Information and material delays effect on price setting, operating contribution margins and cash conversion cycles in feed ingredients supply chain

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Abstract

Purpose – The purpose of this report was to evaluate the effectiveness and practicality of system dynamics modeling in integrating econometric equations to describe the effects of supply chain material and information delays on pricing decisions and consequent financial results in an animal feed export business.

Design/methodology/approach – An empirical dynamic model, loaded with econometric theory of price effect on competitive demand, was used to describe the input data.

Findings – The model simulation outputs proved themselves relevant in analyzing the complex interconnections of multiple variables affecting the profitability in a commercial routine, supporting the decision process among sales managers. The impact of information delay on price decisions and business financial results were estimated using the model proposed.

Originality/value – This paper describes an empirical model, based on system dynamics, that predicts operating contribution margins and cash conversion cycles based on estimation of information and material delays in a supply chain. The method is pragmatic and simple for business routine implementation.

Keywords Information delay, Price, Contribution margin, Supply chain, Feed industry

Paper type Research paper

Introduction

Products for animal feeding include components derived from, or substitutes of, agricultural commodities. Thus, their prices present similar volatility and are influenced by the same forces. Next to trading speculation (Ghosh *et al.*, 2012), the price of agri-commodities fluctuates according to economic activity (Chiaie *et al.*, 2017) and currency exchange rates (Miecinskiene and Lapinskaite, 2014; Bodenstein *et al.*, 2018). Prices can vary on a daily basis for several of these ingredients, as some of them are indexed to the currency exchange rate.

The animal feed industry supply chain is composed of a raw material supplier, a manufacturer and a retailer. A distributor or agent, representing the retailer, are common extensions of the value chain. An important volume of these products is exported, attaining US$15.5bn in revenues in 2019 (Workman, 2019), which makes the supply chain relatively long in terms of delivery time.

Due to the nature of the industry, the cost-plus pricing model is widely adopted among players. In a multi-echelon supply chain, the price of goods exercised in each chain link is an

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essential component of the variable cost for the next link. In practice, material flow delay is associated with its respective price information. In the case described above, this information delay can lead to price-setting decisions that might lead to a low level of optimization of the competitive landscape or of the profitability of a given link, or even of the entire supply chain. As competitors receive updated price information or inventory at different times, their individual assessment of costs and pricing strategies can differ considerably. The consequent profit erosion, price wars and vicious cycle among competitors might be detrimental to the manufacturer, competitors and, potentially, clients.

The economic theory on price strategies along supply chains in multiple scenarios is available (Simon and Fassnacht, 2019; Nagle *et al.*, 2010). However, the static nature of these models leads to a lack of clarity on how decisions influence demand, competitor reaction, the quantity sold and overall inventory planning. Traditional econometric pricing models, based on *ceteris paribus* perfect and instantaneous information and material flow delay-free assumptions, do not solely represent the complexity of a commercial routine.

System dynamics (*SD*) modeling has been applied to describe alternative empirical solutions to production and supply chain stability problems (Yasarcan and Barlas, 2005; Küsler and Hilmola, 2020; Olivares-Aquila *et al.*, 2020). However, our attention focuses on inventory price information delays linked to the respective material flow delay and their consequence effect on price strategies and profitability from the commercial standpoint. *SD* can provide practitioners with good insights into price behavior in systems subjected to nonlinear factors, such as consumer choices and competitive reactions (Inman *et al.*, 2020). In addition, *SD* tools and methods appear to be pragmatic enough for business and sales teams. These teams are versatile in economic, financial and marketing parameters. *SD* could help them to describe, model and follow the consequences of their decisions in a supply chain network flow, based on available commercial data and the practical integration of relatively simple mathematical representations of the challenges at hand.

This paper presents a case description in the form of an empirical model based on *SD* techniques. The objective was to evaluate the effectiveness and practicality of *SD* modeling in integrating econometric equations to describe the effects of supply chain material and information delays on pricing decisions and the consequent financial results of a business routine. Commercial data of an export business dedicated to animal feed ingredients was used to guide the model design and simulations. The actual commercial context is replicated in a stock and flow diagram (*SFD*), where the cross-price elasticity of a given product is used to imitate the competitive landscape.

Methods

Economic theory of price

The underlying economic principles of profit, price and price elasticity are detailed elsewhere, as are the equations used in this paper (Simon and Fassnacht, 2019; Nagle *et al.*, 2010).

