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Design of Key Performance Indicators (KPIs) for the Management of Poultry Supply Chains

Diseño de indicadores clave de rendimiento (KPIs) para la gestión de cadenas de suministro avícolas

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Abstract
Supply chain management must balance multiple objectives, as resilience to disruptions and the ability to deliver finished products regularly, which is an essential value-added for many customers. Achieving this regularity requires specific Key Performance Indicators (KPIs). In Agri-food Supply Chains (AFCs), these KPIs are influenced by biological constraints that determine the duration of production stages. This study identifies KPIs for managing a vertically integrated poultry AFCs. To this end, we developed a Systems Dynamics (SD) model that integrates breeder management, incubation processes, feed requirements, and sales activities with the associated cost and revenue structures. The model uses delays, nonlinearities, and feedback mechanisms, and allows for optimization, sensitivity analysis, and Monte Carlo simulation. This research contributes to the Operations Research literature by providing a decision-support tool for designing more robust, resilient and efficient AFCs. Finally, the proposed KPIs help managers anticipate how disruptions propagate through the system and how they affect profit and deliveries to customers, necessary to comply with European NFRD and CSRD regulations.

Keywords: resilience, disruptions, system dynamics, sensitivity analysis, Monte Carlo analysis.

Resumen
La gestión de la cadena de suministro atiende múltiples objetivos, como la resiliencia ante interrupciones y la regularidad de las entregas. Este estudio identifica Indicadores Clave de Rendimiento (KPIs) para gestionar Cadenas de Suministro Agroalimentarias (CFA), cuyas restricciones biológicas condicionan los tiempos y procesos de producción. Mediante cálculos de optimización, análisis de sensibilidad y simulaciones de Monte Carlo sobre un modelo de Dinámica de Sistemas (DS) se obtienen criterios para diseñar cadenas agroalimentarias más resilientes, robustas y eficientes, cumpliendo así las normativas europeas NFRD y CSRD.

Palabras clave: resiliencia, disrupciones, dinámica de sistemas, análisis de sensibilidad, análisis de Monte Carlo.

1. Introduction

Agri-food supply chains operate under substantial uncertainty stemming from biological constraints, volatile input markets, and operational interdependencies (Esteso et al., 2017; Sarkar et al., 2024). In vertically integrated poultry systems, production outcomes depend on tightly coupled stages as breeder rearing, egg laying, incubation, and broiler growth, where delays and feedback loops shape system behaviour. These interdependencies make the system sensitive to disruptions in supplier deliveries, hatchability, feed availability, or production capacity, enabling disturbances to

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propagate across stages and threaten profitability and service reliability (Ivanov, 2022). Recent global crises have underscored the importance of analytical tools capable of evaluating such disruptions, especially in food systems where continuity and stability are critical. Operations Research (OR) offers powerful methods to address uncertainty, as stochastic optimization, robust decision models, simulation, and network design (Tang, 2006; Dolgui and Ivanov, 2021). System Dynamics (SD) provides a complementary perspective by representing nonlinear feedback structures and time delays, allowing exploration of how policies perform over extended horizons and under disruption propagation (Sterman, 2000; Martín García, 2020; Campuzano-Bolarín, et al., 2025). Prior work has demonstrated SD's value in modelling food systems, resilience dynamics, and poultry operations (Gale and Nikbakhsh, 2018; Abbasi et al., 2023; Esteso et al., 2023), yet integrated SD-OR approaches that explicitly quantify resilience in vertically integrated poultry supply chains remain limited.

Motivated by this gap, the present study applies SD to examine the interplay between biological efficiency, operational decisions, and economic drivers in a vertically integrated poultry supply chain. Three research objectives (ROs) guide the study: (i) RO_1. Develop a dynamic model that integrates biological, operational, and financial processes; (ii) RO_2. Identify profit-maximizing management policies through simulation-optimization (Powell, 1964; Tordecilla et al., 2020); and (iii) RO_3. Define and evaluate resilience-oriented KPIs via sensitivity analysis and disruption scenarios (Pettit et al., 2019; Ivanov, 2023). By linking SD simulation with OR concepts of resilience, viability, and performance measurement, the study offers a decision-support framework for designing efficient and resilient poultry production systems under uncertainty.

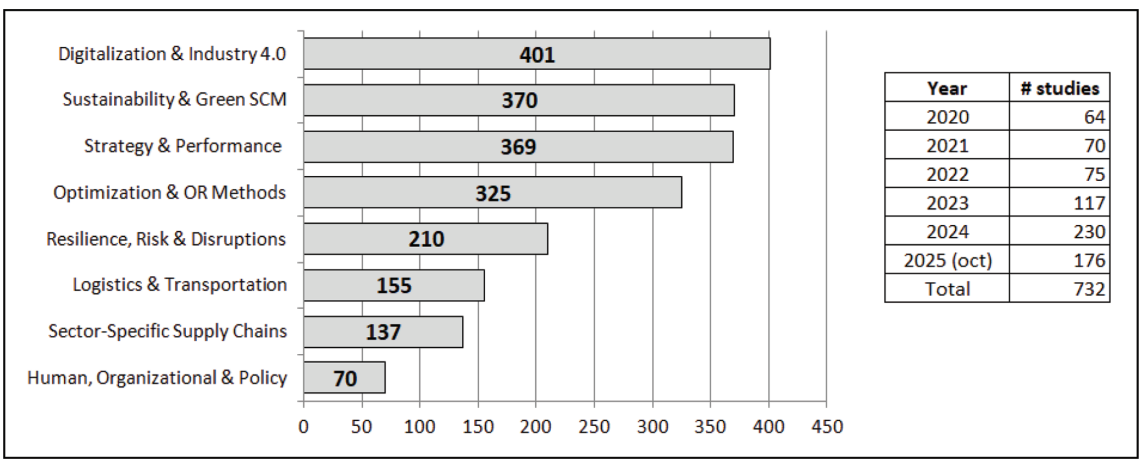
Last but not least, the EU Non-Financial Reporting Directive (NFRD, 2014/95/EU) adopted on 2020 (EU, 2020), and also the Corporate Sustainability Reporting Directive (CSRD, 2022/2464) (EU 2022) obliges large companies to disclose: business model, policies, risks and risk management, and key performance indicators (KPIs) relevant to the business.

2. Literature review

Contemporary literature on supply chain management (Figure 1) shows a predominance of analyses focusing on the impact of technological innovation, environmental aspects, and vulnerability to disruptions. The dominant theme is the digitalization of supply chains, driven by advances in AI, machine learning, IoT, and blockchain. Studies demonstrate how these tools improve visibility, predictive accuracy, automation, and decision-making. Closely linked to digital transformation is optimization, where traditional OR techniques merge with data-driven approaches facilitated by new technologies. Sustainability is another major focus of the analyses, reflecting societal expectations, regulatory requirements, and the commitment to decarbonization (Grillo et al., 2018). Studies examine the integration of circular economy principles, low-carbon logistics, waste reduction, and responsible sourcing into supply chain strategy. These studies blend with digitalization, highlighting how new technologies can boost traceability, eco-efficiency, and environmental monitoring.

