Abstract 025-1610

Describing Regional Knowledge Sharing in the Supply Chain: A Non-Cooperative Game-Theoretic Approach

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Abstract.

Manufacturing competitors in the same region commonly have similar production strategies developed with similar knowledge. They compete against similar organizations in other regions to win manufacturing contracts. In this paper, we propose a game-theoretic approach to describe strategies and their implications when competitors share knowledge to improve regional competitiveness.

1. Introduction

In a supply chain that competes as a single entity, the type of shared knowledge is relevant to the way in which the specific companies, within the supply chain, compete. Each link of the supply chain can offer specific capabilities that are acquired locally. For this reason, manufacturing competitors in the same region commonly share similar production strategies, and such strategies could be developed with similar kinds of knowledge.

The relevant kinds of knowledge include: (i) knowledge applicable to specific processes, (ii) critical number of workers, employees and managers with such knowledge, and (iii) the regional educational and research infrastructure where technology in production is developed. These three kinds of knowledge provide the region competitive advantages (Estrada, 2011).

Organizations are constantly competing against similar groups in other regions to sign contracts for the production of new products. This situation makes the knowledge sharing process among all the involved parties, even among the competitors, a more relevant topic. This is relevant to managers knowing that such knowledge sharing is needed for making the region more competitive.

The above situation presents a dilemma. The interest of local organizations to share knowledge, even among competitors, in order to become more competitive on a regional basis, may conflict with the interest of global knowledge sharing, in the supply chain as a whole, as it could mean loss contracts or in their volume of production (see Figure 1).

Knowledge transfer is an important factor in the evolution of the supply chain. Inside the companies, however, the process of knowledge transfer is thought to be a double-edged sword that causes or increases competition (Myers and Cheung, 2008). Nonetheless, there is literature identifying the mechanisms used by some regions to develop and transfer specific knowledge in order to be competive. Examples of such neutral mechanisms include local academic institutions, professional organizations, labor market and R&D institutions inside the cluster in which competing local Component Suppliers (CS) collaborate with different Contract Manufacturers (CM) (Hisamatsu, 2008; Estrada, 2011).