Profit (P) is defined by equation (1), which is a function of price (p), costs (c) and quantity sold (q). Timely quantity sold variation provides the dynamic aspect of profitability, leading to different sales contribution margins:

$$P = (p * q) - c \tag{1}$$

Considering a steady demand and diverse suppliers, quantity sold variation for a given supplier is defined by the competitive pricing among them and can be derived from the cross-price elasticity ratio (ξ_{ij}) in equation (2), expressed as a change in the quantity sold (δq_i) by the manufacturer per change in the price (δp_j) of a competitor:

$$\xi_{ij} = \frac{\delta q_i}{\delta p_j} * \frac{p_j}{q_i} \tag{2}$$

Equation (3) describes the operating cash conversion cycle (C), given in days, in function of average inventory financial value ($\bar{i}$), variable cost of goods sold ($COGS$) per day (G), average accounts receivable ($\bar{r}$), revenue per day (R) and average accounts payable ($\bar{p}$):

$$C = \frac{\bar{i}}{G} + \frac{\bar{r}}{R} - \frac{\bar{p}}{G} \tag{3}$$

Market share (m) was described by equation (4), which is derived from total product demand (Q). Equations (2) and (4) indicate q variation, when ξ_{ij} is known for a competitive condition:

$$m = \frac{q}{Q} \tag{4}$$

Contribution margin per day (CM_d) is defined by equation (5) and represents p minus G:

$$CM_d \ = p - G \tag{5}$$

According to the theoretical equation (6), which was derived from a linear price-response and linear cost functions to maximize q, the optimal price (p_0) would fall right between the variable unit cost k and the maximum price (p_m) where q becomes zero. This equation suggests that increases or decreases in variable costs should result in only half of that cost being passed on to a price increase or decrease for price optimization (Simon and Fassnacht, 2019, p. 284).

$$p_o = 0.5(p_m + k) \tag{6}$$

System dynamic model description

Causal loop diagram (*CLD*) and *SFD* were designed according to the recommendations from standard references (Richamond, 2013; Pruyt, 2013; Bala *et al.*, 2017). The Insight Maker software (Insight Maker, 2020) was used to generate the graphical representation of the diagrams, as well as the system equations integration and simulations in this exercise.

The simulations were performed in a one-day solution interval for 1,080 days, using the Euler method. The supply chain boundaries were defined as supplier, producing manufacturer and retailer, comprising the periods between August 1, 2017 and July 16, 2020. A sensitive evaluation of the model was performed using the Insight Maker built-in sensitive analysis procedure. In total, 50 simulations were run, using CM_d and q as monitored variables. The variables ξ_{ij}, order interval, inventory level were randomized at 1 ± 0.5 unit less, -10 ± 5 days and 650 ± 50 metric tonnes (*MT*), respectively.

Sales conditions, ξ_{ij}, customer value perception, supply lead-times, product composition information and respective relative cost impacts on final product parameters were estimated based on the sales statistics and interviews for the manufacturer under study. Commercial correspondences registered in emails and meeting minutes between manufacturer and retailer were summarized as a comparison reference to the model simulations. ξ_{ij} was arbitrarily set to 1, as products between manufacturer and competitors were considered perfect substitutes. The purchasing behavior of clients led to near-immediate reaction on sales volumes as competitive prices were announced and compared. The competitor's product composition was estimated by reverse engineering, based on the declared product label.

The retailer under study is located in the Middle East and serves the Gulf region market. All data related to country population and consumption dynamics were obtained from Our World in Data (Our World, 2020), a non-profit organization that consolidates statistical series from the FAO and the World Bank. Product demand was defined by local broiler meat production, amount of product consumed by animals and carcass yield per animal per year. This demand was directly related to domestic chicken meat consumption, minus imports. Meat export was non-existent. Chicken meat consumption has been growing slowly, but steadily, and was positively correlated to population growth and income (data not shown). In the period under study, meat consumption, imports and local meat production variation were negligible and were considered to be constant. The total demand for the product under investigation was also steady and considered stable at 20.500 *MT* per year.

Goods were produced by the manufacturer and exported to the retailer overseas. Purchase orders were regularly placed by the retailer, according to demand. Order and price offer confirmation was followed by production. Goods were shipped by sea freight and subsequently arrived at the retailer's warehouse after importation procedures and in-land transportation. Production lead time, total shipment time and manufacturer payment terms were 15, 35 and 30 days, respectively. The order interval was equal to the summation of production lead time and total shipment.