Economic instability is driving numerous resilience analyses and risk management initiatives. Building resilient supply chains through diversification, redundancy, flexible production, and predictive risk analysis is a frequent concern (Rius-Sorolla et al., 2015). Studies examine the interaction between resilience and digital tools, suggesting that

Figure 1. Distribution of 732 SC-focused studies published between 2020 and 2025 based on their aggregated keywords into eight clusters Source: Consensus.app, request 'Supply Chain 2020-2025'. The result is a non-exhaustive list; a study may appear in more than one cluster.



Year	# studies
2020	64
2021	70
2022	75
2023	117
2024	230
2025 (oct)	176
Total	732

technology-based visibility and forecasting are essential for mitigating disruptions.

While logistics remains a frequent topic, it is integrated into studies focused on digitalization or sustainability, rather than being an isolated subject. Sectoral research, particularly in the food, healthcare, energy, and manufacturing supply chains, highlights the vulnerabilities and structural challenges exposed during recent crises. Human, organizational, and political dimensions, though less emphasized, are valued as critical performance factors in some supply chains. Emerging discussions surrounding skills development, organizational culture, and governance structures indicate a growing recognition of the social contexts in which supply chains operate. Studies frequently demonstrate integrated approaches that combine technological, environmental, risk, and human factors to address supply chain management.

2.1. System dynamics in operations and SC management

System Dynamics (SD) has long been recognised as a valuable approach for examining complex systems characterised by feedback loops, delays, and nonlinear interactions (Martín García, 2020). Within operations and supply chain management, SD models have been applied to analyse production and inventory systems, capacity planning, and demand amplification phenomena such as the bullwhip effect. SD represents internal feedback structures and resulting system behaviour.

A wide range of studies have explored supply chain coordination and performance under uncertainty. Angerhofer and Angelides (2000) provided one of the earliest reviews of SD applications in supply chain management, demonstrating the method's potential for policy analysis and managerial insight. Recent studies combine SD with simulation-optimisation frameworks and digital-twin concepts to enhance resilience and support managerial decision-making (Tordecilla et al., 2020). Dolgui and Ivanov (2021) further developed these ideas through the "viable supply chain" and "ripple-effect" paradigms, highlighting adaptability and survivability as essential dimensions of modern supply networks.

Esteso et al. (2023) applied SD to model the propagation of disruptions and to evaluate resilience in agri-food supply chains, while Gale and Nikbakhsh (2018) demonstrated its effectiveness for assessing improvement strategies in poultry systems.

2.2. Modeling Agri-Food Supply Chains (AFSCs)

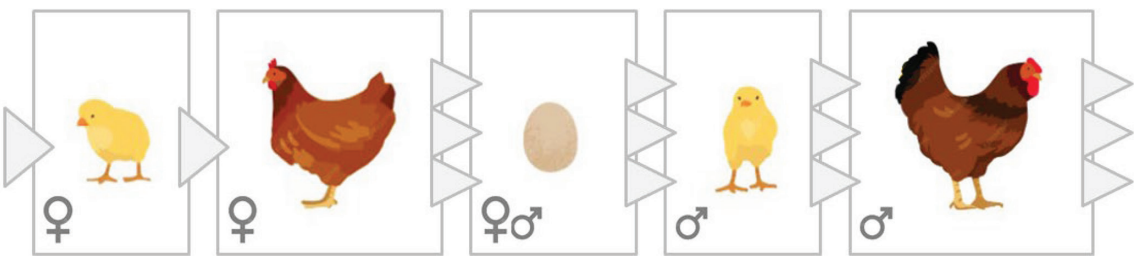
The agri-food industry displays distinctive dynamic behaviour when compared with industrial manufacturing systems. Biological growth cycles and animal-health constraints introduce delays and nonlinearities that make planning and control more complex (Tedeschi et al., 2011; Deppermann et al., 2018). Existing quantitative methods generally rely on deterministic optimisation or statistical forecasting, focusing on production scheduling, transportation, or inventory management (Esteso et al., 2018; Sarkar et al., 2024). Although valuable, these approaches usually assume steady-state conditions and overlook the feedbacks linking biological and economic processes. The production cycle begins with the acquisition of chicks for breeding, followed by their growth to maturity into hens, egg incubation, and chick rearing for final sale (Figure 2).

System Dynamics offers a complementary perspective for agri-food modelling. Recent applications include the design of resilient food-supply networks (Esteso et al., 2023), the assessment of sustainability and resilience factors (Aguado-Gragera et al., 2024), and the simulation of poultry and egg systems in developing contexts (Abbasi et al., 2023; Yuzaria et al., 2023). At a micro level, studies assessing the environmental impacts of Spanish egg production (Abín et al., 2018) and on native chicken breeds (Plata-Casado et al., 2024) provide detailed empirical data. However, SD models that integrate biological production cycles with economic indicators and supply-chain disruptions remain limited.

2.3. Supply chain resilience to disruptions and efficiency

Over the past decade, research on supply chain resilience has grown substantially, reflecting the growing frequency

Figure 2. Basic diagram of a vertically AFSC. The process begins with the purchase of chicks that become breeding hens, continues with the rearing of those chicks to adulthood, and proceeds through egg laying, incubation, and fattening until the chicks reach the desired weight for sale.



and severity of global disruptions such as pandemics, energy crises, and transport breakdowns. Resilience is commonly defined as a system's ability to resist, absorb, and recover from adverse events while maintaining acceptable performance levels (Ponis and Koronis, 2012). Traditional operations research approaches to resilience typically employ stochastic optimisation, scenario analysis, or simulation-based evaluation to quantify the trade-offs between efficiency and resilience (Dolgui and Ivanov, 2021). System Dynamics complements these methods by representing feedback-driven recovery processes and identifying leverage points that influence recovery time, cost, and overall stability. Ivanov (2023) synthesised multiple perspectives on supply chain resilience into an integrated conceptual framework, while Tordecilla et al. (2020) demonstrated how simulation-optimisation methods can support the design of resilient networks under uncertainty.

Despite these advances, applications of SD to agri-food systems remain relatively limited. Nevertheless, recent reviews point to their increasing relevance given the biological constraints and perishability that characterise such systems (Olivares-Aguila and ElMaraghy, 2020; Chokri et al., 2025). These studies underscore the need to extend resilience analysis to biologically dependent supply chains, such as poultry production, where disruptions can propagate through linked biological and operational stages and magnify economic volatility.