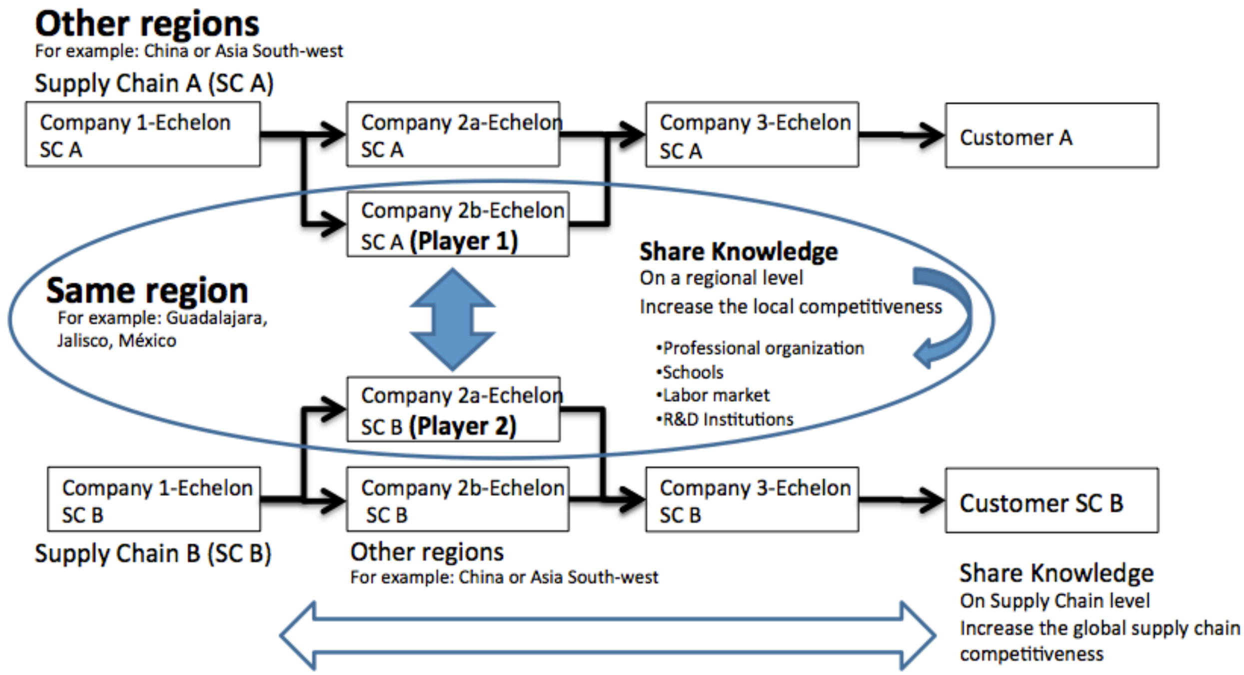

Figure 1. The need of regional knowledge sharing, for regional development, may conflict with competitors interests.

In this context, the knowledge transfer mechanisms are needed to increase the competitiveness in the region regardless of the competition among its local companies. For operations managers and their staff, it is important to achieve regional competitiveness. This is because companies are constantly competing with similar operations of the CM, but in different regions, in order to win manufacturing contracts of the same products.

In this paper, we propose a non-cooperative game model to formally describe (and provide some insights) the knowledge sharing conflict inside a cluster between two competitors (players), that could transfer or not, differentiated, complementary and relevant knowledge to its competitor to increase their/its learning curve benefits. We focus on the actor's preferences representation. Based on co-opetition concepts, if this two competitors share their knowledge, they could reach higher benefits than individually.

The relevance of our study, we believe, relies on the qualitative analysis of regional supply chain problems with game theory. Such framework complements the more commonly used control-theoretic approach. This complementation is because the common approach centers on clearly measurable variables rather than strategic issues.

2. Literature Review

Supply chain coordination strategies as the triple-A supply chain (Lee, 2004) implies that each echelon shares knowledge and information with its suppliers and customers. Myers and Cheung (2008) worked on the problem of knowledge sharing in the supply chain and found a double-edge sword in the process of transfering knowledge that causes or increases competition. This last concept defines a framework in which this work bases the dilemma of transfering knowledge or not between two suppliers at the same level of a supply chain. A germinal idea for this work is information sharing under co-opetition, term coined by Braderburg and Nalebuff (1997).

In Raweewan and Ferrell (2007), authors study information sharing as a two-player game, analyzing information-cost utility functions, various risk-aversion degrees (e.g. risk-averse, risk-neutral, etc.), and two situations: cooperation-competition and co-opetition. Nagarajan and Sošić (2008), analyze cooperation in the supply chain. Authors study cooperation in the sense of coalition using cooperative games. The emphasis is in profit allocation and stability among all supply chain partners. Leng and Parlar (2009) use cooperative games to analyze the problem of cost savings allocation in a three-level supply chain. The players are a manufacturer, a distributor and a retailer. Authors investigate the cost savings splitted among the members of coalitions of two and three players. Fu (2010) studies the innovation value and knowledge cost using dynamic games. The author analyzes, through game equilibrium, the relation between the knowledge sharing and self-learning costs in a two-player game. Ren et al (2010) study forecast sharing and supply chain coordination in one-shot and long-term scenarios. Authors found that, in a one-shot game, information is not truthfully shared, contrasting the argument with a long-term relationship.

Additionally, Cachon and Netessine (2006) survey the most commonly used game-theoretic concepts in supply chain analysis. For a thorough introduction to game theory we refer the reader to Osborne and Rubinstein (1994).

3. Dilemma of Knowledge Sharing in a Regional Cluster

Knowledge and information are sources of competitive advantage in supply chains. Even concepts as triple-A (Agile, Adaptable and Aligned), coined by Lee (2004) to describe strategies that could make more eficient companies and its supply chain, requires knowledge and information sharing between diferent echelons (Lee, 2000). However, not every piece of knowledge has the same impact when it is transferred from one echelon to other as its value depends on the relevance and pertinence for the receiver organization (Myers, 2008).