The product composed of industrial amino acids, vitamins, minerals and feed additives, designed for animal feeding was taken as the study model. From a price perspective, these raw materials behave as traditional commodities whose prices positively correlate to worldwide demand and are indexed to alternative substitutes. Four of these raw materials accounted for around 70% of *COGS* for the period studied. *COGS* were estimated by multiplying the amount inclusion of these four ingredients by the daily raw material prices fluctuation. Due to confidentiality matters, the ingredient price references used were taken from a publicly available source (FeedInfo, 2020). Production, transport and sales costs represented less than 5% of *COGS* in the final price. During the study period, the fixed production and sales costs were constant and were only influenced by exchange rate fluctuations. Based on these observations, the author arbitrarily did not consider those operational costs.

The prices of the product were defined on a cost-plus basis model. The markups for both manufacturer and retailer were arbitrarily set at US$80 per *MT*. All prices were corrected to the daily *USD* to Euro exchange rate, compared to the *COGS* of the manufacturer, for the period under study. The retailer offered a 45 days payment terms to its clients. The retailer reported a steady m of 20% for several years. Competitors were composed of other retailers, mainly consolidated companies with a similar reputation, expertise and purchasing power. One particular competitor has an industrial platform in the region, and thus has a competitive advantage in relation to operations and logistics, and this was the one used as a reference for the comparison.

The supply conditions of lead-times for the manufacturer, as if it was based in the region, were replicated to mimic the competitor's behavior described above. This design enabled the comparison of the effect of material and information delays of the manufacturer on the ξ_{ij} and m, as if the manufacturer were competing against itself. Two supply chains with different lead-times were designed: (1) *LLT* – long (15 and 35 days production and shipment lead-time, respectively, with 50 days total delay) and (2) *SLT* – short (five and ten days production and shipment lead-time, with 15 days total delay) lead-times. The other two independent variables under study were time intervals between orders (50 or 30 days) and the product variable cost transfer (*CT*) to price alternative policy (50% of the variable cost variation, instead of total cost transfer). Since raw material costs, currency exchange ratio, product prices, quantity sold and inventory all varied simultaneously, the dependent variables chosen were daily sales contribution margin and operating cash conversion cycle.

Results

Model designs

The *CLD* in Figure 1 depicts how the manufacturer initially interpreted the dynamics between budgeted and real profit related to respective prices and quantities sold.

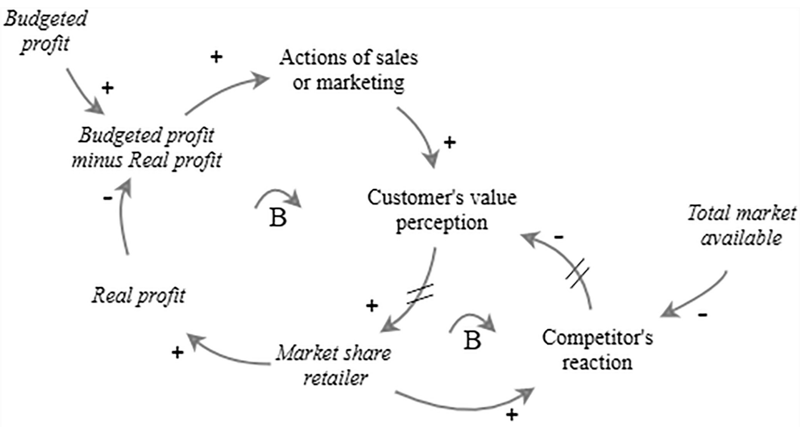
Profit erosion and fierce price battles were reported cyclically by the retailer, which were perceived as a price positioning problem, leading to sales decrease. The marketing teams of the manufacturer were regularly spurred into action by the retailer, to achieve a short-term, fast solution. Based on the definition of profit in equation (1), these teams could do either two things: design and communicate better products or value propositions aimed at achieving greater value perception and price increase acceptance by clients, or reduce costs and prices, with the objective to increase the quantity sold (Figure 1).

As a balancing feedback loop ($\overrightarrow{B}$), the reaction from the competitor (j) induced clients to re-evaluate and lower their value perception elicited by any sales or marketing action from the manufacturer (i) ξ_{ij}, as described in equation (2) above. As clients perceive less value or have replacement alternatives, quantities sold become more sensitive to price variations, indicating an increase in ξ_{ij}. This cycle leads to a fierce battle for m balance toward Q and product commoditization.

Figure 2 shows the summary of an *SFD* representing the manufacturer and retailer sales material and information flow described earlier. The reader can review the complete *SFD*, the description for each element in the model, the respective equations and units, and run simulations on the link https://insightmaker.com/insight/222467/Article-SDR-Case-study-System-dynamic-modelling.