2.4. Research gap and contribution

Currently, most approaches to AFSC management assume biological processes as exogenous (Esteso et al., 2018; Sarkar et al., 2024), and they overlook the delays, nonlinearities, and feedback loops that govern performance (Tedeschi et al., 2011; Deppermann et al., 2018). At the same time, research on SC resilience has advanced through optimisation, scenario analysis, and network design (Tang, 2006; Goda et al., 2018; Dolgui and Ivanov, 2021), but these approaches generally model resilience levers, such as redundancy, inventory buffers, and safety stock, as external decisions, and typically do not represent how disruptions propagate through biologically dependent production stages (Ivanov, 2023; Monostori, 2018). Recent studies (Gale and Nikbakhsh, 2018; Abbasi et al., 2023) demonstrate the value of System Dynamics (SD) for analysing bullwhip effects in poultry production, integrated SD–OR frameworks that combine biological processes, operational decisions, economic indicators, and resilience metrics are still limited (Olivares-Aguila and ElMaraghy, 2020; Chokri et al., 2025).

Much of the works on AFSC resilience considers factors such as biological limits and external decisions as constraints. However, many of these can be represented as endogenous components within a SD model to analyze their effects on resilience and thus define KPIs that allow managers to select, based on daily operational information, those incidents in which they should: (i) do nothing, (ii) give special attention; or (iii) initiate immediate corrective action.

This study addresses this gap by developing a model of a chicken supply chain (Clar, 2024) that explicitly interlinks biological, operational, and financial dynamics. Its contributions are threefold: (i) An integrative modelling framework that represents biologically driven production–inventory interactions often simplified in traditional OR models; (ii) A simulation–optimisation approach that evaluates managerial policies within a dynamic system, showing how optimal decisions differ when endogenous feedbacks and delays are considered (Powell, 1964; Tordecilla et al., 2020; Ivanov, 2022); and (iii) A quantitative resilience assessment using KPIs, sensitivity and Monte Carlo analysis, and disruption scenarios aligned with OR resilience theory (Pettit et al., 2019; Ivanov, 2023)

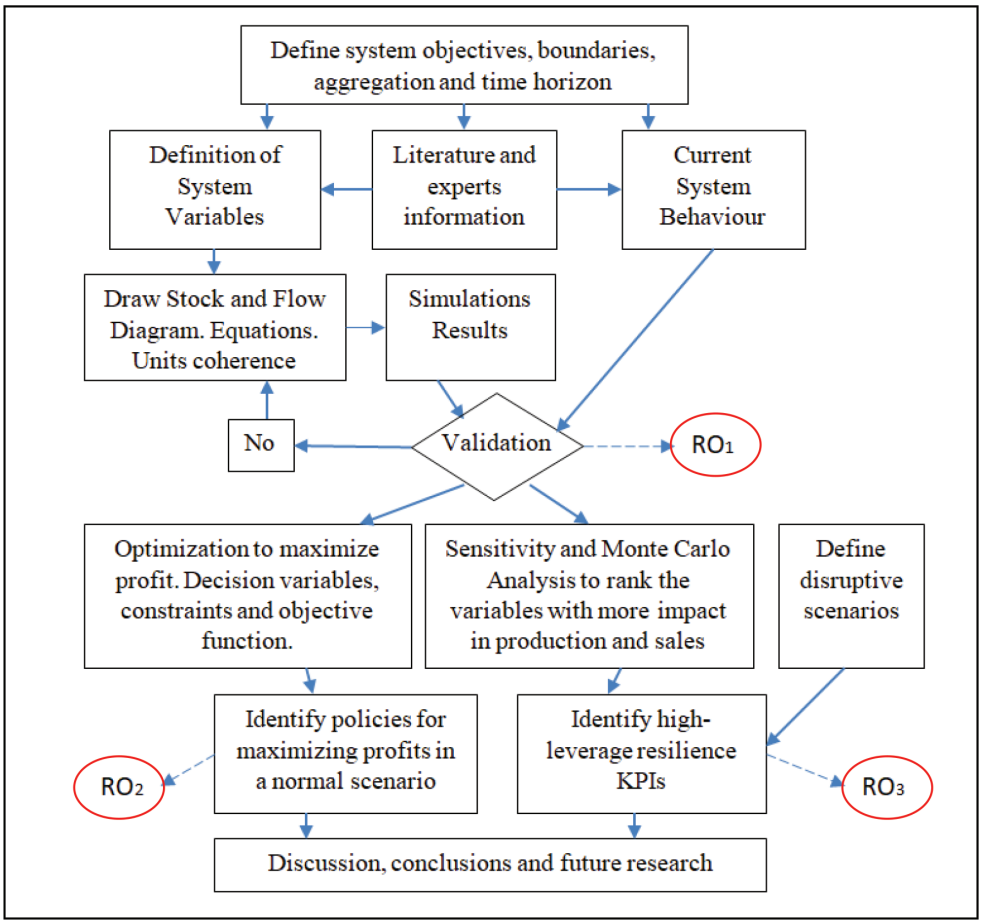
3. Methodology

System Dynamics (SD) enables experimentation with alternative management policies and the evaluation of time-dependent scenarios (Tordecilla et al., 2020; Ivanov, 2022). In the poultry sector, it allows biological processes, such as incubation, fertility, growth, and mortality to be linked with operational decisions related to sourcing, feed procurement, and capacity use. The model developed represents a vertically integrated agri-food supply chain (AFSC) with four stages: breeder chicks, breeder hens, eggs in incubation, and broiler chicks for sale. These stocks are connected through flows describing maturation, mortality, feed conversion, and sales. Economic variables as feed cost, chick procurement, and revenue from meat sales are added to compute weekly profit and profit/revenue ratio, which serve to calculate the performance indicators KPIs. This model captures biological and financial interactions and allows to test how policies influences KPIs and profit.

The steps followed to address the three research objectives ROs are shown in Figure 3. First, an SD model is built (RO_1), using expert judgement and scientific literature to identify variables and parameters. After verifying model behaviour and ensuring dimensional consistency, an optimisation procedure is used to identify profit-maximising policies (RO_2). Finally, resilience-oriented KPIs are defined and evaluated through sensitivity tests and disruption scenarios (RO_3).

The production system modelled represents a continuous, vertically integrated operation. The company purchases 1 000 chicks every 12 weeks. These chicks are reared for 25 weeks and then replace an equivalent number of adult hens, which are sold for meat. Each breeder hen produces an average of 16 eggs per month over a 20-month cycle. Ninety-five

Figure 3. Basic outline of the steps followed in this study to achieve the defined ROs, related to the optimization of profit and identifying the KPIs to improve resilience in disruptive scenarios.



percent of the eggs are viable; the remaining five percent are discarded. The incubation period is three weeks, with a 75% fertility and hatchability rate. After hatching, half of the chicks are grown for 35 days to 1.3 kg and the other half for 56 days to 3.2 kg. Mortality during rearing is 5% per week. Feed conversion is 1.80 kg feed/kg body weight for large chicks and 1.60 kg/kg for small chicks.