Many times, one echelon (e.g. Contract Manufacturer), can have two or more suppliers (e.g. Component Suppliers) that can have similar situations inside a cluster: they need to develop new processes, improve them, design components, acquire new technology and develop new knowledge based on the previous one. That means they require to develop capabilities to accelerate their learning curves by themselves or with the help of other organizations, even their own competitors.

The value of relevant knowledge that is in possesion of each competitor could be levered by sharing and developing groups inside a cluster, even between competitors, in order to achieve situations of higher competitiveness which acelerate their learning curves and increase the total production volume. However, these strategies are based on trust betweeen each decision maker and also involve risk of unfair situations in which one competitor shares its knowledge and the other doesn't. The analysis of these specific situations is within the purpose of this paper.

Nevertheless, in modern business, firms compete in some areas while they cooperate in others in order to increase their benefits. This approach has been called co-opetition (Brandenburger, 1997). Co-opetition strategies can lever the benefits of knowledge sharing to higher stages.

This strategy could be applied to supply chains and specifically to situations, where two competitors, that belongs to the same echelon and cluster, e.g. component suppliers, can transfer relevant knowledge to their competitor. In this way, they produce a combined effect greater than the sum of their separate effects that develop their common cluster making it more competitive at supply chain level. This sinergistic relation can develop the cluster faster than other regions, even for local specialization.

The dilemma of knowledge transfering from one player to its competitor, following a co-opetition strategy, has a negative side that appears when this knowledge make the competitor more competitive without a positive feedback to the firm that is sharing knowledge.

Additionally, we assume that the decision of sharing knowledge is not only rational; it's affected by human behaviour.

From a practical point of view, knowledge transfering is also related to learning. According to the Oxford English Dictionary (2005), "learn" is a verb that means: *gain or acquire knowledge of or skill in something by study, experience or being taught*. Knowledge is transfered by information. However, there is a large list of types of information that could be shared at different levels of the organization. This paper only works with that kind of knowledge that can improve (or decrease) the cost of a unit as the total production volume increases, based on the learning curve concept. At the same time, we assume that the value of this knowledge learned by a competitor can be measured, is relevant and its value can be levered when is shared.

There are some kinds of knowledge, and the information related to this, that can only be shared "all" or "nothing", however there is group of pieces of knowledge that could be shared along a continumm from nothing to everything. Raweewan (2007) states that a mixed strategy has the potential to be useful for many different types of information related to supply chain optimization. We think that this concept can be analyzed to optimize the supply chain for two competitors of the same echelon in the same regional cluster.

4. Learning curve

The learning curve effect phenomenon has helped to predict the trend that input costs decrease smoothly by some consistent percentage each time cumulative production doubles (Wright, 1936; Andrees, 1954; Hirschmann, 1964; Albernathy, 1974; Marshall, 1975). This phenomenon has been explained as a result of the capability of organizations or individuals to potentially improve all inputs of the production process, product design and new technologies.

Nowadays, supply chain strategies for many contract manufacturers and component suppliers are based on the learning curve concept. Frecuently, price decisions require accurate analysis of cost reductions based on future learning and knowledge adquisition (see Figure 2). These learning curves are related to production quantities and capabilities developed by workers, selection processes, training, organizational structure, technology and interorganization knowledge sharing. These learning curves could also be accelerated by sharing differentiated, complementary and relevant knowledge like process improvement.

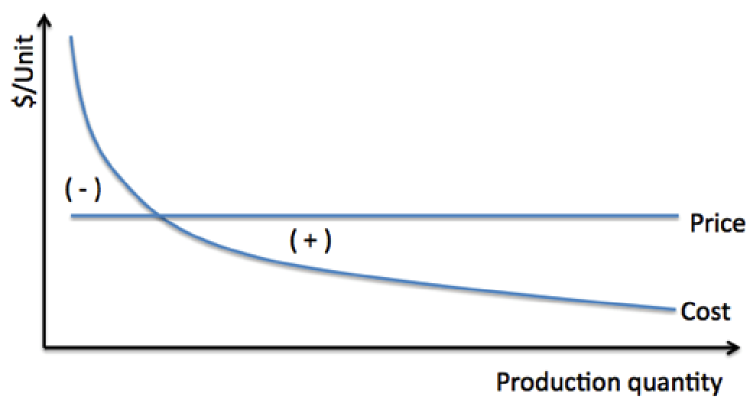

Figure 2. Price and cost decisions as a function of production quantity.