Model simulation analysis

The sensitivity test analysis based on various simulations with random parameters for ξ_{ij}, order intervals and inventory levels resulted in curves representing CM_d and q with varied amplitudes, but their shape remained the same (data not shown). The model was able to produce consistent predictions for the entire range of test parameters proposed above, even in their extremes. All variables described in Figure 2 were expressed in their respective measuring units, and the mathematical integrations ran without any unit conflict. The shortest delay



Note(s): The + sign indicates a reinforcing effect, and the – sign suggests an opposite effect of the two parameters connected.   indicates a balancing feedback loop

Figure 1. CLD representing the competitive market dynamics played by manufacturer, competitors and customers

observed in the current model refers to a five-day lead-time for production in the *SLT* scenario. The choice of one-day simulation solution interval follows the recommendation of previous authors, with the objective to achieve less than half of the shortest time delay described (Bala *et al.*, 2017, p. 129). All these observations suggest a fair robustness for the present model.

Figure 3 represents *COGS* at manufacturer in Euro per *MT* and the *USD* to Euro daily exchange rate for August 1, 2017 to July 16, 2020. The behavior of these two curves presents a correlation coefficient of 0.85.

Inventory size was positively related to lead-times. The higher the production and shipment delay, the bigger the inventory at the warehouse of the retailer (data not shown). This pattern influenced the time between the manufacturer price setting and the availability of the ordered goods at the retailer inventory.

Figure 4 presents the daily retailer product price in *USD* per *MT* for *SLT*, *LLT* 50 d and *LLT* 30 d conditions. Figure 5 presents daily retailer product price in *USD* per *MT* for *SLT*, LLT 50 d *CT* and *LLT* 30 d *CT* scenarios.

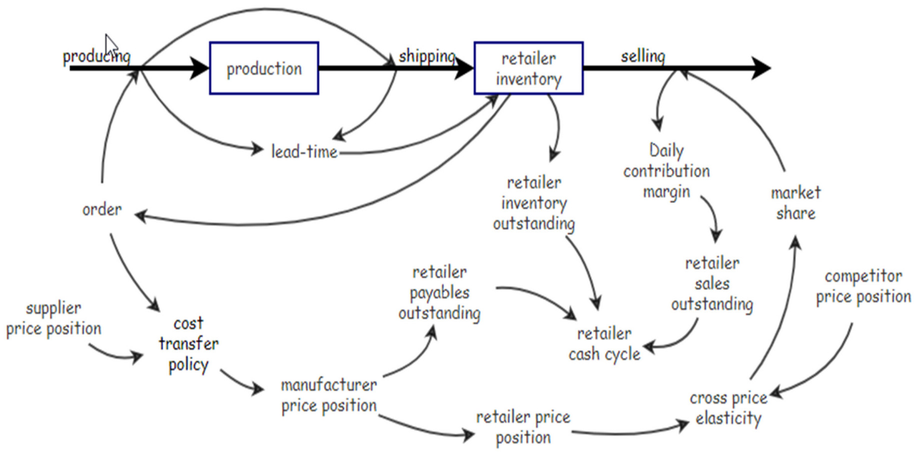
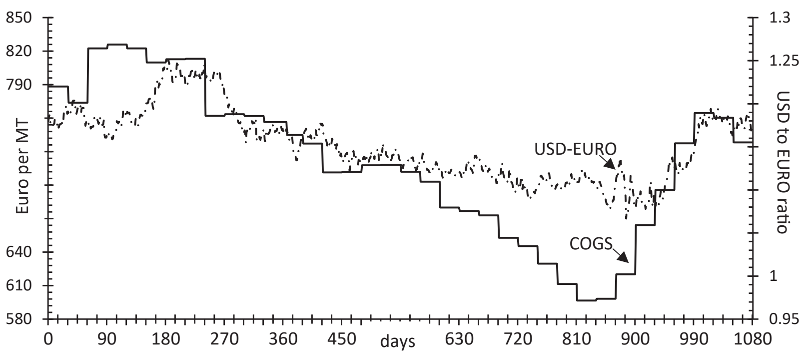


Figure 2.
SFD summary representing: (a) production, supply delays and sales cycle at manufacturer, (b) retailer sales cycle and (c) cash conversion cycle, as affected by supply lead-times and price positions



Note(s): American dollar (USD) to Euro daily exchange rate for August 1, 2017 to July 16, 2020

Figure 3.
Variable *COGS* at the manufacturer in Euro per metric ton (*MT*)

Due to shorter order cycles, the *SLT* retailer received inventory with updated price variations earlier and more frequently than the *LLT* retailer, and presented lower prices during the period of decreasing *COGS*. The opposite was valid when an upward trend in cost variation was observed.