Although similar SD-based supply chain models exist (Abbasi et al., 2023; Esteso et al., 2023), this study integrates biological and economic feedbacks in a unified structure. The model uses representative parameter values from industry sources, allowing applicability to comparable vertically integrated operations. The detailed list of the variables and parameters are listed in Tables 6 and 7 (Annex 1 in Supplementary Materials) providing parameter values and sources. The model includes four stock equations and twelve flow equations, representing accumulations and transitions. Auxiliary variables compute revenue, costs, profit, and profit ratios. Figure 4 shows the simplified stock-and-flow diagram. Parameter values were derived from recent agri-food studies (e.g., Abbasi et al., 2023). The model was implemented in Vensim DSS with weekly time steps over a 52-week horizon.

4. Results

The model replicates the seasonal dynamics of the chick production. Four scenarios were examined: (i) Baseline (no intervention): the model structure and parameters are as shown above, (ii) Supply failure: The shipment of 1 000 chicks for hens in week 5 is not received in full, (iii) Incubation process failure: the incubator experiences a mechanical problem that causes the percentage of fertile eggs to decrease from 95% to 75%, and (iv) the price of feed with ± 5% uniform random variation. The baseline simulation shows that chicks enter the production system (red line), develop into laying hens (blue line), and are removed as they age (Figure 5 left).

The eggs laid by the hens are collected and placed in incubators (Figure 5 right). The evolution of the number of eggs collected depends on the population dynamics of the laying hens. Once incubated, the chicks hatch, are raised, and are

Figure 4. Stock and Flows diagram starting with the purchase of female chicks (lower left flow) and ending with the sale of chicks as food (lower right flow). The model variables and parameters are described in Annex 1 in Supplementary Materials and the equations are described in Annex 2.

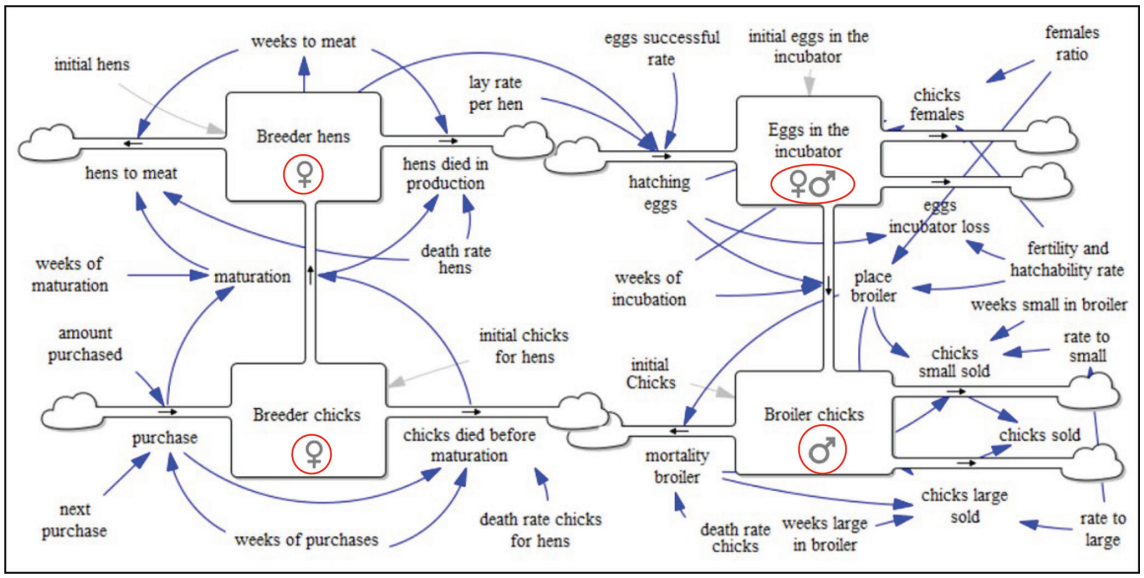
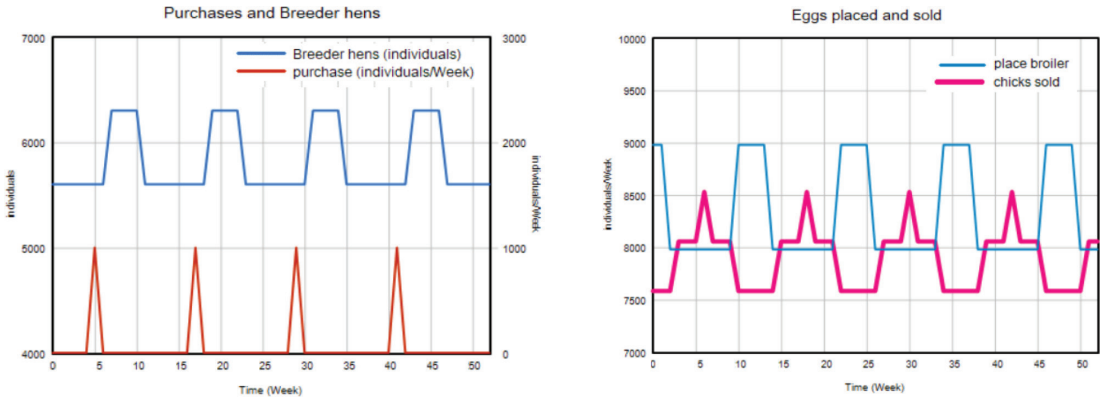


Figure 5. Variables showing the production process, from the arrival of the chickens to their sale in the market.

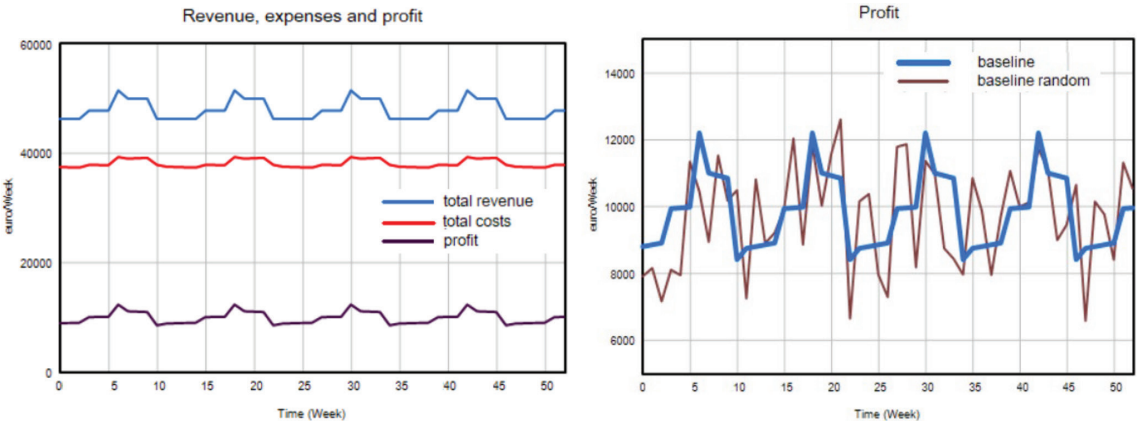


finally sold. As a result of the production process, the company generates revenue, which depends on the number of chickens sold and their weight. It also incurs more uniform expenses throughout the year; since only the amount of feed consumed depends on the number of chickens raised (Figure 6 left side). The company accepts market prices, like most companies in the agri-food sector. To simulate this situation, a random function was added that modifies the selling price by ±5%. It can be observed that variations of this magnitude amplify the usual fluctuations in profits (Figure 6 right side).