This phenomenon has been observed, not only in an isolated organization, but along the supply chain, e.g. Contract Manufacturers (see Figure 3). Henderson and the Boston Consulting Group (1968, 1973) extended the learning effect to activities other than production tasks creating the "experience curve" concept, which is related to management and implementation as a type of knowledge that is based on organizations. However, they explain the performance of this phenomenon in a similar way involving constant improvement rates each time total production doubles.

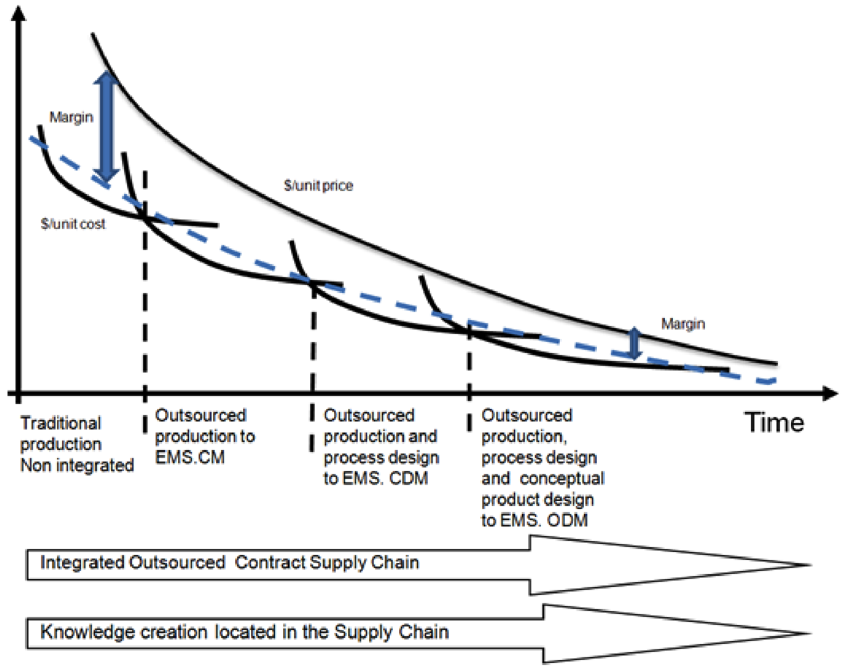

Figure 3. Supply Chain evolution based on Huckman (2006)

The basic rule used for representing the learning curve effect states that the more times a task is performed, the less time will be required on each subsequent iteration. This relationship was probably first quantified in 1936 at the Wright-Patterson Air Force Base in the United States, where it was determined that every time total aircraft production was doubled, the required labour time decreased by 10 to 15 percent. Subsequent empirical studies from other industries have yielded different values ranging from 2% up to 30%, but, in most cases, it is a constant percentage: it did not vary at different scales of operation. Learning curve theory states that as the quantity of items produced is doubled, costs decrease at a predictable rate.

The basic model of the learning curve effect describes the required cost for producing a specified unit in a production run. Let Y_v be the number of direct labor hours required to produce the v-th unit. Therefore, the learning curve equation is given by

$$Y_V = Lv^{\log_2 b}$$

(1)

where L is the number of direct labor hours needed to produce the first unit, v is the number of units produced and b is the learning percentage.

In this paper, we propose using equation (1) to model the effects on the payoffs when two players share certain percentage of their knowledge between them. That is, we assume that sharing information and knowledge has an impact in the learning curve of each player.