As the interval between orders reduced from 50 to 30 days, the difference of inventory price positions between *LLT* and *SLT* also decreased. On the other hand, reducing cost variation transfer from 100 to 50% for both *LLT* 50 d and *LLT* 30 d increased the difference of inventory price positions between *LLT* and *SLT*.

Figure 6 presents CM_d for *LLT 50 d* and *LLT 30 d* retailer scenarios. Figure 7 depicts CMd for the *LLT 50 d CT* and *LLT 30 d CT* retailer situations. These graphs indicate that the longer supply lead-time resulted in higher CM_d variation when compared to the shorter lead-time.

Table 1 compiles the summation of CM_d for different periods for the various lead-times and cost transfer policies. For the total period, *LLT 50 d* yielded the highest total contribution margin. For the period 1 to 90, 1 to 180 and 900–1,081 days, the *LLT 50 d CT* condition resulted in the highest summation of contribution margins for the respective periods. Between 270 and 900 days, *LLT 30 d* produced the highest sum of contribution margin.

Figure 8 shows *C* behavior, expressed in days, for *LLT* 50 d and *LLT* 50 d *CT* scenarios, and Figure 9 presents *C* in *LLT 30 d* and *LLT* 30 d *CT* scenarios. For all scenarios, the initial

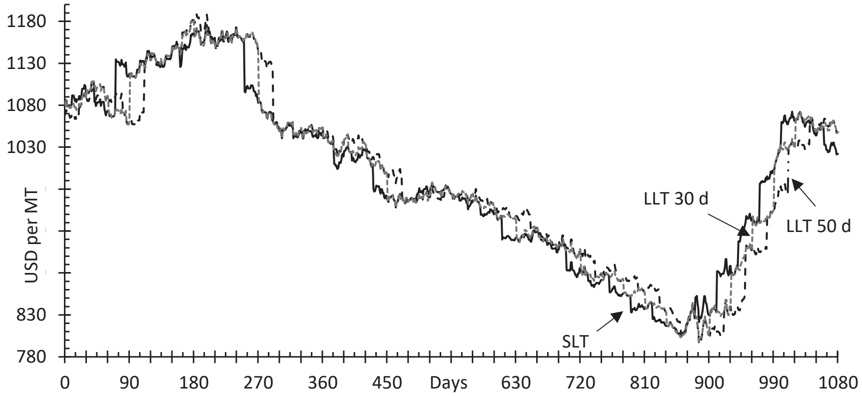


Figure 4.
Daily retailer product price in *USD* per *MT* for short lead-time (*SLT*), long lead-time with 50 days interval between orders (*LLT* 50 d), long lead-time with 30 days interval between orders (*LLT* 30 d)

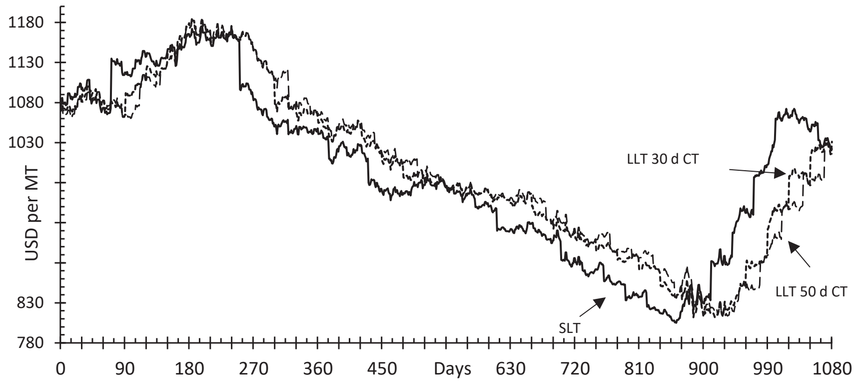


Figure 5.
Daily retailer product price in *USD* per *MT* for short lead-time (*SLT*), long lead-time with 50 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 50 d *CT*), long lead-time with 30 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 30 d *CT*)

inventory size was set at 650 MT at the beginning of the simulations. In the first days of simulation, the strong reduction of *C*, especially in *LLT 30 d* and *LLT* 30 d *CT,* can be explained by the onset of sales, leading to a reduction of $\bar{i}$, while replacement was still in production or shipment. To eliminate this effect of initial inventory size, we estimated the average *C* and respective variances from 90 to 1,081 days of simulation for the four scenarios. The average *C* results were 39.7, 39.6, 33.9 and 34.1 and variance of 8.2, 20.1, 8.4 and 14.3, respectively, for *LLT* 50 d, *LLT* 50 d *CT, LLT* 30 d and *LLT* 30 d *CT*. Order size for *LLT* 50 d and *LLT* 50 d *CT* are bigger to cover for the longer interval between orders, and thus higher variation of $\bar{i}$ observed in Figure 8 as compared to Figure 9.