4.1. Validation

The model was validated through four tests: (i) reproducibility of the observed behavior, (ii) tests under extreme conditions, (iii) consistency of the equation units, and (iv) sensitivity analysis (Barlas, 1996; Schwaninger and Groesser, 2016). The baseline scenario described in (i) shows the pattern of breeding chicks, with variations due to the timeframes of chicks purchased for hens (12 weeks), their maturations into hens (25 weeks), the incubation of eggs until hatching (3 weeks), and the rearing process (5 weeks for small chicks and 8 weeks for large chicks). To test the model under extreme conditions (ii), scenarios of reduced chick purchases and lower egg hatchability were simulated. The model results were as expected and are detailed in the Supplementary Material. The correct consistency of the units (iii), verified by the software, is presented on the Supplementary materials. Sensitivity analysis (iv) is developed below and the results are shown

Figure 6. Dynamics of profits throughout the year, as difference between revenue and costs (left image). Revenue is based on the number of chickens sold and price, this is an exogenous variable for the AFSCs. Price variations (right image) can fluctuate by random and external factors, image showing a random uniform distribution of ±5%.



as a ranking of the variables with the greatest impact on profitability.

4.2. Optimization for profit

The optimization process aims to identify the parameters that maximize profits (Table 1). Biological parameters require fundamental changes in the production system (column A) and are taken as fixed, for example, adopting a different breed of chicken. The parameters in column B are influenced by biological aspects and also by staff training and equipment quality. The company cannot influence the parameters in column C, costs (such as food) and prices (such as meat), since it charges or pays at market prices. Finally, there are parameters (column D) that depend on company decisions, such as producing more or fewer large chickens; this will be the subject of the optimization study.

To calculate the profit optimization using Vensim DSS it has been used the Powell's (Powell, 1964) based on conjugate direction method, which allows finding a local minimum of a function, with a non-stochastic simulation, and with a maximum of 1000 iterations, the multi-start optimization to avoid local optima has not been used for simplicity. The decision variable examined was the proportion of chicks reared to reach the large size, assuming that there are no physical constraints for housing capacity, feed silo capacity or legal constraints as animal welfare regulations (max stocking density). The objective function has been the weekly profit during 2 weeks. As result, the best policy to optimize profit is to produce the maximum possible number or large chicks (100%) and the minimum of small chicks.

The reason lies in a combination of margin per kilo of meat produced (more kilos, more margin, more profit), the time to produce a kilo of meat (more weight, more breeding time) since the price per kilo of meat is the same for the large chicken as for the small one. In essence (see Supplementary Materials) if all production consists of large chicks, compared to the baseline scenario, meat sold increases by 31% and feed consumed by 29%, consequently revenue increases by 28% and total costs by 18%, resulting in a 51% increase in profits.

Table 1. List of parameters that can be modified in the optimization process grouped by their type, which indicates the possibility of being modified.

A. Biology	B. Production skills	C. Costs and prices	D. Management
Lay rate per hen	Fertility and hatchability rate	Cost per kg of feed	Rate to large
Feed breeder chicks	Death rate chicks	Cost per chick for hen	Rate to small
Feed conversion rate large	Death rate chicks for hens	Price per kg	Other cost
Feed conversion rate small	Death rate hens		Raw materials cost
Feed hens per week	Eggs successful rate		Weeks purchases
Weeks large/ small broiler			Amount purchased
Weight large and small			
Weeks on incubation			
Weeks of maturation			

4.3. Sensitivity and Monte Carlo analysis

To identify the variables that need to be addressed to achieve efficient results, Vensim DSS generates a tornado diagram that ranks, from highest to lowest, the impact of each parameter on the variable of interest (in this case, profit), as shown in Figure 7. The variable with the greatest impact is the egg successful rate, a variable that is amplified by the lay rate per hen. The next variables in this classification are the rate of chicks raised to a large size, the weight of the large chickens, and the cost per kilogram of feed. This analysis shows which variable is the most effective for managing and improving profit. In this case, it appears that trying to take care of the eggs successful rate, using technical measures and personal training has the greatest impact on profit.

The sensitivity analysis with the impact of ±10% variations in the parameters on the average weekly profit during the year is shown in Table 2. The calculations differ, but in this case, the ranking yields the same results for the first two variables.

The sensitivity analysis is complemented by a Monte Carlo simulation in which 200 scenarios are generated from uniformly distributed random numbers (Figure 8). These scenarios summarises the outcomes of 200 simulations, grouped by probability ranges (50, 75, 95, and 100%), showing how changes in the parameters can generate a range of nonlinear behaviors.

4.4. Disruptions and resilience

Supply chains are continually exposed to disruptions arising from unforeseen events and market fluctuations. These disturbances can affect production continuity, logistics efficiency, and overall service levels, thereby threatening business sustainability and food security in particular (Ghadge et al., 2021). Evaluating the resilience of a supply chain is therefore essential for understanding its capacity to maintain acceptable performance levels under adverse conditions. Resilience assessment enables decision-makers to identify vulnerabilities, design adaptive strategies, and implement mitigation policies before disruptions occur. By quantifying the degree to which key performance indicators -as profit, production or sales- fall below the acceptable minimum, organizations can make informed trade-offs between efficiency and resilience (Pettit et al., 2019).

Each scenario (ii) is characterised by the types of disruption under consideration and, for each type, the magnitude of the disruption. These scenarios are then compared to the

Figure 7. Tornado chart showing the sensitivity of year-end (week=52) profit to ±10% changes in model constants.

