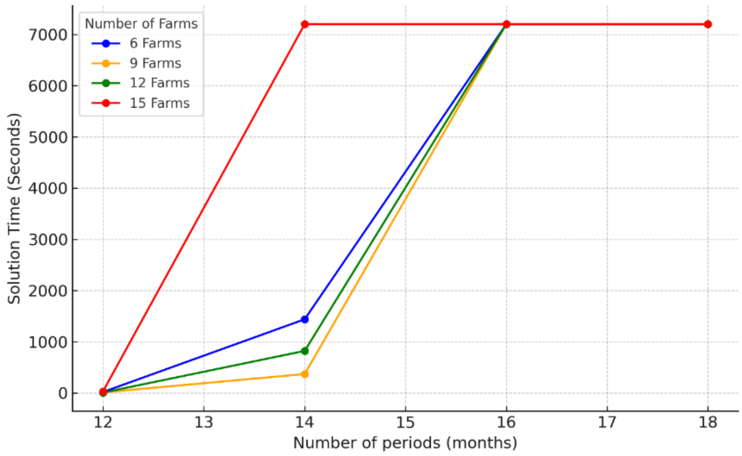

Figure 3 Solution Time by Number of Farms and Planning Periods

Table 9 Percent Cost Increase from Optimal Value by Number of Farms and Planning Periods

Periods	6 Farms	9 Farms	12 Farms	15 Farms
12	0.00%	0.00%	0.00%	0.00%
14	0.00%	0.00%	0.00%	0.56%
16	4.24%	3.32%	2.23%	1.44%
18	6.51%	1.82%	6.29%	4.15%

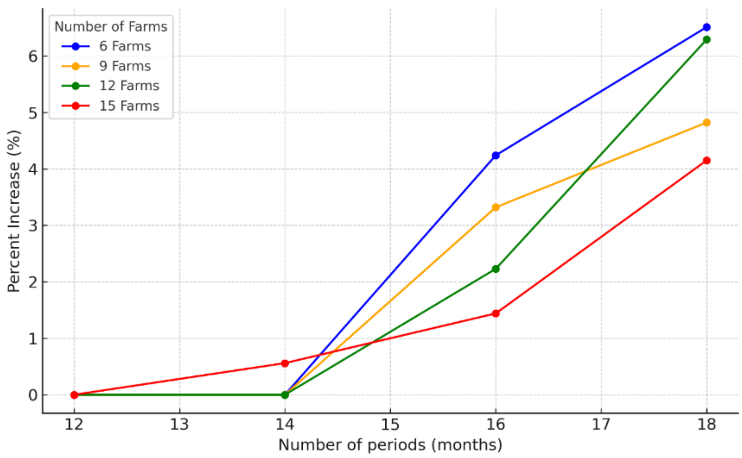

Figure 4 Percent Cost Increase from Optimal Value by Number of Farms and Planning Periods

7. Conclusion

This research introduced a mathematical optimization model tailored to a vertically integrated supply chain of pork production, integrating essential cost components including pig farming activities, in-house feed manufacturing, outsourced feed acquisition, and initial subcontracting costs. Through a series of computational experiments, the model's performance was evaluated under various scenarios involving different farm sizes and planning horizons. The results confirmed the model's capability to generate efficient solutions, while also revealing its sensitivity to the complexity introduced by extended planning periods and increased farm counts.

Notably, the model demonstrated strong performance for planning horizons of up to 14 months, consistently achieving optimal solutions within acceptable computational times. However, when the planning horizon was extended, solution times grew significantly, and the quality of feasible solutions deteriorated. While the number of farms also influenced computational effort, its impact was less pronounced compared to the length of the planning period. Furthermore, the results showed that the optimality gap, the difference between the best feasible solution and the lower bound, tended to widen as the planning period increased.

The insights gained from this work offer valuable implications for decision-makers in pork production enterprises, particularly in the areas of cost efficiency and strategic planning. Future research may focus on the development of advanced heuristic or metaheuristic algorithms to overcome scalability limitations and address the computational challenges associated with longer planning horizons. Additionally, further exploration of integrated supply chain features unique to livestock production may yield enhancements in both model realism and practical applicability.

The insights derived from this study provide practical guidance for pork production companies seeking to enhance their operational efficiency and cost management. Future research could focus on developing advanced heuristics to address the computational challenges of longer planning horizons or exploring unique aspects of the supply chain that arise in integrated environments.

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9. References

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