The communication registered between manufacturer and retailer management teams in the period under study, related to the days simulated in the model, is shown in Table 2. These exchanges reflect the commercial decisions taken by the managers in charge. The tone of the exchanges and topics indicates a business-as-usual routine before December 2018, a challenging sales period from December 2018 to January 2020, and a positive business outlook from June 2020.

COGS and *USD* to Euro ratio curves presented a high correlation for the period reported (Figure 3). This sign confirms the price variation influence among diverse commodities, including currency, based on the current trading practices of currency and agri-commodity futures. Chiaie *et al.* (2017) indicate that the overall world economic activity is the common driver for agri-commodity price trends in the long term. This observation suggests that demand sets the perception of value for these products, hence their price. In practice, for the present case, this implies that sales managers have a narrow window to set a competitive

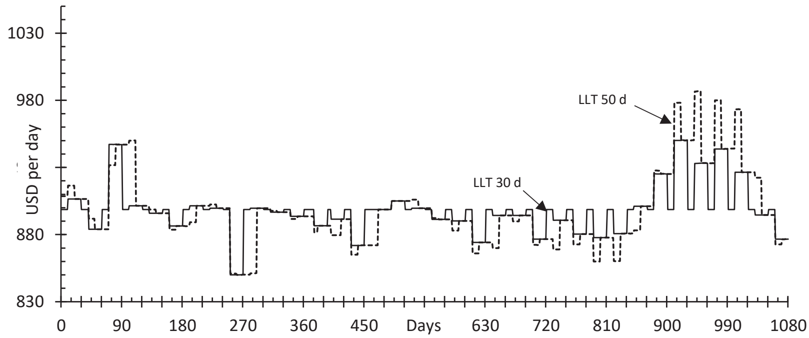


Figure 6. Sales daily contribution margins (CM_d) in *USD* at retailer long lead-time with 50 days interval between orders (*LLT* 50 d), long lead-time with 30 days interval between orders (*LLT* 30 d)

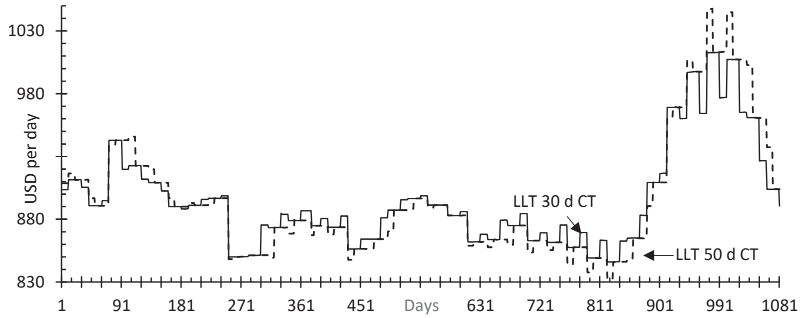


Figure 7. Sales daily contribution margins (CM_d) in *USD* at retailer long lead-time with 50 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 50 d *CT*), long lead-time with 30 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 30 d *CT*)

price that maximizes CM_d in the face of competition, and information delays of day-magnitude can impact q, CM_d, and C.

Discussion

C, expressed in days, indicates how long it takes for a company to convert its inventory investments into cash from sales. A negative C suggests that suppliers finance the inventory

Table 1. Summation of daily contribution margins (CM_d) for different simulation periods for the different lead-times and cost transfer policies

	Contribution margins in *USD*			
Days simulation	*LLT* 50 d	*LLT* 50 d *CT*	*LLT* 30 d	*LLT* 30 d *CT*
1 to 1,081	1,941,602.30	1,936,194.25	1,941,488.58	1,936,760.94
1 to 90	82,664.66	82,984.98	82,608.91	82,846.30
1 to 180	164,265.84	165,555.37	163,240.54	164,603.97
270 to 900	559,457.86	546,953.46	563,960.71	551,086.05
900 to 1,081	169,966.54	178,763.54	166,262.16	175,777.16

Note(s): *LLT* 50 d – long lead-time with 50 days interval between orders; *LLT* 30 d – long lead-time with 30 days interval between orders; *LLT* 50 d *CT* – 50 days interval between orders and 50% of cost variation transfer to price policy; *LLT* 30 d *CT* – long lead-time with 30 days interval between orders and 50% of cost variation transfer to price policy