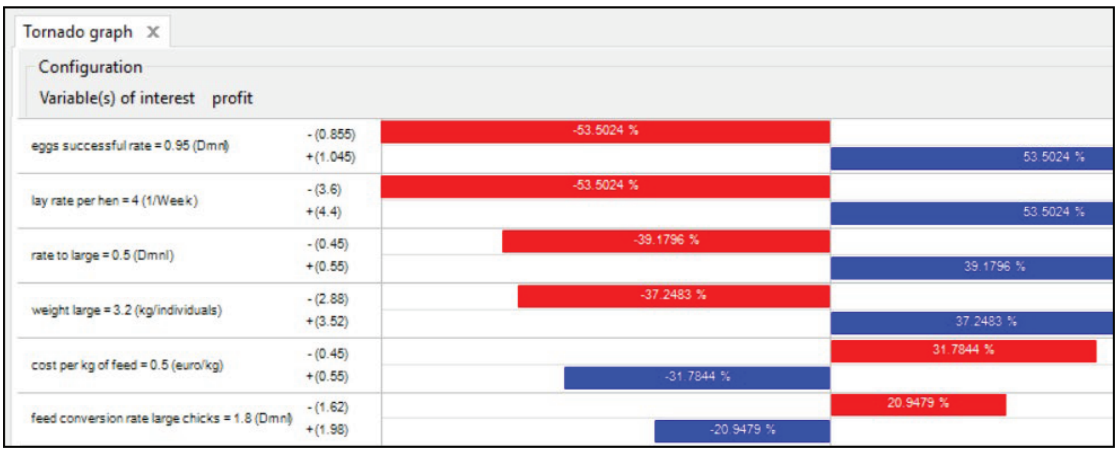
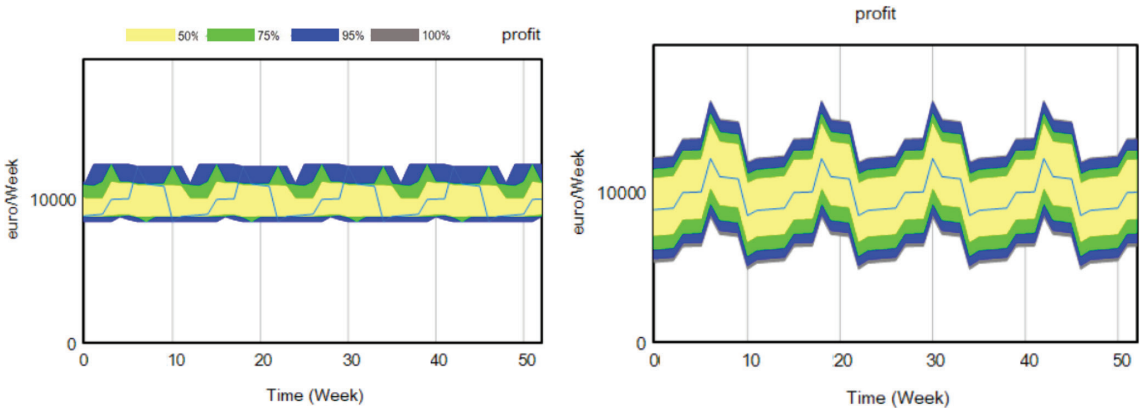


Table 2. Variables ordered by their greatest impact on average profit during a year.

	value			profit var. (weekly aver.)		profit (weekly aver.)	
	baseline	**-10%**	**+10%**	**10%**	**+10%**	**-10%**	**+10%**
Eggs successful rate	0.95	0.855	1.00	**- 23,94**	12,26	7.479	11.038
Lay rate per hen	4.00	3.60	4.40	**- 23,94**	23,09	7.479	12.103
Weight large	3.20	2.88	3.52	**- 20,19**	19,76	7.847	11.776
Cost per kg of feed	0.50	0.45	0.55	**18,89**	- 18,89	11.691	7.975
Feed conv. rate large	1.80	1.62	1.98	**11,53**	- 11,53	10.967	8.699
Rate to large	0.50	0.45	0.55	**- 11,34**	11,18	8.717	10.93

Figure 8. Monte Carlo results showing the probability distribution. Left image: Maturation weeks: from 25 (from chick to hen), values from 20 to 30; the profit shifts, but maintains its max and min values. Right image: Cost per kg of feed: from 0.4 to 0.6. In this case, profit exhibits greater variability, although the seasonal pattern remains the same.

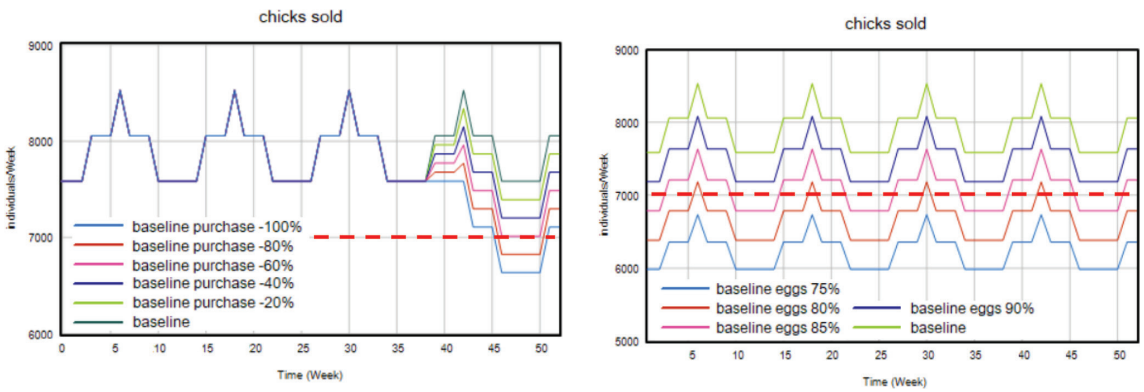


baseline scenario that assumes no disruption for evaluating the consequences of the disruptive cases (Monostori, 2018). In this model two possible disruptive scenarios are simulated: (i) that due to external causes, one or more egg purchases, expected for week 5, do not arrive complete, or (ii) that due to internal causes (as maintenance failures) the eggs successful rate drops from the usual 95% to 75 %. A simulation must be conducted for each disruptive scenario. To implement a specific scenario, it is necessary to adjust the input data corresponding to the studied interruptions and to rerun the System Dynamics model accordingly. One of the principal risks in the supply chain is the occurrence of a disruption at any stage of the process. This study examines an external impact, simulating the non-delivery of a purchase, and an internal impact in which egg production from breeding hens is interrupted.

The options to receive 0%, 20%, 40%, 60%, 80%, and 100% of the purchase are shown on the left side of Figure 9. The red line indicates the lower limit of chicks sold to be considered a resilient SC. For the options of receiving 0%, 20%, and 40% of the expected purchase in week 5, the scenario shows that the target (7 000 chicks/week) is not met. As shown on the right side of Figure 9, the reduction in hatchability due to technical issues causes a decrease in the hatching of eggs and chicks that are sold; if this parameter drops from 95% to 85%; in this case, the target is not met.