5. Problem Model

In this section, we first introduce the notation that is used throughout this paper and set the game estrategies followed by two players that are assumed to be co-opetitors. We then describe the methodology that we use to model the utility functions and the procedure to find the equilibrium points of the game.

5.1 Notation

Let P_1 and P_2 be two players that have valuable knowledge about their products and processes but this knowledge might differ from each other. Both players most decide if they share or not, their knowledge and, if they do, the extent of knowledge that they share. In a co-opetition framework, there are two basic pure strategies:

{does not total transfer knowledge, total transfer knowledge} = {*DNT*, *T*}

When players interact with each other, each one of them assume one of the following positions: loner, giver, receiver, or exchanger (see Table 1). Let s_k, $0 \le s_k \le 1$, be the strategy followed by player k regarding the degree of knowledge transfering. The value for strategy s_k, assuming player k follows either one of the pure strategies described above, is given by:

$$s_1 = \begin{cases} 0, & \text{if } P_1 \text{ decides } DNT \\ 1, & \text{if } P_1 \text{ decides } T \end{cases} \quad ; \quad s_2 = \begin{cases} 0, & \text{if } P_2 \text{ decides } DNT \\ 1, & \text{if } P_2 \text{ decides } T \end{cases}$$

(2)

Under this context of knowledge sharing, strategy pairs $(s_1, s_2) \in [0,1]\times[0,1]$, provide the percentage of knowledge that both players are willing to share in the game.

		P_2	
		Does not transfer knowledge (*DNT*): $s_2 = 0$	Transfer knowledge (*T*): $s_2 = 1$
P_1	Does not transfer knowledge (*DNT*): $s_1 = 0$	Loner / Loner	Receiver / Giver
	Transfer knowledge (*T*): $s_1 = 1$	Receiver / Receiver	Exchanger / Exchanger

Table 1. Interaction decisions between two players

As described in the previous section, in this research we consider the payoffs for each player, under the chosen strategy, as a function of the required labor hours needed to complete a certain number of units in a production run assuming the learning curve model given in equation (1). That is, let $c_{i,j}^{k}$ be the payoff of player k when strategy chosen is i and the strategy chosen by the other player is j. Therefore,

$$c_{i,j}^{k} = v^{\log_2 b_{i,j}^{k}} \quad (3)$$

where $b_{i,j}^{k}$ is the learning percentage for player *k* under strategy pairs (*i, j*). Thus, payoffs are directly related to the learning percentage of each player and knowledge transfering consists of sharing a portion of a player's knowledge that could improve the competition's knowledge (e.g. process improvement). The result of such interaction is a payoff matrix that describes the value of information under a co-opetition framework.

5.2 Payoff Matrix and Utility Functions

The objective in this model is to determine the percentage of knowledge that each player should share in order to improve his processes and, ultimately, achieve cost reductions that could increase the player's competitiveness. We follow the methodology proposed by Raweewan and Ferrell (2007) to model the utility functions for both players and calculate the equilibrium points of the game. The methodology works as follows:

1. Calculate the payoff matrix of the pure strategies for each player.
2. Calculate the mixed strategies for each player, that is, the possible strategies that incorporate percentages of knowledge sharing between the two players.
3. Determine the utility function for each player as a function of the payoffs for the pure and mixed strategies. This utility function provides the corresponding payoff surface.
4. Standardize the payoff surfaces of each player to determine optimal payoffs at equilibrium. The standardization is calculated, as proposed by Sun and Xu (2005), as follows:

$$u(s_k) = \frac{\text{payoff associated with strategy profile } s_k}{\text{the highest payoff that a player can gain}} \quad (4)$$

5. Find the equilibrium points generated in the intersection of the standardized utility surfaces and determine the marginal utility functions for each player.
6. Calculate the optimal levels of knowledge sharing for each player at equilibrium and determine the optimal learning percentage that corresponds to the optimal strategy.

Payoffs for player k are calculated using equation (3), where $c_{i,j}^{k}$ is the estimated payoff for player k when player k follows strategy i and the other player follows strategy j. The corresponding payoff matrix associated with pure strategies for both players is given in Table 2.