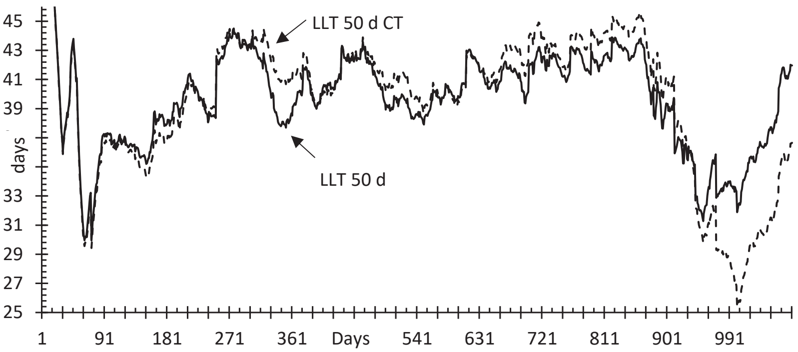


Figure 8. Cash conversion cycle (C), expressed in days, for long lead-time with 50 days interval between orders (*LLT* 50 d), long lead-time with 50 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 50 d CT)

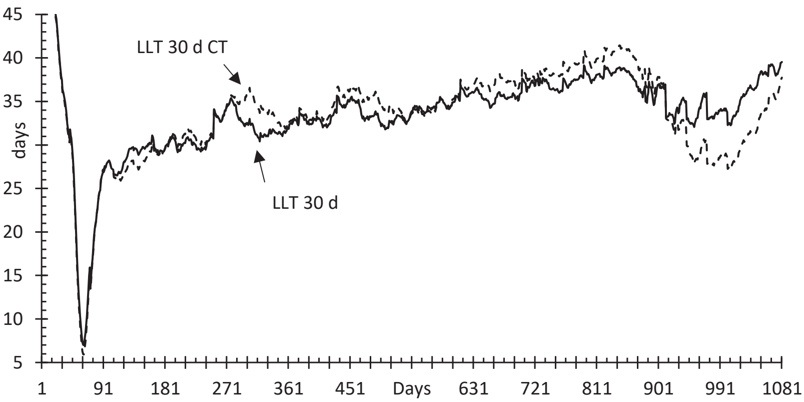


Figure 9. Cash conversion cycle (C), expressed in days, for long lead-time with 30 days interval between orders (*LLT* 30 d), long lead-time with 30 days interval between orders and 50% of cost variation transfer to price policy (*LLT* 30 d *CT*)

Table 2.
Communication between manufacturer and retailer management teams in the period under study, related to the days simulated in the model

Days in simulation	Date	Communication
0–499	August 2017 to December 2018	Regular contacts on daily operation, market demands and competitors, technical support and after-sales, business development
500	December 2018	Manufacturer proposes portfolio expansion to retailer aiming at diversifying to less competitive segments
550	January 2019	Manufacturer proposes new service to end clients aiming at loyalty building
610	April 2019	Retailer requests product composition review and optimization aiming at feature improvement and price reduction
620	April 2019	Retailer reports a major client lost to competitor due to price
640–650	May 2019	Retailer reports new competitor in the market, with competitive prices and better credit terms Retailer compares product specifications against main competitors and requests product features update aiming competitiveness Retailer reports competitor able to offer feature richer and cheaper product Retailer discard service for loyalty introduced in January as ineffective
670	June 2019	Manufacturer offers redesigned product aiming at price competitiveness
880	January 2020	Retailer requests a new product brand and marketing positioning hoping for competitiveness
1,035	June 2020	Quantity sales reported by retailer in an all-time high levels

of their clients. A low and stable C is desirable from a managerial perspective. CM_d represents earnings available to fund fixed expenses and generate business profit. In this exercise, a low C and high CM_d are the parameters to identify the best alternatives.

The *SFD* describes a dummy competitor as a reference point to measure the supply chain delay effects on the chosen dependent variables. The apparent solution for the manufacturer under study would be moving production closer to the retailer's warehouse, which demands investment or acquisition. The alternative optimization measure simulated here was the increase in the frequency of smaller orders. The total lead-time would not change, but its effect on the contracted price position would reduce, as replacement inventory with updated prices would arrive in a higher frequency. In this scenario, LLT 30 d improved C in almost six days, compared to LLT 50 d, and the difference in CM_d for the total period in both scenarios was negligible. The invoice date or credit terms were not relevant for the retailer's price-setting process, as the price was agreed with the manufacturer at the moment of order confirmation at the beginning of the cycle. In turn, this price became the variable cost of the retailer's price toward their clients.