The value of each resilience indicator is calculated for all simulated scenarios and compared against the predefined minimum threshold. The supply chain is considered non-resilient in those scenarios where the indicator fails to reach the desired minimum level (Rojas-Reyes et al., 2024). In this case, the system analyzed is not resilient in those circumstances that seem feasible: (i) a 50% drop in a purchase, (ii) a 10% drop in the success rate of the eggs. If the analysis reveals that the supply chain lacks resilience under certain disruption levels, it becomes necessary to evaluate and select preventive policies aimed at enhancing its resilience (Banomyong, 2025). Based on that information, the company should assess the risk of the two events mentioned occurring, and consider preventive measures to take, such

Figure 9. Impact on chicks sold of (i) external disruption, missed purchase in week 5 (left) from 20% to 100%, and (ii) internal disruption, a reduction from 75 to 95% in hatched eggs (right).



as (i) having an emergency supplier in case of purchase failures, and (ii) improving the maintenance service to avoid a decrease in the successful egg ratio.

5. Selection of KPIs

The selection of KPIs requires identifying those most appropriate for AFSC (Table 3), together with their permissible variation limits, in order to determine whether the SC can be considered resilient. Resilience is a subjective measure, dependent on the risk-aversion of the user (Zhao, 2020). It must be defined acceptable thresholds for each KPI. The greater the degree of risk-aversion, the higher the desired values of the resilience indicators (Tang, 2006).

Table 3. KPIs selected and the results obtained in a total loss of week 5 purcase.

KPI	Equation, threshold and result
KPI-1: Minimum Weekly Output (MWO)	MWO(t) : Min(Chicks sold (t)), Threshold: Chicks sold (t) > 7 000 chicks/week. The system is non-resilient if output falls below this threshold for ≥3 consecutive weeks (risk of market loss). This KPI directly detects disruptions caused by missed chick purchases or sharp drops in hatchability. A complete loss of the week-5 purchase results in MWO=0 in week 46.
KPI-2: Service-Level Deviation (SLD)	SLD(t)=TargetOutput−ChicksSold(t)/ TargetOutput Threshold SLD=7 000 chicks per weeks, the system is not resilient if target>sold during 4 consecutive weeks. A total loss from the week 5 purchase makes SLD=0 in week 47.
KPI-3: Effective Hatchability Ratio (EHR)	EHR(t)=HatchedChicks(t)/ EggsIncubated(t) Threshold: EHR(t)≥0.90 A drop in hatchability is an early-warning indicator of internal failures (e.g., incubator malfunction, breeder-health issues). This KPI acts as a leading indicator for future declines in chicks sold. A constant value for EHR=0.95 has been taken in the model.
KPI-4: Breeder Productivity Index (BPI)	BPI(t) = BEH(t) × Laying Rate. This tracks hen laying. Threshold= 20 000 eggs per week, the system is not resilient if production falls below the threshold for four consecutive weeks. A total loss since the purchase in week 5 results in BPI = 0 in weeks 39–43 and 51–52 due to a four-week lag in the hen population.
KPI-5: Feed Cost Volatility Impact (FCVI)	FCVI(t)=FeedCost(t)/TotalCost(t) A shock such as a sudden increase in feed prices immediately raises the FCVI. A high FCVI indicates vulnerability to input price fluctuations. The current model: 0.51 > FCVI > 0.47
KPI-6: Profit-at-Risk (PaR)	PaR=Quantile α[Profit(t)] Quantify the worst-case profit generated by disruptions. The system is not resilient if profit falls more than 30% below the annual average. In the base scenario, the average annual profit is 9 833, with weekly fluctuations between +24.0% and -14.6%. A total loss from the week 5 purchase results in PaR=0 for weeks 46 to 50.
KPI-7: Time to Recovery (TTR)	TTR=min{t / ChicksSold(t)≥TargetOutput} Measures how quickly the system regains output after a disruption (e.g., missed chick delivery). Lower TTR = stronger resilience. The chicken production chain does not recover from a missed delivery unless another order of the same quantity is placed (assuming capacity is not a constraint).
KPI-8: Performance Loss Area (PLA)	PLA=∑ [TargetOutput−ChicksSold(t)] This reflects the magnitude of the 'resilience triangle'. The poultry production chain resumes normal operations when a new order for the same quantity is placed. If no order is placed, normal production resumes after 38 weeks, the timeframe in which the chickens from the pending order would have been sold.

In this model, the profit/revenue ratio in the baseline scenario is 20.5% as an annual average, with weekly fluctuations between 18.2% and 23.7% (Supplementary Materials) can be used in the PaR. In the analyzed production chain, there is a delay of 38 weeks on average between the purchase of a batch of chickens for hens breeding and the sale of chickens on the market. This means that a disruption in the arrival of an order has little impact on the average annual profit/revenue (52 weeks). Furthermore, internal technical problems affecting a batch of eggs or chicks for sale not affect the average annual profit/revenue, as egg and chicken stocks allow demand to be met without appreciable effects in the PLA. For this reason, resilience indicators in this case cannot refer to annual values, but rather to weekly parameters. The indicator chosen is that the weekly quantity of chickens sold cannot be less than 7 000 for 3 consecutive weeks (MWO), due to the serious damage to the reliability in the eyes of customers (Table 4), who should look for other options to buy chickens.

The KPIs based on the KPI-8-PLA concept measure the impact of different degrees of disruptions on weekly profit (Table 5) to detect failures in the production stages (shown as flows in the model).

Table 4. KPI values for weeks 42 to 50 simulating the total loss scenario of the week 5 purchase. Gray cells indicate when a KPI does not meet the defined resilience criterion.

KPI	Target	42	43	44	45	46	47	48	49	50
KPI-1: Minimum Weekly Output (MWO)	> 7000 chcks	7582	7109	7109	7109	6635	6635	6635	6635	6635
KPI-2: Service-Level Deviation (SLD)	> 0	0,0083	0,016	0,016	0,016	-0,052	-0,052	-0,052	-0,052	-0,052
KPI-3: Effective Hatchability Ratio (EHR)	> 0.90	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95	0.95
KPI-4: Breeder Productivity Index (BPI)	> 20 000 eggs	22404	25204	25204	25204	25204	22404	22404	22404	22404
KPI-5: Feed Cost Volatility Impact (FCVI)	< 0.50	0.51	0.50	0.50	0.50	0.48	0.48	0.48	0.48	0.48
KPI-6: Profit at Risk (PaR)	> 6 833 euro	9817	8380	8504	8428	5903	6241	6293	6346	6398

Table 5. KPIs measuring the impact on weekly profit of differences between real and expected production values. Profit deviation=(week value – expected average)xprofit per chick or egg.