		P_2	
		Does not transfer knowledge (*DNT*): $s_2 = 0$	Transfer knowledge (*T*): $s_2 = 1$
P_1	Does not transfer knowledge (*DNT*): $s_1 = 0$	$c_{0,0}^{1}$ \ $c_{0,0}^{2}$	$c_{0,1}^{1}$ \ $c_{0,1}^{2}$
	Transfer knowledge (*T*): $s_1 = 1$	$c_{1,0}^{1}$ \ $c_{1,0}^{2}$	$c_{1,1}^{1}$ \ $c_{1,1}^{2}$

Table 2. Matrix payoff associated with pure strategies.

As stated before, each player need to determine the mixed strategies that he will be following. The values of the strategy –the percentage of knowledge transferred to the other player, ranges between zero and one. The next step is to determine a suitable nonlinear utility function which value at the pure strategy pairs (s1, s2) is equivalent to the corresponding payoff at those points.

In this research, we have selected the nonlinear utility function proposed by Luenberger (1998). Let $f_k(s_1, s_2)$ be the utility function for player k, which could have a convex or concave shape depending on the profile of the player. For the concave case, the nonlinear function is given by

$$f_k(s_1, s_2) = c_{0,0}^k - s_1^n - s_2^m - \left(c_{1,0}^k - c_{0,0}^k + 1\right)s_1 + \left(c_{0,1}^k - c_{0,0}^k + 1\right)s_2 + \left(c_{0,0}^k - c_{1,0}^k + c_{1,1}^k - c_{0,1}^k\right)s_1 s_2$$

(5)

where s_1^n and s_2^m, $n, m \geq 2$ are terms that define the steepness of the function, that is, they define the power of the strategy followed by each player. In a similar way, the convex nonlinear utility function:

$$f_k(s_1, s_2) = c_{0,0}^k + s_1^n + s_2^m - \left(c_{1,0}^k - c_{0,0}^k + 1\right)s_1 + \left(c_{0,1}^k - c_{0,0}^k + 1\right)s_2 + \left(c_{0,0}^k - c_{1,0}^k + c_{1,1}^k - c_{0,1}^k\right)s_1 s_2$$

(6)

The above functions have the following interpretation: when no player share information ($s_1 = 0$, $s_2 = 0$), the value of the utility for each player k is exactly $c_{0,0}^k$, the corresponding payoff when knowledge is not shared. Similarly, when both players interact transfering their total knowledge ($s_1 = 1$, $s_2 = 1$), the utility functions reflect the benefits of such transfer which comprises, the own payoff $c_{0,0}^k$ for player k, the payoff associated with knowledge transfer

$\left(c_{1,0}^{k} - c_{0,0}^{k} + 1\right)$, the corresponding payoff for receiving information $\left(c_{0,1}^{k} - c_{0,0}^{k} + 1\right)$ and, the payoff associated with mutual transfer of knowledge given by $\left(c_{0,0}^{k} - c_{1,0}^{k} + c_{1,1}^{k} - c_{0,1}^{k}\right)$.

Given the utility functions defined above in equeations (5) and (6), the standardized utility function is given by:

$$u(s_i) = \frac{f_k(s_1, s_2)}{\left|\max\limits_{s_i} f_k(s_1, s_2)\right|}$$

(7)

In the next section, we show a numerical example for two players that have different learning curves.

6. Numerical example

In order to illustrate the implementation of this methodology and their payoffs we assume players P_1 and P_2 that produce the same product, with same length of production run but at different levels of learning percentage. Table 3 summarizes these differences in the learning curves. The starting points of the game is player P_1 which is at the 90% level of learning and player P_2, which is at the 85% level. If P_1 decides to kept his knowledge (s_1 = 0) and receive knowledge from player P_2 (s_2=1), P_1's learning percentage decreases to 70% (reduces production cost) while P_2's learning level increases to 87% (increases production cost). A similar impact occurs when P_1 decides to share knowledge while P_2 decides to keep it. On the other hand, if both players decide to transfer their total knowledge, both players observe benefits in their learning percentages as described in Table 3.