Based on equation (6), theoretically, sales managers should pass on only half of the cost changes onto their prices to maximize q, compensating unit margin loss in case of price increases. Some success cases in the fast-moving consumer goods sector are available (Simon and Fassnacht, 2019, p. 284). For the current study, this cost transfer strategy recommendation depended on the cost upward or downward trends. As observed in Table 1, in the period between 270 and 900 days, CT reduced the total CM_d for the period with a downward cost trend. On the other hand, in the period between 900 and 1,081 days, CT increased the total CM_d. It is worth noticing that in the cost downward trend period (270–900 days), the increase in order frequency with a 100% cost transfer to price resulted in improved CM_d. These findings agree with the rationale behind equation (6), where extra q compensates for a lower p and unit P, provided cross-price elasticity remains unchanged.

For the period between 500 and 900 days in the model, the communication between the manufacturer and the retailer (Table 2) confirms their concern about lack of competitiveness, fear of new entrants, risk of lost clients and need for new product designs, which is evident on account of the emails and sales meeting minutes recorded during the period. These complaints reduced after the 1,000 days, as the sales quantity increased. This report did not propose a proper methodology to compare the simulation output with the subjective behavior of the sales teams. Nevertheless, the mathematical simulation and communication appear to coincide.

ξ_{ij} in this exercise was arbitrarily set. Based on the reported purchasing behavior of customers and the nature of the animal production cycle, it was fair to assume that the products were purchased, meaning that final users were unable to delay the decision when their inventories run out, as animals need to be fed. The price quotation process is relatively simple, and costs to change suppliers are low, leading clients to base their decisions on the best offers of quality and price. Finally, the offering, expertise, quality, cost structure and brand reputation of the manufacturer and competitor were considered to be similar. In the present model, we simulated the outcome of halving or doubling ξ_{ij} proposed and observed a lower and a higher variation, respectively, on the CM_d and cash conversion cycle curves during the 1,080-day simulation. This observation of the behavior of these curves is in line with ξ_{ij} conceptual framework, as it indicates how quantity sold will shift away from competitors increasing their prices.

Yasarcan and Barlas (2005) predict three types of delays in inventory flow: material supply, information and secondary stock control delays. These authors demonstrate how the different departments of a company contribute to the buildup of various delays and propose a model framework to group and analyze them in one structure to better organize production and ensure supply stability (Yasarcan and Barlas, 2005). Our interest, however, is to look at a different aspect of the effect of specific price information linked to material flow delays. For such a delay in inventory price information does not have direct relevance in optimizing inventory flow and supply stability. However, it impacts the price decisions of sales teams downstream the supply chain, as demonstrated by our results. In this paper, we expand the ideas developed by Inman *et al.* (2020) into a real case scenario. Those authors initial intention was to predict supply and demand curves in the energy sector (Inman *et al.*, 2020). Our data suggest that one can forecast sales volumes and profitability in a different economic sector.

To evaluate the applicability of the knowledge derived from the above exercise, one should recognize the psychological component among sales managers in observing and interpreting financial parameters. Mathematical models will exert a relative influence on how they craft business decisions, and their perceptions, experience and beliefs will play a decisive role. A similar behavior is observed in client value perception and price acceptance (Nagle *et al.*, 2010, p. 74), as well in emotions, risk tolerance, judgments and post-purchase experiences (Simon and Fassnacht, 2019, p. 221).

Long series data analysis, multi-parameter commercial modeling, similar to those plotted in the present exercise, are not typical in day-to-day business. Sales managers perceive the cause–effect connections in much shorter cycles. Accordingly, variations in CM_d can lead to the wrong interpretation of their causes. Negative variation in contribution margin could lead to pricing decisions that trigger a vicious cycle among players or clients in the market.

Conclusion

The model designed fulfilled the original objective of evaluating *SD* modeling as a practical tool to integrate econometric price equations into a dynamic model to assess material and information flow delays in supply chains. In this specific case, the model estimated the effect of information and material delays on CM_d and C. Increasing the retailer's frequency of orders was the best strategy to optimize CM_d and C, based on the current parameters.

The cause and effect connections in the system became evident only after the model was completed. Business departmentalization, varied experience, communication styles among managers and the cognitive challenges to mentally handle the amount of information dumped in a software model cannot be grasped by a team alone.

The effectiveness of modeling a business operation lies in expanding the understanding of the interconnections among the different activities and the consequences of managerial decisions. This cognitive expansion leads to a broader analysis of creative options that could not be visualized otherwise. The final objective is not a precise prediction, but rather to improve communication and understanding among the sales managers in charge.

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