KPI 8	Expected weekly average		Profit per chick or egg		Past week value	Profit deviation
Chicks for hens purchased	83,3	female chicks	117,99	euro/chick	85	106,7
Maturation of chicks	58,3	female chicks	168,56	euro/chick	60	290,9
Hatching eggs from hens	22.102,3	eggs	0,44	egg	22.050	- 23,2
Chicks placed to broilers	8.307,3	male chicks	1,18	euro/chick	8.200	- 127,3
Chicks sold	7.892,2	male chicks	1,25	euro/chick	8.180	358,6
					Total week	**686,7**

6. Discussion

The results highlight how the links between biological processes, operational decisions, and market conditions shapes the dynamic behaviour of vertically integrated poultry systems. From an operations-research perspective, this structure constitutes a multi-stage production-inventory system governed by causal links, feedback loops and delays. The model shows how disturbances propagate and generate nonlinear responses (Dolgui and Ivanov, 2021).

The baseline scenario reveals cyclic patterns driven by biological delays-maturation, incubation, and fattening. These cycles resemble classic amplification mechanisms found in production-inventory theory as the bullwhip effect. Sensitivity analysis further identifies a small set of high-leverage parameters-egg viability, lay rate, feed price, and feed conversion efficiency-that disproportionately influence profitability and volatility. These insights align with resilience-optimization literature (Tang, 2006; Goda et al., 2018), where input-cost volatility and process reliability are recognised as major drivers of stability.

By using service reliability (weekly chicks sold) as a resilience KPI, the model offers a quantitative view of how disruptions influence performance. Specifically, the threshold of maintaining chick production and sales above 7 000 units per week captures service reliability. The system absorbs minor deviations through built-in buffers, but significant reductions in chick supply or egg hatchability lead to KPI violations within a few weeks. This behaviour corresponds to ripple-effect patterns observed in multi-stage supply networks (Dolgui and Ivanov, 2021), and demonstrates the value of dynamic simulation for assessing disruption propagation beyond what stochastic or optimization alone can capture (Pettit et al., 2019).

The nonlinearity observed across both sensitivity and Monte Carlo analysis (Figures 7, 8 and Table 2) indicates a non-linear pattern of performance degradation: small improvements in hatchability deliver outsized gains in resilience. Conversely, losses in this parameter produce rapid declines in service level (weekly chicks sold) and as consequeance in profit stability. Such asymmetry reinforces the importance of preventive interventions rather than reactive recovery measures.

The integrated simulation-optimization approach used here complements established OR models by embedding endogenous biological feedbacks and time delays into policy evaluation. The optimization of production mix (proportion of large chicks) provides an example: while

deterministic optimization identifies a profit-maximizing policy, the dynamic model clarifies how the same policy behaves under disruptions and parameter uncertainty (Tordecilla et al., 2020; Goda et al., 2018). This dual insight is consistent with viable and resilient supply chain concepts in OR (Ivanov, 2022), where feasibility depends on both structural configuration and temporal adaptability.

7. Conclusions

With the aim of identifying which Key Performance Indicators (KPIs) in an Agri-food Supply Chain (AFSC) enable the monitoring of resilience to potential internal and external disruptions that affect company profitability and customer service quality, this study develops a Systems Dynamics (SD) model that integrates biological processes, operational decisions, and economic aspects to support the planning of a vertically integrated chicken supply chain. The study makes three main contributions to the operations research (OR) literature. First, it offers a dynamic framework that embeds endogenous biological feedbacks and delays, enabling the analysis of behaviour and the propagation of disruptions, elements difficult to capture with static or purely stochastic models. This addresses RO_1 by demonstrating how SD can complement OR methods in modelling biologically constrained production systems.

Second, the integration of simulation with local optimization identifies profit-maximizing operational policies (RO_2). While many parameters are biologically or market-determined, managerial decisions regarding product mix significantly influence profitability. The optimization results show that producing a higher share of large chicks substantially increases revenue and overall weekly profit.

Third, the study identify resilience KPIs derived from sensitivity analysis and Monte Carlo simulation (RO_3). These metrics quantify how disruptions in supplier delivery or hatchability affect service performance. The results reveal that resilience hinges not on single redundancy measures but on managing interdependent feedbacks across production stages. This provides a quantitative basis for preventive policies such as dual sourcing of chicks or enhanced equipment maintenance. Overall, the study demonstrates the value of combining System Dynamics with OR-based resilience concepts to support evidence-based decisions in agri-food systems. It provides a reproducible tool for analysing vulnerability, designing specific KPIs, and evaluating alternative strategies under uncertainty. Future research could refine this framework by integrating stochastic optimization, agent-based decision models, or multiple production lines, thereby expanding the analytical toolkit available for managing complex, biologically dependent supply chains. Resuming, the study offers a practical decision-support tool and guide for managers planning vertically integrated biologically constrained supply chains, indicating four key lines of action:

(i) Locate and prioritize high-impact parameters. Investments that improve egg viability, lay rate, or feed efficiency deliver the greatest improvements in profitability and resilience.
(ii) Strengthen proactive risk management. Because biological cycles are long, disruptions propagate slowly but persistently; early actions such as preventive maintenance to safeguard hatchability or securing alternative suppliers can significantly reduce service level failures.
(iii) Use KPIs as early-warning indicators. Declines in hatchability or unexpected increases in feed cost may signal upcoming performance losses weeks before they appear in weekly profit.
(iv) Evaluate policies to optimize profits. Decisions such as altering the production mix between large and small birds should be assessed for maximize profitability.

8. Limitations and future research

Despite its analytical advantages, the model presented in this study remains an aggregated representation of a poultry supply chain. It does not capture heterogeneity across farms, or stochastic variations in demand. These simplifications, while necessary for transparency, limit the model's ability to reflect the diversity of those systems. Future research could integrate System Dynamics (SD) with stochastic optimisation or agent-based modelling to allow the analysis of distributed decision-making, and uncertainty propagation (Ivanov, 2022). Incorporating multiple production lines could broaden the model's relevance across different agri-food sectors. Ultimately, advancing the combined use of SD and OR will provide richer insight into the interactions between efficiency, resilience, and sustainability in biologically supply chains.

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Supplementary materials and software availability

The Vensim DSS software is available at https://vensim.com/free-downloads/. No programming knowledge is

needed to use the software or the model. The Vensim simulation model is available at https://www.atc-innova.com/Chicks.mdl, additional information at https://www.atc-innova.com/DyO-README.docx.

CRediT authorship contribution statement

Francisco Campuzano-Bolarín: Software, Methodology, Formal analysis, Validation. Ángela Martín-Méndez: Writing - review and editing, Writing - original draft, Visualization, Supervision, Resources, Project administration, Investigation, Data curation, Conceptualization.

Declaration on the use of AI in the writing process

In preparing this study, the authors used ChatGPT first to identify relevant references and then to perform linguistic polishing. It was not used to create the model, define the equations, simulation, calibration or analysis.

Declaration of interest

The authors declare no competing financial or non-financial interests.

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