Moreover, in order to narrow our research, we also assume that utility functions of players are concave, which means that both players are willing to take risks when sharing knowledge and information about their processes.

		P_2	
		Does not transfer knowledge (DNT): $s_2 = 0$	Transfer knowledge (T): $s_2 = 1$
P_1	Does not transfer knowledge (DNT): $s_1 = 0$	85% 90%	87% 70%
	Transfer knowledge (T): $s_1 = 1$	75% 93%	65% 55%

Table 3. Matrix percentage learning associated with pure strategies.

As mentioned before, the payoff function for player k is given by $c_{i,j}^k = v^{\log_2 b_{i,j}^k}$. Hence, setting $v = 50$, the corresponding payoff matrix for P_1 and P_2 is determined as in Table 4. Assuming that the utility surface is concave and $n = 2$ and $m = 2$, i.e., both players are willing to colaborate in the same degree, P_1's payoff surface can be constructed using equation (5) as follows:

$$f_1(s_1, s_2) = 0.5517613858 - s_1^2 - s_2^2 + 1.112168616 s_1 + 0.5818229743 s_2 - 0.2115042551 s_1 s_2 .$$

The above surface equation is depicted in Figure 4 for different vlaues of s_1 and s_2.

		P_2	
		Does not transfer knowledge (DNT): $s_2 = 0$	Transfer knowledge (T): $s_2 = 1$
P_1	Does not transfer knowledge (DNT): $s_1 = 0$	0.3996 0.5517	0.4556 0.1335
	Transfer knowledge (T): $s_1 = 1$	0.1971 0.6639	0.0879 0.0342

Table 4. Payoff matrix

P1's concave payoff surface

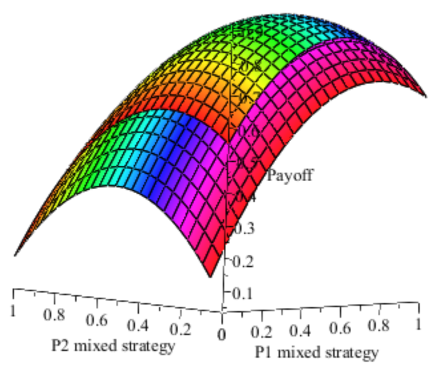

Figure 4. Concave payoff surface for Player 1.

For player P_2, we use the values given in Table 4, when $n = 3$, and $m = 2$ to build the concave payoff surface using equation (5) as follows

$$f_2(s_1, s_2) = -0.3996230840 - s_1^{\ 3} - s_2^{\ 2} + 0.7975573136 s_1 + 1.056052081 s_2 - 0.1653079822 s_1 s_2 .$$

This is graphically illustrated in Figure 5.

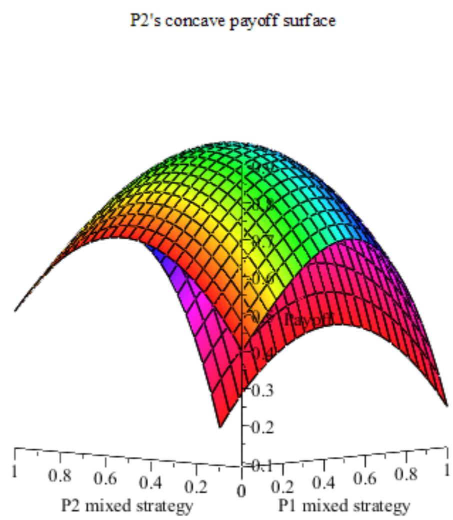

Figure 5. P2's concave payoff surface.

Next, we show the procedure used to find optimal strategies for P_1 and P_2. After the payoff matrices and payoff surfaces have been determined for both players, each payoff surface is standardized by the associated maximum payoff of each player. Here the maximum payoff of P_1 and P_2 is 0.9154 and0.9104, respectively. These values can be found at the global maximum on the payoff surface. The numerical results and their graphic representations obtained from the process of determining equilibriums are presented below. Figure 6 shows the intersection of the standardized P_1 and P_2 payoff surfaces.

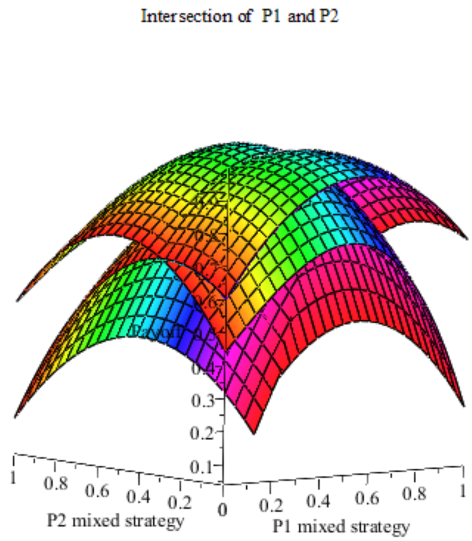

Figure 6. Intersection of P1 and P2.

The intersection of the surfaces is defined by the set of points showed in Figure 7. From this point, the values of the equilibrium points can be easily obtained as well as the corresponding marginal functions of the payoffs.

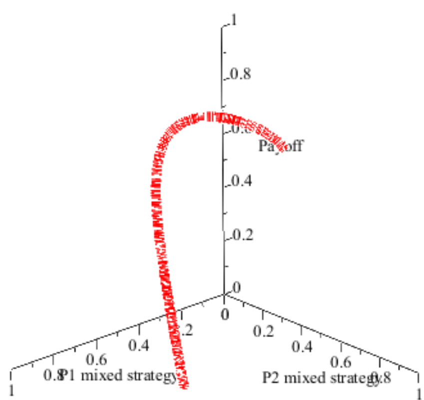

Figure 7. Intersection curve

Once the equilibrium points have been identified, the next step is to determine the optimal strategies (s_1^*, s_2^*) for both players. An analysis carried out in Table 5, shows that strategies $(s_1 = 0.5, s_2 = 0.36)$ are optimal because they lead to the highest payoffs for both players. That means that under equilibrium, the strategy for player 1 is to share 50% of his total knowledge while player 2 must share a less percentage of his knowledge (36%).

Equilibrium points	P1's mixed strategy	P2's mixed strategy	P1's payoff	P2's payoff	P1 and P2's rate satisfaction
1	0	0.31	0.635882	0.632400	0.6984
2	0.1	0.36	0.725793	0.721818	0.7972
3	0.2	0.37	0.796996	0.792632	0.8754
4	0.3	0.37	0.851083	0.846423	0.9348
5	0.4	0.36	0.886139	0.881287	0.9733
6	0.5	0.36	0.899394	0.894469	0.9878
7	0.6	0.38	0.886729	0.881874	0.9739
8	0.7	0.44	0.839387	0.834791	0.9219
9	0.8	0.53	0.738197	0.734155	0.8108
10	0.9	0.68	0.545471	0.542484	0.5991
11	1	0.89	0.194604	0.193538	0.2137

Table 5. Equilibrium points.

7. Conclusions

The methodology developed in this paper can be applied to a specific situation in a supply chain where two competitors, at the same echelon level, share relevant knowledge and develop it under a co-opetition strategy as a way to compete with other clusters. This specific situation is a common case in some industries. Thus, this paper pretends to understand how competitors in a cluster can work together and lever their knowledge. Mixed strategies analyzed by a game-theoretic approach helps to define optimum quantities of knowledge to maximize the payoff function of a learning curve. This optimum strategy is the best point along a continuous line defined by the intersection of two payoff surfaces.

Further research can be developed to analyze different scenarios in which volume and learning rates vary describing different situations related to capacity management (reactive-passive capacity; off-shore, near shore, local production, or high-low volume vs. wide-narrow mix) for specific product-process technologies, industrial sectors and under different competitor-player behavior.

There are clear limitations related to the lack of precise tools to measure human behavior, risk-aversion and the corresponding learning curve. We believe this approach opens a rich field for further research.

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